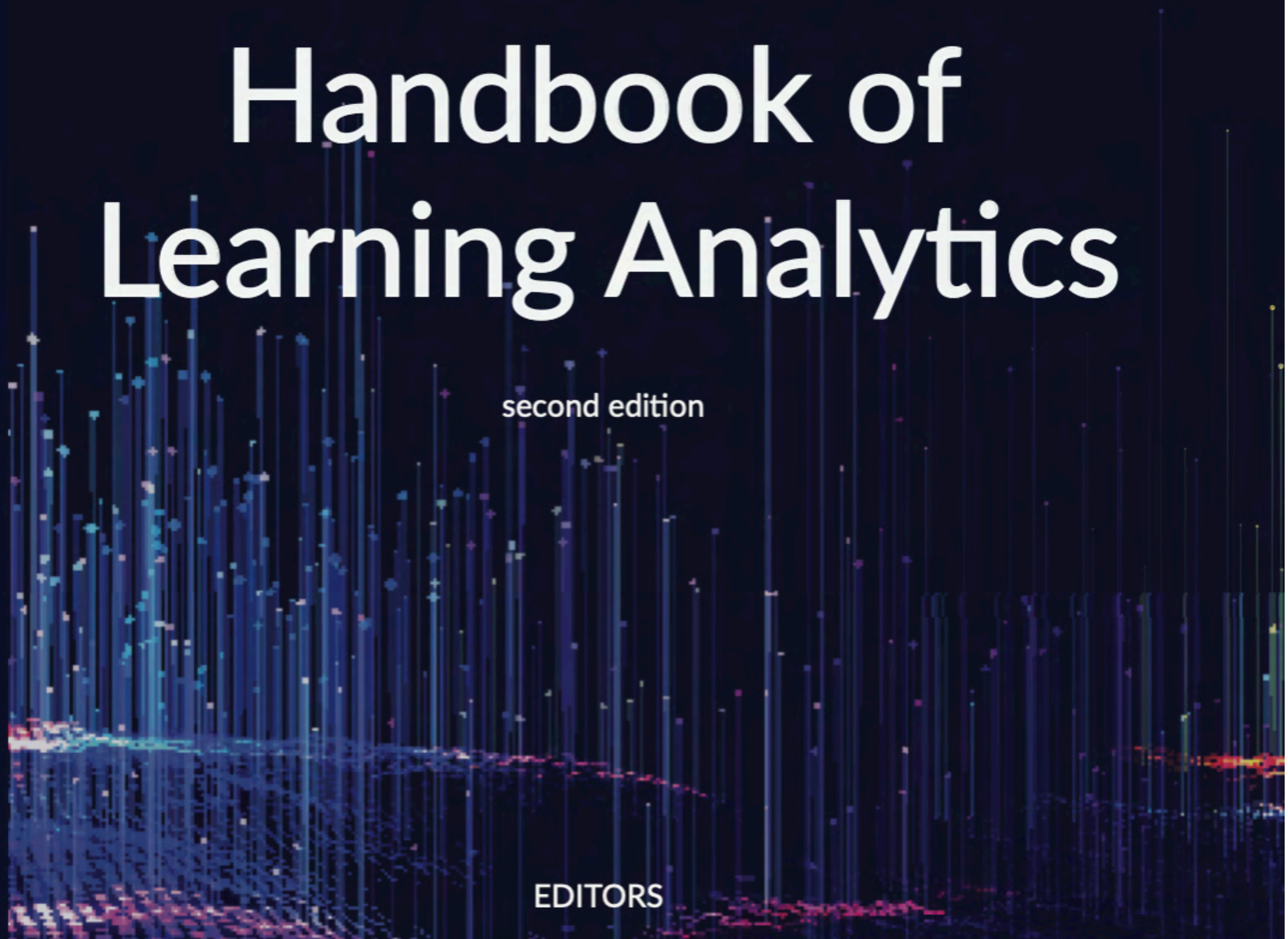
SOLAR
SOCIETY for LEARNING ANALYTICS RESEARCH

Handbook of Learning Analytics

second edition



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INTRODUCTION

Chapter 1: What is Learning Analytics?

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ABSTRACT

Over the last ten years learning analytics (LA) has grown from a hypothetical future into a concrete field of inquiry and a global community of researchers and practitioners. Although the LA space may appear sprawling and complex, there are some clear through-lines that the new student or interested practitioner can use as entry points. Four of these are presented in this chapter, 1. LA as a concern or problem to be solved, 2. LA as an opportunity, 3. LA as field of inquiry and 4. the researchers and practitioners that make up the LA community. These four ways of understanding LA and its associated constructs, technologies, domains and history can hopefully provide a launch pad not only for the other chapters in this handbook but the world of LA in general. A world that, although large, is open to all who hold an interest in data and learning and the complexities that follow from the combination of the two.

Keywords: Learning, analytics, data, technology, education, field, domain

Pinning down the precise nature of “learning analytics” (LA) is a non-trivial task and although attempts at standard definitions abound, there remains a wide variety of interpretations. A literal definition such as, “learning analytics is the analytics of learning”, simply shifts focus onto the two terms separately, both of which are contested. “Learning” carries the baggage of being a universal experience and therefore open to interpretation by anyone, including a range of academic fields that claim the definitive meaning (Anyone pursuing an interest in LA will quickly become an expert in parsing LA research from machine learning research for example). Even within the domain of human learning, vast differences arise when it is considered to be an individual cognitive process or a participatory one in which people come to take part in particular cultural practices [15]. Perhaps less obviously, “analytics”, a term that conjures up the precision and concreteness of quantitative analysis, is also somewhat fuzzy, its meaning being older and more changeable than these concepts belie. Even among professionals in the LA space, the distinction between “analytics” and “analysis” remains muddied [65]. This is not surprising since well into the 20th century the term “analytics” was more often associated with the nature of prime numbers than any area of applied data analysis [23].

Rather than provide a dictionary definition of LA, the following chapter seeks to explain LA across four dimensions: 1) As a concern, 2) as an opportunity, 3) as a field of inquiry and 4) as a community. Through these four lenses we hope to give a more holistic picture of the field and its subtleties and to provide a launching point for the other chapters in this book. While this chapter deals with the question "What is learning analytics?" in an epistemological sense, subsequent chapters answer the question, "What are learning analytics?" in terms of specific methods, applications, systems and problems that make up the field.

1 A CONCERN

From its conception LA has been concerned with solving the problems associated with the growth in the availability, quantity, speed and type of data in learning environments. The first International Learning and Knowledge Conference in Banff in 2011 posed LA as a problem in need of a solution:

> The growth of data surpasses the ability of organizations to make sense of it. This concern is particularly pronounced in relation to knowledge, teaching, and learning. [13]

Initially these problems were largely technical issues and to be sure this remains a strong concern within LA, but substantial progress has been made on how to effectively deal with standards, technical architectures, and the edtech landscape, particularly within institutions of higher education [51, Chapter 23]. In 2022, LA is at a place where, through the joint efforts of research and industry, the technical problems are at least tractable, MOOCs and the shift to remote instruction during the COVID-19 pandemic have demonstrated that large scale acquisition and analysis of its data trails about learner interactions with educational content and each other are at least possible [50, Chapter 18]. What remains less certain though are whether educational systems can meet the adaptive challenges such as changes to behavior, attitudes and processes that arise in response to these technical changes [28]. As argued by Macfadyen in Chapter 17 of this handbook, the challenges of institutional adoption pose a substantial hurdle to the widespread use of LA, and successful large-scale implementations in which LA has become a key tool to solve educational problems remain elusive [34, Chapter 17]. At the same time, although comprehensive, systematic adoption is in its infancy, the breadth of concerns that the field now considers has grown substantially.

A decade since that initial conference in Banff, LA continues to be framed as a concern, but the scope of that concern has expanded substantially. Although the wider range of problems may emanate from the proliferation of data, they now also include the contexts and purposes for which data is collected. The list of concerns has grown each year to include areas such as privacy [42], ethics [47], data ownership [30], equity [57, Chapter 20], usability [35], and the state and direction of learning analytics itself [21] to name a few. The growth in the breadth of concerns has also been accompanied by a greater sense of clarity around specific problems adjacent to data. In particular, this includes the idea that data cannot be divorced from the modes of technology that facilitate its collection, and that the relationship between humans and machines raises myriad issues in need of exploration [55, 35]. For example, questions have been raised about the introduction of technology into the classroom through sensor technology [40, 63, Chapter 6], what can be lost through mechanization [26], and the tension between learning as a creative and social endeavor and analytics as a reductionist process that is removed from human relationships [44]. Within all of this, attention has expanded beyond questions of how to deal with existing data to also examine means for collecting better, more useful, and extensible kinds. This also necessitates acknowledgment of the kinds of data that have not traditionally been collected and the dynamics of power in who makes these decisions [62, 14].

At its most fundamental level then, when considering what LA is we can point to an ever growing list of concerns that emanate from educational data and the technologies that facilitate their collection. Indeed, the problems of making sense of accumulated data that Long et al.[12] identified as important concerns back in 2011 remain as does the core hypothesis that education will experience consequences as a result of changes in the data landscape and that these consequences should be examined. However, LA is not only motivated by the existence of these issues and finding solutions to them. In addition, it arises from the premise that LA can help to solve long standing problems and create new opportunities in education.

2 AN OPPORTUNITY

The concerns thrown up by the acceleration of computing speed and storage in education are only one side of the LA coin. As well as identifying issues, LA has also been framed as a wide array of opportunities. To some extent these mirror the promises of technology more generally, from efficiency and reducing work [32, 22, 20, Chapter 16] to more sweeping claims that LA could remake education systems and ameliorate ills such as inequality and access [57, 2, 39, 37, Chapter 20, Chapter 22].

To some extent the evolution of LA as opportunity has flowed from that of the eponymous business analytics (BA). In the 1970s, some businesses saw competitive advantage in replacing intuition with insights derived from data in the decision making process [27]. This approach, although by no means universal nor having a universal implementation, has grown to be advocated for by many of the most profitable businesses in the world [7]. BA has had many and varied influences on LA, through the adoption of ideas, practices and tools within universities, schools and Human Resources (HR) departments. The logical question that is asked is, "What might translate between the management of resources and the management of learning?" Over the 1980s and 1990s, finance and administrative offices within universities began to utilize data and computational methods to make decisions and identify "actionable insights". These methods and platforms soon made their way out of budget and finance and into other administrative units such as registrars' offices where the data available involved the basic administrative operations that were much more specific to education. By the first decade of the 21st Century, "academic analytics", the application of analytics to educational administrative functions, had grown to include sophisticated modeling of enrollment and retention, as well as tentative steps to model student outcomes such as risk of dropout [9]. This was mirrored in K12 schools with the growth of data-centric improvement strategies and the development of data skills among teaching staff [36, Chapter 19].

The promise of BA is often construed not as a specific method but rather in terms of missed opportunities - there are important insights and therefore revenue left behind when data goes uncollected or unanalyzed. This sense of undiscovered wealth has been imported into LA, with data management and analytics software companies emphasizing that analytics is necessary to prevent institutions from missing important opportunities for learning, supporting students or revenue generation. In addition, in the US fifteen years of the "No Child Left Behind" legislation has emphasized the connection between student progress and robust data systems. It is important to note that whether analytic systems produce improvements in student learning remains an open question in LA, but if there was one driver of the opportunity for impact that has demonstrated enduring presence and remains the backbone of the analytics enterprise, it is the rise of use in the Learning Management System (LMS).

For the development of LA, it is difficult to overstate the opportunity that the marriage of utility (delivery of educational materials) to data (student activity) through LMSs has meant. LMSs expanded the extant data pool beyond administrative activities to actions directly taken by students in relation to their learning. At the same time this is accomplished in a centralized way that can overcome institutional barriers that might have otherwise prevented the data collection and combination [51, Chapter 23]. Such systems took some time to develop though and mirrored the development of Content Management Systems (CMS) and software as a service (SAAS) models generally [59]. MIT had experimented with a system, Project Athena, that predated the widespread uptake of personal computers in 1983 [10], but the advent of offerings in the 1990s such as FirstClass, NKI Distance Education Network and NB Learning Network, and then the creation of the open source Moodle platform in 2000 [18] opened the door to extensive, organized and centralized data streams that could be utilized to investigate learning. As these systems became integrated into the everyday operations early adopters such as the Open University in the UK began to see the possibilities of observing patterns in student data almost immediately [49]. It is no surprise that LA took root first within institutions of higher education that often have more centralized data and technology infrastructure than K-12 education.

Dominant within the rationale for much of the work motivated by the availability of LMS data was the opportunity to better understand learning, what Macfadyen calls the "LA imperative" [34, Chapter 17]. The idea that within these new data sources, either through their scale, type, or temporal characteristics, lies uncovered insight into learning - the corollary of the promise of uncovering sources of profit in BA. But learning is an altogether different phenomena from profit. As we began this chapter noting, learning is a far more slippery construct than a dollar. The potential opportunity of LA was therefore always posed as a research endeavor (the "knowledge" in the naming of the Learning Analytics and Knowledge conference is not an accident). The consequences of the availability of data about learning is a key aspect of the opportunity but what will be found within the data is far more uncertain. Nevertheless, this framing of the value learning analytics, to deepen our knowledge about learning, is a call that has been reaffirmed many times over the last decade [16].

Growth of knowledge about learning has only ever been half the imperative of LA though. Rather, LA also represents the opportunity for, "new routes for teachers to understand their students and, hence, to make effective use of their limited resources" [11]. In addition to informing teachers' learning designs and pedagogical actions, LA has also been seen as a route to offer insight directly to students that can inform their studying, collaboration or other learning activities [van Leeuwen et al. Chapter 15]. LA is applied in nature, the insight provided by data has always been for the purpose of application to educational experiences in their varied forms. Rather than limiting inquiry though, this has spawned questions around: What constitutes improvement [24, Chapter 2]. How can the application of LA be done responsibly? What should the relationship between data and instructor [36, Chapter 19]? How can the implementation of LA be done responsibly [48]? What role does the student play in the system [60, Chapter 8]? And in what way will analytics aid in the development of Artificial Intelligence and vice versa [8, Chapter 3]?

3 A FIELD OF INQUIRY

The concerns and opportunities listed above provide a clear motivation for research within LA, but these motivations are not unique to LA. Rather they are major lines of inquiry across education research in the early 21st century. It is therefore important to ask, "What makes LA a field of inquiry in its own right?", both in terms of the ideas that hold the field together and the boundaries that distinguish it from other fields and education research writ large.

What constitutes the internal connective tissue of LA, the shared concepts that hold the field together, is dependent on how we define the field. We might argue that LA holds some weight in the Khunian sense of paradigms, that there are model problems and answers that lead to a shared understanding of scientific advancement [31]. As far as such a majority view exists within LA, it is in the form of the "human in the loop" argument. The core of the human in the loop concept is that, although automation is powerful, education as a social enterprise requires human decision making [56, 19, 11]. To some extent, this is a working assumption within the field, a paradigm, and it has spawned inquiry into where and how humans and machines should interact in the processing and consumption of educational data - through data collection, algorithms, dashboards, alerts, simulations, and/or policies . More so than other concepts within LA the human in the loop acts as a North Star for the field and creates a level of internal consistency, to the extent that it provides a set of values upon which research goals are based. A successful line of inquiry within LA can be defined as one in which data is utilized to investigate the partnership of machines and humans (or the partnership of humans mediated by machines for that matter) in the learning process. Progress is made when a greater understanding of these interactions is uncovered, or applied in ways that facilitate the process. Moreover, this paradigm stands in opposition to research that seeks to supplant humans in the educational process, for example, to replace teachers with machines [52, 29].

Another approach to characterizing the scope of the field has been through bibliometrics. As of writing, there are no fewer than 14 studies that seek to characterize LA according to the relationships between published material. Universally these studies point to the substantial growth of the field from almost nothing in 2011 to thousands of published articles and book chapters ten years later. To understand how these studies might help us define LA the ten that have attempted thematic analysis are listed in Table 1 Common themes are clearly associated with

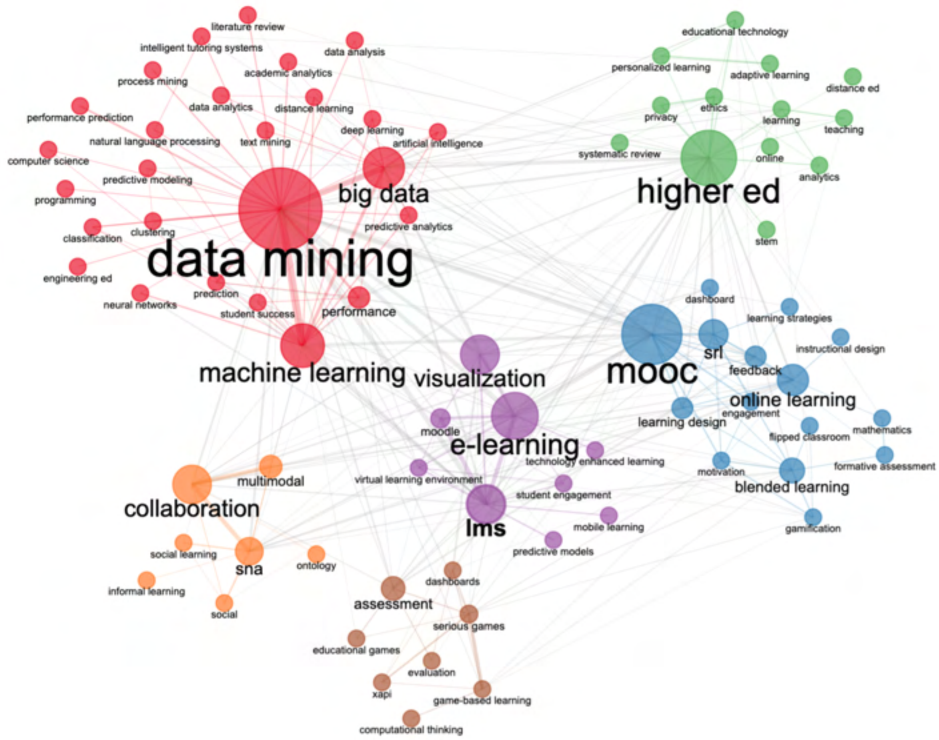

Figure 1: Keyword co-occurrence network of author assigned keywords from documents that mention "learning analytics".

technology, data, and education. Beyond these big three though there are multiple mentions of higher education, big data, data mining, and prediction. An intrepid researcher with an interest can replicate this pattern for themselves using the Web of Science Core Collection and the code appended to this chapter to produce Figure 1 - a co-occurrence network of author-supplied keywords across 4,293 articles within the topic of "learning analytics", using leading Eigenvalues-based clustering. This confirms the outsize presence of data mining and higher education but also points to the influence of MOOCs and learning management systems as well as important practices such as visualization, collaboration, and assessment.

Whether these themes are enough to distinguish LA from other fields though is an open question though. There are several closely related fields that would likely claim to share the same concerns and see the same opportunities in the growth of technology-mediated data in education [6]. These related fields include educational data mining, artificial intelligence in education, the learning sciences, computer supported collaborative learning, and the more recent educational data and learning engineering. The exact divisions between these areas are fuzzy with many researchers and their work belonging to two or more. Several attempts have been made to draw divisions empirically, Baek and Dolek [5] argue that LA and EDM continue to be used interchangeably while Dormetzil et al. [17] go as far as arguing that EDM is a sub-field of LA. More often though the two distinguishing dimensions that are most commonly appealed to as differentiating factors are methodology and the historical origins of the separate fields.

Siemens [56], Baek and Dolek [5] and Gray & Bergner [3, Chapter 2] have identified that a defining feature of LA is an expansive approach to methodology. Methodology within LA is far ranging and there is no truly common language or processes across the field by which researchers demonstrate evidence. In the Popperian sense of a research field, one that is based on shared logic and doctrines of falsification, LA may well fall short due to this methodological agnosticism [46]. However, this has not necessarily been detrimental, if anything, methodological openness has contributed to an inclusive community and may well have assisted membership growth. But there is a trade off: methodology, and specifically how arguments are made and evidence is demonstrated, are key factors in differentiating one field from another and a lack of standard methods hinders both communication between members and their ability to make convincing arguments to each other [53]. It also makes it difficult to differentiate LA from the broader world of education research, though one can contrast the short-cycle, direct and local impact of LA on the learning populations from which data is collected with the relatively extended time scale, indirect and generalized impact of educational research writ large [61].

Historical differentiation is a clearer argument to make for LA. Clow [11] ties the emergence of the field directly to the growth of the learning management system, others

Table 1: Keyword themes across bibliometric studies of learning analytics.

Paper	Education/EdTech	Data & Computing	Other
[4]	Education	Computer science, artificial intelligence, software engineering, information systems, telecommunications, electrical engineering	Scientific disciplines
[17]	Education computing, computer-aided instruction, mobile learning, ubiquitous learning, students' behaviors, assessment, curricula, design, knowledge building, learning dispositions	Computational linguistics, natural language processing, information systems, mobile applications, information science	Statistics, conceptual frameworks, linguistics, ontology
[25]	Educational theories	Methods and data analysis, data governance	Stakeholders, ethical issues, structural factors, research results
[43]	Learning design, learning performance prediction, learning theories, learning environment, learning interaction analytics, collaborative learning	Multimodal dataset, sensor, multimodal processing, machine learning related learning	
[45]	Prediction of student success or failure, analytics to inform instructional design		Policy implementation concerns
[54]	Performance, education, student, higher education, MOOC, knowledge, motivation, pattern, online learning, design	Big data, analytics, environment, educational data mining, model, online, system, technology	Framework
[58]	Student, performance, activity, learner, teacher, intelligent tutoring system	Analytics, data, environment, development, big data, application, tool, computer, outcome, system	Challenge, approach, review, case study, game, framework, use, impact
[64]	Computer-based science inquiry, multiliteracies assessment, educational curriculum, visually-enabled active deep learning, instructional sensitivity	Big data, educational data mining, spatio-temporal data	Recent work
[1]	Accuracy, correlation, predictor, higher ed institution, multimodal, semester, frequency, student, policy, collaborative learning, discussion forum, Educational-Data Mining, interoperability, expertise, lecture	Workshop, conference, privacy, risk, emergence, study	
[41]	Students, learning, activity, education	Data analytics	Use

have similarly claimed that other fields have been driven by the prevalence of new technologies. Each field is preceded by the growth of different technologies and their educational impacts: AIEd with early computerized systems such as CAROL in 1970s and 1980s, EDM with the growth of intelligent tutors in the 1990s such as AutoTutor and Cognitive Tutor and LA with the growth of Learning Management Systems such as Moodle and Blackboard in the 2000s. To some extent the field is thus culturally defined as an association between technologies, those who pioneer them and the research agendas that stems from them.

4 A COMMUNITY

LA does not exist independent from the people who utilize and participate in the label. It is therefore worth considering who these communities are and how they approach LA. Since 2011 a very sizable community has coalesced around the problems and opportunities of LA through the Society for LA Research (SOLAR). SOLAR boasts a membership just south of 1000, predominantly from the United States (46%) but located across the globe. The flagship conference (LAK) regularly boasts more than 500 attendees, with further auxiliary events supported by the Society including the annual LA Summer Institute (LASI), podcasts and webinars. Complementing these events, SoLAR also publishes the Journal of LA (which has released 24 issues to date and is indexed in Scopus and Clarivate Web of Science), this Handbook (now in its second edition) as well as position papers, a blog and a periodic newsletter to communicate with its membership.

As influential as SOLAR has been in the development of LA globally, a great deal of activity within LA also occurs outside the organization. Other LA organizations exist such as the Learning Analytics Learning Network (LALN), the Bay Area Learning Analytics Network (BayLAN) and even the Learning Analytics in European Dental Education special interest group (LAEDE). Online communities have also arisen including the popular, colorful discussions on the @learninganalytics Google Group. These less formal organizations tend to be of similar make up, largely comprising academic audiences with a smaller number of people representing commercial interests.

An important source of codification of LA practices are the various formal educational programs ranging from micro-credentials, through advanced certificates, on to Master's degrees and PhD programs. These programs reflect the diversity in approaches to the question of what LA is, and can vary widely in content. Even within a class of qualifications such as graduate certificates there is a wide range of interpretations on what the necessary skills and competencies that a graduate from a LA program should have. The University of North Dakota program is strongly technical and methodological, Monash University focuses on problem solving and practical application, Northeastern focuses more on administration and institutional decision making, while North Florida has a strong focus on psychology.

A more concrete picture of what constitutes LA is provided by the current job market. Table 2 is a summary of job advertisements from February, 2022, collected across a range of regions from the job sites: Indeed, Glassdoor, LinkedIn, Monster, PNet, Wuzzuf and Yingjiesheng. Countries were included that had at least ten advertisements that included the term "learning analytics" (roles that involved no explicit educational component were excluded, IE - "machine learning analytics"). As a snapshot from a limited number of job sites the generalizability of this data is limited, but it affirms trends that have been identified by other findings about what the practicing LA community looks like outside of research institutions [33, 38].

Overall, the job market is clear about the venues that are considered to be LA and these can be categorized quite precisely into: corporate training, education technology, government/non-profit and education providers such as schools and universities. The dominant category is corporate training, supporting the conclusions of Littlejohn [32, Chapter 16], hat a key economic driver for the field appears to be around professional LA. These jobs tend to be located within the Human Resources departments of companies and relate to the measurement of training and staff development. The range of companies that require these services span a huge diversity of areas from financial services, construction, health and sports, but tend to be focussed on analytics of the behavior of knowledge workers. It is worth noting that some also extend analytics to include customer behavior though. Similarly, within government and NGOs there appears to be a need to provide quantitative measures of human behavior as it relates to the administration of educational programs, especially those utilizing technology. In this sample there appear to be fewer opportunities with education technology providers and these roles are largely dominated by established companies such as Pearson and Wiley rather than startups. Universities are also well represented with a smaller number of positions within K12 private institutions.

With respect to skills there appears to be some diversity in expectations but not as wide as that presented by LA degrees and certificates. Educational providers themselves have clear demands of their prospective employees, largely looking for people who can manage data systems and processes or be an instructor on these topics. Within companies there is a split between roles looking for data visualization and analyses with tools such as Tableau, and roles that are more process oriented and involve data management. Roles tend to be focused on report generation, insight identification and improving decision making rather than automation though. This may indicate that automation remains the purview of engineers rather than data analysts or scientists. Whether that will change over the coming years is one of the key open questions for the field. Within government and NGO profiles there also appears to be demands for data visualization and knowledge and experience in data stewardship.

Table 2: Number learning analytics targeted jobs per region and sector.

Region		Corporate Training	Education Technology	Government/ NGO	K12/Higher Ed
Africa & Middle East					
	Egypt	8			2
	Nigeria	5	2	6	
	Saudi Arabia	10		1	
	South Africa	17		2	
Americas					
	Canada	5		2	3
	Chile	2		7	2
	Mexico	3		6	4
	USA	8	3	1	2
Asia & Pacific					
	Australia	5		1	4
	China	5	8		1
	India	7	1		2
	Singapore	13		1	4
Europe					
	Germany	3	6		4
	Ireland	7	3	1	
	Spain	3	2	4	2
	UK	15	1	2	
Total		**116**	**27**	**33**	**30**

5 CONCLUSION

There is clearly more than one answer to the question, "What is learning analytics?" Over the last decade a community has coalesced around a common set of problems stemming from the proliferation of digital data within education, made possible by advances in computing. It was not the only community to do so, but there was an early acknowledgement that the acceleration was particularly acute within higher education, where data was generated in closed systems that also had people with the necessary expertise to make use of it readily available. From this starting point the field has grown in both its membership and the expansiveness of its areas of interest. If there is a common thread though it may well lie in the etymology of the word "analytics". The word analytics comes from the Greek "to set free" or "loosen" and in a sense that remains a key part of the promise of LA. The opportunity to set free learning with new knowledge and the promise of this new knowledge leading to a sense of improvement. While the promise remains attractive, there is a need to clarify the kinds of improvement we seek to make, the most productive paths towards them, and to start to generate compelling evidence of the positive changes possible through learning analytics.

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SECTION 1

Methods & Techniques

Chapter 2: A Practitioner's Guide to Measurement in Learning Analytics - Decisions, Opportunities, and Challenges

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ABSTRACT

What is our data measuring, why are we measuring it, and what can we infer from our measurements? These are key questions for models of learning, and the focus of this chapter. This chapter discusses the role of measurement in transitioning from predictive models of learning to models from which meaningful explanations about learning can be inferred. We consider how to associate latent constructs of learning with observable data from a variety of data sources relevant to learning contexts, illustrated with examples from recent LAK proceedings. We also review common sources of errors that arise with a variety of data collection instruments, and highlight the challenges and opportunities for progressing valid and reliable measurement of both learning itself and factors related to the learning process.

Keywords: Measurement, educational data sources, latent constructs, sources of error, explanatory models of learning

In the first edition of this handbook, the corresponding chapter on Measurement linked the foundational ideas of latent trait theory and methodology as they apply to learning analytics and educational data mining [5]. For this second edition, we have sought to supplement that work with more guidance for practitioners. We have thus structured the chapter in terms of decisions, opportunities, and challenges that practitioners face in using measurement methods for learning analytics. In particular, we look at measurement choices, and their consequences for inferring explanations from learning analytics models. The first section explores measurement more generally, and decisions related to why and what to measure. The second section looks at measurement choices for a selection of learning constructs, and the challenges and opportunities that arise from each choice.

1 DECIDING WHY AND WHAT TO MEASURE

1.1 Why measure? Understanding, explanation, optimization, and/or prediction

Practitioners often use the word "measure" synonymously with "observe", including essentially all data collection. For the purpose of asking why and what we measure, with a lowercase m, there is no need yet for the kind of distinction that marks the statistical Measurement models of psychometricians, distinguished here with a capital M. Nevertheless, it is good practice to ask some *why* questions at an early stage in planning learning analytics projects. In particular, practitioners should be mindful of whether their ultimate goal is predictive or explanatory in nature. Findings that may serve predictive purposes well are not easily turned into explanatory results after the fact. Among the various definitions of learning analytics, most contain a purpose statement which references both "understanding" and "optimizing" (or "improving") learning experiences. These words reinforce one another, and learning analysts pursue both goals. In practice, however, understanding and optimization do not always go hand in hand. We begin by clarifying some of these distinctions.

The function of understanding, which is used interchangeably with explanation, is necessarily bound up with theories of learning (and, more broadly, psychology, social-cognition, etc.) and even with value systems (i.e., the desirability of behaviors and other outcomes). Explanations of learning outcomes, unless very strictly behaviorist, inevitably appeal to concepts that are not directly observable (e.g., motivation, self-concept, aptitude). Understanding is usually labored and rarely simple. Explanation must admit challenges—alternative explanations—to the validity of its arguments. Optimizing or improving learning outcomes and environments need not be so. Optimization, however, must involve a step beyond prediction.

Frequently used in learning analytics research are various types of predictive modeling. (Authors use x and y to predict z.) (to cite chapter 3 in this edition [8]). Note that predictive analytics are not necessarily causal. As is often pointed out, one variable can be predictive of another when both have a common cause. For example, more time spent in a discussion forum of a course may be predictive of (that is, it may correlate positively with) more time spent using interactive simulations. But whatever lever might be used directly to get students to spend more time in the discussion forum is not necessarily going to increase simulation usage, or vice versa. We would most likely *explain* the correlation between these two observations by appealing to overall effort commitment and/or conscientiousness. In fact, if students truly have limited (but individually variable amounts of) time to allocate to a course, then forcing them to spend more time on one learning resource might, in principle, reduce the time they allocate elsewhere.

For prediction to be used for optimization on the student side, there must at least be a causal mechanism by which some design decision, adaptation, or intervention may be expected to change outcomes. It should be noted that causal relationships may still not rise to the level of explanations. Consider this: even a child knows that pressing on the rocker switch causes the ceiling lamp to light. But this is a far cry from understanding electric circuits or what to do if the light does not go on. Detached from a larger theoretical framework of mediators and moderators, causal findings in learning analytics may still guide future research. But optimization without explanation tends to be, at best, unsatisfying and, at worst, unethical. Computer algorithms that ignore the web of interconnected personal and social variables can perpetuate and exacerbate inequitable systems [53].

All of this is not to put down all predictive modeling. Indeed prediction or classification, as ends in themselves, often involves substantial and impressive technical progress. Optimization of the learning environment does not always require explanation. An illustrative example can be chosen from slightly outside the scope of learning analytics. Trained on large image data sets, computers today can identify dogs and fire hydrants with impeccable accuracy. Using deep neural network architectures, machines can even generate new, creative images of non-existent dogs. But does a computer with such capabilities "understand" the difference between a dog and a fire hydrant? Of course not. By contrast, a visually-impaired person understands that dogs are tail-wagging, domesticated wolves that develop strong bonds with humans who feed and care for them. But that won't help in classifying a visual image that they can't see clearly. One can know things that contribute to understanding while still struggling with specific tasks, and one can optimize performance in a specific task without a general understanding. It is tempting to point out deficiencies in the computer model—for example, it won't be able to predict which one, the dog or the fire hydrant, is more likely to scratch itself or walk into the road. But of course a computer can be trained for those tasks too. Computer vision can be helpful for everyone, visually impaired or not, and self-driving cars may in time prove safer than human drivers. Understanding, sense-making, and explanation, however, will remain distinctively human pursuits.

In the remainder of this chapter, we will become a bit stricter about what constitutes Measurement with a capital M. As we shall describe, Measurement is an emergent relationship between data and latent or hidden constructs that is mediated by a model. Insofar as "measures" are used in learning analytics for explanatory purposes, practitioners should be aware of several issues and challenges (sometimes called "validity threats") that are pointed out in this chapter. We acknowledge that these issues may not apply uniformly to all data analyses, such as efforts to streamline or automate grading using machine learning methods.

1.2 What to measure? Learning constructs

The connection between data collected in a learning context and a construct of learning is not always direct. Learning analytics may be concerned, for example, with increases in student abilities or changes in student affect. Knowledge, ability, affect, and specific cases thereof are *learning constructs*. They are latent variables because they are not directly observable, so they must be inferred from directly observed indicators. It could even be said that learning constructs such as knowledge and ability are invented to explain patterns in observations, such as a tendency to solve problems correctly. Marks awarded for solving problems correctly in a test (test scores) or scale (survey) scores are directly observed indicators. Tests or surveys are instruments whose questions are considered to be Measurements of specific constructs. This is equivalent to saying that these constructs explain the observed data. However, there are limitations, some of which come down to common sense, about what should be considered a measure of what. For example, we might measure attendance and find it to be predictive of test scores. However, we do not consider attendance itself as a Measurement of ability. Given a Measurement model for the construct of conscientiousness, however, attendance might reasonably be considered a relevant indicator. Whether attendance is a high quality measure of conscientiousness, however, is still another matter.

Recent publications from Learning Analytics and Knowledge (LAK) conferences provide a sense of how the field uses Measurement. Some references are collected as elements in Table 1. Each paper is categorized by a column heading indicating a class of latent constructs (learning gains as well as traits, processes, and affective states, etc.) and a row heading representing the principle data sources for those constructs.

Determining if data collected in a learning context is a reasonable Measure of a construct of learning involves a number of steps. The first step is to identify the learning construct of interest. For example, a study may be generally interested in conscientiousness, or may be interested in a specific facet of conscientiousness like industriousness. The second step is to select an appropriate measurement model for the construct, i.e. what can be measured (observed) as an indicator for the latent (unobservable) construct of interest? As illustrated by the examples cited in Table 1, there can be a number of measurement models to choose from. For example, *boredom* could be measured by a self-reported survey, third party observation, or by analysing images of facial expressions captured during the learning task. Each measurement model has its advantages, shortcomings, and sources of error, which will be explored later in the chapter.

The third step is implementing the measurement model as a data collection instrument. For example, what facets of facial expressions will be recorded to indicate *boredom*, and how frequently should features be sampled? The goal of measurement instruments is to capture a Measurement that is both **valid** and **reliable**. **Validity** refers to the interpretation of collected data as measures of the construct of interest. For example, do questionnaire answers or facial expression, actually measure *boredom*? For what intents and purposes? **Reliability** refers to the repeatability or consistency of the instrument observations. If validity is analogous to systematic error, then reliability is akin to random error. For example, how much range in facial feature detection might be attributed to the same level of boredom? Evaluating a Measurement instrument is often an iterative process of refinement and reevaluation. Some level of error is inevitable. For example, a systematic error could be caused by questionnaire items being interpreted differently in a particular context or culture that resulted in all responses underestimating *boredom*. Another source of error could be due to individuals' facial gestures varying in their level of expressiveness, resulting in random errors of both over- and under- estimates of *boredom*.

In sum, generating Measurement models of learning constructs involves a chain of methods for data collection, data cleaning, preprocessing, exploration and modelling. As the variety of chapters in this handbook testifies, there is a rich, eclectic mix of methods used in the field of learning analytics. The resulting methodology can be considered a chain of evidence from data to inference, as illustrated in Figure 1. Every step in the chain is a potential source of both error and alternative explanation. The next section explores some of these sources of error in more detail, specifically focusing on Measurements of constructs related to learning processes, learning gain, and potential data sources for each as exemplified by the elements in Table 1.

2 CHALLENGES AND OPPORTUNITIES

2.1 Measurement of Learning Process

As illustrated by the column headings in Table 1, a range of constructs are understood to influence the learning process. These include learner disposition, learner affect, pedagogical approach and epistemological beliefs [36, 27]. Measurements that capture aspects of the learning process are important in progressing explanatory models. The following paragraphs discuss a selection of measurement models used to measure facets of the learning process, to highlight decisions and considerations relevant to their Measurement.

2.1.1 Survey data, challenges and opportunities

Surveys are a data collection instrument for a variety of learning constructs. Using existing, validated survey instruments has the benefit of ensuring results can be compared and reproduced. In addition, tried and tested statistical techniques to assess internal validity (e.g. factor analysis) and internal reliability (e.g. Cronbach alpha or McDonalds Omega) are easily applied to survey items. A challenge with this measurement model is its inherent biases, particularly for self-reported scales. Sources of error include individuals or groups interpreting scale items differently, not remembering correctly, or individual perception being an under- or over- estimate of subjective measures such as abilities, emotions, or motivation levels [49]. In some cases, self-report measures are directly connected to the construct, such as when attitude surveys ask about the learner's enjoyment and perceived value of studying math. Other times, the target construct may be significantly moderated by the respondent's own perceptions, such as a survey that asks student's about their tendency to work well in a team.

2.1.2 Trace data, challenges and opportunities

Trace data from educational technology has the advantage of removing the need for self-reporting, thus potentially eliminating biases inherent in survey data [49], as well as eliminating the effort in administering an additional data collection instrument. There is a wealth of data generated by educational technologies. Experimenting with a variety of static and dynamic features derived from trace data has generated relatively accurate predictive models in specific contexts. The challenge arises when attempting to draw inferences and explanations from these models. Recall the steps outlined earlier to evaluate observable data as a reliable indicator of a construct of learning, starting with defining the unobservable construct of interest. When analysis starts in the middle of these steps, with the observable data itself, working backwards to evaluate the measurement instrument as an indicator of a learning construct is problematic. This is because trace data reflects the instructional context that generated it. So the learning constructs it may measure, and the validity of that measurement, is dependent on how the technology was used in that instructional context. Reasonable validity and reliability in one context is unlikely to generalise to other contexts because working backwards from collected data to a measurement model is context specific. A good example of this from Table 1 is Motz et al. [36], who discuss the lack of portability of indices from VLE activity as a measure of behavioural engagement, based on an analysis of data from 829 courses. It's another side of the coin of "one model does not fit all" [17]. The evaluation of readily available trace data in one context does not fit all contexts.

For trace data to be considered a valid Measurement of a

Table 1: Citations sorted according to categories of constructs related to the learning process and 21st century skills

Data sources	Affect	Cognitive load	Collaborative learning	Non-cognitive traits	Behaviors	Domain knowledge
Image/Video	[46, 11]		[10, 52]		[10]	[25]
Text data	[9, 18]		[9, 32, 52]	[48]	[3, 15, 40, 39]	[4, 21, 26, 25]
Survey data	[20, 11]	[31]	[52]	[21, 45, 1]	[36]	
Trace data	[11]	[31]	[52]	[1, 20, 36]	[34, 36, 40, 45]	[26, 50]
Wearables/biometric	[11, 21]	[31, 46, 47]				
Network data			[41]			[43]

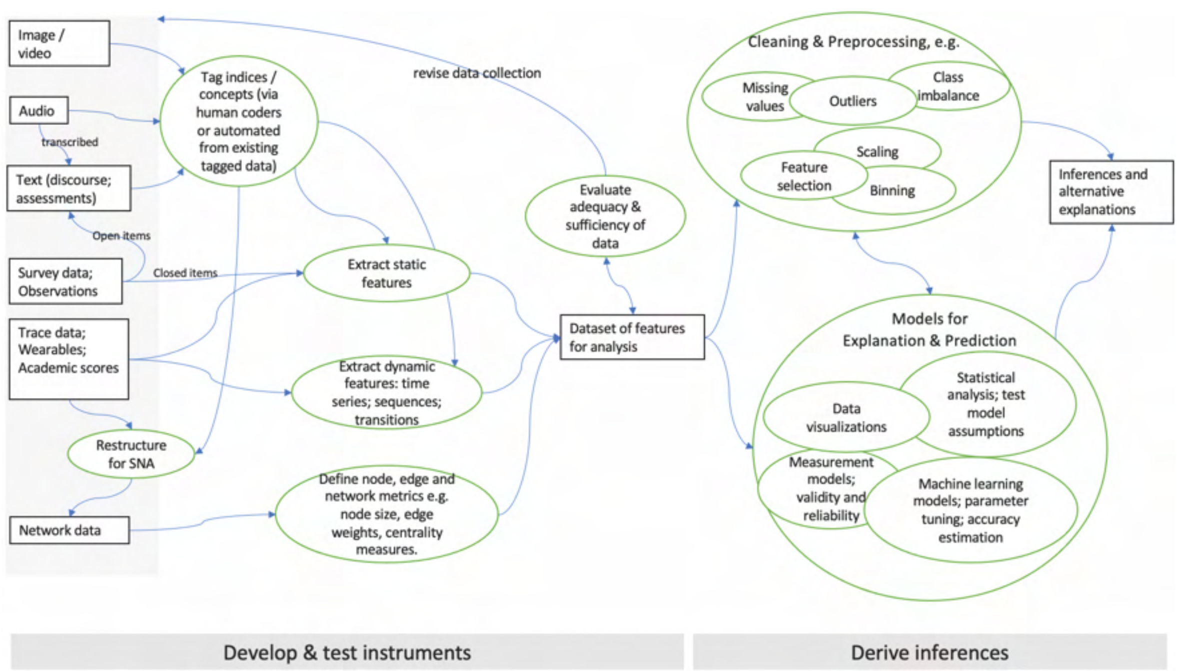

Figure 1: Chains of Evidence

learning construct, data collection should be preceded by identifying the learning constructs of interest, and defining the measurement model. For educational technology, this means deliberately designing the collection instrument (and so the consequential trace data it collects) around constructs of the learning process [24]. Examples from Table 1 include data from simulations using *Science Classroom Inquiry* that were designed around a specific pedagogical approach [40] so the instructional context is embedded in the tool. In another example, Harpstead et al. [20] configured the game *Decimal Point* to vary their construct of interest, *agency*. Simpler solutions, such as designing activities and resources on a VLE or MOOC to deliberately reflect a pedagogical approach are also viable (e.g. Matcha et al.[34]). In all these examples, the data collection instrument was configured to collect data about a latent construct of interest, increasing the likelihood of more generalisable estimates of construct validity from trace data.

While building instructional design into education technology can address model variance across pedagogical contexts, inferences should also consider variance due to learner contexts [44]. Trace data from electronic devices, such as wearables and image data, can capture data from contexts where learning is happening offline (e.g. face to face, or collaborative learning environments). They also collect data about the learner themselves. Therefore, such devices are a potentially useful addition to the landscape of trace data about learners and learning as discussed in (to cite Ochoa [38]). Biometric devices are measuring an observable construct directly (e.g. skin temperature). Image data requires some preprocessing, but libraries exist to automatically extract simple measurements from image data like posture, eye tracking and other motions. The challenge again arises when determining if the trace data is an indicator of an unobservable construct of learning. Validation typically uses manual coding and/or comparison with a second, validated data source, such as a validated questionnaire for the same construct. So one measurement model is validated with another, both of which have sources of error. Larmuseau et al. [31] provides an example of this. They found correlations between skin temperature and self-reported cognitive load in some instructional contexts only. So exploring the merit of such trace data as Measurements of constructs of the learning process offers opportunities for further research.

2.1.3 Text data, challenges and opportunities

Text data can capture the student voice directly, with the potential to provide different, and potentially richer insights than both surveys and trace data, as discussed in chapters 5, 10 and 11 or this text [2, 19, 12]. Indicators from text data can relate to the learning process and learning gain. So how does text data map to measurement? Models of learning require input data to be structured. Therefore, unstructured text data must be converted to structured data where features are the constructs of interest, and the data are based on counts of those features. Counts can be simple, such as term or phrase counts. More interestingly for explanatory modelling, counts of features derived from language usage that evidence learning constructs can also be extracted from text. Tools like *Linguistic Inquiry and Word Count* (LIWC), and *Coh-Metrix*, automatically extract linguistic measures such as psychological processes (e.g. affect) and aspects of writing cohesion respectively. Natural language is inherently imprecise and its meaning can be subjective. In spite of this, a number of studies have confirmed the validity of automatically extracted Measures from these tools when the assessment/writing brief reflects the constructs of interest, for example, Kovanović et al. [29] and Jung & Wise [23]. Where an automated feature extraction tool is not available for a construct of interest, training a model to extract more complex features from text requires a training dataset of text that has been manually coded (labelled). For example, Stone et al. [48] trained a model to infer a selection of non-cognitive traits from a 150-word essay about extracurricular activity, and reported good agreement with human coders of the same essays. Although Eagan et al. [14] warns of the potential for high Type I errors when using human coders to assess reliability in learning contexts.

2.1.4 Temporal considerations

Regardless of the measurement model, many constructs of learning have a temporal aspect. For example, cycles between positive and negative emotions can have a positive impact on the learning process compared to maintaining a consistent emotion [16]. Similarly, a change in student behaviour over time might be more insightful than a snapshot or aggregate of their behaviour. So, as well as verifying indicators from a measurement instrument, an additional step in the evidence chain may be warranted to define, measure, and model transitions between states of a construct.

2.2 Measurement of Learning Gain

Learning gain may refer to growth in knowledge, skills, or competencies during a period of interest. For specific content domains, such as algebra, developing reliable measures is a straightforward if laborious process. However, as the learning domain becomes more complex, so do the Measurement challenges [54, 27]. Assessment of competencies such as ways of thinking and ways of working, is a challenge facing educators more generally [30, 35]. Indeed, the difficulty in settling on agreed terminology related to non-cognitive dimensions (defining the constructs) evidences the range of opportunities that exist in this under explored space [22]. As with *learning process*, technology offers interesting opportunities for Measurement of non-cognitive skills (see, e.g., [42, 13]).

Another consideration when measuring learning gain is the period during which the learning was gained. Ideally, an instrument would measure learning gained as a change over time [51], for example, differences in pre- and post-test scores as discussed in [37]. Learning analytics models more frequently use existing post-test scores or assessment aggregates such as end of term grade (without a pre-test). While these scores reflect measurement in a real context, there is an assumption that the learning was gained during the period of analysis.

The granularity of measurement also impacts on the resulting interactions captured by a model. Proficiency in coarse grained or complex learning outcomes is a continuous variable. Reporting learning gained as alpha grades aims to compensate for errors inherent in the subjective nature of marking assessments. While this is good practice from pedagogical perspective (see, e.g. Kohn [28]), from a data modelling perspective, this reduces the granularity of the information content to an ordinal scale with somewhat arbitrary bin boundaries. Data preparation for modelling academic performance may reduce granularity further by dichotomising to a label such as pass/fail. There is information loss when a continuous attribute is discretized. For example, resulting analysis underestimates linear relationships between the original, continuous variables and other independent variables of interest, thus increasing the chance of type II errors [33, 7]. Dichotomisation may also introduce main effects not present in the original, continuous variables [33].

3 CONCLUSION

This chapter has considered a variety of sources of observable data that offer potential indicators of unobservable constructs of learning, and discussed some of the challenges of using observable data to measure latent constructs. As was said in the introduction, explanations of models of learning must acknowledge these challenges and sources of error, and consider the resulting implications on explanations that are inferred from models of the data.

Sources of error do not end with the measurement model. Every method applied to the data during cleaning, preprocessing, operationalization choices, feature selection, modelling, parameter tuning and estimates of model fit can add additional sources of error [6]. The resulting model will inevitably include bias as models are based on the data that is available, which is incomplete. There will be subgroups of learners missing from the data. For the learners that are included, there will be mediators, moderators and confounders not captured that explain some of the model variance. Some gaps in the data may be obvious to us and so easy to identify. Other gaps could be related to factors that impact on learning, or categories of students, we haven't thought to consider yet.

So do we give up on Measurement? No, we accept the sources of error as part of a robust argument evaluating all methods used, to ensure measurement, methodology and resulting models and inferences are honestly critiqued. The key point is that we know that our models aren't perfect, and we interpret the data in full knowledge of its limitations. Overtime, as the body of robust evidence builds around Measurement of learning and resulting optimisations and explanations, we can progress as a field.

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Chapter 3: Predictive Modelling in Teaching and Learning

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ABSTRACT

This chapter describes the process, practice, and challenges of using predictive modelling in teaching and learning. In both the fields of Educational Data Mining (EDM) and Learning Analytics (LAK) predictive modelling has become a core practice of researchers, largely with a focus on predicting student success as operationalized by academic achievement. In this paper we aim to provide a general overview of considerations when performing and applying predictive modelling, the steps which an educational data scientist must consider when engaging in the process, and a brief overview of the most popular techniques in the field.

Keywords: Predictive modelling, machine learning, educational data mining (EDM), feature selection, model evaluation

Predictive analytics are a group of techniques used to make *inferences* about uncertain future events. In the educational domain, one may be interested in predicting a measurement of learning (e.g. student academic success, or skill acquisition), teaching (e.g. the impact of a given instructional style or specific instructor on an individual) or other proxy metrics of value for organizations (e.g. predictions of retention or course registration). Predictive analytics in education is a well established area of research, and several commercial products now incorporate predictive analytics in the learning content management system (e.g. D2L[1], Starfish Retention Solutions[2], Ellucian[3], and Blackboard[4]). Furthermore, specialized companies (e.g. Blue Canary[5], now a part of Blackboard learning, Civitas Learning[6]) now operate to provide predictive analytics consulting and products for higher education.

1 INTRODUCTION TO PREDICTIVE MODELLING

In this chapter, we aim to introduce the terms and workflow related to predictive modelling, with a particular emphasis on how these techniques are being applied in teaching and learning. While a full review of the literature is beyond the scope of this chapter, we encourage readers to consider the conference proceedings and journals associated with the Society for Learning Analytics and Research (SoLAR)[7], the International Educational Data Mining Society[8] (IEDMS), and the International Artificial Intelligence in Education Society[9] (IAIED) for more examples of applied educational predictive modelling.

It is useful to distinguish *predictive modelling* from *explanatory modelling*. In explanatory modelling, the goal is to use all available evidence to provide a explanation for a given outcome. For instance, observations of age, gender, and socioeconomic status of a learner population might be used in a regression model to explain how they contribute to a given student achievement result. The intent of these explanations is generally to test causal hypotheses (versus correlative alone, described well by [26]). In predictive modelling, the purpose of the activity is to create a model that will predict the values (or *class* if the prediction does not deal with numeric data) of new data based on observations. Unlike explanatory modelling, predictive modelling is based on the assumption that a set of known data (referred to as *training instances* in data mining literature) can be used to predict the value or class of new data based on observed variables (referred to as *features* in predictive modelling literature). Thus the principle difference between explanatory modelling and predictive modelling is with the application of the model to future events, where explanatory modelling does not aim to make any claims about the future, while predictive modelling does.

More casually, explanatory modelling and predictive modelling often have a number of pragmatic differences when applied to educational data. Explanatory modelling is

[1] http://www.d2l.com/
[2] http://www.starfishsolutions.com/
[3] http://www.ellucian.com/
[4] http://www.blackboard.com/
[5] http://bluecanarydata.com/
[6] http://www.civitaslearning.com/
[7] https://www.solaresearch.org/
[8] http://educationaldatamining.org/
[9] https://iaied.org/about/

a *post-hoc* and reflective activity aimed at testing an understanding of a phenomena. Predictive modelling is an *in situ* activity intended to make systems responsive to changes in the underlying data. It is possible to apply both forms of modelling to technology in higher education. For instance, [24] describe a student-success system built on explanatory models, while [9] describe an approach based upon predictive modelling. While both methods intend to inform the design of intervention systems, the former does so by building software based on theory developed during the review of explanatory models by experts, while the latter does so using data collected from historical log files (in this case, *clickstream* data).

The largest methodological difference between the two modelling approaches is in how they address the issue of evaluation. In explanatory modelling, all of the data collected from a sample (e.g. students enrolled in a given course) is used to describe a population more generally (e.g. all students who could or might enroll in a given course). The issues related to generalizability are largely based on sampling techniques. Ensuring the sample represents the general population by reducing selection bias, often through random or stratified sampling, and determining the amount of power needed to ensure an appropriate sample, through an analysis of population size and levels of error the investigator is willing to accept. In a predictive model a *hold out* dataset is used to evaluate the suitability of a model for prediction, and to protect against the *overfitting* of models to data being used for training. There are several different strategies for producing hold out datasets, including k-fold cross validation, leave-one-out cross validation, randomized subsampling, and application-specific strategies.

With these comparisons made, the remainder of this chapter will focus on how predictive modelling is being used in the domain of teaching and learning, and provide an overview of how researchers engage in predictive modelling process.

THE PREDICTIVE MODELLING WORKFLOW

Problem Identification

In the domain of teaching and learning, predictive modelling tends to sit within a larger action-oriented educational policy and technology context, where institutions use these models to react to student needs in real-time. The intent of the predictive modeling activity is to set up a scenario which would accurately describe the outcomes of a given student assuming no new intervention. For instance, one might use a predictive model to determine when a given individual is likely to complete their academic degree. Applying this model to individual students will provide insight into when they might complete their degrees *assuming no intervention strategy is employed*. Thus, while it is important for a predictive model to generate accurate scenarios, these models are not generally deployed without an intervention or remediation strategy in mind.

Strong candidate problems for a successful predictive modelling approach are those in which there are quantifiable characteristics of the subject being modeled, a clear outcome of interest, the ability to intervene in situ, and a large set of data. Most importantly, there must be a recurring need, such as a class being offered year after year, where the historical data collected about learners (the *training set*) is expected to capture patterns and relationships that will hold true of future learners (the *testing set*).

Conversely, there are several factors that make predictive modelling more difficult, or less appropriate. For example, both sparse and noisy data present challenges when trying to create accurate predictive models. Data sparsity, or missing data, can occur for a variety of reasons, such as students choosing not to provide optional information. Noisy data occurs when a measurement fails to accurately capture the intended data, such as determining a student's location from their IP address when some students are using virtual private networks (proxies used to circumvent region restrictions, a not uncommon practice in countries such as China). Finally, in some domains, inferences produced by predictive models may be at odds with ethical or equitable practice, such as using models of student at-risk predictions to limit the admissions of said students (exemplified in [27]). Lastly, domains where the types of data available change are not well suited to predictive modelling. For example, if a course undergoes significant redesign, shifting coursework from a single term-paper to weekly quizzes, it would be difficult to make predictions about end of term course grades based on term work, as the data about the training and testing populations are no longer directly comparable.

Data Collection

In predictive modelling, historical data is used to generate models of relationships between features. One of the first activities for a researcher is to identify the outcome variable (e.g. grade or achievement level) as well as the suspected correlates of this variable (e.g. gender, ethnicity, access to given resources). Given the situational nature of the modelling activity, it is important to choose only those correlates which can be known at or before the time in which an intervention might be employed. For instance, a midterm examination grade might be predictive of a final grade in the course, but if the intent is to intervene before the midterm, this data value should be left out of the modelling activity.

In time-based modelling activities, such as the prediction of a student final grade, it is common for multiple models to be created (e.g [8]), each corresponding to a different time period and set of observed variables. For instance, one might generate predictive models to be applied each week of the course, incorporating into each model the results of all weekly quizzes, student demographics, and the amount of engagement the students have had with different digital resources to date in the course.

While *state-based* data, such as data about demographics (e.g. gender, ethnicity), relationships (e.g. course enrollments), psychological measures (e.g. grit [14] and aptitude tests) and performance (e.g. standardized test scores, grade point averages), are important for educational predictive models, it is the recent rise of big *event-driven* data collections that has been a particularly powerful enabler of predictive models (see [2] for a deeper discussion). Event-data is largely student activity-based, and is derived from the learning technologies that students interact with, such as learning content management systems, discussion forums, active learning technologies, and video-based instructional tools. This data is large and complex (often on the order of millions of database rows for a single course), and requires significant effort to convert into meaningful features for machine learning. At the same time, while we observe this growth of event-based data we caution that it is not universally more suitable for the generation of predictive models, and the quality and breadth of the data available may depend highly on other factors such as modality of education. For instance, in large online courses such as MOOCs, event-based data is rich because the learning activity is highly instrumented with data collection *and* there is a lack of socioeconomic state-based data describing learners. However, in many higher education residential courses the state-based data is rich (e.g. learner demographic and previous performance measures, such as standardized tests) and the learning technologies are often used shallowly (e.g. as file repositories for lecture material).

A second taxonomic dichotomy exists when considering whether the data was *self-reported* (e.g. a psychological survey) or *observed* (e.g. grades, click-stream log files, or eye tracking measurements). While in recent years predictive models in the field of learning analytics have emphasized the latter, the field of education and educational psychology has explored heavily the former, and instruments to measure psychological states including motivation, aptitude, disposition, and other forms of self-regulation are commonly used.

Of pragmatic consideration to the educational researcher is obtaining access to event data and creating the necessary features required for the predictive modelling process. The issue of access is highly context-specific, and depends on institutional policies and processes, as well as governmental restrictions (such as FERPA in the United States). One solution is to conduct research using previously established publicly available datasets, such as the Open University Learning Analytics Dataset[22], or the MITx and HarvardX Dataverse[17]. Alternatively, some institutions, such as the University of Michigan, have created standardized and streamlined access procedures for institutional data assets to enable their faculty members to conduct learning analytics research grounded in their unique institutional context.[10]

Classification and Regression

In statistical modelling there are generally four types of data considered: categorical, ordinal, interval, and ratio. Each type of data differs with respect to the kinds of relationships, and thus mathematical operations, which can be derived from individual elements. In practice, ordinal variables are often treated as categorical, and interval and ratio are considered as numeric. Categorical values may be binary (such predicting whether a student will pass or fail a course) or multivalued (such as predicting which of a given set of possible practice questions would be most appropriate for a student). Two distinct classes of algorithms exist for these applications; *classification algorithms* are used to predict categorical labels, while *regression algorithms* are used to predict numeric labels.

Feature Engineering

The raw event data available to researchers is rarely suitable for direct use in the fitting of a predictive model. Instead, it is often transformed through the process of feature engineering (a research field unto itself) into *candidate* features. As one example, timestamped resource access logs may be used to compute "time on task" sessions [21]. When using free-form text from essays or discussion posts, it is common to transform the raw data into more compact representations, including vectorized "bag of words" (e.g. through word2vec [25]), or other computational linguistic measures (e.g. [13]. Lastly, a range of network measures can be applied to quantify the social network characteristics of individual learners, such as their number of connected peers, their centrality in a larger network, or even embeddings within a larger network context (e.g. [15, 19]).

Feature Selection

In order to build and apply a predictive model, features which correlate with the value to predict need to be selected. When choosing what data to collect, the practitioner should err on the side of collecting more information rather than less, as it may be difficult or impossible to add additional data later, but removing information is typically much easier. Ideally, there would be some single feature that perfectly correlates with the chosen outcome prediction. However, this rarely occurs in practice. Some learning algorithms make use of all available attributes to make predictions, whether they are highly informative or not, whereas others apply some form of variable selection to eliminate the uninformative attributes from the model.

Depending on the algorithm used to build a predictive model, it can be beneficial to examine the correlation between features, and either remove highly correlated attributes (the *multicollinearity* problem in regression analyses), or apply a transformation to the features to eliminate the correlation. Applying a learning algorithm that naively assumes independence of the attributes can result in predictions with an over-emphasis on the repeated or correlated features. For instance, if one is trying to predict the grade of a student in a class and uses an attribute of both attendance in-class on a given day as well as whether a student asked a question on a given day, it is important for the researcher to acknowledge that the two features are not independent (e.g. a student could not ask a question

[10] See, for instance, `https://enrollment.umich.edu/data-research/learning-analytics-data-architecture-larc`

if they were not in attendance). In practice, the dependencies between features is often ignored, but it is important to note that some techniques used to clean and manipulate data may rely upon an assumption of independence.[11] By determining an informative subset of the features, one can reduce the computational complexity of the predictive model, reduce data storage and collection requirements, and aid in simplifying predictive models for explanation.

Missing values in a data set may be dealt with in several ways, and the approach used depends on whether the data is missing because it is unknown or because it is not applicable. The simplest approach is to either remove the attributes (columns) or instances (rows) that have missing values. There are drawbacks to both of these techniques. For example, in domains where the total amount of data is quite small, the impact of removing even a small portion of the data set can be significant, especially if the removal of some data exacerbates an existing class imbalance in the data set. Likewise, if all of the attributes have a small hand full of missing values, then attribute removal will remove all of the data, which would not be useful. Instead of deleting rows or columns with missing data, one can also infer the missing values from the other known data. One approach is to replace missing values with a 'default' value, such as the mean of the known values. A second approach is to fill in missing values in records by finding other similar records in the data set, and copying the missing values from their records.

The impact of missing data is heavily tied to the choice of learning algorithm. Some algorithms, such as the Naïve Bayes classifier can make predictions even when some attributes are unknown; the missing attributes are simply not used in making a prediction. The nearest neighbour classifier relies on computing the distance between two data points, and in some implementations the assumption is made that the distance between a known value and a missing value is largest possible distance for that attribute. Finally, when the C4.5 decision tree algorithm encounters a test on an instance with a missing value, the instance is divided into fractional parts which are propagated down the tree and are used for a weighted voting. In short: missing data is an important consideration which both regularly occurs and is handled differently depending upon the machine learning method and toolkit employed.

Methods for Building Predictive Models

After collecting a data set and performing attribute selection a predictive model can be built from historical data. In the most general terms, the purpose of a predictive model is to make a label prediction, given some related known information. This section will briefly introduce several such methods for building predictive models. A fundamental assumption of predictive modelling is that the relationships that exist in the data gathered in the past will still exist in the future. However, this assumption may not hold up in practice. For example, it may be the case that (according to the historical data collected) a student's grade in *Introductory Calculus* is highly correlated with their likelihood of completing a degree within 4 years. But, if the instructor of the course, the pedagogical technique employed, or the degree programs requiring the course change, this course may no longer be as predictive of degree completion as was originally thought. The practitioner should always consider whether patterns discovered in historical data should be expected to be present in future data.

A number of different algorithms exist for building predictive models. With educational data, it is common to see models built using methods such as:

1. **Linear Regression**, which is used to predict a numeric label from a linear combination of features.
2. **Logistic Regression**, which is used to predict the odds of two or more labels, allowing for categorical predictions.
3. **Nearest Neighbours Classifiers**, which use only the most similar data points in the training data set to determine the appropriate predicted labels for new data.
4. **Decision Trees (e.g. C4.5 algorithm)**, which are repeated partitions of the data based on a series of single attribute "tests". Each test is algorithmically chosen to maximize the purity of the classifications in each partition.
5. **Naïve Bayes Classifiers**, which assume statistical independence of each of the features given the classification, and provide probabilistic interpretations of classifications.
6. **Bayesian Networks**, where graphical models are often manually constructed and provide probabilistic interpretations of classifications.
7. **Support Vector Machines**, which make use of a high dimensional data projection in order to find a hyperplane of greatest separation between the various classes.
8. **Neural Networks**, which are biologically inspired algorithms that propagate data input through a series of sparsely interconnected layers of computational nodes (neurons) to produce a label. While neural networks have been the subject of research for more than 70 years, the area has received renewed interest (and commercial success) due to the advances of *Deep Learning*.
9. **Ensemble Methods**, which use a voting pool of either homogeneous or heterogeneous classifiers. Two prominent techniques are bootstrap aggregating, in which several predictive models are built from random sub-samples of the data set, and boosting, in which successive predictive models are designed to account for the misclassifications of the prior models.

Most of these methods, and their underlying software im-

[11] The authors share an anecdote of an analysis that has fallen prey to the issue of assuming independence of attributes when using resampling techniques to boost certain classes of data when applying the synthetic minority over-sampling technique [10]. In that case, missing data with respect to city and province resulted in a dataset containing geographically impossible combinations, reducing the effectiveness of the attributes and lowering the accuracy of the model.

plementations, have tunable parameters that change the way the algorithm works depending upon expectations of the dataset. For instance, when building decision trees, a researcher might set a minimum leaf size or maximum depth of tree parameter used in order to ensure some level of generalizability.

While R and Python are the two most commonly used programming languages for predictive modelling in the field[12], there are numerous specialized software libraries available for the building of predictive models in these and many other programming languages. Choosing the right package depends highly on the individual researchers experiences, the desired classification or regression approach, and the amount of data and data cleaning that needs to be done. While a comprehensive discussion and comparison of these platforms is out of the scope of this chapter, the authors will suggest that the freely available and open-source package Weka [16] is a an excellent starting point for those who are interested in predictive modelling but have little or no prior programming experience. Weka provides implementations of a number of the previously mentioned modelling methods, does not require programming knowledge to use, and has associated educational materials including a textbook [33] and series of free online courses [32].

While the breadth of techniques covered within a given software package have led to it being commonplace for researchers (including educational data scientists) to publish tables of classification accuracies for a number of different methods, the authors caution against this. Once a given technique has shown promise, time is better spent reflecting on the fundamental assumptions of classifiers (e.g. with respect to missing data or data set imbalance), exploring ensembles of classifiers, or in tuning parameters of particular methods being employed. Unless the intent of the research activity is to specifically compare two (or more) statistical modelling approaches, educational data scientists are better off tying their findings to new or existing theoretical constructs, leading to a deepening of understanding of a given phenomena. Sharing data and analysis scripts in an open science fashion provides better opportunity for small technique iterations than cluttering a publication with tables of (often) impenetrable and uninteresting measurements.

Evaluating a model

In order to assess the quality of a predictive model, a test data set with known labels is required. The predictions made by the model on the test set can be compared to the known true labels of the test set in order to assess the model. A wide variety of measures are available to compare the similarity of the known true labels and the predicted labels. Some examples include prediction accuracy (the raw fraction of test instances correctly classified), precision, and recall.

Often, when approaching a predictive modelling problem, only one omnibus set of data is available for building a predictive model. While it may be tempting to reuse this same data set as a test set to assess model quality, the performance of the predictive model will typically be significantly higher on this data set than would be seen on a novel data set (due to the model *overfitting* the training data set). Instead, it is common practice to "hold out" some fraction of the data set and use it solely as a test set to assess model quality.

The most simple approach is to set aside half of the data, and reserve it for testing. However, there are two drawbacks to this approach. First, by reserving half of the data for testing, the predictive model will only be able to make use of half of the data for model fitting. Generally speaking, model accuracy increases as the amount of available data increases. Thus, training using only half of the available data may result in predictive models with poorer performance than if all the data had been used. Second, our assessment of model quality will only be based on predictions made for half of the available data. Generally, increasing the number of instances in the test set will increase the reliability of the results. Instead of simply dividing the data into training and testing partitions, it is common to use a process of k-fold cross validation in which the data set is partitioned at random into k segments. k distinct predictive models are constructed, with each model training on all but one of the segments, and testing on the single held out segment. The test results are then pooled from all k test segments, and a generalized assessment of prediction quality can be performed. The important benefits of k-fold cross validation are that every available data point can be used as part of the test set, no single data point is ever used in both the training set and test set of the same classifier at the same time, and the training sets used are nearly as large as all of the available data.

An important consideration when putting predictive modeling into practice is the similarity between the data used for training the model and the data available when predictions need to be made. Often in the educational domain, predictive models are constructed using data from one or more time periods (e.g. semesters or years), and then applied to student data from the next time period. If the features used to construct the predictive model include factors such as students' grades on individual assignments, then the accuracy of the model will depend on how similar the assignments are from one year to the next. To get an accurate assessment of model performance, it is important to assess the model in the same manner as will be used in situ: to build the predictive model using data available from one year, and then construct a testing set consisting of data from the following year, instead of dividing data from a single year into training and testing sets.

PREDICTIVE ANALYTICS IN PRACTICE

Predictive analytics are being used within the field of teaching and learning for many purposes, with one significant body of work aimed at identifying students who

[12]see for example the number of workshops and tutorials introducing new researchers and practitioners to these tools at recent LAK and LASI events

are at risk in their academic programming. For instance, [1] describe the use of predictive models to determine whether students will graduate from secondary school on time, demonstrating how the accuracy of predictions changes as students advance from primary school through into secondary school. Predicted outcomes vary widely, and might include a specific summative grade or grade distribution for a student or class of achievement [9] in a course. Baker et al. [7] describe a method which predicts a formative achievement for a student based on their previous interactions with an intelligent tutoring system. In lower-risk and semi-formal settings such as Massive Open Online Courses (MOOCs), the chance that a learner might disengage from the learning activity mid-course is another heavily studied outcome [34, 28].

Beyond performance measures, predictive models have been used in teaching and learning to detect learners who are engaging in off-task behavior [35, 5] such as "gaming the system" in order to answer questions correctly without learning [6]. Psychological constructs such as affective and and emotional state have also been modeled with predictive models [11, 30], using a variety of underlying data as features, such as textual discourse or facial characteristics. More examples of some of the ways predictive modelling has been used in Educational Data Mining in particular can be found in [20].

At the same time, there are both warnings and criticism of the creation of predictive models for education which focus on the issue of deployment. Writing in [18], Andrew Ho reminds the reader that "...the purpose of education is not prediction but learning". He goes on, writing:

> In short, we want educational predictions to be wrong. If our predictive model can tell that a student is going to drop out, we want that to be true in the absence of intervention, but if the student does in fact drop out, then that should be seen as a failure of the system. A predictive model should be part of a prediction-and-response system that a) makes predictions that would be accurate in the absence of a response and b) enables a response that renders the prediction incorrect. In a good prediction-and-response system, all predictions would ultimately be negatively biased.

[18, p. 36]

In the broadest sense, we agree with this perspective – the intention of an applied predictive model should be to enable better education outcomes for learners, not simply to measure existing education outcomes. At the same time we argue that the issue is nuanced and that there is value in accurate educational predictive modeling both as a field of research and in real-world educational technologies. In the former the argument largely rests on the value of interdisciplinary teams to address the prediction-and-response system; whether tightly or loosely coupled, there is opportunity to the marriage of technical experts (e.g. computer scientists, statisticians, engineers) who might build models to the pedagogical experts (e.g. educational researchers, domain experts, cognitive psychologists) who might design interventions. Without these accurate models the job of building an intervention becomes not only harder to make, but harder to measure the effects of. Of pragmatic concern is the issue of limited resources within education systems. Simply put, most educational predictive models not only tell you who is likely to fail, but also who is likely to succeed, and allow institutions (and researchers) to focus their interventions directly towards specific populations of interest. Narrowing the population of students to whom an intervention is applied allows for more targeted and better resourced interventions. This is of specific value when engaging with educational policy makers who are often asked to resource a breadth of intervention programs and must balance the anticipated outcomes of different approaches. With this nuance explored, we reiterate that the key agreement we share with Ho is that the predictive model is only one half of the prediction-and-response system, and it is important for researchers and practitioners to keep this in mind.

CHALLENGES AND OPPORTUNITIES

Computational and statistical methods for predictive modelling are mature, and over the last decade a number of robust tools have been made available for educational researchers to apply predictive modelling to teaching and learning data. Yet there are a number of challenges and opportunities in this space, and we address a few areas of growth which could use investment from the learning analytics community in order to increase the impact predictive modelling techniques can have. These are:

1. **Supporting non-computer scientists in the educational predictive modelling workflow** Learning analytics is becoming normalized in higher education. Providing support in the interpretation and understanding of predictive modelling techniques, whether it be through the innovation of user-friendly tools or development of educational resources on predictive modelling, could help to assuage fear and uncertainty about algorithmic predictions.
   Related to this, the rise of Master of Data Science programs in recent years has greatly increased the number of highly skilled individuals capable of engaging successfully in predictive modelling. However, *Data Engineering*, the practice of provisioning data suitable for analysis, is a growing challenge. Students engage with a greater variety of learning tools than ever before, which provides an opportunity for incredibly rich analysis. But, these learning tools do not necessarily track comparable log events, retain log data in comparable formats, or have APIs (application programming interfaces) to integrate this data together. Many institutions are now engaged in the creation of learning record stores or data lakes to support the analysis of learning data aggregated across the range of learning tools that students interact with. As the number of technologies students use in their studies continues to grow, the need for data engineers to become a part of the interdisciplinary learning analytics

team is more apparent.

2. **Creating community-led educational data science challenge initiatives.** It is not uncommon for researchers to address the same general theme of work but use slightly different datasets, implementations, and outcomes and, as such, have results that are difficult to compare. This is exemplified in recent predictive modelling research efforts around dropout in massive open online courses, where a number of different authors (e.g. [9, 34, 28, 31]) have done work all with different datasets, outcome variables, and approaches.
   Moving towards a common and clear set of outcomes, open data, and shared implementations in order to compare the efficacy of techniques and the suitability of modelling methods for given problems could be beneficial for the community. This approach has been valuable in similar research fields[13] and the broader data science community[14], and we believe that educational data science challenges could help to disseminate predictive modelling knowledge throughout the educational research community while also providing an opportunity for the development of novel interdisciplinary methods, especially as it relates to feature engineering. Ryan Baker's six problems for the learning analytics community are an example of this community challenge initiative[4].

3. **Engaging in 2nd order predictive modelling.** In the context of learning analytics, we define second order predictive models as those which include historical knowledge as to the effects of and intervention in the model itself. Thus a predictive model which used student interactions with content to determine drop out (for instance) would be a example of first order predictive modelling, while a model which also includes historical data as to the effect of an intervention (such as an email prompt or nudge) would be considered a second order predictive model. Moving towards the modelling of intervention effectiveness is important when multiple interventions are available and personalized learning paths are desired.

4. **Bias in educational predictive models.** A growing concern in the predictive modeling and machine learning community is the potential for models to become biased with respect to their performance for different classes of people. In addition to being addressed within existing scholarly communities, this concern has spawned the creation of new academic conferences focused specifically on issues of bias and fairness (e.g. the ACM Conference on Fairness, Accountability, and Transparency (FAccT)[15]). Within the area of learning analytics specifically there have been a number of works looking at how to measure bias in predictive models [29], the impact of user choice on bias in models [23], and the bias in underlying methods applied in educational models [12]. What is lacking within the field, however, is an understanding of how evidence of bias should influence the use of predictive models in education. For instance, if a model has a bias against a given subpopulation, does that mean the model shouldn't be used at all? How big must the bias be before it is a concern? What subpopulations are important in a given learning context? These thorny sociotechnical issues need further exploration, as the work to date has largely been technical or measurement focused.

Despite the multi-disciplinary nature of the learning analytics and educational data mining communities, there is still a significant need for bridging understanding between the diverse array of scholars involved. An interesting thematic undercurrent at learning analytics conferences are the (sometimes heated) discussions of the roles of theory and data as drivers of educational research. Have we reached the point of "the end of theory" [3] in educational research? Unlikely, but this question is most salient within the subfield of *predictive modelling in teaching and learning*: while for some researchers the goal is understanding cognition and learning processes, others are interested in predicting future events and success as accurately as possible. With predictive models becoming increasingly complex and incomprehensible by an individual (essentially black boxes), it is important to start discussing more explicitly the goals of research agendas in the field, to better drive methodological choices between explanatory and predictive modelling techniques.

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Chapter 4: Cacophony of Networks in Learning Analytics

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ABSTRACT

Network analysis, a suite of techniques to quantify relations, is among core methods in learning analytics (LA). However, insights derived from the application of network analysis in LA have been disjointed and difficult to synthesize. We suggest that such is due to the naïve adoption of network analysis method into the methodologies of measuring and modelling interpersonal activity in digital learning. This chapter describes the diversity of empirical research using network analysis as a cacophony of network approaches. Focusing on LA studies that evaluate social behavior of individuals or model networks, the chapter exemplifies aspects of the analytical process that require rigor, justification, and alignment to overcome the cacophony of empirical findings. The chapter argues that the clarity of network definitions, hypotheses about network formation, and examination of the validity of individual-level measures are essential for coherent empirical insights and indicators. Future work should also make effort to model the temporal nature, multiplex ties, and dynamic interaction between the levels where interpersonal interactions unfold.

Keywords: Online networks, digital traces, digital learning, network modelling

Learning analytics (LA) have been a part of the scholarly discourse now for almost a decade. LA scholarship continues to mature, and institutional adoption of LA is on the rise. Against this backdrop, researchers are urged to demonstrate how LA impacts the practices of teaching and learning [10]. Addressing such a call for impact today is feasible in some areas of LA, such as predictive modelling, writing analytics, and analytics of self-regulation processes. Their applications in LA have been used across diverse technologies, courses, and institutions, and can provide insights to inform teaching and learning practices. However, some areas of LA have not advanced to offer the trusted insights.

Among areas in need of refinement and rigor is that of social learning analytics, here defined as the analysis of interpersonal activity in digital learning. The interest in social learning analytics is driven by the premise that social learner activity contributes to the quality of learning and student experiences. Among mainstream approaches used to examine online interactions is network analysis, a suite of techniques for analyzing relations between objects. LA studies that have used network analysis to understand interpersonal activity offer limited insight, as their disjointed empirical findings are difficult to synthesize. This chapter argues that this lack of coherence is due to the complexity of analytical decisions that arise on the intersection of network analysis and LA. This chapter critically discusses extant LA studies that apply network analysis and highlights aspects of the analytical process that require rigor, justification, and alignment across diverse cases.

1 FOUNDATIONS OF NETWORK STUDIES IN LEARNING ANALYTICS

Analysis of learner networks and social network analysis (SNA) has been adopted in LA since the first LAK conference. In 2010, online teaching practices centered on learner-to-learner interactions via educational technology and web 2.0. Early LA studies built on student retention research in higher education, where social aspects of learning such as social integration, social capital, and the sense of belonging were emphasized [46, 54]. Within such a context, networks constructed from digital data in learning environments could capture social interactions between learners and potentially improve social aspects of university experience.

Analysis of social learning in digital settings was enabled by the social scientists whose tools, examples, and conceptualizations are widely used in LA. SNA as an approach for the analysis of social relations has a long-standing tradition in social sciences [14]. SNA differs from other approaches that analyze randomly sampled individual-level observations. Instead, SNA quantifies patterns within the sets of interdependent relations. Research on social networks, where network ties represent self-reported relationships between people, is widely used in LA, drawing on SNA insights about social structures, theories of how they evolve, and SNA techniques [57].

SNA has played a prominent role in learning sciences, offering tools to understand activities and social processes that students and teachers engage with in technology-mediated settings. For instance, Haythornthwaite [23, 22] analyzed types of exchanges and types of media that support collaboration, socializing, and emotional support in an e-learning environment. Haythornthwaite examined networks of online interactions, where ties represented interpersonal activity captured online, not the self-reported relations between individuals as common in SNA. Early LA work navigated between the insights and interpretations from SNA research towards social structures gleaned from digital relational data. Dawson [8] examined to what extent position of centrality in a network of learners was associated with beneficial learning outcomes, such as individual's sense of belonging. The hypothesis linking network position with benefits reflected the prevailing understanding from the SNA literature that centrality to the network, i.e. positioning within the network ties, can be associated with enhanced access to resources and information [13, 18].

Computer-supported collaborative learning and networked learning also influenced LA network research. De Laat et al. [35] suggested to integrate network analysis that reflects who talks to whom with content analysis that reflects what they are talking about. De Laat et al. [35] utilized SNA to reveal the most influential participants in learning discussions and to explain patterns of connections between the peers. The authors further applied a qualitative coding scheme for analyzing negotiation of meaning and social construction of knowledge. Haythornthwaite and De Laat [23, 22] explored the intersection of learning and social structures, discussing various possibilities for what could constitute a tie in a learning network. They also proposed analytical questions that SNA can explore in learning settings, such as 'who learns from whom', 'what learners learn from each other', 'what kinds of interactions happen between people who learn together', 'which directions do resources flow', 'how frequently do learning interactions happen', and 'how important are they for people involved' (p.354).

To summarize, from the early studies in LA, to interpret patterns in digital interaction networks, researchers borrowed the constructs derived from SNA and learning sciences. To this end, they often contextualized observed digital data by complementing it with other information, such as types of media used for interaction [21], self-reported instruments [8], and content of what was exchanged online with interaction trace data [35].

This link between digitally mediated interactions and their interpretations borrowed from SNA remained in LA network studies. To maintain the distinction between social relations and digitally mediated interactions, we will use SNA to refer to the studies of social networks, i.e. where ties are operationalized as self-reported relational states between people, such as 'trust' or 'friendship'. We will use network analysis to refer to the studies of other networks. Since networks, also known as graphs, can include any objects, or nodes, linked by any relations, or edges [61], LA has adopted network analysis to analyze diverse data sources. Analytical techniques and method-related principles that quantify patterns in a graph are the same, regardless of the network type. Studies of social digital environments in LA that analyze relational data are not limited to social networks, and include networks of learner interaction, text networks, networks of individual clickstream activity, or networks of curriculum modules, among others.

2 NETWORK STUDIES IN LEARNING ANALYTICS

Today, a large portion of network analysis in LA is geared towards a better understanding of the social aspects of the student experience and their relevance for learning and student success. Digital traces of interactions in socio-technical systems have been collected in a vast variety of settings. Some studies have examined university online courses [16] where groups of learners are bounded by similar motivation, similar curriculum trajectories, and likely higher homogeneity in prior knowledge. Other studies focused on MOOCs [28] where learners heterogeneous in their motivation and prior knowledge are bounded by course enrolment, but their patterns of social participation and commitment are fluid [45]. Network analysis has also been applied to open-ended social contexts where group boundaries are ill-defined, to inquire into informal learning in open Internet communities [20, 34]. Finally, network analysis has gained prominence in social text- and video-annotation contexts [24, 36] where artefacts that mediate student learning are explicit and have affordances of their own. Artefact-driven social contexts have often been analyzed using two-mode networks where artefacts and learners are equal actors shaping the structure of interactions [26].

In a digital learning setting, network analysis makes use of the patterns of relations between individuals and artefacts. For instance, network analysis can derive node-level metrics, such as describing the position and a relative importance of a node (a person, a word, a web page in the course, or other) in a network. Alternatively, network analysis can reveal closely interconnected groups of nodes, or provide network-level metrics that describe the entirety of the network structure. Research questions that network analysis can address can be broadly classified, though not limited to: (1) What is the relationship between node characteristics, node positioning, and the outcomes of such a position; (2) Why ties form, i.e. what mechanisms generate observed network structure; and (3) How node attributes influence network formation, as well as how network structure impacts node attributes.

LA studies have addressed the entire spectrum of such network analytical questions. For example, node-level analyses in LA examined how individual positioning captured through network centralities relates to performance and learning-related outcomes in a co-enrolment network [15]; or how a position in a communication network relates to learner linguistic properties [11]. Sub-graph analyses have been prominent in bipartite networks (i.e. where nodes are of two types). In such studies, researchers can detect learner communities based on engagement patterns [26] and identify clusters of learners based on similarity in learning and social activities [24]. Network-level studies have provided metrics to describe structures that represent interactions in different technological and pedagogical contexts [5, 6]. In addition, network-level analyses are applied in epistemic network analysis (ENA, see [48]), a particular methodology that represents epistemic views of individuals and groups as network structures to demonstrate similarities and differences between them. Using network-level studies in LA, researchers also have statistically modelled online learner networks to describe the mechanisms that can explain what drives the formation of network ties [29, 45].

3 CACOPHONY OF NETWORKS IN LEARNING ANALYTICS

These diverse examples show how flexible network analysis can be. The intuition for network analysis is, in part, responsible for its naive applications. That is, any set of relations can be viewed as a graph, and network tools will provide metrics describing them. The problems may begin when the metrics from network analysis are used to interpret indicators, constructs, or processes related to learning. In these instances, network analysis is no longer just a tool, but becomes a methodology with its own theoretical assumptions. Such assumptions include an understanding of what networks represent, but these assumptions are often implicit within the research choices.

Insufficient attention to the assumptions underlying research design can result in the naïve adoption of network analysis [37]. In our view, LA studies often take up network analysis without reflecting on the methodological decisions associated with it. The danger of naïve adoption is that the results are then interpreted through eclectic claims potentially incompatible with the design of the study [59]. Put simply, as methodologies of applying network analysis are not explicit, it is difficult to draw any conclusions as to the meaning of the metrics, even before metrics can be compared across different studies. We refer to this problem as the cacophony of network approaches in LA. We use cacophony to contrast this development with the notion of productive multivocality [53] where diverse disciplines with divergent views build upon one another to produce complementary insights.

Cacophony of findings in network studies results from the misalignment between network construction, analysis choices, and interpretations, impacting generalizability. To highlight areas of misalignment, we distinguish between (1) using network analysis as a method to reduce high-dimensional data and (2) using network analytical methodologies to understand socially shared communication and interpersonal activity in learning settings. When network analysis is a methodology, network construction, metrics and ways of modelling, as well as metric interpretations are at risk of misalignment. By discussing how LA studies evaluate social behavior of individuals and model networks in their entirety using network analysis methodologies, we outline areas where caution is needed and suggest potential ways forward.

4 NETWORK ANALYSIS AS A METHOD

Network analysis as a method summarizes relational data, without particular theoretical meaning assigned to the metrics. The method quantifies relational patterns and identifies clusters based on the relations between the observations of interest. These relations are, at least in part, interdependent, and node-level metrics quantifying them are often non-normally distributed. In LA, nodes linked by relationships can be people, words, learning resources, types of learning behavior captured through clickstream data, topics in the course, and similar. Applying network analysis techniques to these data can reduce its dimensionality and classify nodes. For instance, Joksimovic et al. [30] utilized community detection in networks of words to identify topics discussed in the course. Sirbu et al. [50] deployed 'coherence network analysis' to group learners based on the similarity in the linguistic properties of their discourse. Van Labeke and colleagues [56] used network techniques applied to text networks to help identify text quality for automated essay analysis. Besides applying graph analytical techniques to text networks, graph analytical techniques have been shown useful in analyzing relations between clickstream data. For example, Matcha et al. [39] demonstrate that learning strategies can be detected from networks of learner-level clickstream data, where ties between events represent co-occurrence of learning actions.

5 NETWORK ANALYSIS AS A METHODOLOGY

The challenges associated with network studies in LA come through when networks are used to represent sociotechnical systems in learning environments. As we argue throughout this section, this shift from representing relational data as a network to representing a theorized construct as a network transforms network analysis from a method to a methodology. The way ties, and therefore, the entire network, are defined, may not work well with the metrics selected by the researchers. Chosen statistical models, i.e. hypothesized generative mechanisms that underpin statistical network analysis, may also be at odds conceptually with the chosen representation. Finally, the theory used to interpret the metrics may also be only in part relevant to the analyzed network.

5.1 Network Construction Issues

Naive adoption of network analysis in LA starts with naive network construction. When network ties, nodes, and boundaries are arbitrary, so are the selected data points, networks metrics derived from them, and their interpretations. Wise and colleagues [58] and Fincham et al. [12] show the variation that results from identical analyses of differently constructed online learner networks. Decisions about network constructions should be theory-based and systematic, and '... a network model should be viewed explicitly as yielding a network representation of something' [2, p. 2]. A close relationship between theoretical definition and interpretation "commits one to assumptions about what is interacting, the nature of that interaction, and the time scale on which that interaction takes place' [3, p. 416]. To align parts of the network analysis methodology, analyzed phenomenon needs to be theorized through literature, abstracted to the network concept, and represented in the network data through theorized and systematic definition of ties and non-ties, nodes, and network boundaries (for guidelines, see [27]).

Networks where ties represent students responding to one another may only to some extent overlap with social networks between interacting students. Therefore, a large degree of caution is required when networks of student communication are interpreted using SNA theories. More complex tie operationalizations, such as aggregating interactions across different types of exchanges, across longer periods of time, or as validated by self-reported measures of affect, may be a better fit to provide insights about social networks from digital data. For instance, Gruzd & Haythornthwaite [19] only include ties between the learners who address one another by names or nicknames. Poquet et al. [44] includes interactions only between learners who sustain participation over a longer period of time. Goggins et al. [17] and Suthers [52] combine information about where, when, or why interpersonal interactions took place, using diverse clickstream information, with semantic similarity between the text, to derive the presence of a tie between learners.

5.2 Choosing and Interpreting Centrality Measures

Learner centrality metrics, i.e. node-level metrics derived from ties in the network describe learner position in relation to others within a network. In LA, measures of learner centrality (e.g. degree, betweenness, closeness centralities, among others) are often contrasted with other process indicators or final assessment results [7]. Researchers also have investigated the relationship between learner centrality in communication and co-enrolment networks with measures of perceived belonging [8], creativity [9]), social capital [28], and discourse features [11].

These studies, however, often are conducted on networks where ties are operationalized differently. Beyond these issues of validity, the misalignment in research design can occur when network measures and their interpretation embed SNA assumptions, but the specific network representation does not afford those assumptions. To explain, we can look at measures of degree, betweenness and closeness centrality. The premise that learner network position, captured through the centrality, is associated with particular benefits stems from SNA. In social networks, an individual's position represents access to resources, such as information flow or support [1]. In SNA, degree centrality, a local measure of centrality that takes into account the number of connections an individual has, is equivalent to the number of social relationships an individual has. LA studies use degree as a measure of popularity, influence or capital, transferring interpretations of centrality that assume that ties represent relationships. But the interpretation for centrality in online settings can be different from that in social networks. Based on an empirical experiment, Poquet et al. (2020) modelled online interaction networks to demonstrate that degree centrality in online learner interactions is associated with in-course individual-level activity, rather than social choices made by learners. The authors use empirical simulations to claim that centrality is merely a proxy of individual learner characteristics and not of social dynamics, as is in SNA.

Interpretation of betweenness and closeness centrality measures in online settings is even further away from their use in SNA. Their use in learner interaction networks can be controversial not only in interpretation, but the metric itself may be inapplicable. Centrality measures such as betweenness and closeness are distance-based, i.e. the formula takes into account the entire network structure. For instance, betweenness centrality is derived from the number of shortest paths that go through each node. In SNA interpretation of this measure presumes that the absence of ties is equivalent to the absence of access. Hence, in SNA nodes with high betweenness can be interpreted as having privileged access to resources. Online interaction networks are constructed from event data where ties are transient events (e.g. A replied at time X) not relational states (e.g. A is friends with B). The absence of a tie in the context of ties as events does not imply limits of access. Therefore, distance between the individuals in the network and uniqueness of positioning (embedded in the measure) in communication environments is not at all equivalent to its SNA counterpart, or its interpretation.

5.3 Comparing, Interpreting, and Modelling Networks

Further challenges arise when network-level studies are conducted. Research questions asked at a network level can describe network structures and mechanisms generating them (e.g. [4, 29, 60]). This becomes useful because a network structure can serve as group-level indicator caused by a specific pedagogical and technological setting [5, 42] or as a signal of desired outcomes, such as team's performance [43]. In such network-level studies, methodological flaws can easily occur (1) when researchers directly compare descriptive networks metrics from different settings, and (2) when they use hypothesis from SNA theory to model how socio-technical networks in learning environments form.

For instance, researchers conduct descriptive analysis of several courses in the same study, and then descriptively compare their network metrics, such as density (overall interconnectedness of the graph), transitivity (presence of triads in the graph) or centralization (reliance of graph connectivity on one or several nodes). Such studies then commonly report that as the course progresses interaction networks increase in the number of connections between the individuals (density), in reciprocation between pairs (reciprocity), and in triad formation (transitivity) [33, 41, 55, 62]. The challenge arises when researchers start explaining forces behind these metrics. A network in course A may have evolved from a different generative mechanism than in course B. This implies that network density observed in course A may have been random, whereas network density observed in course B may have been beyond chance. Descriptive cross-network comparisons do not provide this information.

Comparing descriptive indicators across networks requires statistical analyses that rely on the so-called null models that explain how socio-technical networks form. Null models are random networks simulated using hypothesized generative rules, such as 'learners are likely to respond to those who interacted with them earlier' or 'learners interact on a given day when the assignment was posted'. These generative principles should explain why networks form in digital settings, derived from the theories about digital learning and social processes. By comparing observed network to the distribution of random networks generated from the null model, a researcher can interpret if density, transitivity, or any other network measure appears in the observed network by chance or resulted from some particular influences. Many different approaches exist to how null models can be generated, such as tie permutation [40], exponential random graph modelling (ERGM) [38], stochastic actor-oriented modelling [51], among others approaches to network reconstruction [25].

LA largely lacks validated null models that explain how networks form in digital learning environments. Thus far, statistical modelling of networks in digital settings had predominantly used hypotheses derived from why ties form in social networks [29, 12, 60]. For instance, SNA hypothesizes that 'the tie will form between A and C, if A and B as well as B and C are already connected' – based on the principle 'a friend of a friend becomes a friend' observed in social networks. LA researchers can adopt this principle and model online communication network to observe if it describes the random structure, i.e. can explain observed patterns. To demonstrate that these theorized principles can explain formation of ties, researchers need to show that random networks generated by the same principles are similar to the observed network through the goodness of fit plots. Creating network models supplemented with goodness of fit plots would demonstrate where the generative models fail to explain the data. LA studies rarely include such plots for statistical modelling of networks that uses SNA hypotheses. By implication, there is little ground to evaluate how well the models reflect the data.

This highlights the need for formulating and testing generative principles that suit digital learning. Theoretical considerations currently omitted from statistical modelling of digital learning networks include diversity of contexts, as well as lack of attention to time and learner activity level. First, social contexts where LA examines technology-mediated interactions between learners, instructors, online platforms, and course artefacts are markedly different. Given the diversity of social contexts examined in LA, it is likely that the processes generating ties between individuals in them are also different, and theories as to how they form are yet to be put forward. Second, statistical modelling in LA has only recently started to explicitly include temporal aspects of learner activity in socio-technical networks and overall participation levels at the node level (e.g. [4]). Otherwise, researchers used ERGMs to model forum communication as a network of binary ties between the learners, not as a network of valued ties (e.g. where a tie has a value equal to the sum of posts shared between two learners). Excluding information about the weight of ties from a communication network removes some dyadic observations from the modelled data, and therefore, requires a conceptual justification. In light of these shortcomings, current evidence derived from statistical modelling that validates network-level indicators to evaluate socially shared learning and communication can be perceived as limited.

6 FUTURE RESEARCH

The chapter reviewed empirical studies in LA that utilize network approaches. The chapter highlighted the aims of network studies and major caveats associated with them. We emphasize that the researchers who use network analysis as a methodology need to be more explicit about the assumptions they bring from the literature. We call for explicit and rigorous operationalization of networks as phenomena they represent. At minimum, a clear description of network models is needed, to enable further synthesis of insights and prevent naive transfer of interpretations from self-reported network research into the network measures of online learner networks.

Addressing the issues presented throughout the chapter can help constrain LA to better model and understand socially shared learning, with diverse ties and actors at different levels and scales interacting dynamically. That is, learning in socio-technical systems unfolds through temporal interactions between socio-material agents, linked through diverse interactions, and at different levels. A socio-technical view of learning emphasizes that these networks form through mutually interdependent interactions between the artefacts, technology, people, and ideas [31, 32, 49]. Socio-cognitive processes underpinning the diverse interactions drive community development and knowledge building [47]. Knowledge building processes unfold through the interaction of words, topics, themes, social norms stated through discourse, linguistic markers of identity, and similar.

Despite these rich theorizations, current network modelling approaches in LA do not reflect this theoretical richness. A new generation of network studies is needed to use the potential of complex network modelling to integrate dynamic, relational, spatial, multi-level, and multiplex nature of models of social learning with technology. For network analysis methodologies to deliver on the promise for rich insights and indicators to inform about learning, explicit modelling of socio-technical learning processes and better alignment of theory with the methodologies is needed.

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Chapter 5: Natural Language Processing as a Tool for Learning Analytics - Towards a Multi-Dimensional View of the Learning Process

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ABSTRACT

As educators turn to technology to supplement classroom instruction, the integration of natural language processing (NLP) into educational technologies is vital for increasing student success. NLP involves the use of computers to analyze and respond to human language, including students' responses to a variety of assignments and tasks. While NLP is widely used to deliver students with formative feedback, it can also be used to provide educators with information about task difficulty, students' individual differences, and student performance. In this chapter, we will first provide an overview of NLP, followed by a discussion of how NLP could be used to examine the learning process across a number of time points. Finally, we consider the future applications of NLP in the learning analytics domain.

Keywords: Linguistics, natural language processing, language, writing

Educational technologies are an increasingly popular supplement to classroom instruction, as they provide students with added opportunities for deliberate practice along with formative feedback. In many domains, these systems require students to input natural language in response to a variety of task demands, such as essays, reflective writing, metacognitive prompts, and even message board posts [17, 13]. For instance, AutoTutor [20] is an intelligent tutoring system (ITS) that trains students on science concepts through conversations in natural language. Similarly, iSTART [35] provides students with training on reading comprehension strategies by prompting students to self-explain difficult science texts.

These systems, along with many other educational technologies, rely on natural language processing (NLP) techniques to analyze and respond to students' responses. These responses can be in the form of explicit feedback messages delivered by the system; however, they can also be used to model information about the student (e.g., individual differences in knowledge or skills) as well as the task (e.g., the difficulty of the texts they are reading). For instance, Slater and colleagues [44] used NLP to examine how the different properties of mathematics word problems affected students' engagement with the ASSISTments tutoring system.

The integration of NLP into educational technologies is critical for increasing student learning in our globalized, digital world. In the rest of this chapter, we will first provide a broad overview of NLP, followed by an example of how NLP could be used to examine the learning process across a number of time points. We will then conclude with a description of the current and future applications of NLP in the learning analytics domain.

1 WHAT IS NATURAL LANGUAGE PROCESSING?

At its core, NLP is simply a methodology that relies on computers to automatically analyze human language [7]. The specific real-world applications of these analyses can range quite broadly, however, from the automatic translation of text from one language to another (e.g., Google Translate) to the development of virtual assistants or the classification of spam emails. Relevant to the field of learning analytics, NLP methodologies have a number of advantages over other methods of analyzing language data. In particular, because NLP does not rely on human raters, it can analyze large amounts of text data at surprisingly fast speeds. Impressively, NLP can also deal with both written text and speech data effectively. Thus, in handling large and often complex datasets, NLP is often recommended over human coding, as it offers both faster and less-biased analyses.

In considering how to use NLP to analyze linguistic data, it is important to consider the characteristics of human language. One of the key properties of language is that it is multi-dimensional and therefore constrained by both surface- and deep-level features [21, 43]. When using NLP methodologies, then, we must consider these various dimensions in our models containing linguistic content. In particular, we can automatically analyze texts along numerous dimension such as descriptive, lexical features, cohesion and semantic features [7, 10]. It is essential to capture the multi-dimensional aspect when analyzing linguistic data to create a clear picture of what the text really is – in essence, "The whole is better than sum of its parts." Below, we provide a brief overview of some of the most common dimensions of language that can be analyzed using NLP techniques.

1.1 Descriptive

NLP techniques can be used to calculate indices that relate to basic descriptive characteristics of a text, such as number of words, sentences, and paragraphs. Further, you can use these same techniques to calculate frequency counts at different levels of analyses – for instance, letters per word or words per sentence. Analyses such as these can be helpful for understanding a host of learning-related concepts, such as task completion or student engagement. For example, the average length of a student's forum posts in a MOOC has been shown to be a reliable predictor of whether that student will complete the online course [12, 11]. Descriptive NLP indices can also be essential for ensuring that students are given similar types of materials for practice or assessment purposes. For example, NLP techniques can be used to guide which texts or assignments to give students for homework or exams; by relying on descriptive features of the texts or assignments, the instructor or technology developer can have the power to control their materials by ensuring each text has similar features (i.e., they contain a similar number of words, paragraphs, etc.).

1.2 Lexical

The lexical properties of a text relate to characteristics of its words, such as their frequency in a given language (e.g., are the words common or rare?) and their concreteness (i.e., is the word more abstract or concrete?). These word-based features of language can be useful for understanding a host of information about educational materials and content [30]. For instance, NLP techniques can be used to calculate information about the degree to which a given text contains academic language, which can help with the classification of texts into genres or with the scoring of academic writing. Similarly, lexical indices can be used to calculate information about the readability of a given text – in other words, what age or grade level is a given text appropriate for? This information can then be used to help educators understand whether the language input is easy or difficult to read and if this difficulty level is appropriate for a specific population (e.g. 5th grade students or adult learners). Prior research indicates that information about word frequency can inform our understanding of text difficulty, with more frequently used words being easier for readers than less frequent words [24, 26]. Importantly, lexical information can be calculated by simply examining the individual words in a text. This therefore renders lexical indices particularly useful for examining a variety of text types regardless of their length, ranging from tweets or discussion posts [13] to reflective essays [17].

1.3 Syntax

Syntactic indices provide information about the structure of the sentences in a given text [31, 40]. One of the primary means through which individuals computationally analyze syntax in natural language is to measure its complexity – or, the ways in which discrete language units (e.g., words) can be combined to convey meaning [16]. Information about the complexity of syntactic structures can provide a wealth of insight into language, such as the quality of an essay or the readability of a text. Further, syntactic complexity measures have served as a powerful method for assessing the development of language, particularly in the case of second language learning (Ortega, 2003). Numerous indices can be calculated to describe the complexity of syntax in a given language, such as the mean length of clauses, mean length of t-units, or the number of words before the main verb. A number of writing studies have used these indices to discriminate between high- and low-skilled writers in both first and second language contexts [30]. Similarly, research has found syntactic complexity indices to be an indicator of text difficult, as more complex syntactic constructions tax the reader's working memory more heavily [19].

1.4 Cohesion

Cohesion measures provide information about the connections that are made between the ideas in a text. The presence of cohesion is beneficial for comprehension as it assists in coherence building [22]. For example, explaining causal relations in a text increase coherence, as using "because" connects two pieces of information and establishes a causal relation. Cohesion indices analyze these connections and provide a proxy for measuring coherence, examining how ideas are connected by looking at textual links between the sentences or the paragraphs. In education settings, measures of cohesion can provide insight into if students are making connections, which are important signs of comprehension.

1.5 Semantic Content

NLP techniques also provide information about the semantic content of the text. For example, the indices could reveal the main emphasis of the text and whether there is emotional or affective information. Additionally, if a text is written in response to another text, such as a summary or a source-based essay, NLP indices provide information about semantic overlap between texts. Semantic overlap is useful for educators because it provides insight into the students' understanding of a given text.

A multi-dimensional approach to analyzing language provides generous information about word and text level features, which can be used to analyzing many different types of language like tweets, discussion forums, essays or large documents. NLP also helps computers to communicate with humans in their own language and perform language-related tasks. Because of the language related benefits of NLP, it is an important tool for education. The information provided by NLP can assist educators in better understanding the problems students encounter across a variety of settings. For example, by looking at common mistakes, NLP can produce personalized feedback for improving writing. Additionally, such information can be provided quickly, making NLP very useful for effective formative feedback to students.

2 WHAT CAN NLP TELL US ABOUT LEARNING?

So far, we have provided an overview of NLP, particularly focusing on the multi-dimensional nature of language that can be captured with these techniques. It is important to then consider how these methodologies can be leveraged to provide critical information about the learning process. A large assumption of work in this domain is that the language of others can provide important data that can guide models in educational technologies, ranging from student-level variables (e.g., individual differences, performance) to task-level variables (e.g., difficulty). Thus, in utilizing NLP to analyze the language within their technologies, educational technology developers and researchers can better model the primary factors of the learning process. When this information is leveraged, we can provide more nuanced adaptive and personalized instruction and practice to students.

When considering how to best use NLP for learning analytics, the ideal methodology is to consider and analyze language across the multiple dimensions. This information can then be used to develop predictive models of student outcomes, allowing for targeted feedback and interventions. In the hands of educators, this provides a powerful instrument for individualized instruction. Importantly, these models must not only account for the multidimensional nature of language, but also the many stages at which language is involved in student learning. In light of these aims, we can consider three primary stages of analysis: input, process, and output. Below, we provide a brief overview of these stages along with examples of how NLP can be leveraged to improve models at each stage.

2.1 Input

Students are required to process language within educational contexts in a variety of forms, such as the texts they are asked to read, prompts to complete tasks, and questions that attempt to tap into their comprehension of the material. Further, they often receive information from their instructors and peers in the context of written language, particularly in the case of online platforms such as MOOCs.

Thus, one primary challenge that students face in online learning environments relates to their ability to understand the information they receive from these varied sources. For instance, an individual word or sentence may carry multiple meanings or require domain-specific prior knowledge. Therefore, the true meaning of the written language is implicit, leaving readers to make inferences in order to comprehend the text. NLP can provide insight into the different characteristics of the written language students are asked to process, as well as the impact of these features on student outcomes. These types of analyses can provide educators with important information about how they and their materials are impacting student achievement.

NLP can calculate features related to the readability of the text. A number of language features impact the overall readability of a given text, such as syntactic complexity, lexical sophistication, concreteness, genre, and cohesion [19, 21, 34]. Some of these features have an overarching impact. For example, the degree to which a text is narrative or expository impacts readability, with more narrative texts considered easier [24].

Additionally, reader factors can interact with text factors to impact learning. For example, readers' skill levels impact the text features that best support their learning. Increased levels of text cohesion have been shown to help readers with low prior knowledge, whereas decreased levels of text cohesion can help readers with high prior knowledge [34]. Reader engagement is also critical to learning outcomes. Linguistic features of math problems are related to student affect, which are associated with concentration and confusion [44]. These types of interactions can be helpful in improving the efficacy of educational technologies. For instance, if the system is able to understand the needs of the individual student, it can provide learning material that is most appropriate for that student to learn.

Knowledge about how text features interact with student outcomes has already been implemented within ITSs, such as iSTART [23, 34]. For example, iSTART adjusts the texts assigned to students to align with their vocabulary skills [35]. When a student has low vocabulary skills, iSTART will assign texts with more familiar and concrete words, compared to those assigned to peers with higher vocabulary skills. As student's vocabulary skills increase, iSTART can adapt and likewise increase the sophistication of the texts that students receive.

Analyzing the language students receive is one level at which NLP can be employed to improve student outcomes. In understanding the how the features of the text students interact with impacts learning, NLP can be used to adapt materials and enhance learning. However, NLP can be implemented at other levels to develop a clearer picture of student learning.

2.2 Process

Students' learning processes can also be modeled using features of their natural language input to educational technologies. For instance, students are often asked to type their thoughts during reading or while completing complex tasks. Researchers have long tapped into students' online processing and understanding by assessing the content of their verbal protocols or constructed responses to educational tasks. Verbal protocols ask students to report the content of their thoughts as they perform a task—providing insight into how they process information. In analyzing these verbal protocols, researchers have been able to explore and identify the cognitive mechanisms underlying various complex processes such as reading science texts or solving physics problems [14, 41, 42]. This methodology has allowed researchers to understand more about the strategies, processes, and knowledge involved in reading comprehension [36, 37].

One problem with these analyses is that they are often time-consuming and difficult for humans to conduct. Thus, NLP can help to automatically analyze students' verbal protocols, which can in turn provide critical insights into the meaning students construct during reading [5]. To illustrate, consider the way in which students comprehend complex science texts. Research suggests that text comprehension relies on an individual to construct a mental representation of the text. To achieve this, readers rely on their knowledge of language and domain of the text content, as well as reading skills and strategies [27, 36]. This includes generating connections among the concepts in the text and prior knowledge, which establishes coherence and promotes deep comprehension [28]. The overall coherence of a reader's mental representation is positively associated with the degree to which readers active and use prior knowledge, to develop these connections amongst information [36]. This is supported by evidence that skilled and knowledgeable readers are more likely to generate such connections [38, 39].

The use of NLP to examine reader's think aloud responses have provided insight into the processes involved in the development of a coherent mental representation of the text. For example, the level of cohesion, or explicit cues in a text that signal readers to make connections among ideas, can be used as a proxy for coherence [9, 25]. The presence of connectives in a reader's constructed response can indicate that they are making connections between information as they read. Additionally, the type and amount of cohesion (assessed through NLP) can provide insight into the processes in which students engage to achieve comprehension. For example, Allen et al. [1] found that when readers engaged in deep comprehension through self-explanation training, readers' constructed responses were less lexically cohesive, but more causally and semantically cohesive.

Some ITSs implement NLP to analyze students' verbal protocols to gain insight into students' understanding of particular concepts and formulate targeted feedback. For example, AutoTutor [20] uses NLP to analyze tutor dialogues to assess student understanding and provide appropriate feedback. Likewise, the Reading Strategy Assessment Tool [18] prompts students to answer two types of open-ended questions during reading: direct and indirect questions. Direct questions ask students about the content of the text, and analysis of student answers provide insight into comprehension. Indirect questions ask students about their thoughts during reading, which taps into comprehension processes that students employ. Analysis of these answers reveal students' use of paraphrasing, bridging, and elaboration strategies that support comprehension [32]. Students benefit from this individualized instruction and adaptive content.

2.3 Output

Finally, students' produce language as output that can take many forms, such as a short-answer, message board response, or essays. NLP methodologies can be used to analyze these student responses, and further contribute to modeling student learning and achievement outcomes.

For example, a large body of research has looked at using NLP to analyze student writing and develop automated essay scoring (AES) engines. These engines are designed to model expert human raters and provide fast, quality feedback on student writing. Using AES techniques, NLP can be integrated into current writing instruction and improve student's writing skills [29]. Additionally, feedback need not be surface level detail but can also encompass high-level feedback such as structure and organization [15, 46]. Modeling how students present and connect topics in an essay can generate feedback to help students elaborate on underdeveloped ideas, reduce redundancy, and improve essay coherence [46]. Multi-dimensional analysis through neural sequence modeling of student writing can likewise provide instant feedback on essay structure and actionable steps for essay modification [15]. Such feedback is highly personalized to the student and provides a powerful tool for educators to recognize patterns in student's understanding.

Work in developing these engines have revealed the linguistic features of high-quality writing. For example, essays are considered high-quality when they contain more diverse and sophisticated word choices and more complex syntax [9]. Notably, features of high-quality student essays are not the same as high-quality texts. While syntactic complexity is related to higher ratings of essay quality, texts that contain more syntactic complexity have been shown to increase working memory load and decrease comprehension [19].

Additionally, features of students' essay writing, as assessed by NLP, can also reveal individual differences. For example, lexical properties of student essays have been used to predict student vocabulary knowledge [3]. Modeling students' individual differences can give educators insight into students' strengths and weaknesses, providing additional opportunities for specific and personalized instruction.

In considering not only the multidimensional nature of language, but also the multiple dimensions across which language is utilized in learning, models can become a powerful educational device. Educators can learn how, and for whom, to adapt their materials to promote better learning outcomes. Students' online processing of materials can trigger adaptive feedback to prevent misunderstanding. Students' learning outcomes can be used to predict course performance, and prompt tailored assistance. Students' continued interaction with the system continuously updates the model, representing more personalized instruction based on students' knowledge and performance.

3 WHERE ARE WE HEADED?

The use of linguistic data in learning analytics allows for a more comprehensive view of the educational experience. To this end, we suggest that the strongest potential avenues for research in this area are multimodal in nature. In particular, we suggest researchers focus on methodologies that allow for the integration of NLP analyses with the expansive work that is already being conducted in the field.

One example of this multimodal integration is found in work that emphasizes the dynamic nature of language production processes [2]. Education and cognitive science researchers, for instance, have relied heavily on reading times and eye-tracking to provide information about students' cognitive processes while engaging with educational materials [26, 33, 47]. Although researchers have made a significant effort to leverage these methodologies, there has been a significantly smaller amount of research conducted on students' online language production processes [45].

Thus, one area for future research lies in the temporal tracking of the keystrokes produced by students while writing [6, 45]. NLP analyses generally focus on the final written product; however, keystroke analyses focus on the writing process by examining the keys that are pressed while writing, and in particular, the timing of the keystrokes as well as the backspaces that are invisible within the final product. Recently, tools have been developed to facilitate recording the individual keystrokes pressed by individuals during writing [1, 8, 45].

Bixler and D'Mello (2013) provided preliminary results supporting the promise of keystroke analyses in the detection of affective states. They found that a combination of keystroke and individual difference measures (i.e., scholastic aptitude, writing apprehension, and exposure to print) afforded the diagnosis of self-reported affective states (i.e., neutral, boredom, engagement) during writing with accuracies of 11% to 38% above baseline. Similarly, Allen et al. [4] predicted engagement and boredom across multiple writing sessions using a combination of academic ability (e.g., scholastic aptitude), linguistic text properties, and keystroke indices. The combination of these indices achieved an accuracy of 77% in classifying high and low engagement and boredom in writing sessions.

These studies represent initial explorations of writing using online keystroke analyses. Many more questions on the contributions of various factors can be explored using this approach. Consider, perhaps as a more real-world example, pausing to search the internet for a word, a concept, or to check the correct syntax for a particular phrase. What are these processes and how can we use information about them to understand writing? How can an integration of technologies, such as keystroke logging and NLP inform writing theories? Our strong sense is that pursuing answers to these (and other) questions will help to inspire theories of the cognitive and sociocultural processes that drive writing performance.

4 CONCLUSION

The purpose of this chapter was to provide a brief overview of NLP techniques and methodologies, and to propose new areas of research that leverage NLP within the learning analytics domain. In this chapter, we have pointed toward several directions that we consider particularly fruitful. However, any number of directions might be taken to establish a more comprehensive understanding of writing. We have also made an explicit argument for the integration of NLP into broader work in learning analytics. Research on the linguistic aspects of natural language has largely been conducted separately from learning analytics research. One objective here is to encourage researchers in the learning analytics community to extend their research to the study of language, and to encourage researchers to draw on literature from this community to help move our research forward. We believe that such an approach is essential to developing a more well-rounded view of the learning process.

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Chapter 6: Multimodal Learning Analytics - Rationale, Process, Examples, and Direction

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ABSTRACT

This chapter is an introduction to the use of multiple modalities of learning trace data to better understand and feedback learning processes that occur both in digital and face-to-face contexts. First, it will explain the rationale behind the emergence of this type of study, followed by a brief explanation of what Multimodal Learning Analytics (MmLA) is based on current conceptual understandings and current state-of-the-art implementations. The majority of this chapter is dedicated to describing the general process of MmLA from the mapping of learning constructs to low-level multimodal learning traces to the reciprocal implementation of multimedia recording, multimodal feature extraction, analysis, and fusion to detect behavioral markers and estimate the studied constructs. This process is illustrated by the detailed dissection of a real-world example. This chapter concludes with a discussion of the current challenges facing the field and the directions in which the field is moving to address them.

Keywords: Multimodal, audio, video, data fusion, multisensor

The defining goal of Learning Analytics is the study of the low-level traces left by the learning process in order to better understand and estimate one or more learning constructs that are part of the process and, through carefully designed information tools, help the participants of that process to improve some desired aspects of it. The first works of Learning Analytics focused on the traces that were automatically generated when learners interacted with some type of digital learning tool. For example, Kizilcec, Piech, and Schneider [21] used the log of the actions performed by different groups of students in massive open online courses (MOOCs) to study course engagement, or Martin et al. [26] that use the low-level actions of students playing an educational video game study learning strategies. While these tools fulfill the goal of Learning Analytics, if we only focus on a single type of traces that are recorded in logs of digital tools, we risk oversimplifying the process of learning or even worse, misunderstanding the traces due to the lack of contextual information, two of the main critiques directed towards Learning Analytics from the educational research community [36].

The initial bias to base Learning Analytics works solely on the data of interactions of students with digital learning tools can be explained by the relative abundance of this type of data. Digital tools, even if not initially designed with analytics in mind, tend to automatically record, in fine-grained detail, the interactions with their users. The data describing these interactions is stored in many forms; for example, log-files or word-processor documents can be later mined to extract the traces to be analyzed. Also, the low technical barriers to process this type of data make digital the ideal place to start Learning Analytics research. On the other hand, in learning processes that occur without the intervention of digital tools, for example, face-to-face blackboard-based collaborative problem solving, the actions of learners are not automatically recorded. Even if some learning artifacts exist, such as student-produced physical documents or photographs, they need to be converted before they can be processed. Without traces to analyze, computational models and tools used traditionally in Learning Analytics are not applicable.

The existence of this bias towards learning contexts where digital tools are the main form of interaction could produce a streetlight effect [17] in Learning Analytics. The streetlight effect consists of looking for solutions where it is easy to search, not where the real solutions are most probable to be found. Translating this effect to Learning Analytics, it to use a given learning trace, for example, access to materials on the LMS, to estimate a learning construct, for example, engagement, just because we only have access to that data, not because we have a theoretically or empirically strong indication that level of access is a robust predictor of engagement. A more holistic analysis of even the simplest learning construct requires the examination of different sources of evidence at different levels of complexity. For example, a human instructor trying to assess the level of engagement of students could review not only their online actions but their participation in face-to-face activities, their academic and social interactions with others, the quality of their work, and even their body language during lectures. Even if no single dimension independently is a very robust indicator of the desired construct, the triangulation between different but related and complementary sources of information is bound to provide stronger evidence upon which an intervention decision could be taken with confidence [30].

Addressing the streetlight effect in Learning Analytics requires that, instead of being guided by the data that is available, the study start with theory- or experience-based analysis of how the desired learning construct manifest itself through behavioral markers in different contexts and identifying what low-level traces can be used as evidence of those behaviors. Then, technological solutions need to be found to record the learning process in the context where it occurs and extract the identified traces. Finally, these traces need to be analyzed and fused to detect the behavioral markers and finally to robustly estimate the learning construct of interest and feedback the information to the participants of the learning process in an understandable and actionable way. The nascent sub-field of Multimodal Learning Analytics (MmLA) strives to fulfill this tall request. This chapter is an initial guide for researchers and practitioners who want to explore this sub-field. It will discuss in detail the MmLA focus of study, its processes, and current examples of how it instantiates in real-world scenarios.

1 WHAT IS MULTIMODAL LEARNING ANALYTICS

In its communication theory definition, multimodality refers to the use of diverse modes of communication (textual, aural, linguistic, spatial, visual, et cetera) to interchange information and meaning between individuals [23]. It is different from the concept of multimedia, using diverse media to communicate information. The media — movies, books, web pages, or even air — are the physical or digital substrate where a communication mode can be encoded. Each mode can be expressed through one or several media. For example, speech can be encoded as variations of pressure in the air (in a face-to-face dialog), as variations of magnetic orientation on a tape (in a cassette recording), or as variations of digital numbers (in an MP3 file). As well, the same medium can be used to transmit several modes. For example, a video recording can contain information about body language (posture), emotions (face expression), and tools used (actions).

Multimodal Learning Analytics is rooted in the Multimodal Interaction Analysis framework (Norris, 2020) that exhort the integration of multimodal information (human verbal and non-verbal forms of communication together with information about the objects used as part or medium of the communication and the contexts in which this communication occurs) to better study and understand how humans act and interact with others, with technology, and with the environment. Translating this framework to educational settings, Paulo Blikstein first formally introduced the concept of Multimodal Learning Analytics at the 3rd Learning Analytics and Knowledge Conference (LAK) 2013 in a homonymous paper [5]. In this paper, MmLA is defined as "a set of techniques that can be used to collect multiple sources of data in high frequency (video, logs, audio, gestures, biosensors), synchronize and code the data, and examine learning in realistic, ecologically valid, social, mixed-media learning environments." Unpacking this definition, we can observe the three main operative processes of MmLA, already hinted in the introduction of this chapter: use of diverse sources of learning traces (multimodal data), processing and integration of these traces (multimodal analysis and fusion), and the study of human behavior in real learning environments (learning behavior detection and learning construct estimation).

While the term Multimodal Learning Analytics was formally coined in 2013, the application of the Multimodal Interaction Analysis framework to educational context has always been part of the Learning Analytics agenda. Already in the first LAK conference, [6] proposed its use in the then-nascent field. Before LAK, what can now be considered bonafide MmLA works were published at the International Conference for Multimodal Interaction (ICMI), which hosted the 1st Multimodal Learning Analytics workshop already in 2012 [34]. However, the idea of using different communication modalities to study learning predates even the terms Multimodal Interaction and Learning Analytics and it is common in traditional experimental educational research. In this research tradition, a human observer, which by nature is a multimodal sensor, is tasked with noting and annotating relevant interactions that occur in real-world in-the-wild learning contexts for further qualitative analysis [18]. Technologies such as video and audio recording and coding and tagging tools have made this observation less intrusive and more quantifiable [9, 25]. MmLA, however, presents several important differences with traditional educational research practices: 1) In MmLA, the collection of the data is performed by low-cost high-definition sensors that enable the capture of the traces with a level of detail that was not feasible before, 2) in MmLA, early coding happens automatically through the use of machine learning and artificial intelligence algorithms, eliminating the limits in both the number of codes and the time length that is imposed by the manual nature of human coding. 3) In MmLA, the analysis and fusion of the data can be (semi-) automated providing systems that could be used in real- or near real-time and, 4) in MmLA, the result of the analysis is not only used to expand our understanding of the learning process being observed but could also be used to create an analytic tool to provide information back to students and/or instructors to generate a feedback loop to improve learning as it is happening. While both traditional multimodal educational research and MmLA share a common interest in the different ways in which humans interact during learning activities, the affordances provided by the speed and scale of MmLA open a different set of opportunities to understand and improve learning processes.

A good way to understand the kind of opportunities that MmLA affordances provide is to review some of the most notable examples of this sub-field available in the literature. Table 1 presents a non-exhaustive list of examples of successful applications of MmLA techniques in diverse learning settings. The list mentions the different modalities used in the work and the learning construct being studied or estimated. As it can be seen in the table, MmLA has been used in contexts as dissimilar as traditional classrooms to medical simulations and educational games. While a great variety of modes are explored video- and audio-based modes such as gaze, movement, gestures, and speech are the most common, followed by bio-signals (mental activity and electrodermal activity). However, depending on the circumstances specialized modes are used (pen strokes for calligraphy and manikin interactions in medical simulations). The variety of learning constructs being studied is even more diverse than the learning settings, exemplifying the great flexibility of MmLA as a research and practice tool. Di Mitri, Schneider, Specht, and Drachsler [13] can provide the reader with a wider and deeper review of existing MmLA systems together with their modalities and investigated constructs. While all the systems in Table 1 and the ones mentioned in Di Mitri et al. have different objectives and implementations, they all follow a similar process. This high-level MmLA process will be explained in the next section.

2 THE PROCESS OF MMLA: FROM CONSTRUCT TO TRACES AND BACK AGAIN

Due to its nature, most of MmLA studies and tools, even if it is not explicit in their published description, follow a common process. This process can be roughly divided into two reciprocal phases: Mapping and Execution. During the mapping phase, a logical path is found between theoretical learning constructs of interest and multimodal data traces that can be observed during the learning process. During the execution phase, that path is reversed and extracted multimodal data traces are used to estimate the desired learning constructs. While the second phase, execution, receives a great deal of attention due to its technical complexity, it is the first phase, mapping, where MmLA directly tackles the streetlight effect problem in Learning Analytics. The following subsections will explain the different steps inside these two phases together with the main concerns that emerge with the use of multimodal data.

2.1 Mapping Phase: From Learning Constructs to Multimodal Data Traces

Thanks to some of its roots in Experimental Psychology and Educational Research, Learning Analytics have adopted the idea of a construct, most commonly referred to as a learning construct, to organize and explain the reason behind the measurements, analysis and interventions conducted [11]. A learning construct can be defined as a concept or idea related to students' behaviors, attitudes, learning processes and experiences. By definition, a construct is not directly observable or measurable but manifests itself through behaviors that occur when the learner interacts with the learning environment. Those behaviors can then be used to estimate the value, graduation, or intensity of the construct. For example, intelligence is a common construct used in education. To be able to estimate the intelligence of individuals, we expose them to situations where their need to use their complex cognitive abilities, for example exposing them to a set of complex problems, puzzles, or an IQ test and using the time and number of correct answers to estimate how intelligent they are. The mapping phase has four steps and results in a tree-like map that links the learning construct of interest with the observable data traces. Figure 1 presents a detailed view of this tree, while Figure 2 shows this phase as a part of the MmLA process. This mapping process is not unique to MmLA and has been proposed initially by Worsley et al. [41] and refined by Echeverria [14]. However, this model is especially well suited for studies that involve multimodal data.

The first step in the mapping phase is the definition of the learning construct of interest. This selection is ideally guided by the needs of the learning process stakeholders as discovered by the researcher but sometimes is determined by the interest or curiosity of the researcher. The initially selected construct could encompass a large set of diverse behaviors, for example, "collaboration skills". In this case, we could divide the learning construct into sub-constructs. We can divide the "collaboration skills" construct into "participation" and "active listening" sub-constructs each one capturing a different subset of the behaviors connected to collaboration skills.

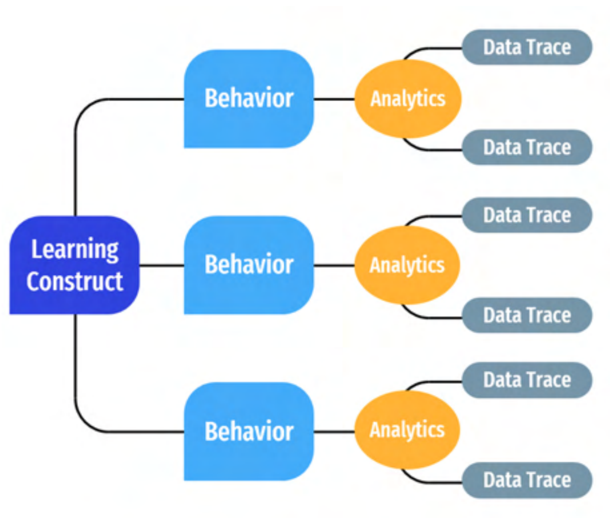

Figure 1: Construct Mapping detail tree-structure, adapted from [14].

2.2 Execution Phase: From Multimodal Data Traces to Learning Constructs

Once the mapping between Learning Constructs and low-level multimodal data traces is complete (at least as a first draft in the mind of the researcher or practitioner), a Multimodal Learning Analytics System can be built. In general, this system could have two different goals. The first one is research-oriented and starving to generate new gen-

Table 1: Non-exhaustive list of examples of the application of MmLA system in different learning settings.

Learning Setting	**Reference**	**Main Multimedia Data**	**Main Learning Construct**
Calligraphy Learning	[24]	Gaze location on screen (eye-tracking), pen strokes, movement	Mental effort
Classrooms	[32]	Gaze direction (eye-tracking), mental activity (EEG), movement, subjective view (video), subjective hearing (audio)	Classroom orchestration
Collaborative Problem Solving	[15]	Touch coordinates, speaking time, participant hand position	Contribution to solving the problem
Dance	[33]	Facial expression, gaze, posture, movement	Dance skills
Educational Games	[19]	Keystrokes, mental activity (EEG), Gaze location on screen (eye-tracking), facial expression (video), electrodermal activity (EDA)	Learning gains
Embodied Cognition	[2]	Gaze, gestures, movement	Concept understanding
Intelligent Tutoring Systems	[20]	Scores, time on task, number of tasks, speech pauses and length	Affect
Making	[40]	Human video coding, skeletal tracking	Efficacy of learning practices
Medical Simulation	[27]	Interactions with a patient manikin, use of digital checklist, location, speech	Team collaboration
Oral Communication	[35]	Posture, gestures, speech volume and cadence	Oral presentation skill
Programming	[10]	Usage of digital system, speech	Collaboration and communication

eralizable knowledge about the learning construct. For example, what are the main differences between the engineering building processes of novices and experts [42]. The second could be practice-oriented, striving to provide an analytic tool to improve the learning process for the participants. For example, an automated feedback system to improve oral presentation skills [29]. While these two objectives are not necessarily mutually exclusive, MmLA works tend to align with one or the other due to implementation requirements that will become apparent when this phase is discussed in detail.

The execution phase can be seen in the second lower part of Figure 2. It runs in reverse order compared to the mapping stage and consist usually of four steps. First, multimedia signals are recorded from the relevant participants in the learning activity. Then, these recordings are automatically processed to extract low-level multimodal data traces. These low-level traces are then (semi-) automatically analyzed and fused to produce high-level traces. These high-level traces are used to detect the occurrence of desired behaviors and to estimate the studied learning (sub-)constructs. Finally, if the final goal of the system is to build an analytic tool, the obtained estimations are used to feed the tool providing the information back to the learning process participants. The following subsections will present the requirements and operation of these steps in detail.

2.3 Multimedia Recording

The first step in the execution phase is to be able to register or record all the relevant signals that contain the data traces identified in the mapping phase. In the case of the interactions of digital tools, this capture could be as simple as adding a logging statement in relevant parts of the tool's code. On the other hand, in situations that require the capture of non-computer-mediated actions, such as a face-to-face conversation between two individuals, the use of different types of sensors is needed. These sensors could be as simple as a webcam or as sophisticated as a magnetic resonance imaging (MRI) machine. Moreover, the multimodal aspect of MmLA systems usually requires the use of several sensors, each one specialized in a different type of media. For example, a webcam for video, a microphone for audio, a digital pen for the learner's notes. There is a large range of sensors and modalities that have been used in MmLA systems [13]. While the selection of the right type of sensors and the design and setup of the recording apparatus is an engineering problem, researchers and practitioners alike should be aware of the affordances, limitations, and scalability of these components to create effective MmLA systems.

2.4 Multimodal Feature Extraction

Once the raw multimedia data is captured, the next step is to extract the identified multimodal data traces embedded in those recordings. This extraction, in general, requires a computer algorithm that can process the raw recording or data file and isolate or generate the trace for the required modality. For example, if we require the body posture of the participants and we have a video recording, we can use computer vision algorithms, more specifically Convolutional Pose Machine [39], for example, that implemented in OpenPose [7], to obtain the position of the skeletal joints and pose of all the individuals present in each video frame. In another example, speech to text algorithms, for example, the one provided as a service by Google Speech, can be used to extract the verbal content of the audio signal recorded by a microphone. Similar to the recording step, while it is not necessary to possess full knowledge of how each extraction algorithm operates, it is highly recommended that researchers or practitioners understand the affordances and limitations of those algorithms.

2.5 Multimodal Analysis and Fusion

The traces extracted from raw data are defined for a single modality. For example, feature extraction might compute student eye gaze direction or voice pitch. While there are some cases in which low-level unimodal traces are enough to estimate the desired behavior, most commonly these traces need to be processed and fused together to create higher-level traces that are more accurate and robust predictors. For example, if the behavior of joint visual attention in a collaborative activity around a table is of interest, the estimated individual gaze direction from each participant has to be fused together with the direction of the other participant's gaze to detect if two or more of them intersect inside a given region in the table. In another example, turn-taking information can be extracted from the change in the current speaker trace. In a more complex example, turn-taking information, paired with idea identification information obtained from speech, could be used to identify idea uptake traces. The development of these fusion algorithms is still an open challenge in MmLA and very much guided by the analytic description during the mapping phase. The recommended approach to tackle the construction of these algorithms is to develop a human rubric to measure as objectively and reproducible as possible the observation of the high-level traces, then using a mixture of theoretical knowledge and Principal Factor Analysis to select promising low-level traces to model the desired high-level one. This technique is explored in Chen, Leong, Feng, and Lee [8].

2.6 Behavior Detection and Construct Estimation

This step in the execution phase is not particularly different for MmLA when compared with more traditional works in Learning Analytics and Educational Research. Once the results of the analysis and fusion phase provide information about the occurrence of the identified behaviors, computational or statistical analysis (or qualitative analysis in the case of research-oriented MmLA systems) can be used to estimate the level, grade, or intensity of the studied learning (sub-)construct(s). The only main consideration for MmLA systems is the increased level of uncertainty in the detection of behavioral markers. In a similar way in which the estimation of inter-rater coefficients is used to assess the reliability of the coding of the

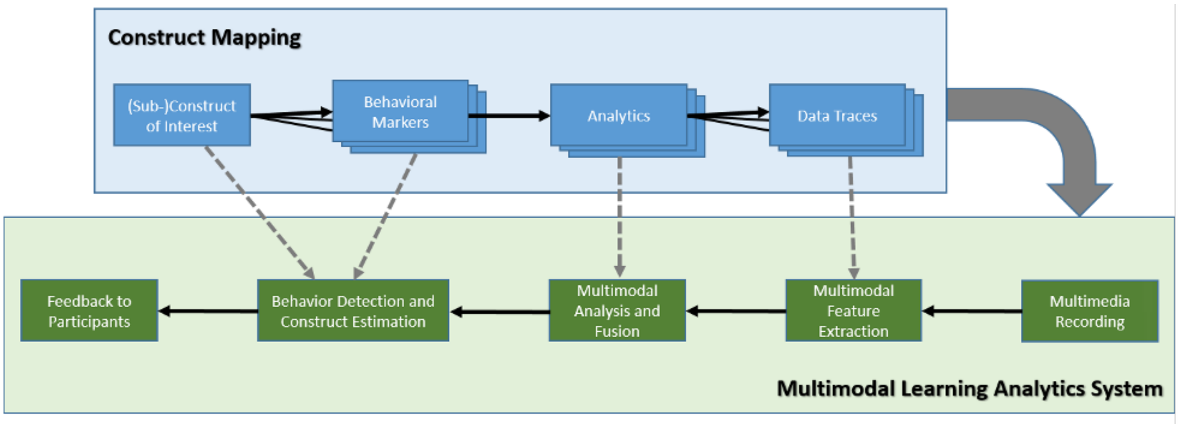

Figure 2: Diagram of the MmLA Process.

ground truth, the measured accuracy of the automated detection should be calculated against one or more human coders. If this a research-oriented MmLA system, this is the final step in the process. The estimation of the construct(s) can be used to draw generalizable conclusions about the nature, workings, or efficiency of the learning process, and through the publications of these results, improve the general knowledge about how humans learn and maybe improve new designs of the studied or similar learning process.

2.7 Feedback to Participants

If the goal of the system is to provide reflection opportunities and actionable feedback to the participants of the learning an analytic tool has to be built and fed with the data generated during previous steps. For this kind of tool to be effective, it has to consider what information to present, when to present it and how to present it [22]. For instance, letting a teacher know that a group was struggling after the activity has been completed is less effective than letting them know during the activity when there is the possibility to intervene. Notwithstanding, there may be instances where it is best not to intervene, as well as situations where instructors wish to reflect on how their prompts impacted student-student collaboration. Switching to the student perspective, it might be the case that providing each student with a dashboard presenting several collaboration-related measurements in their smartphones during the activity could distract them from the activity itself. The information provided by MmLA systems enables the exploration of new and innovative ways to close the loop of Learning Analytics.

Multimodality embedded in the system can be used to create more natural ways to provide the right information, in the right moment and in the right modality. These multimodal interfaces predate MmLA but have been described in other research communities. As an example, Alavi and Dillenbourg [1] successfully tested ambient signaling lights to support teachers to easily identify struggling groups during supervised collaborative problem-solving. Bachour, Kaplan, and Dillenbourg [4] experimented with the use of an illuminated interactive tabletop to provide real-time feedback to students about their participation in the conversation.

3 MMLA PROCESS IN ACTION

To demonstrate how the diverse steps of the MmLA process are implemented, a real MmLA study will be dissected and analyzed. This study is a representative of one of the oldest and widest applications of MmLA, providing feedback for oral presentations [29, 29].

3.1 Oral Presentation Feedback System

This example describes a multimodal system for automated feedback for oral presentation skills [28, 29]. This system was designed and implemented in a mid-size polytechnic higher education institution on the coast of Ecuador. In a nutshell, this system allows students to practice oral presentations in front of a recorded audience and to receive a report that indicated if they made common presentations errors such as looking at the slides for long periods or speaking too softly. Figure 3 present the physical layout of the system. The following subsections will describe the MmLA process followed in the implementation of this tool.

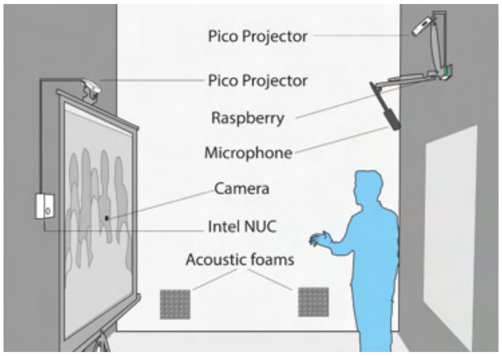

Figure 3: Physical layout of the multimodal system for oral presentation feedback, taken from [28].

3.2 Construct Mapping Phase

Figure 3 presents the construct mapping for this first example. The main objective of this tool was to help learners to develop basic oral presentation skills. By consultation with communication professionals, the "Basic Oral Presentation Skill" construct was connected with four observable behaviors: 1) Looking at the audience; 2) Maintaining an open posture; 3) Speaking loudly; and 4) Avoiding filled-pauses. The next step in the mapping was to identify the analytics to detect the behaviors. For example, looking at the audience can be detected when the gaze of the presenter was directed towards the camera (that was embedded in the middle of the recorded audience projection. In another example, the presence of filled pauses ("ahh", "umm", among others) was detected by an analysis of variance of speech formants. Finally, the multimodal data traces needed for each analytic was extracted. In this case, each analytic is connected to just one trace. In total, four traces need to be extracted: gaze, posture, speech volume, and speech formants. This mapping is very simple, there no triangulation for behavioral detection, there is no multimodal fusion strategies. A consequence of this design is that the accuracy of the feature extraction needs to be high in order to avoid behavior misidentification.

3.3 Execution Phase

The first step of the execution phase was to determine the sensors needed for the multimedia recording. It was determined that gaze and posture could be extracted from a video feed of the presenter recorded by a webcam embedded in the middle of the screen where the recorded audience was projected. Alternatively, a hardware depth sensor, such as Microsoft Kinect could have been used to extract these to modalities, but a camera was preferred due to implementation cost, leaving the heavy processing for a centralized software implementation. The speech volume and speech formats were capture in the audio signal recorded by a mono-channel microphone located above the presenter.

For the multimodal feature extraction step, diverse software libraries were used. For the posture, OpenPose, a convolutional pose machine, was used to obtain the 2D position of the skeletal joints. Using part of the skeletal joints the head posture (relative position of ears, nose, and neck) was calculated as a proxy of gaze, given that the video quality was not enough to perform a landmark analysis of the face. Given that only a coarse gaze direction is needed (looking at the audience, looking away from the audience) was needed, this setup was determined be a good compromise between precision and implementation cost. For the speech features (volume and formants), a commonly used software package for analysis of speech characteristics (PRAAT) was employed. The accuracy of the extraction of these characteristics was performed [29] and was determined to be sufficient for the application at hand. The multimodal analytics and fusion step was straightforward given the lack of any fusion between features. For the detection of an open posture, the random forest model was trained with human coded images of open and close postures, mostly related to the position of the arms with respect to the body, especially the hips. This model was then used to classify the postures as open or closed. In the case of volume, a simple threshold detector was used to differentiate between loud and soft speech.

The detection of the behaviors was also straight-forward. An error rate approach was used to provide a value to how much a given behavior was observed. For example, the percentage of time that presenter keeps their gaze looking towards the projected audience versus away from it. These percentages were used then to calculate a score (based on recommendations by the original communication professionals). These scores were linearly added to estimate the level of oral presentation skills in the participant.

Finally, the calculated scores, together with the information generated through the whole execution phase was used to create a multimedia feedback report (Figure 5). This report presented the final score together with the scores for each one of the behaviors. The presenter was also able to see or hear recordings of good and bad examples of each of the scored behaviors.

4 CHALLENGES & DIRECTIONS

It is the intention of this chapter to introduce the sub-field of MmLA, its process, its potentialities, and to provide examples of its state-of-the-art. However, no discussion about MmLA is complete without addressing the multiple methodological, technical, practical, and ethical challenges that it currently confronts and how the MmLA community is trying to address them moving forward.

4.1 Methodological Challenges

One of the most pressing issues that MmLA, as a field, faces is the lack of homogeneous methodological approaches and a compendium of best practices. Due to the novelty of the field, which is the intersection point of several research traditions (multimodal interaction, educational research, artificial intelligence, among others), each study uses different approaches for the validation of its measurements, fusion of multimodal information, and even the definition of constructs, behavioral markers, analytics, and modalities. This complete diversity, while initially beneficial as a way to explore the affordances and limitations of the field, it is now generating problems in the generalization, reproducibility, and sharing of results. It also limits the capacity of MmLA to contribute to a common theoretical body-of-knowledge as each study is a one-off enterprise.

The need to share definitions, methods, and best practices was early identified by the community. The first MmLA workshop was already organized in 2012 [34] and has been repeated yearly since. The MmLA community has also formally created a Special Interest Group (SIG) inside the Society for Learning Analytics Research (SoLAR). All these efforts have started to bear fruit in recent years as several publications have started to catalog and sys-

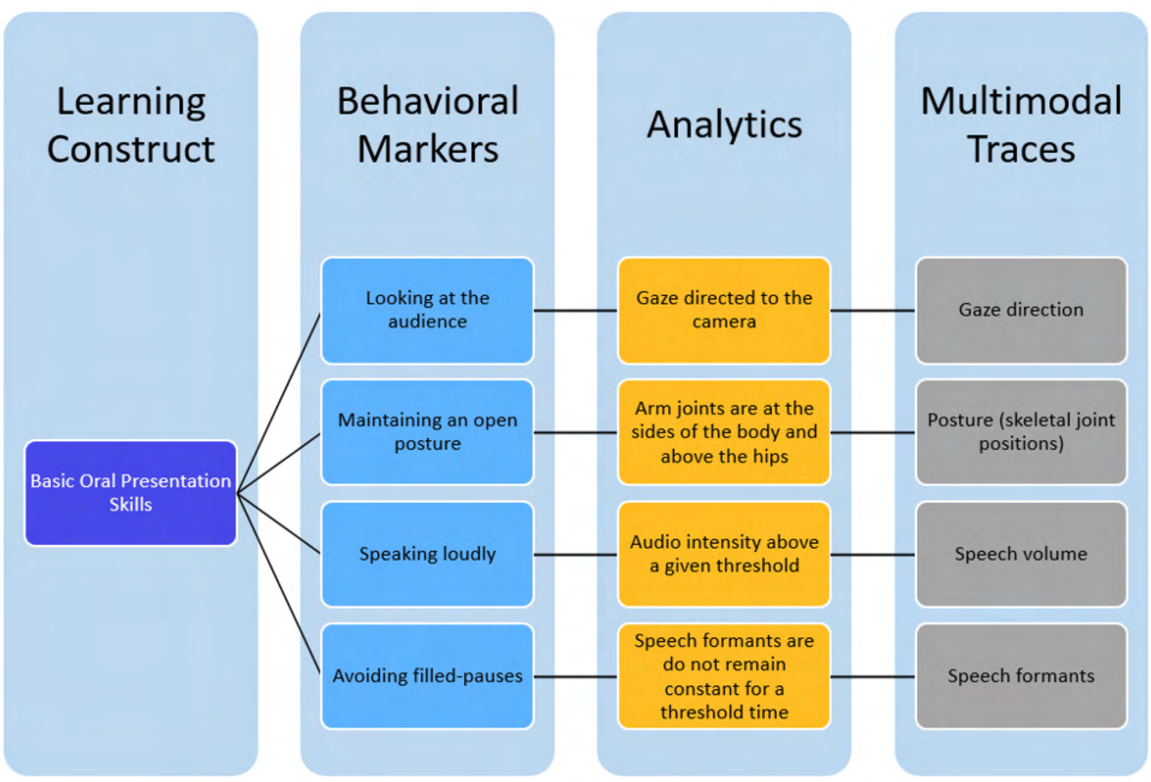

Figure 4: Construct Mapping for the Oral Presentation Feedback Tool.

Figure 5: Example the multimedia report from the oral presentation feedback tool, taken from [29].

tematize the different approaches used by MmLA work and proposing common conceptual and methodological frameworks to better align the different research traditions inside MmLA. Examples of this new wave of integrative research are the frameworks proposed by Worsley et al. [41], Eradze, Rodríguez-Triana, and Laanpere [16], Di Mitri et al. [13], Sharma, Papamitsiou, and Giannakos [37], and Echeverria [14]. This last example has been used as a base for the MmLA construct mapping process presented in this chapter. It is expected that in the following years, these frameworks will provide a common ground for MmLA works to be more comparable, generalizable, and incrementally improved by others outside their original creator team.

4.2 Technical Challenges

Another aspect that hinders a more accelerated progression of MmLA is the technical difficulty that implementing multimodal analytic systems entails. While MmLA benefits from state-of-the-art developments in sensor technologies, digital signal processing, machine learning, and artificial intelligence in general, it also requires technical experts in these areas to be involved in the design and implementation of MmLA systems. Technical issues raised by the distributed operation of the sensors, synchronization of the signals, advanced feature extraction, and multimodal fusion strategies keep most educational-focused teams, without access to those experts, away from exploring MmLA solutions to study real-world learning processes. This is a problem shared by the Multimodal Interaction community in general. Tentative technical solutions have started to emerge in germane fields. For example, Social Signal Interpretation (SSI) framework [38] provide a software framework that offers connection with a wide variety of sensor, warrantied synchronization even with sensors distributed across a network, machine learning model training and use, multimodal fusion and behavior detection. While not easy-to-use by any metric, this is a step in the direction of simplifying the design and implementation of MmLA systems. Another emerging, but not currently widely tested, software framework available is the Microsoft Platform for Situated Intelligence [3] that promises a more robust set of development and visualization tools. It is expected that in the immediate future the construction of MmLA systems to be greatly facilitated by this kind of software solutions that remove the need to pay close attention to the technical details and facilitate the researchers to concentrate on the study of the learning process.

4.3 Practical Challenges

Most of the current MmLA tools only reach the prototype stage [12]. While useful for research on MmLA and its potential, these tools have almost no impact on real-world learning processes. To bridge the gap between an interesting technical prototype and a pedagogically-integrated solution, MmLA, as a field, need to pay more attention to practical issues that affect the attractiveness of the MmLA systems for educators and educational institutions. The most important of these issues are cost (initial cost and maintenance cost), easy-of-use (no technician should be required for day-to-day use), robustness (the system should graciously manage hardware, network, or software problems), and scalability (it should be feasible to deploy the system institution-wide). These are common requirements for any learning technology, including any Learning Analytics tool. However, solving these practical problems is beyond the interest and knowledge of most researchers, requiring stronger participation of learning technology practitioners that seeing the potential of MmLA translate the prototypes into solutions that can be easily deployed in-the-wild. Ochoa and Dominguez [28] offers an example of a MmLA tool that was successfully implemented in-the-wild.

Ethical challenges are the "elephant-in-the-room" for MmLA. Not so much because it is not spoken about (they are a constant theme of debate among MmLA researchers and practitioners) but because they generate issues that can overweight any methodological, technical, or practical consideration. Capturing interaction information with digital tools already raises privacy concerns among students and instructors [31]. The installation and use of recording systems that technically mimic (and sometimes exceed) "1984" levels of surveillance are bound to meet understandable strong resistance from the learning process stakeholders, especially those under observation. While these issues are less problematic for research-oriented MmLA systems used in laboratory settings, they can completely block even the idea of using them in real learning environments.

The main way in which the MmLA community is trying to address these challenges is by clearly separating research from practice. The data captured in research-oriented MmLA systems in-the-lab, after the required consent forms are signed, could be used to advance the state of the knowledge in the field with just the minimum required safeguards for the privacy of the participants and their immediate benefit. The data produced in these settings usually belongs and is controlled by the research team that built the tool. On the other hand, data produced by a practice-oriented MmLA system in-the-wild can only be used for the immediate benefit of the observed participant. Also, the data belongs and its use and storage should be controlled by the participant. Strong safeguards should be in place to deter the use of this data for something different than its original purpose to feedback the learning process participants. Only with these safeguards, practitioners should be able to address natural negative perceptions of technology that could be misused for unduly monitoring and surveillance.

5 CONCLUSION

Learning Analytics has revolutionized the way in which we study and try to improve learning processes. However, its initial bias towards studies and tools involving only computer-based learning contexts jeopardizes its applicability and conclusions for learning in general. The MmLA strives to widen the horizons of Learning Analytics, including richer and possible more relevant sources of data and including also learning context to which traditional Learning Analtyics could not be applied due to the lack of pre-existing data. As it can be inferred from the discussions in this chapter, especially for the current challenges and directions, MmLA is still young with many issues to be addressed. However, it is also a fast-growing and connected community of researchers and practitioners in constant search of innovative solutions to those issues. This community is also showing strong signs of maturing, such as the recent proposal of methodological frameworks integrating learning theories and multimodal interaction analysis and lowering the technological barriers of entry. This chapter, apart from being an introduction to MmLA, is an invitation for existing Learning Analytics researchers and practitioners to explore the use of multiple modalities in their own studies and tools. The MmLA community will openly share its knowledge, methodologies, code, successes, and failures. While current MmLA is considered a sub-field of Learning Analytics, is the belief of the author that in the future most of Learning Analytics studies will be multimodal in nature as learning itself is.

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Chapter 7: Temporal Aspects of Learning Analytics - Grounding Analyses in Concepts of Time

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ABSTRACT

This chapter represents an effort to lay out a common framework for the concepts of time to (a) support diverse researchers working on temporal aspects of learning analytics to communicate better, (b) facilitate an understanding of how different approaches to studying time in learning articulate and (c) map out the space of temporal analysis to reduce redundancy of efforts. We distinguish two concepts of time, namely the passage of time and order in time. Passage of time considers time as a continuous flow of events and order in time focuses on the organization among events. Within the passage of time we distinguish four metrics: position, duration, frequency and rate. Within order in time we discriminate between consistency, recurrent and non-recurrent change and irregular change. Metrics extracted to index passage of time can be used in many different statistical methods, whereas analysis of order in time commonly requires the usage of advanced analysis methods. For either, decisions about the level of granularity at which time is considered and segmentation of time into "windows" have important effects on analysis results. We argue that understanding the value of temporal concepts and implications for the related analysis, is foundational for closing the loop and advancing learning analytics design with temporal insights.

Keywords: Temporal analysis, sequential analysis, concepts of time, metrics

The primary goal of learning analytics is to understand and optimize learning, a process that occurs over time; thus a consideration of temporality is relevant to the vast majority of research in the field. The "measurement, collection, analysis and reporting of data about learners and their contexts" [15] inherently requires conceptualising time and the underlying assumptions about its relation to learning. The importance of time in analyses of learning is emphasised by Reimann [40] in his seminal work "Time is Precious" and a number of researchers since [20, 23, 31, 33]. Despite its central importance to learning, rarely is a conceptualisation of time or its underlying assumptions treated explicitly by researchers. A notable exception is the two-part special section dedicated to temporal analyses of learning data in the Journal of Learning Analytics [7, 25]. Here two dramatically different conceptualizations of temporality are sketched out. The first relates to the passage of time addressing questions about how often or for how long particular activities take place during learning. The second relates to temporal order investigating how activities during learning are organized in relation to each other. In this chapter, we elaborate on these two conceptualizations, relate them to common temporal metrics used in learning analytics research, and propose a framework for thinking about time that can be instrumental in learning analytics research. We additionally outline how this framework supports closing the loop in designing interventions and learning environments that translate temporal insights into pedagogical action and new learning designs.

1 WHY TIME MATTERS IN LEARNING ANALYTICS

One of the main arguments made in Learning Analytics research is that learning does not happen in an instant [14]. Whether considered cognitively as a process of acquiring knowledge or socio-culturally as a process of becoming, it is rare that in a single moment we move from a state of naivete to one of competence [4]. Rather, learning has long been considered as a developmental process [31] and thus changes over time are inherent in its definition. While the basic notion that time is important to learning is not new [5, 11], the attention given to it has often been of a general, rather than specific nature. For example, learning research of a psychological bent has traditionally relied on pre- and post-test designs, which employ a very impoverished treatment of time as "before" and "after." In contrast, more sociologically oriented educational work has often traced the chronological evolution of phenomenon holistically but without precise attention to defining temporal constructs involved.

Within learning analytics research an important focus is on how learning evolves over time [25]. The increased availability of fine-grained data sources in online learning environments [15] as well as the integration of technology in physical learning environments [47] provide the opportunity to investigate the temporal and sequential character of phenomena during learning [33]. The field has adapted a wide range of analytic techniques for this purpose from other fields; for example, time series analysis [43], lag-sequential analysis [21] and Markov Modelling [46]. In addition, it has increasingly added innovative new approaches which incorporate temporal concerns (e.g. statistical discourse analysis, [8]; epistemic network analysis [45].

There is a growing recognition of several distinct values that investigations using such temporal analysis provides. First, temporal analyses can be used to explain differences in learning outcomes by unpacking the mechanisms (processes) by which particular results are achieved [23, 40]. For example, Molenaar and Chiu [10] showed that different sequences among students' cognitive, metacognitive and relational activities are linked to different levels of group performance. Specifically, high performing groups showed more and longer sequences in which they questioned and elaborated on the topic studied and more instances of monitoring while reading new information compared to low performing groups. This shows how both the frequency of particular activities as well as their organisation supports learning in groups. Second, temporal analysis can identify and describe variations in learning processes not apparent from cumulative measures. For example in Nystrand, Wu, Gamoran, Zeiser & Long [36] temporal analysis revealed differences between high-track and low-track schools on measures that appeared identical under aggregate analysis. Similarly in Wise, Speer et al.[53] temporal micro-analysis demonstrated that two seemingly distinct learning prototypes actually demonstrated notable similarities at certain points in time. Third temporal analysis can help to detect transitions in the type of activities during learning. For example Wise and Chiu [9] were able to show that online group discussions in an educational technology course tended to take place in two stages, the first dominated by simple sharing of ideas and the second dominated by their negotiation. The transition between the two was often marked by a post synthesizing the comments that had come before. Fourth, temporal analysis supports questions of emergence such as how do macro-level phenomena (like group learning) emerge from and constrain micro-level phenomena, such as the dynamics of interaction i.e. the patterns of discourse or gestures, or emergence/ of ideas. For example Wise, Hsiao, Marbouti, & Zhao, [53] used a temporal microanalytic method to show how individuals' reluctance to explicitly disagree in an online discussion led to a premature group "consensus." Similarly, Paans et al. [38] showed that low social challenges during group work supported better essays, increased high level cognitive activities and process mining pointed out that these groups did not get stuck in a vicious circle when social challenges occur but were able to resolve these with cognitive and metacognitive activities.

While attention to time has increased and methods for including it in analysis have proliferated, theorization of temporal constructs for learning has not kept pace. Thus one of the biggest current challenges for research involving temporal research is a lack of clearly articulated concepts about time to undergird analyses [33, 25]. The lack of a common language for talking about time is a result of a history of isolated research efforts. Work examining temporal aspects of learning have been dispersed across diverse literatures (such as classroom dialogue [31], intelligent tutoring systems [26], self-regulated learning [33] and computer supported collaborative learning [23], just to name a few. To make collective progress in understanding the temporal aspects of learning, we need a common framework for thinking about time specified at a level of precision that research efforts can use to effectively to talk to each other and communicate based on the temporal questions that are being asked. As a field that touches on each of these areas (as it intersects with fine-grained data analysis about learning as it occurs in many contexts) learning analytics offers a unique opportunity to meet the urgent need to develop a shared conceptual conceptualization and vocabulary. This chapter represents an effort to lay out such a common framework and language to (a) support diverse researchers working in this space to communicate better, (b) facilitate an understanding of how different approaches to studying time in learning articulate and (c) map out the space of temporal analysis to reduce redundancy of efforts.

2 A CONCEPTUAL FRAMEWORK FOR CONSIDERING TEMPORALITY

Building on general theoretical discussions of time, we take as our starting point the two distinct temporal concepts mentioned in the introduction, passage of time and order in time [25]. When events are analysed following the passage of time, they investigate time as it occurs in a continuous flow. This entails examining the temporal characteristics of individual events within a stream of activities. An example is time-on-task which considers the amount of time students spend working on a particular task [27]. In contrast order in time refers to events as part of a series of discrete events which occur in particular temporal relations to each other. For example productive failure indicates that when students first have a chance to wrestle with a problem, explanations given after tend to become more meaningful for understanding new concepts compared to receiving the explanation immediately [22]. This involves investigating the relative arrangement of multiple events among each other.

An important distinction between the two concepts is the type of temporal information used in the analysis. When analyzing events for the passage of time, researchers often focus on specific time related characteristics of a single event. Most of this work informs us how variations in temporal characteristics of events are associated with learning. For example, research indicates that when students spend enough time with others' discussion posts to read (rather than just scan) them, they are more likely to contribute high quality posts themselves [52]. On the other hand, when focusing on order in time the way events are related to each other is central. This shows how variations in organization of different events over time influences learning. For example, research indicates that successful groups have a different order in their regulation process compared to unsuccessful groups. Specifically monitoring and control activities are more integrated with the processing information [3]. Within the two categories of passage of time and order in time a number of different of metrics that can be distinguished as explained in the following sections.

3 PASSAGE OF TIME: CONSIDERING TIME AS A CONTINUOUS FLOW OF EVENTS

As discussed above, central in analyzing time as a continuous flow of events is incorporating the record of specific time related characteristics of an event in the analysis. This record includes different types of information about an event, such as the moment when an event starts and when it stops. Based on this information, the, position, duration and frequency of the event can be determined as well as the rate (i.e. how often an event occurs over a period of time), see figure 1 and table 2.

Position refers to when an event occurs in a given time window, see figure 1. The absolute sense uses the conventional system for measuring time, whereas the relative sense represents the temporal characteristics in relation to internal characteristics. Research discusses position quite frequently. For example, Paans et al. [39] showed that planning activities occur more frequently in the beginning of learning task compared later. Similarly, Moos & Azevedo [35] revealed how planning, monitoring and strategy actions are distributed differently over different phases in a learning episode. Kapur & Bielaczyc [24] showed that scaffolding interventions too early in the learning process are detrimental to the groups own exploration process, yet scaffolds too late in the learning process do not affect the group learning

Duration indicates how long an event continues during a given time window. Absolute duration indicates how long an event lasted (from start to end time). Alternatively, duration can be calculated summatively for all events of a given type, adding the duration of each individual event. Relative duration refers to the percentage of time an event takes in a total time window. Research dealing with duration is relatively common. For example, Nystrand et al. [36] employed absolute duration measures to document an overall low level of in-depth discussion in the classes they observed (average times of between 15 and 50 s per class period) and highlighted the relatively longer duration of in-depth discussion in high-track versus low-track classes (almost twice as much time spent on discussion in high-track classes). Sande et al. [50] showed that children with reduced attention control spend less time play a serious game compared to children with high attention control. Kovanović et al. [27] emphasize the importance of careful decision making in determinations of how to calculate time-on-task in online environments from clickstream data in which estimates must be made to account for task abandonment and the lack of formal log-out procedures.

Frequency refers to how often an event occurs in a given time window. Absolute frequency indicates the number of events over the given time window. The relative frequency indicates the percentage of planning activities out of the total number of activities engaged in. Much research investigates associations between frequency of events and learning. For instance in collaborative learning research an association between the frequency of a groups' elaboration and its collective learning has been found [48]. Molenaar et al. [34] showed that frequency of metacognitive activities was increased by scaffolding and supported learners development of metacognitive knowledge.

Rate indicates how rapidly events of the same type succeed each other, in other words the pace at which the events occur over time [18]. Rate can be calculated by dividing the total frequency of an event over a time window by the duration of the event. Absolute rates can also be calculated more locally over smaller sub time-windows, for example in the first half of the study session, planning events happened on average every 2 minutes (.50 events per minute) while in the second half of the study session they only happened every 4 minutes (.25 events per minute). Relative rates can then be used to compare events to themselves over different sub time-windows (e.g. the rate of planning was twice fast as in the first half of the study session) or to other events (the rate of planning events in the first half of the study session was three times that of evaluation events). There are several studies that use rate and illustrate the increased sensitivity of measures of rate over frequency. For example, Nystrand et al. [36] examined the differential ability of the frequency and rate of student question asking to predict dialogic spells in an middle school class. Frequency was operationalized as the cumulative number of student questions asked up, while rate was operationalized as the percentage of the last five questions asked by students in the class students. Results showed that while both approaches were able to predict dialogic spells, rate was a better predictor than frequency. In another example Wise et al. [52] showed that while the overall frequency with which "Broad Listeners" logged-in to their online discussions was greater than that of "Concentrated Listeners," most of their activities were heavily condensed towards the end of the allotted timeline, making the two participation patterns similar in rate during this time.

To conclude there are four different metrics of time commonly used when considering the passage of time. Frequency seems the most prevalent metric, whereas posi-

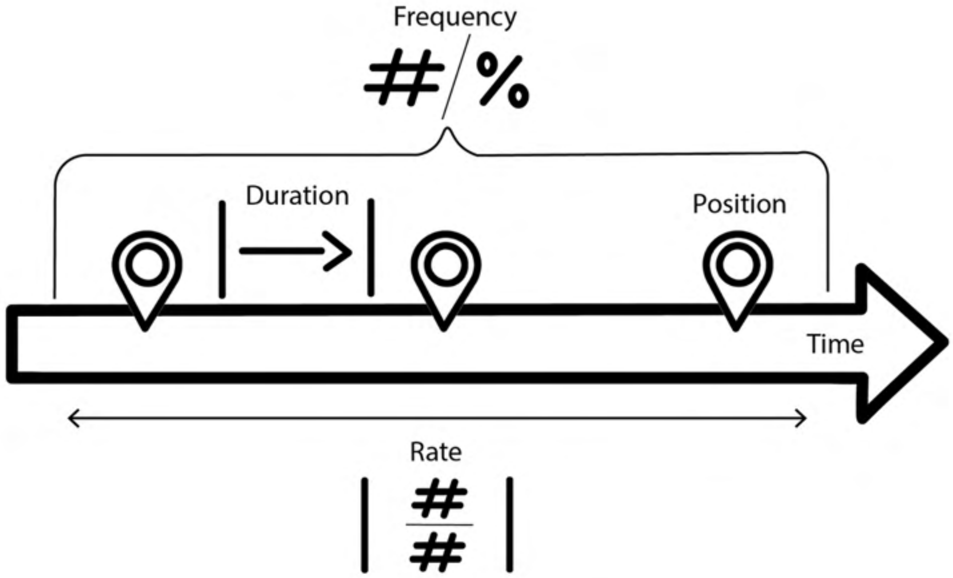


Figure 1: Passage of Time and the metrics.

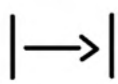
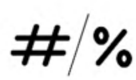
	Position 	Duration 	Frequency 	Rate 
Absolute	The first planning action occurred after 2 minutes	The first planning action took 2 minutes / all planning actions together took 8 minutes.	There were 3 planning actions.	Planning actions took place approximately every three minutes
Relative	The first planning action occurred after 13% of time had past	Planning actions took up four times as much of the learning episode than monitoring ones.	Planning actions were 33% of all actions taken during the learning episode.	Planning actions occurred 2.5 times as often as monitoring ones.

Figure 2: Metrics of Order in Time.

tioning, duration and rate are less applied. All these metrics can be expressed in an absolute or a relative metric. There can be different motives to use absolute or relative indicators. Absolute is very useful for to make comparison across the same time window for different students, whereas relative numbers are needed to make comparisons among students when the time windows vary across subjects. Also the comparison between absolute and relative indicators for the same students can be very insightful. For example, a high absolute duration of strategy use indicates that students are applying strategies, whereas a high relative duration of strategy use could also provide insights into the fact that students are spending too much time on strategies during the learning task. These metrics under passage of time are a natural starting point for most research with an interest in time and has provided valuable insights unpacking mechanisms of learning and showing variations in learning processes not apparent from cumulative measures. In order to address transitions and emergence in learning processes conceptualizing the order in time is needed.

4 ORDER IN TIME: CONSIDERING TIME AS A RELATIVE ARRANGEMENT OF MULTIPLE EVENTS

In contrast to considering the passage of time, which generally focuses on the temporal characteristics of one type of event, a relative arrangement of multiple events perspective examines how different kinds of events are temporally organized in relation to each other. There are four ways to think about the relative arrangement of multiple events, see table 3. The first entails looking for relative stasis in events, i.e. time periods in which the same events repeat. This is observed as Consistency (a lack of change); for example when learners repeatedly experience strong emotions along with a high electro dermal activity (EDA) signal during intense moments in a learning experience [12]. The next two arrangements are different kinds of Regular Change. One version, Regular Recurrent Change, refers to a specific organization among different types of events that occurs repeatedly; for example learners first tend to orientate to a task before they plan for it [38], and this sequence can be found to happen multiple times. Regular change can also happen once in non-reoccurring sequences, where the same ordering is observed across learners, but not multiple times for one learner. For example, beginning readers start verbalizing individual letters after which they transition into recognizing small words [44]. Such Non-Recurrent Regular Change represents an ordering of events that does not repeat, and is often examined as part of developmental series, learning progressions or various knowledge growth cycles. Finally, there are a number of processes that do not show any specific organization among events that are specified as Irregular Change. In this case different events occur after each other but without a discernable pattern, for example tipping points in treatment of mood disorders [37].

Consistency refers to relative stasis of the same kind of events over a given window of time. This concept of time can be powerful for identifying periods of stability (which themselves may have varying durations or occur in particular sequences). Questions that can be addressed by analyzing consistency among events may to relate different phases of learning. For example, Wise and Chiu [51] showed that online discussions could often be divided into different stages, each dominated by a single phase in Gunawardena Lowe and Anderson's [16] model of Knowledge Construction. In this example, consistency was identified using statistical discourse analysis [9], but sequential lag analysis and t-pattern analysis [6] and latent transition analysis [19] can also be used for this purpose. These methods can be used to assess recurrent regular change, as described below. Regular change across events point towards a sequential organization of events, i.e. patterns that can be defined as a particular organization concerning the relative positions of events among each other [41]. When that change happens repeatedly over time within a learning activity, it is referred to as Recurrent Regular Change. The same notion has also been referred as a common transitions between events [51]. One example is the repetitive sequences of planning, monitoring and evaluation events in self-regulated learning; Engelmann and Bannert [13] applied process mining to show that these events occur in different patterns for more and less successful students. In another example, Matcha et al. [30] used First Order Markov Modelling (FOMM) and an expectation-maximization (EM) algorithm to detect four different learning tactics exhibited by students in different temporal ordered learning strategies, which are distinctive patterns of learning actions students took in a MOOC. A final example that focuses on adjacent recurring sequences (a pair of events where an event directly follows another) are micro level interaction between group members during collaborative learning; specifically in studying specific instances of argumentation Lu, Chiu and Law [29] found that competing claims are commonly followed by evidence to support the claim. Adjacency is an important notion within the analysis of re-occurring sequences and adjacent sequences, in which events follow each other immediately, are most commonly analyzed using techniques such as lag sequence analysis, various Markov models and statistically discourse analysis. Alternatively non-adjacent sequences occur when other events occur in between the elements of the recurring pattern. T-pattern analysis can be used to analyze non-adjacent sequences. Kuvalja et al. [28] showed the importance of non-adjacent sequences detected by t-pattern analysis. In their study of self-directed speech and self-regulatory behaviors by children with and without specific language impairment (SLI), they did not initially find any differences in the frequency or (adjacent) sequences of the behaviors. However, T-pattern analysis revealed that temporal sequences of self-directed speech and self-regulatory behavior of children with SLI were more in number, more complex and typically featured self-directed utterances. Process mining can also be used to detect non-adjacent sequences in learning processes. For example, Heirweg [17] showed that high achieving learners engage in more strategic and adaptive approach to learning compared to low and middle ability learners

Consistency	Recurrent Regular Change	Non-Recurrent Regular Change	Irregular Change
[11111111111]	[12121212121212]	[11111122222333]	[479328301702948]
A repeating pattern of the same event	A repeating pattern of events 1 and 2 in sequence	A non-repeating pattern progressing from event 1 to 2 to 3	Change without a clear detectable pattern

Figure 3: Metrics of Passage of Time.

using process mining. Finally inclusion of multi-lag variables can be used as a technique to model non-adjacent sequences in statistical discourse analysis.

Non-Recurrent Regular Change deals with a different kind of temporal patterns; one in which the focus is not on repetition but shifts from one type of event to another. The same notion has also been referred as consequential transitions between events [51]. For example, Bannert et al. [3] showed that successful students followed planning and monitoring in their regulation process with evaluation, while less successful students did not. These transitions can be indicative of phases in development, i.e. sequences that include evaluation are more advanced than those featuring planning and monitoring only. Non-recurrent sequences can be investigated to occur universally across all learners (e.g. this is expected to be the case for Piaget's developments stages), but also can differ for different segments of a population. The latter is powerful in identifying how different kinds of processes lead to different outcomes. To investigate this, an important step is to make the division of cases. For example in the Bannert et al. [3] example about successful and unsuccessful groups, the researchers placed students in two groups based on learning gains during the task and then investigated the different sequences of activity each group engaged in. In other studies, the division of cases is based on similarities in the developmental sequences. For example van der Graaf [49] used latent transition analysis to classify children solving a balance beam problem into 5 different profiles based on the ordering of the strategies they used. Non-recurrent sequences can be analyzed in between subject designs as illustrated above, but also within-subject designs. For example, there may be interest in when a specific consequential transition occurs for a learning. Research on literacy indicates that students learning how to read initially spell all letters and then continue to verbalize the word [44]. This initial period of spelling transforms into automatically detection of groups of letters, which is indicated by a faster verbalization of the words. An initially phase in which students spell letters can be perceived which transitions into a phase where children verbalize clusters of letters together which can be considered a consequential sequence. This transition only occurs once in a subject and is consequential for the development or learning process.

Irregular Change indicates patterns that are neither regular over time nor over cases. As such these change appear difficult to explain. Advanced scientific approaches such as system dynamics can be used to explain these types of processes [42]. To this point, this have been less of a focus in the learning analytics community thus far. To illustrate the kind of claims possible, an example from psychopathology shows that critical fluctuations occurring in multiple variables within a particular time window can indicate tipping points in human change processes such as transitions in treatment of mood disorders [37].

5 TEMPORAL ANALYSIS, SEGMENTATION AND GRANULARITY

From the above presentation, we see a clear difference between analysis in the passage of time and order in time. One important distinction is that study of the passage of time often leads to metrics (e.g. of rate, frequency, duration) that can be input as variables into a variety of different statistical methods. In contrast, the study of order in time generally requires the usage of advanced methods such as statistical discourse analysis, sequential lag analysis, main path analysis, t-pattern analysis, process mining, Markov modeling, or latent transition analysis. Within order in time depending on the type of concept considered, different methods are more appropriate. For example adjacent sequences can be detected with Markov modeling while non-adjacent sequences require t-pattern analysis or process mining. Beyond the specific concepts of time and analysis approaches taken, the approach to segmentation of time (the time window) and granularity of time (size of time units within the window) have a profound influence of the kinds of patterns that can be detected. Segmentation deals with the question how to determine the window(s) of time that frame the study; for example do we care about how often a study studies in a lesson, a week, or a school year? Windows of time can be set in different ways. A common way used in learning analytics research is to leverage the pedagogical units already present in instruction; for example taking the duration of a whole course, a class meeting, or an online lesson as the overarching time window for research. Another approach is to follow clock-based units, for example a week of interaction or an hour of studying as the time window. Many researchers also take segmentation decisions based on randomly selected time units, for instance by dividing an overall study period of an hour into 6 periods of 10 minutes. These are all time windows determined prior to analysis, but one can also determine a time window based on the data present. For example looking for the period of time over which a construct is acting in a similar way. For example, time windows can be determine based on the prevalence of low versus high cognitive activities [10]. Choices made about segmentation can have dramatic impacts on results and therefor for clear justification the method used to determine time windows is important.

Granularity is another important issue, specifically in the case of studying order in time. Granularity defines the "size" of the events whose sequence will be studied and can be considered at the level of which we record, code and analyze the data. It is important to note that the level of granularity at these different levels is not necessarily the same. Often the level at which we record entails smaller units then the units coded. For example, EDA data has a much higher resolution compared to discourse coded during collaborative learning [12]. This entails that decisions have to be made about how to synchronize the data and at which level of granularity to code the data. Hence different levels of granularity between recording and coding are a challenge for meaning making. Similar some methods pose restrictions on data to be useful. For example process mining requires a minimal frequency of each code which often times requires researchers to merge codes and analyze at a high aggregation level to fulfill these methodological requirements. Finally, the relation between theoretic constructs and data is problematic. Theories are often defined at an macro level whereas most data is recorded at a micro level. Combining different methods, such as think aloud analysis and data-mining has the potential to bridge between micro level analysis and macro level meaning making.

6 CLOSING THE LOOP: TEMPORAL CONSEQUENCES FOR DESIGN

We close this chapter with a short note on how this temporal research in learning analytics supports closing the loop in learning analytics through its capability to yield insight into questions about when and in what order certain actions may be most effective to support learning and how can we design interventions and learning environments that translate such temporal insights into new learning designs? In learning analytics responsiveness to learners needs is central, temporal analysis can support this in two ways. First, research into to the passage of time helps unpack how learning outcomes are related to activities during learning. This provides insights into important elements that could be induced by learning design. For example, when planning turns out to be highly related to learning, this can be triggered by instructional design features such as scaffolds [1, 34], prompts [2] or dashboards [32]. Second, consistency and recurrent sequences can be used to asses the current state of the learner, which is foundational from most methods to personalize learning [32]. For example, children's moment-by-moment learning curves based on individual errors made, provide insights into how learners regulate their accuracy over time and can be used to adjust the level of regulation support provide to a learner [32]. Insights into consequential sequences help determine trajectories in which development and learning take place. When factors contributing to consequential transitions are identified, they can be leveraged intentionally. For example, Wise and Chiu [10] found that when students were asked to summarize an online discussion in the middle, rather than at the end of the conversation, it often led them to reach more advanced phases of knowledge construction. Lastly, the detection of recurrent sequences at a micro level can help asses the evolvement of in-learning processes at a macro level, which can be the ground for predictions and adjustment in the design.

7 CONCLUSION

To conclude, we propose two concepts namely the passage of time which considers time as a continuous flow of events and order in time which focuses on the organization among events. Within the passage of time we distinguish four metrics: position, duration, frequency and rate. With order in time we discriminate between consistency, recurrent and non-recurrent regular change and irregular change. In learning analytics research we find both conceptualizations of time. Metrics extracted under the Passage of time can be used in many different statistical methods, whereas order in time requires the usage of advanced methods such as statistical discourse analysis, sequential lag analysis, t-pattern analysis, process mining, Markov modeling, or latent transition analysis. Segmentation of time windows and level of granularity are important decisions in temporal analysis for which we need a clear justifications. Understanding the value of temporal concepts and the related analysis, is foundational for closing the loop and advancing learning design with temporal insights.

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SECTION 2

Applications

Chapter 8: Learning Analytics for Self-Regulated Learning

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ABSTRACT

The Winne-Hadwin model of self-regulated learning (SRL) [27], elaborated by Winne's [16, 18, 28] model of cognitive operations and motivation, provides a framework for conceptualizing key issues concerning kinds of data and analyses of data for generating learning analytics about SRL. Trace data are recommended as observable indicators that support valid inferences about metacognitive monitoring and metacognitive control constituting SRL. Characteristics of instrumentation are described for gathering ambient trace data via software learners use to carry out everyday studying. Critical issues are discussed: what to trace about SRL, attributes of instrumentation for gathering ambient trace data, computational issues arising when analyzing trace data alongside complementary data, scheduling and delivering learning analytics, and kinds of information to convey in learning analytics intended to support productive SRL.

Keywords: Metacognition, Self-Regulated Learning (SRL), traces

Self-regulating learners "actively research what they do to learn and how well their goals are achieved by variations in their approaches to learning" [17, p.472]. One widely cited model characterizes SRL as four loosely sequenced recursive phases that unfold across a task's timeline ([16, 18]; for other models, see Panadero [12]).

In phase 1, a learner surveys resources and constraints the learner predicts may affect work, the probability specific actions lead to particular results, and consequences of those actions. Factors external to the learner include access to information, characteristics of sources of information, software tools designed to support learning in various ways and time allowed for work. Examples of factors internal to the learner include knowledge, misconceptions, biases for ways of working, topical interests, and a disposition to interpret slow progress as a signal of low ability versus need to apply more effort (see Winne [22, 18]).

Having identified resources and constraints, a learner sets goals and plans how to approach them in phase 2. Goals are standards for the workflow and the products of work. Ipsative goals compare current results to earlier ones; they measure personal growth or decline. Criterion-referenced goals compare ideal to actual process-related features (e.g., effort, pace) or achievements. Norm-referenced goals compare products to a peer's or a group's. Goals and what they reference may be framed by the learner, an instructor or another person. Many goals concern content studied: additions to knowledge, errors corrected or misconceptions replaced. Learners also set goals for learning processes. Which study tactic is most straightforward, more likely to succeed or more familiar (practiced)? Topics of goals may concern motivation and emotion, such as curiosity satisfied or anxiety avoided. Goals may refer to external properties such as number of pages read or written, deadlines for assignments and opportunity to impress others.

In phase 3, the learner engages with the task by enacting and making minor course corrections to plans. Working on a task inherently generates feedback updating the task's conditions across the task's timeline. Feedback may originate outside the learner when software beeps or a peer comments on a post to an online discussion. Or, feedback may arise internally as the learner monitors pace, effort and certainty about knowledge (judgments of learning; see Dunlosky and Tauber [6], Part 3). For example, a search query may be deemed unproductive because results were not what was expected or don't satisfy the standards for particular information. Goals can be updated as tasks progress.

Phase 4 is when the learner disengages from the task as such, monitors properties of phases 1 to 3, and elects to make a large-scale adjustment. Examples might be a learner suspending work on a problem and returning to assigned readings with a revised goal to repair major gaps in knowledge. Or, if re-studying is not predicted to be successful, the learner may seek help from the instructor. Changes may be applied immediately, reshaping the task's multivariate profile in a major way. Or, plans for adaptations may be filed for future tasks, effecting forward reaching transfer.

A 5-slot schema frames events throughout theses phases of SRL. It is summarized by a first-letter acronym, COPES [21]. C refers to conditions, factors bearing on whether and how an event unfolds. Time allocated, resources available and exposure to scrutiny by peers or the instructor are common conditions. Internal conditions are psychological features the learner brings to the task. Examples are previously developed knowledge, beliefs about the topic, a toolset of tactics for learning, and motivational and affective descriptions of one's self.

O in the COPES schema is operations learners use to manipulate information. Like conditions, operations are external and internal. External operations are a learner's observable behaviors, such as posing a question or copying information from an instrument readout into an online document. Internal operations manipulate information in the learner's working memory. I posit five primitive cognitive operations transform information in ways that cannot be further decomposed: searching, monitoring, assembling, rehearsing, and translating; the SMART operations [16]. Table 1 describes each with examples of traces, observable behaviour tightly coupled to the unobservable cognitive operation [20]. More complex descriptions of cognition, study tactics and learning strategies, are modelled as patterns of SMART operations [17]. An example study tactic is: Highlight every sentence containing a definition. An example learning strategy is: Survey headings in an assigned reading, generate a key question about each, then, after completing the entire reading assignment, go back to answer each question to test understanding.

The P slot in the COPES schema represents products created by operations. A product can be simple, such as an ordered list of British monarchs; or it can be complex, for example, an argument about privacy risks in social media or an explanation of catalysis. Some products are unforeseen because the learning environment is not completely predictable. E is a monitoring operation that generates a special product, an evaluation comparing a product to standards, S. Standards for a product equate to the goal for that product.

Three more characteristics of SRL are significant for learning analytics. First, SRL is observable only when a learner adjusts conditions, operations, or standards. Such observations require data gathered across time and showing change. Second, learners are agents. They regulate learning based on conditions and standards they judge to matter. As agents, learners always and intrinsically have choices. Therefore, learning analytics are recommendations, not dictates. A learner may think, "I did it because I had to." But, this learner elected to do what they did because they forecast negative consequences for doing something else outweighed costs of doing what they did. Goals reflect decisions that weigh costs against benefits. For example, learners sometimes are not provided standards for evaluating a product because instructors expect learners already have knowledge or skill to evaluate a product. A learner bereft of learning objectives might search for examples against which to compare their products. It can be inferred the learner has a goal to develop standards by analyzing (disassembling) examples. In the classroom, this learner may withdraw and wait for classmates to offer examples. Online, this learner may search the internet using whatever knowledge they have and evolving successively more relevant queries. Third, the COPES model identifies classes of data for developing learning analytics about SRL and suggesting targets for adaptation.

This chapter centers on self-regulated learning (SRL) in which learners are the prime actors amidst others, human and algorithmic. All reciprocally shape conditions within which each learner forges self-regulate learning. Notably, SRL is risky because it may have productive or counterproductive results.

The next section overviews characteristics of learning analytics. Then four main classes of data are distinguished by their origin: traces, learner history, reports, and materials studied. Then computations and reporting formats for learning analytics relating to SRL are described. Together, these sections sketch an architecture for learning analytics designed to support SRL. In a final section, several challenges are raised to designing these learning analytics.

LEARNING ANALYTICS

Four descriptions of learning analytics guide the field. Siemens [14] described learning analytics as "the use of intelligent data, learner-produced data, and analysis models to discover information and social connections, and to predict and advise on learning." The website for the 1st International Conference on Learning Analytics and Knowledge posted this account: "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs." Educase [8] defined learning analytics as "the use of data and models to predict student progress and performance, and the ability to act on that information." Building on Eckerson [7]'s framework, Elias [9] noted "learning analytics seeks [sic] to capitalize on the modelling capacity of analytics: to predict behaviour, act on predictions, and then feed those results back into the process in order to improve the predictions over time" (p. 5).

These descriptions beg fundamental questions. What data should be gathered for input to methods used to generate learning analytics? Answering this question bounds and shapes two questions: First, what are approaches to computations underlying analytics? Second, what can analytics say about phenomena? For instance, if data are not ordinal, A cannot be described as greater than B, nor are transitive statements valid: if A > B and B > C, then A > C. Also, ordinal (rank) data preclude arithmetic operations on them, such as addition or division.

What bearing do properties of data have on the validity of interventions based on learning analytics developed from those data [20]? For example, if a learner's age, sex, or lab group predicts outcomes, intervening without other data is not warranted. None of these data classes are a direct, proximal (i.e., sufficient) cause of outcomes. More-

Table 1: SMART Cognitive Operations

Operation	Description	Sample Traces
Search	Directing attention to particular information	Opening successive bookmarks Using a search tool
Monitor	Comparing information presentations in terms of standards	Highlighting text (information highlighted meets a standard, e.g., important) Selecting a particular website to review (e.g., judgment of learning)
Assemble	Relating items of information	Tagging Assigning two bookmarks to a titled folder
Rehearse	Maintaining or re-instating information in working memory	Reviewing a note Copying, then pasting
Translate	Transforming the representation of information	Paraphrasing Describing a graph, equation, or diagram in words

over, age and sex can't be manipulated; and, changing lab group may be impractical (e.g., due to scheduling conflicts with other courses or a job). Finally, because prediction is insufficient to establish causality, it is unknown whether changing any of these characteristics will have any effect.

Who generates data? Who receives learning analytics grounded in which data? Learning ecologies are populated by multiple actors. Authors of texts, videos and webpages vary cues they intend to guide learners about how to study; font styles and formats such as bullet lists and sidebars that translate text to graphics, are examples. Instructional designers and front-line instructors augment authors' content, for example, by setting goals for learning and adding content to the author's. Instructors also set schedules for learning and control most opportunities for feedback to learners. Learners study solo, form and disengage from online cliques or face-to-face study groups where they exchange topical information, announce beliefs about topics, and share products of learning activities (e.g., questions, notes). Their educational institution provides a multifaceted infrastructure intended to elevate motivation and promote wellness. Each category of actors adds data and may be a legitimate candidate to receive learning analytics.

What are temporal attributes – onset, duration, and offset – describing data collection, data processing, and delivery of learning analytics? Will learning analytics be delivered just in time or just in case? Will learners need reminding about past context if learning analytics are temporally delayed from the activites in which the data were generated? Should temporal delimiters be elastic or rigidly fixed across the timeline? Whose model of a learning session — the analyst's or the learner's — overlays data and analytics [25]?

Finally, what are learning analytics designed to do? What standards should be used to gauge uptake and benefit? Suppose after receiving learning analytics about scheduling work on assignments, a learner starts work on projects sooner, spends more time on tasks, but achievement remains unchanged. Is this a benefit?

DATA FOR LEARNING ANALYTICS ABOUT LEARNING AND SRL

Traces

As learners work, they generate ambient data (or accretion data; [15]). For example, clicking a URL to open a web resource creates data about a learner's cognition and motivation. Based on context (perhaps the title of the resource), the learner forecast this URL might contain information of sufficient value to motivate examining it. This click is a trace, an ambient datum affording relatively strong inferences about one or more cognitive, affective, metacognitive, and motivational states and processes (CAMM processes; [2, 20]). Following are two further examples of traces and inferences developed with an explicit caveat: inferences are probabilistic, not certain.

Highlighting Content. To highlight particular text amidst hundreds of sentences read in a typical study session, the learner metacognitively monitors attributes of information the text conveys relative to standards. Standards discriminate whether and why particular text should be highlighted. The learner might monitor information for "structural" forms, such as definitions or principles; or for motivational/affective features, such as interestingness or novelty. Authors often signal information for highlighting using font styles (e.g., italics) or phrasing: "It is interesting that…" A highlight also traces the learner's plan to review highlighted text. Why else would the learner permanently selectively mark text?

Reviewing a Note. Before reviewing a note, the learner metacognitively monitors whether information needed now can be recalled and is understood. Review is executed if what can be recalled is judged inaccurate, incomplete, or not understood. Searching for and re-viewing a particular note traces motivation to repair some deficiency in knowledge. If the learner highlights information in the reviewed note, that traces which information the learner monitored and judged deficient.

Features of Traces. Four features describe ideal trace data gathered for learning analytics to support SRL. First, the sampling proportion of observed traces to cognitive operations should approach unity. Ideally, but not realistically, every operation is traced throughout each learning session. Second, information operated on is identified. Third, traces are time stamped. Fourth, the product(s) of operations is (are) recorded. Data having this 4-tuple structure would permit an ideal playback machine to read trace data and output a nearly perfect rendition of every learning event and its product(s) across the timeline of the learning session. With 4-tuple trace data, raw material is available to generate rich learning analytics.

In reality, every trace datum has some degree of imperfection and unreliability [20]. For example, a highlighting event traces a monitoring operation and generates a product: the mark plus the content marked. At a future time, the mark facilitates locating information. What is vague about this trace is standards the learner used to identify the marked content. Better designed traces can fill this gap. If learners are invited to tag content they highlight – interesting, important, unclear, project1, tellMike, etc. – the tag exposes the standard used to metacognitively monitor the highlighted information. Some tags reveal a strong signal about a plan – e.g., use this content in project1, in the next chat tellMike about this information.

Learner History

Instruments for tracing the history of a learner's activities are available in at least three environments: paper systems, learning management systems (LMS), and systems offering learners tools for studying "on the fly."

Paper Systems. In a paper-based environment, examples of traces are content highlighted, notes, marginalia such as *!*, *?*, and $\surd$ added to the whitespace of textbook pages, a pile of books or papers stacked in order of use (e.g., the topmost was most recently used), and multicolored post-it tabs attached to pages in a notebook.

Consider the *?* symbol written in the margin of a textbook page. This trace signals the learner metacognitively monitored the meaning of nearby content and judged it confusing or needing more information to understand it. A further inference is available. Why would the learner spend effort to write ? in the margin? The metacognitive judgment does not require recording a symbol. It's likely the learner is motivated to and plans to resolve a gap in understanding. The ? marks where that resolution should be applied.

Tracing in a paper-based environment is easy for learners but gathering and preparing paper-based trace data to generate learning analytics is massively labour intensive. In software-supported environments, this burden is greatly eased.

Learning Management Systems. Modern LMSs seamlessly record various time-stamped records of learners' work. Examples include: logging in and out of the LMS, resources viewed and downloaded, assignments uploaded, quiz items attempted, and forum posts identifying intended recipients. Some data allow inferences about goals. For example, clicking a button labelled "practice test" traces a learner's judgment that recall is below a confidence threshold. Other trace data could describe (a) learners' preferred work schedules that mildly support inferences about procrastination, (b) resources learners judge are more relevant or appealing, (c) motivation to calibrate judgments of learning and efficacy, and (d) value attributed to contributing, acquiring, or clarifying by exchanging information with peers.

Data gathered across time can mark when learners first study a resource, if and when they review it, if and when they choose to self test, and when they take a test for marks. Coupled with other data about factors such as credit hours completed or characteristics of peers with whom information is exchanged, data like these provide raw material for building models about how learners self-regulate managing time in a study-review-practice-test cycle [1, 4, 5].

When students use an LMS, costs are slight to collect and prepare ambient data for input to computations generating learning analytics. However, LMSs rarely gather trace data about operations learners carry as they study and review, and particular information on which they operate. A time-stamped datum describing a file downloaded provides no information about whether the learner studied that content or how the learner studied it.

Software Tools for Studying. Data about motivation, metacognition and SRL are "raw material for engineering the bulk of an account about why and how learners develop knowledge, beliefs, attitudes and interests" [26, p.1]. Developing these data requires attention to three factors: operationalizing indicators, gathering data to trace these constructs and filtering noise that obscures signals about constructs (see also [13, 20]).

Operationalizing indicators to trace COPES calls for imaginative interfaces that encourage learners to use software tools without overly perturbing currently preferred work habits. Table 2 illustrates opportunities to gather trace data when a learner uses software tools to:

- Search a repository of resources provided by an instructor and for artifacts the learner creates (e.g., terms, notes, concept maps).
- Select content in a resource to highlight, tag or annotate it.
- Make a note guided by a schema, e.g., a TERM NOTE: term, definition, example, see also …; a DEBATE NOTE: claim, evidence, warrant, counterclaim, my position.
- Organize artifacts, e.g., in a directory of folders.

Phase 4, strategically revising learning tactics and strategies was excluded from Table 2. This phase is addressed in the section on Learning Analytics for SRL.

"Self-regulated learning (SRL) is a behavioural expression of metacognitively guided motivation" [26, p.3]. Therefore, every trace reflects a motivated choice about learning. Beyond representing aspects of COPES, traces reveal learners' beliefs about which operation is worthwhile effort for approaching goals.

The Learner's Reports

Paper-based questionnaires (surveys) and oral reports recording ideas "thought aloud" while a learner studies or interviews after studying are common methods for gathering data about learning. In both, learners are prompted to describe features of COPES. The prompt given is critical because the learner uses it to set standards for deciding what to report. A thorough review is beyond the scope of this chapter; see Winne and Perry [30] and Winne [17, 19]. In general, prompts for questionnaire items present conditions too generally (e.g., When you study . . .). Also, all self-report data suffer loss, distortion, and bias due to frailties of human memory. Consequently, self-report data may correspond weakly to how a learner goes about learning in a particular study session and how learning varies (is self-regulated) as learning conditions vary. Self-report data are important, however. They reflect general beliefs learners hold about COPES. Beliefs shape what learners attend to about tasks, themselves, and standards they set.

Materials Studied

Materials learners work with can be sources of data about conditions that shape SRL. Texts can be described by various analytics including readability and cohesion (e.g., Coh-Metrix). Content can be indexed for opportunity to learn it plus characteristics of what a learner learned previously. Materials a learner studies also can be indexed by rhetorical features such as examples and summaries; and media, such as a quadratic expression described in words (semantic), an equation (symbolic) and a graph (visualization).

LEARNING ANALYTICS FOR SRL

Learning analytics to support SRL have three facets: calculation, delivery factors and recommendation(s). The calculation – e.g., observing presence/absence, count, proportion, duration, probability — is based on traces of operations performed during one or multiple study sessions [13]. Delivery factors fall into two main groups: timing and characteristics of the delivered analytic, for example, as text ("You created 3 notes on average per website."), a table or a visualization (e.g., a radar chart with axes labeled by website titles and markers representing the number of notes at each website). Table 3 illustrates trace data that might be mirrored about a learner's engagements.

A "simple" history of trace data mirrored back to a learner may be conditioned or contextualized by other data: features of materials such as length or a readability index, demographics describing the learner (e.g., prior achievement, hours of extracurricular work, postal code), or other characterizations such as disposition to procrastinate, degree in a social network (the number of people with whom this learner exchanged information) or context for study (MOOC vs. face-to-face course delivery, opportunity to submit drafts for peer review).

The third facet of a learning analytic, the recommendation, updates conditions the agentic learner may attend to by describing what the learner might change. The recommended change may be supplemented by guidance about effecting the change and a rationale for change. Changes recommended are limited to four learner-controllable facets of COPES: some conditions, operations, triggers for making an evaluation and standards [23]. Products are only indirectly controllable because their characteristics are a function of (a) conditions a learner can change and then chooses to change, particularly information the learner selects to be operated on; and, (b) operation(s) the learner chooses for manipulating information. Rationale for recommendations may be grounded in "common sense," theory, findings mined from data, and results of empirical research in learning science.

When recommendations are operationally defined as how a learner uses tools in software – for example, "highlight more selectively" (meaning highlight fewer words and more relevant content) or "open and review notes not viewed for 5 days" – the learner's uptake and the degree of match between recommendations and the learner's behavior can be tracked.

CHALLENGES FACING LEARNING ANALYTICS ABOUT SRL

As software systems gathering trace data evolve, they are being distributed across widening spans of learners' ages, subjects studied and learners' whereabouts. Using these systems to advance research must respect learners' preferences and legislated boundaries regarding the distribution and uses of data. Hopefully, learners will embrace a social responsibility to improve learning science, a stance that clearly depends on how learning science gathers data and uses learning analytics.

Learning is a Multiplex of Skills

Self-regulating learners choose how they operate on information under particular conditions. If characteristics of operations, e.g., efficiency or effort, and products are substandard, they strive to adapt skills or, as may be possible, remove or reconfigure conditions that bear on applying skills. A useful model here is a production, IF-THEN-ELSE [18].

Selecting and sequencing operations for learning when learners gain useful feedback (e.g., internal feedback and external analytics) about practice over successive trials. Two categories of feedback are distinguished. Knowledge of results feedback describes accuracy or correctness. Because skills are operations applied conditionally (IF), knowledge of results feedback has two dimensions: Were conditions appropriate for choosing a particular skill and was the skill executed correctly [18]? When skills are operationally defined as patterns of traces [23], describing whether a skill is executed correctly is straightforward. A pattern of traces *is* the skill in operation. Algorithms are available to generate knowledge of results feedback

Table 2: Illustrative Traces and Inferences about Phases of SRL

Phase of SRL	Trace	Inference
One.		
Survey resources and constraints	Search for a "marking rubric" or "requirements" at the outset of a study session	An internal condition, namely, a learner expects guidance is available about standards for a task
	Open several resources, scan each for 15–30s, close	Refreshing information about previous work if documents were previously studied; or scanning for particular but unknown information
Two.		
Plan and set goals	Start timer	Plan to metacognitively monitor pace of work
	Fill in fields of a GOAL note with slots: goal, milestones, indicators of success	Assemble a plan with goals divided into subgoals (milestones), set standards for metacognitively monitoring progress
Three.		
Engagement	Select and highlight content	Metacognitive monitoring, unknown standards
	Select and tag content	Metacognitive monitoring; the standard used to monitor is revealed by the tag (e.g., confusing, good point)
	Select a bigram (e.g., greenhouse gas, slapstick comedy) and create a term	Metacognitive monitoring content for technical terms, assembling the term with a definition
	Select content and annotate it using a DEBATE note form, filling in slots: claim, evidence, warrant, counterclaim, my position	Metacognitive monitoring using standards to test whether content is an argument + assemble and rehearse information about elements of the argument
	Open a note created previously	Metacognitive monitoring knowledge relative to a standard of completeness or accuracy, judge knowledge does not meet the standard
	Put documents and various notes into a folder titled PROJECT INTRO	Metacognitively monitor uses of content; The standard is "useful for the introduction to a project"; assembling elements in a plan for future work)

when learning skills are operationalized as traces. A remaining challenge is engineering tools learners work with that generate traces with a strong coupling to cognitive, metacognitive and motivational constructs in learning science. This recommends fusing designs for learning analytics with findings from research in learning science [10].

In the context of achievement testing, feedback can elaborate knowledge of results by adding information intended to help a learner understand why a given answer was correct or incorrect and, if incorrect, what the correct answer is and why it is correct. When traces of learning skills are tightly coupled to constructs in learning science, elaborated feedback has different form. Beyond describing differences between a learner's multiplex of traces and a model pattern (strategy) for learning, theory borrowed from learning science can help form explanations for self-regulating learners about why adapting skills has utility. The question of whether learners act on learning analytics therefore relates to motivation (see [28]).

Across successive learning sessions, each learner tests the main and side effects of recommendations supplied by learning analytics. Across a multitude of learners, today's software systems are positioned to analyze big data about which learning analytics are offered, learners' uptake of recommended adaptations, and the effects of adaptations. This sets a stage for learning science and learning analytics to form a scientifically and practically progressive symbiotic system [24, 25].

Time

Other research issues arise because developing skills requires practice. How should analytics be adapted to help learners *develop* multiplex learning skills? Should learning analytics be delivered just-in-time or just-in-case? If just-in-case, what is the optimal delay between learning events in which traces are gathered and when learning analytics are delivered? Modeling skills in IF-THEN-ELSE form, how should context (IF) be reinstated? Are particular kinds of learning skills more productively served by schedules for delivering analytics? Questions of these kinds further commend a union of learning science and learning analytics.

Learning science has researched how achievement covaries with time spans between studying, reviewing, and test taking sessions [4], forgetting as a function of time [11] and knowledge lost over summer holidays [3]. Otherwise, time data have been underused. Traces and other data available for composing learning analytics commonly are timestamped. New research should investigate how time and timing matter in supporting progressive SRL. The

Table 3: Sample Analytics Describing COPES Facets in SRL

Facet	Sample Analytics
Conditions	Presence/absence of a particular (set of) condition(s) within a learning session Onset/offset along the timeline of one study session or across a series
Operations	Frequency of SMART operations (see Table 1) Sequence, pattern, conditional probability relating multiple SMART operations
Product	Presence Completeness (e.g., number of fields with text entered in a note's schema) Quality
Standard	Presence of the standard Precision Appropriateness
Evaluation	Presence of an evaluation Validity

requires identifying patterns in COPES events across time [29]. Vexing questions here are how to define boundaries for time windows and how to determine which events should be filtered out (see [31]).

More Data and New Systems

Learning analytics are accounts about how learners work and of relations between conditions, forms of learners' work and products. Operationally defining data needed for these purposes is challenging [20]. Bootstrapping successively more refined and more effective learning analytics can profit from big data [24]. In turn, this recommends designing and widely distributing ensemble software to gather these data. As such learning systems come online, the field of learning analytics will be positioned to replicate what productively self-regulating learners do. At the same time, learners will be afforded regularly upgraded learning analytics to guide self-regulating their learning.

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Chapter 9: Learning Analytics for Understanding and Supporting Collaboration

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ABSTRACT

Collaboration is an important competency in the modern society. To harness the intersection of learning, work, and collaboration with analytics, several fundamental challenges need to be addressed. This chapter about collaboration analytics aims to highlight these challenges for the learning analytics community. We first survey the conceptual landscape of collaboration and learning with a focus on the computer-supported collaborative learning (CSCL) literature while attending to perspectives from computer supported cooperative work (CSCW). Grounded in the conceptual exploration, we then distinguish two salient strands of collaboration analytics: (a) *computational analysis of collaboration* that applies computational methods to examining collaborative processes; and (b) *analytics for collaboration* which is primarily concerned with designing and deploying data analytics in authentic contexts to facilitate collaboration. Examples and cases representing different contexts for learning and analytical frames are presented, followed by a discussion of key challenges and future directions.

Keywords: Collaboration, collaborative learning, computer-supported collaborative learning, computer supported cooperative work, collaboration analytics, teamwork

Collaboration has long been the subject of scholarly inquiry to test the assertion that "two heads are better than one." Characterizing how and when learning happens as people work together has vexed researchers across a number of fields, including education, psychology, and business. A contemporary understanding of the social nature of learning and the power of the Internet to connect people over time and space, coupled with the recognition that collaboration is an essential competency in the modern workforce), continues to keep this topic salient—if not essential—for an educated and productive society.

In the field of learning analytics, the context for investigating collaboration is often, unsurprisingly, *collaborative learning*, which has been the focus of Computer-Supported Collaborative Learning (CSCL)—a scholarly community that was launched in the 1990s to investigate collaborative learning in computer-mediated settings [10]. The intervening 30 years of CSCL has produced a wide body of research that demonstrates a diversity of methodologies intended to identify and capture the complex set of variables that determine the success of any collaborative effort. CSCL has contributed to the formation of learning analytics [51, 62] and also benefited from methods and tools developed in learning analytics.

In addition to CSCL, several other fields including Computer Supported Cooperative Work (CSCW), Human-Computer Interaction (HCI), and Social Computing are also deeply invested in investigating collaboration, particularly as it relates to the ways in which information technology is used in the workplace. CSCW is a research community that emerged in the 1980s as "an effort by technologists to learn from economists, social psychologists. anthropologists, organizational theorists, educators, and anyone else who could shed light on group activity" [20, pp. 19–20] and focused on the twin goals of (a) examining how people work in groups, and (b) how computer systems and *groupware* can support collaborative activities [60]. Although one of the earliest papers on computer supported collaborative learning appeared at a CSCW conference [44] until very recently, the CSCW and CHI communities were primarily interested in studying how groupware was used by adults in the context of work rather than educational systems used by students in formal and informal learning contexts. However, with the ubiquitous nature of information technology in everyday life, both the CSCW and CHI conferences now include tracks for papers where the context is learning, education, and families.

As discussed above, CSCL and CSCW overlap considerably in both research interests and design methodology. This overlap was explored in three workshops (ACM Group 2010, ACM Group 2012 and CSCL 2013) and resulted in an edited book, CSCL@Work [18]. The two communities also share a strong interest in applying computational methods to understanding and coordinating collaborative activities. Given emergent trends in modern societies, such as the blurred boundary between learning and work [30] and the rise of learning in the openly networked settings [23, 58], it becomes important to bridge perspectives from CSCL, CSCW, HCI, Social Media, and other fields where collaboration is explored.

To harness the power of learning analytics for scholarly research at the intersection of learning, work, and collaboration, several fundamental challenges need to be addressed. Specifically, the conceptualization of collaboration varies greatly across different communities, leading to a myriad of collaboration *constructs* researchers theorize and investigate. While multiplicity of ideas is championed within interdisciplinary fields like CSCL and CSCW, the scarcity of cross-community exchanges can lead to a disconnect between scholarly communities, efforts wasted on "reinventing the wheel," and missed opportunities caused by different terminologies and epistemic cultures. This chapter about collaboration analytics aims to highlight these challenges for the learning analytics community. We first survey the conceptual landscape of collaboration and learning while attending to perspectives from CSCW and HCI. Then, we distinguish between two salient strands of collaboration analytics: (a) *computational analysis of collaboration* that applies computational methods to examining collaborative processes; and (b) *analytics for collaboration* which is primarily concerned with designing and deploying data analytics in authentic contexts to facilitate collaboration. To articulate these two distinct strands, we introduce examples and cases that represent contexts of different scale, space, and analytical frames. Finally, we conclude by discussing challenges that lie ahead for collaboration analytics and point to future directions for research.

1 COLLABORATIVE LEARNING

Collaboration as a term is treated differently across scholarly communities. In the fields of CSCW and HCI, collaboration is used interchangeably with cooperation, broadly meaning cooperative work in a group [11, 20]. In contrast, the CSCL community has specific ideas about what can be considered collaboration. For many CSCL researchers, collaboration necessitates having a joint problem space [41], being intersubjective [47], and making deliberate efforts to coordinate group activities [10]. Despite these differences in defining collaboration, these communities overlap on the core constructs of collaboration. For example, much attention is given to *group awareness* in both CSCW [11] and CSCL [34]. The same parallels could be drawn about other collaboration constructs such as *joint attention*, *shared understanding*, *transactivity*, and *intersubjectivity* [3, 10, 49]. It is desirable to interrogate these constructs as new contexts for learning, such as Twitter and Microsoft Teams, continue to emerge.

The conceptualization of learning is also multifaceted. In CSCL, multiple traditions of learning co-exist, representing *cognitive* views of learning that foreground individual cognition, *inter-subjective* views that stress interactional sensing-making, and *inter-objective* views that locate learning with heterogeneous networks of learners, tools, artifacts, and practices [46, 26]. These frameworks guide research on learning in various contexts and also respond to emergent contexts in which learning happens. While much attention is given to learning in formal education spaces such as classrooms, new learning paradigms in informal education and at workplace challenge traditional conceptions of learning [7, 14, 32]. For instance, networked professional learning treats work as continual problem solving and learning as an integral part of such problem solving [5]. As the boundary between learning and work gets further blurred, cross-fertilization between research communities to enrich our understanding of learning is needed.

Building on the exploration of collaboration and learning, the following two sections discuss two salient strands of collaboration analytics: (a) *computational analysis of collaboration* that involves the application of computational methods to examining collaborative processes; and (b) *analytics for collaboration* which is primarily concerned with designing and deploying data analytics in various contexts of collaboration.

2 COMPUTATIONAL ANALYSIS OF COLLABORATION

Both CSCL and CSCW communities have been applying sophisticated computational methods to analyze collaborative processes, practices, and outcomes. The rise of data science has resulted in new computational methods to cope with large datasets, assist humans in laborious analysis of complex phenomena, and offer means to examine these phenomena from novel angels. While computational methods are sometimes touted as a silver bullet, Wise & Schwartz [63] remind us that "the substantive question is not if we should embrace computational approaches to understanding collaborative learning, but how to develop practices and norms around their use that maintain the community's commitment to theory and situational context" (p. 441).

In the CSCL literature, methodologies from various disciplines including psychology, linguistics, and anthropology are adopted to examine collaboration learning [26]. Multiple data sources and mixed methods are often used to understand complex CSCL processes (e.g., [39]. Even with the same dataset, collaboration can be examined at different levels—e.g., individuals, small groups, the whole class, a massive online community—and at various units of analysis such as verbal utterances, gestures, discussion threads, and sessions of collaboration. Methodological richness and tensions have inspired research teams to explore the potential of "productive multivocality" by applying multiple analytical methods to shared datasets [50]. Growing awareness and access to computational methods are intensifying this exploration (e.g., [16]). Below we survey the specific ways in which computational methods can be applied to investigating collaborative learning (see Table 1 for an overview).

First, the cognitivist tradition focuses on the analysis of individuals. Within this tradition, while some may view collaboration as merely stimuli for internal cognitive processes (e.g., the Piaget's [38] theory of cognitive conflict), others recognize the situated and embodied aspects of cognition (e.g., Hutchin's [25] theory of distributed cognition, and Greeno's [19] theory of situativity). As a result, computational analysis could examine the impact of participating in collaborative activities on individual learning or the extent to which cognitive content is reflected in group exchanges. For example, a collaborative intelligent tutoring system, COMET, was developed to support medical problem-based learning in small groups. This system involved student groups to collaboratively form hypotheses of medical problems by examining shared medical images and chatting via text [48]. Students' clinical *reasoning* was then modelled as Bayesian networks based on their hypothesis structure and their use of medical concepts in group chats. This analysis centered on students' reasoning and cognitive content. In another study that involved group dialogues, Howley et al. [24] examined the cognitive constructs of reasoning and *transactivity*. The unit of analysis is the minimum amount of text in a dialogue that can adequately express reasoning. Transactivity is captured by first identifying reasoning in discourse and then recognizing new instances of reasoning that build on or evaluate existing ones. Computational linguistic techniques can be applied to measure semantic overlaps between contributions; machine learning models are built using linguistic features to automatically label the transactivity of discourse contributions.

Intersubjective frameworks are oriented more to the social and cultural levels of analysis. Computational analysis in this tradition emphasizes social and linguistic interactions in often messy group processes. In an example of collaborative problem-solving, student dyads collaborated remotely to understand human brains while they were able to review a set of diagrams and communicate with each other via audio [42]. Being interested in the construct of *joint visual attention*, researchers designed a condition where learners could see the eye gaze of their partner on the screen while solving the problem. Using natural language processing, the researchers found higher correlations between students' learning gains and their verbal coherence in the condition with shared eye gaze. In another case of collaborative problem-solving by triads, Spikol et al. [45] attempted to build machine learning models to predict collaboration constructs including *physical engagement* and *synchronization* based on face and hand tracking data. In a similar example from a collocated, face-to-face context, Echeverria et al. [12] investigated teamwork from four intertwined aspects including physical, social, epistemic, and affective. Using multimodal data collected from location sensors, physiology wristbands, and microphones, they instrumented a data representation named the *multimodal matrix* and carried out matrix operations to derive proxies of teamwork related to *awareness* and *accountability*.

The inter-objective tradition requires more attention to the mediational objects and object-related activities in collaboration. Analyses abiding to this tradition could trace the trajectories of objects and unpack nuanced human activities around them. To analyze collaborative knowledge work on a wiki-based platform named Wikiversity, Halatchliyski and colleagues [22] adopted the main path analysis to examine the dynamic relations of knowledge artifacts and map the trajectories of ideas in different domains of the platform. In another example, an analytic tool named Knowledge Building Discourse Explorer (KBDeX) is designed to represent the evolving relations among key terms in collaborative discourse [37]. Rather than linking learners based on their social interactions, KBDeX connects learners based on the co-occurrence of key terms in their discourse contributions. The intricate, dynamic evolution of collaborative discourse is then represented by network representations that center on key terms, making it possible to assess constructs of collaboration such as *collective responsibility* using network indices [31].

To summarize, this strand of collaboration analytics is interested in applying a variety of computational approaches toward the study of collaboration. The application of these approaches is informed by theoretical frameworks and shaped by researchers' epistemological stances. As demonstrated by these examples, computational methods have shown promise in making laborious analysis more efficient, creating new representations of data, and offering novel means to make sense of collaboration data.

3 ANALYTICS FOR COLLABORATION

Computational analysis also makes it possible to provide timely feedback for collaboration. In this section, we locate the central concern of *analytics* at the translation or transformation of findings from *analysis* to *actions* in the learning analytics cycle [43]. While the analysis of collaboration is dictated by epistemological and conceptual ideas, the use of analytics for collaboration deals with the distribution of agency between human and computer, as well as a wide range of other design decisions. Below we advance a typology of analytics built for collaboration based on how they are deployed in socio-technical systems of collaboration to make an impact. We choose to articulate these two important dimensions (see Table 2) as they are central to the human-computer partnership that have concerned CSCL and CSCW since their inceptions.

3.1 Analytics as Partner vs. Regulator of Collaboration

The first dimension is concerned with the power distribution between analytics and humans. Along this dimension, we distinguish analytics as a *regulator* versus a *partner* of collaborative interaction.

When analytics functions as a *partner* of collaboration, it acts to facilitate collaboration but still turns to humans for decision-making and action-taking. For instance, analytics applications are designed to support time coordination, a surprisingly challenging task for today's organizations and teams. To confront this challenge, HCI and CSCW

Table 1: Applying computational methods to investigating collaboration.

Traditions	Studies	Constructs	Data	Computational techniques
Cognitive	[48]	Clinical reasoning	Chat logs, graph-based hypotheses	Bayesian network modeling
Cognitive	[24]	Reasoning and transactivity	Learner dialogues	Computational linguistic techniques; Machine learning
Intersubjective	[45]	Physical engagement, synchronization, and individual accountability	Face and hand tracking data	Machine learning
Intersubjective	[42]	Joint visual attention	Eye tracking data	Natural language processing; eye gaze analysis
Intersubjective	[12]	The physical, social, epistemic, and affective dimensions of group activity	Temporal interaction data; multimodal data	Multimodal matrix; Quantitative ethnography
Interobjective	[22]	Trajectories of ideas	Log data of wiki edits	Main path analysis
Interobjective	[31]	Collective responsibility in knowledge building	Learner dialogues	Socio-semantic network analysis [37]

Table 2: Two dimensions of collaboration analytics.

Dimensions	As Partner	As Regulator
Loosely Coupled	• Wikipedia SuggestBot [8] • Idea Thread Mapper [65] • Reactive conversational assistants [61]	• Awareness lantern [1] • Sociometric badges and feedback [27] • CSCL teacher dashboard [28]
Tightly Coupled	• A.I. scheduling assistant • Group formation in MOOCs and WikiProjects [59, 67] • Proactive conversational assistants [61]	• Software agents in scripted collaborative inquiry [54] • Conversational agents for collaborative problem-solving [52] • Wikipedia ClueBot NG [66]

researchers have created A.I. scheduling assistants that act just like human agents to schedule meetings [9, 36]. Based on a combination of heuristics, machine learning, and natural language processing, such A.I. assistants are trained to extract meeting information, such as meeting subject, time, and attendees, from emails and engage in back-and-forth messages to coordinate meetings [9]. In this case, the A.I. agent serves as a partner delegated to solve the mundane and yet non-trivial task of time coordination.

Analytics can be a partner for team formation in large-scale collaboration settings. NovoEd is a social learning environment that supports team formation processes in massive online classes. Teams can be formed algorithmically based on instructor-specified factors such as size of the team and geographical location of the members [40]. Another analytics-based team formation approach draws on discussion data and algorithmically assigns learners to teams based on their transactive interaction with each other [59]. On Wikipedia, a variety of algorithms are designed to recommend newcomers into WikiProjects based on their interests in or relationships with project topics; human agents including project leaders remain "in the loop" to carry out the action of inviting newcomers [67].

Besides temporal coordination and team formation, analytics can also be a partner that provides content-specific support relevant to the task. For instance, Winkler et al. [61] developed a smart personal assistant using Alexa to facilitate collaborative problem-solving by providing *proactive* structured facilitation and *reactive* help for humans' content-specific questions. When analytics act as a partner in such cases, they provide important affordances that contribute to key constructs of collaboration but do not evaluate collaboration or prescribe actions on the human's behalf.

When analytics acts as a regulator, in contrast, it takes responsibility in monitoring the status of collaboration and taking actions to shape the ongoing progress of collaboration. One example is the awareness lantern designed by Alavi & Dillenbourg [1]. Combining colors, lightness, and blinking, the lantern creates an ambient display of the status of collaborative groups designed to attract the tutor's attention. Student teams can press the lantern to call for help and the lantern blinks and adjusts the blinking frequency based on the wait time. In this case, the lantern directly mirrors the status of collaborative groups and regulates the help-seeking process in a classroom. In a another example, sociometric badges are used to collect and analyze data from geographically distributed teams and provide instant feedback about team participation [27]. Based on interaction patterns captured by sociometric badges, feedback is provided each team to promote active and balanced participation and frequent turn transitions [27]. In classrooms where multiple collaborative teams are in action, teacher dashboards are designed to capture multiple group indicators (e.g., task progress, participation balance) and alert the teacher when a group deviates from a norm [57]. In these cases, analytics provide evaluative information about collaboration to different analytics "consumers" (the teacher, participants, software) for them to take regulatory actions towards collaboration.

3.2 Action-taking Being Closely vs. Loosely Coupled with Collaboration

The second dimension is about the ways in which analytics are integrated with collaboration processes. Here we distinguish analytics that are closely vs. loosely coupled with collaborative actions. This distinction is concerned with the relation between analytics-based action-taking and the other components of a collaboration workflow.

On one side of the continuum, analytic outputs present merely outcomes of computational analysis of collaboration and it is up to humans to choose whether, when, and how to act upon the presented information. On Wikipedia, quality management in the editorial process increasingly relies on algorithmic agents or "bots" [17]. For instance, the SuggestBot applies a combination of text analysis, collaborative filtering, and hyperlink following to suggest editing tasks to Wikipedia editors based on their edit histories; suggestions are made directly to an editor who would decide how to react [8]. In this case, analytics is loosely coupled with any individual or collaborative editing efforts. In contrast, the ClueBot NG is designed to automatically detect vandalism based on a machine learning approach and autonomously revert vandalism as soon as it is discovered [66]. While both bots act as *partners* (see *Dimension 1*), they differ in how closely their analytic actions are coupled with the overall editing process on Wikipedia.

In knowledge building classrooms, teachers and students have had access to analytics tools embedded in the Knowledge Forum since the '90s [4, 53]. Much like teacher dashboards in CSCL classrooms (van Leewen, Wise & Teasley, this volume), these analytics, such as social network and lexical analysis tools, are loosely coupled with the knowledge-building workflow. A more recently developed "meta-discourse" tool known as the Idea Thread Mapper shares the same characteristic [65]. With assistance from topic modeling techniques, this tool helps learners identify "idea threads" in their Knowledge Forum dialogues and then reflect on their collective progress [65]. Similar to the Wikipedia SuggestBot, the Idea Thread Mapper is also loosely coupled with students' knowledge work and it is up to the humans to trigger its use during knowledge building.

On the other side of the continuum, analytic actions are deeply embedded in collaboration processes. Analytic tools embody ideas about how actions should be taken in response to a collaborative situation. In scripted collaboration, software agents can be specially designed to process student interactions in real-time in response to both pre-specified scripts and emergent collaborative scenarios. For example, in a "smart learning space" designed to facilitate sophisticated collaborative inquiry, high-school students work together as a community to address science problems [54]. Tablets, large displays, multi-touch tables, and the teacher play distinct roles in supporting the inquiry. In particular, multiple real-time software agents are present to sort students into groups, monitor whether groups have achieved consensus, and track individual, group, and class-wide progress. Drawing from various computational techniques, these software agents automate important parts of the collaboration scripts and help the teacher make orchestrational decisions [54]. The roles played by these software agents are akin to the *operators* in an orchestration graph [6, 21]. Analytic actions (such as distributing student-generated post-it notes based on groups and topics) are embodied by these operators, setting the condition for the next collaboration activity (such as making sense of the assigned post-it notes as a group). Here, analytics are tightly coupled with predefined collaboration scenarios or workflows.

Conversational agents developed to facilitate peer collaboration can also embody analytic supports tightly within the flow of collaborative conversations. For example, MentorChat asks learners to collaborate on open-ended learning tasks through online chats. Drawing on the Accountable Talk framework that details productive classroom discussion practices and norms [33], MentorChat processes each dialogue contribution, updates students' domain models, decides whether an intervention is desirable, and if so, delivers its intervention verbally using a text-to-speech engine [52]. Analytics, including semantic analysis based on WordNet, directly responds to the unfolding student dialogue; the agent directly intervenes and hereby triggers further student conversations [52]. In contrast with the Alexa-based conversational agent that acts as a partner who answers student questions [61], MentorChat serves a regulatory role by monitoring students' domain understanding and directly intervening when necessary.

In summary, we have identified two important dimensions of analytics for supporting collaboration: analytics as regulator vs. partner, and analytic actions being tightly vs. loosely coupled with collaborative interaction. This typology can provide a roadmap for future development of collaboration analytics. It is important to note that these two dimensions function as continuums and, as illustrated in these aforementioned cases, one analytics application could serve multiple roles that cut across multiple areas of the space.

4 CONCLUSIONS AND FUTURE DIRECTIONS

Collaboration is widely considered to be an important competency in modern society. As educators and researchers, we actively theorize what collaborative learning means, debate where collaboration sits in the curriculum, and develop interventions to facilitate collaboration at all levels of education. Given the importance of collaboration, coupled with the emerging quest for human-computer or human-A.I. partnerships, analytics and computation are destined to play an essential role in future efforts to facilitate collaboration in all domains of human activity.

Because analytics can be used to both examine collaborative processes and support the design of systems to facilitate collaboration, analytics can be leveraged to make progress on two essential questions: How do successful collaborations work? How can we design supports to promote collaboration? Learning analytics has the potential to inform the research on collaboration by contributing to good learning design, effective pedagogy and increasing learner self-awareness [13]. To do so, we see several important challenges and future directions in the area of collaboration analytics. First, more efforts need to be invested in bridging research communities that have been actively investigating collaboration from distinct but overlapping theoretical viewpoints. A number of projects are ongoing to bridge perspectives from CSCL, CSCW, HCI, Social Computing, and Learning Analytics (e.g., [12]). Such work would alleviate the scarcity of theory underlying learning analytics since its earliest days [15, 64]. At the same time, learning analytics has the opportunity to contribute to our theoretical understanding of successful collaboration by creatively integrating sources of data (such as demographic information, physiological data, and behavioral data) and modeling collaboration processes [2].

Second, as the world is increasingly connected, it is important to consider the factor of *scale* and ways to harness scale in collaboration. In CSCL, scale is considered from both group size and time but heavily focused on small group collaboration within a limited timeframe [10], typically in single classrooms, after-school clubs, and museums. By contrast, CSCW and social computing researchers have a more expansive coverage given their stronger interests in open online communities such as Wikipedia [67] and software development projects [35]. Compared to small-scale collaboration scenarios in highly controlled educational contexts (e.g., collaboration scripting software, intelligent tutoring systems), the mechanisms or interactive processes to support collaboration may be different in open, large-scale environments where the participants have very different motivations to collaborate than do students. The ubiquity of the Internet has not only created new opportunities for geographically unbounded interactions, the rise of "Web 2.0" technologies have also blurred the lines between school, home, and the workplace. Following Bransford's notion of "lifelong and lifewide" learning [29], we need to utilize learning analytics to conceptualize collaborative learning whenever and wherever it occurs. This remains a challenge for the field of learning analytics where the research has to-date been conducted primarily in formal educational settings, particularly higher education and professional training.

Third, the distribution of agency between humans and analytics is a critical and contentious issue that needs to be carefully navigated when designing and deploying collaboration analytics. In Wikipedia, the delicate relations between human editors and bots, as well as among bots, are especially illuminating [17, 56]. The learning analytics community needs robust design approaches to help us cope with value tensions and ethical dilemmas in a learning analytics system [55, 67]. As human activities are shaped by various analytics tools, we need to critically examine the structures (temporal, spatial, social, material, conceptual) created for collaboration, and the ways in which human and computer agents are collectively shaping these structures.

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Chapter 10: Natural Language Processing - Writing Analytics

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ABSTRACT

Writing analytics uses computational techniques to analyse written texts for the purposes of improving learning. This chapter provides an introduction to writing analytics, through the discussion of linguistic and domain orientations to the analysis of writing, and descriptive and evaluative intentions for the analytics. The chapter highlights the importance of the relationship between writing analytics and good pedagogy, contending that for writing analytics to positively impact learning, actionability must be considered in the design process. Limitations of writing analytics are also discussed, highlighting areas of concern for future research.

Keywords: Writing Analytics, natural language processing, NLP, linguistics, pedagogy, feedback

Writing analytics (WA) is a sub-field of learning analytics (LA) that uses natural language processing (NLP) technologies to analyse written text for the purposes of improving learning. WA may be directed at obtaining insight on the writer, the writer's thinking, or the writing itself. While theoretically it could be applied to any written text, the majority of WA research has focused on learning contexts and associated writing artefacts. Common applications include analysing student writing ability, providing feedback to students and teachers on writing content and style, researching learning, investigating interactions through analysis of dialogue, analysing opinion, and automated grading. The significance of language to LA can be seen in the extent of language related chapters in this handbook, such as social network analysis [43], reading [1], multi-party interaction [16], and writing on which we focus here.

1 THE PURPOSE OF WRITING ANALYTICS

Many of the different applications of WA make use of the same computational NLP techniques. For example, tokenising, parsing, and vectorisation are used in many WA applications. Other NLP approaches such as word embedding, information extraction or topic modelling may only be used for specific applications. NLP is an extensive and fast-moving computer science field which has recently adopted contemporary machine learning practices to address many language problems [54]. Most WA work takes advantage of relatively mature NLP techniques and uses readily available open source software. Therefore, in this chapter we focus more on how WA uses NLP to obtain analytics relevant to learning, than on the NLP technologies themselves.

Although WA has been used for purposes tangential to learning (e.g. curriculum document analysis, or sentiment analysis of student surveys), here we concentrate on applications which are pedagogically driven and closer to student learning contexts.

The way in which learning relates to writing is important, particularly when WA is mostly focused on features of the writing artefact, as opposed to characteristics of the learner or aspects of the learning context. When students are learning to write, they are learning the vocabulary and the syntactic and stylistic rules for writing for a specific purpose (e.g. writing a persuasive essay as opposed to a piece of short fiction). When WA is applied to such "learning to write" tasks, the analytics are generally constructed around the key requirements of a style of writing (e.g. well-formed sentences and appropriate use of domain vocabulary). By contrast, many tasks involve "writing to learn". In these tasks, the rules of the writing may be of secondary importance, or only necessary for comprehensibility, with the primary focus being the content of the writing. With this kind of writing task, WA is used more to ascertain whether the writer has grasped important domain concepts and is expressing them in a way that demonstrates their learning (e.g. expressing relevant domain knowledge appropriately).

The difference between learning to write and writing to learn is not always clearly distinguished in writing tasks, however these different emphases tend to require selection of different NLP techniques and a difference in orientation to the analysis. The *orientation* of learning to write tasks tends to be more linguistic where formalities of language are primary, whereas writing to learn tends to demand more of a domain orientation where meaning associated with a topic is primary. Regardless of the orientation adopted, the *intention* for the WA tends to be a mix of description and evaluation. Descriptive analytics identify the presence or absence of certain features, the extent to which they occur, and how they interrelate. Evaluative analytics make judgements about the nature of the writing and the extent to which is or is not fit for purpose. The relationship between orientation to the writing and intention for the writing analytics is described in more detail next.

2 ORIENTATION TO ANALYSIS OF WRITING

Writing is a complex activity involving skilful management of cognitive, social, and affective processes [18, 24]. A writing artefact not only includes information about the subject of writing, but also incorporates information about the writer's skill in writing, stylistic characteristics of their writing, and can at times reveal information about how the writer thinks about the subject , as well as personal information about themselves.

The analysis of writing precedes the use of computational tools [20], and WA has been extensively influenced by non-computational approaches to analysis. Fundamentally, analysis tends to be approached from a mixture of two orientations, one from a *linguistic* standpoint and another that comes from a *domain* standpoint.

2.1 Linguistic Orientation

A linguistic orientation to writing draws heavily on the field of linguistics, and when applied to WA makes extensive use of computational linguistics to inform the analysis. This orientation is typically concerned with the technical aspects that apply to most writing and is heavily influenced by theories of language including Universal Grammar [11], and Functional Grammar [15]. This orientation can also result in division of analysis approaches that align with areas of linguistics, and which value the structural characteristic of natural language and associated features.

Linguistically oriented WA tends to focus on language features that are formally defined. These can include, but are not limited to: parts of speech, grammatical rules of sentence structure, word relationships in the form of syntactic dependencies or phrase structures, and vocabulary use including spelling and lexical diversity. Tools such as Linguistic Inquiry and Word Count or LIWC [42], Stanford CoreNLP [34], and Coh-Metrix [38] derive such linguistic measures, which can further be used to generate higher order writing analytics. Formal definition of language features allow WA to build on the linguistic rules and definitions towards a meaningful representation of the writing. Linguistic features can usually be determined with an accepted level of accuracy by NLP algorithms, and as long as the writing follows accepted language conventions.

2.2 Domain Orientation

Until recently, almost all of NLP technologies were heavily influenced by linguistics. With the advent of neural machine learning approaches to NLP, many contemporary NLP technologies use models trained on large corpuses of billions of words (or more) and are able to converge on the conventions of language without explicit coding of the formal structures. Some of the most successful language technologies are essentially based on complex computational models which require little or no understanding of linguistics. This shift in NLP approach resulted in significant debate between linguists and computer scientists [41] as to whether a linguistic understanding was actually necessary in order to computationally work with language [53]. Differences in perspective along these lines have not only informed the direction of NLP research, but have also influenced the WA community, particularly in the choice of underlying NLP technologies.

An ability to analyse writing without recourse to linguistics increased the relevance of taking a domain orientation to the analysis of writing. In contrast to the linguistic orientation which is interested in the technical and formal aspects of language, a domain orientation focuses more on the purpose of the written text and its content. Characteristics of writing that are of primary importance include but are not limited to: the topic or subject of the text, the meaning of text with particular relevance to the domain context, the tone and use of emotion and affect, and overall characteristics related to style and genre - the "abstract, socially recognized ways of using language" [26, p. 149].

For example, a domain orientation may be more interested in whether the writing addresses a domain topic in a required style or genre, as opposed to whether it follows language conventions or specific linguistic rules. This can be seen in machine learning classifiers that predict user-defined categories for a text (Say, predicting if an argumentative written text is a premise or a claim, built on human-annotated data sets and no linguistic rules). The context in which the writing is generated plays a major role in determining which features are of interest in a domain orientation, making them hard to generalise to different contexts.

As WA is practical field, approaches to WA tasks tend to be a mixture of the above orientations. For WA that is strongly aligned with pedagogy, this mixture of orientations can be determined by directing the analysis towards the task Knight, Gibson & Shibani [31], following a pragmatic approach towards a practical effect in the learning.

3 INTENTION FOR WRITING ANALYTICS

Regardless of the orientation towards analysing the writing, writing analytics tend to reflect an intention that blends *describing* features of the writing, and *evaluating* the writing with respect to some expected utility. These are not distinct categories, but rather ways of understanding the nature of analytics and its relationship to the written text and/or the writing task. The extent to which one is more or less prominent is governed by the intended purpose and the alignment with relevant pedagogy.

3.1 Descriptive Writing Analytics

Descriptive WA makes visible and summarizes features of the writing to inform the writer or other stakeholders (e.g. teacher). Such analytics are based on technical constructs at word-level, sentence-level, paragraph-level or whole document-level, and various structural features of the writing.

One basic measure that provides summary information is the frequency of occurrence (count) of a feature within a given scope. The total number of words, paragraphs, and sentences in document may be calculated to provide counts as feedback to the writer, to make sure that they are adhering to task requirements. Word processors, most text editors and grammar and spelling software provide this simple form of feedback. Although a simple form of analytics, this type of feedback can highlight aspects of the writing that do not adhere to accepted language conventions and can therefore aid the writer in editing their writing. However, feedback dominated by simple metrics associated with the mechanics of writing can lead to a focus on error correction, which may be of minimal pedagogic value for the writer [10], particularly in writing to learn tasks.

Descriptive WA can also be metrics of more complex linguistic features or a mix of simple features that are indicative of a more complex construct. These can include measures of cohesion, complexity, connectives in a text, and psycholinguistic data such as textual familiarity, sentiment, and effect. Examples of descriptive WA that bring together both simple frequency counts and more complex linguistic and psycholinguist constructs include Linguistic Inquiry and Word Count or LIWC [42], and Coh-Metrix [38]. Several studies have explored how these indices predict writing quality and writer characteristics, by finding correlations between selected indices and human ratings of essay quality [13, 37, 46].

Specific structural patterns of interest such as rhetorical moves and connectives in writing can also be identified using NLP technologies. Examples of this type of WA are found in AcaWriter [48], Research Writing Tutor [12], and AntMover [4], which identify rhetorically salient sentences associated with a given genre. Descriptive WA can also be generated based on the content of the written text. Key words, concepts and topics in the text can be identified with a range of NLP techniques from simple frequency measures to more advanced techniques such as word embedding [39] or using topic modelling algorithms like Latent Dirichlet Allocation [7]. Tools such as Glosser [52] and Essay Critic [40] use such analytics to bring to the writer's attention to key ideas in the text.

Some descriptive WA have also been employed by teachers and administrators to analyze writing. One example of this application is Quantext [36], which has been used for teacher professional development and analysis of student feedback surveys. Another example can be found in the combination of Coh-Metrix with Social Network Analytics to examine how learners engage with discourse [17].

In addition, how the analytics gets presented to the user plays a major role in how they engage with it. Descriptive analytics may be provided as a report, highlighted in text, and/ or displayed in a dashboard. They may also be graphically represented as plots and graphs to provide visual cues to the users. For examples, see word clouds and rainbow diagrams in OpenEssayist, Concept maps in Glosser [52] and dynamic Revision maps in ArgRewrite [55]. Indeed, visualizations and dashboards are an important part of the conversation in provoking thinking and self-regulated learning in learning analytics [19, 28]. Similarly, visual representations contribute to research on writing by studying products and processes using multiple sources such as drafts, writing logs, keystroke activities, and access logs. They examine writing products: Recurrence Quantification Analysis for instance, which visualizes recurrent word patterns over time [3], and the dynamics of writing processes like revision [2, 49, 50].

Descriptive WA generally leaves meaning making to the writer, teacher or researcher. For the most part, descriptive WA requires a level of understanding from the user to draw reliable and valid conclusions from the analytics. The analytics are simply representations of textual features which require further reflection to be meaningful. Hence, without an explicit meaning-making process, the pedagogic value of such analytics can be questionable. We cannot assume that the descriptive WA is useful for a learner to improve their writing simply because it has been provided to them. Actionable feedback is required for learners to make improvements in their writing, and descriptive WA usually needs to be augmented with this feedback from another source (such as the teacher, or additional materials).

3.2 Evaluative Writing Analytics

Evaluative WA for written texts involves making judgements on the writing to inform the learner about its quality with respect to the writing context. In contrast to descriptive WA, the evaluative WA aims to give students more information on the quality of their writing, rather than requiring them to make their own judgements. This intention for WA holds the potential to provide actionable feedback, informing about the next steps the writer can take. Evaluative WA implementations can vary significantly depending on the educational contexts in which they are used, and some have been developed for very specific purposes, such as analysing for metacognition in reflective writing [22].

A widely used application of evaluative WA is in the provision of automated feedback on writing. This feedback tends to be formative with the aim of supporting the writing process, and hence directly impacting learning. A significant goal is making the feedback actionable, by intervening and guiding the learner to make improvements, thereby completing a learning analytics loop where the analytics is derived from the writing and writing is improved based on the analytics. Examples of tools in this growing research area include AcaWriter [22, 31] , Research Writing Tutor [12] and Turnitin Revision Assistant [35].

Evaluative WA also includes technologies that make judgements on the quality of writing, without necessarily providing feedback to the writer. The most common of these are Automated Essay Scoring (AES) systems which grade assessment tasks that are generally summative rather than formative. This form of evaluative WA is often used in conjunction with high-stakes assessment, and has attracted significant criticism from sectors of the educational community [6] due to the way it is used to support performativity agendas rather than more directly helping learners. The potential for disconnect between summative assessment and learning is well established in the educational literature [51, 25], and AES systems tend not to address this nor other larger pedagogical issues [29, 44]. Further, encoded human judgements in the analytics can carry human biases and errors which may ultimately impact learning decisions.

With respect to WA, an improvement on AES systems are Automated Writing Evaluation (AWE) systems which supplement judgements with feedback. Examples of AWE include Criterion [5] and MyAccess! [32]. While the usefulness of such systems has been demonstrated to support writing instruction at varied levels [9, 33], they have also attracted criticism due to the reduction of writing to merely formulaic features of text, rather than a process of meaningful engagement [10]. Another form of evaluative WA can be found in Intelligent tutoring systems (ITS) such as Writing Pal [47]. ITS provide adaptive and interactive support for learning by providing strategy instruction of writing that are modelled around closed writing tasks. However, such ITS (and AWE and AES) cater to a specific task/ prompt and encourage and evaluate students based on a standard path, which does not necessarily reflect the messy process of learning nor consider outliers. As with descriptive WA, the value of these evaluative WA systems rests to a large extent on how they are situated within good pedagogy. When used to provide formative feedback, it should also provide learners with the opportunity to think critically about their writing, and to push back against the evaluative WA when required, to result in meaningful learning experiences.

4 PEDAGOGY AND WRITING ANALYTICS

Increasingly LA practitioners are attending to the need for LA to make a positive impact on learning [14]. Within the field there is a growing critique of LA approaches that are merely analysing learning related data without due consideration of how that analysis might inform improvements in learning and teaching [21]. WA is no exception to this, and so it is important to consider its relationship to pedagogy.

What constitutes good pedagogy is beyond the scope of this chapter, and in fact dominates the field of Education and Learning Sciences. What is important for an understanding of WA is that its success depends not only on the quality of the technology, but also on the quality of the pedagogy which ultimately determines how WA is put to work. Traditionally, a common educational technology approach has been to take high quality existing technologies and then investigate out how best to apply it within educational contexts. This approach largely rests on the assumption that what makes good technology and what makes good pedagogy are independent static factors. An alternative approach that is often adopted in WA, is to view WA as co-design process which includes both technological and pedagogical aspects, and where each aspect informs design in the other. When adopting this approach, WA naturally tends to be learning focused to augment existing practice, as it grows out the synergistic design of both the technology and the pedagogy. Explicit examples of this approach can be found in task centric WA which builds on both technical and social infrastructure [31].

Good pedagogy demands that WA account for the quality of feedback that is facilitated by its intervention in the learning context. What constitutes good quality feedback is well established in the literature [27], and feedback being actionable, contributing to improvements in learning is a top concern for WA. Therefore, when WA is providing analytics directly to the student, it is important that the student be able to take action based on the analytics received. For WA provided to a teacher, the teacher needs to be able to use the analytics in order to positively impact the learning. There is little that a student or teacher can do if they are presented with feedback that holds no meaning for them, although how they decide to act is a separate issue. Hence, the burden for ensuring that feedback is actionable should fall on the designers of the WA together with the practitioners that implement it. For WA, feedback actionability and quality should be designed in from the beginning, not considered as an afterthought.

Some WA researchers and developers have addressed this need for ensuring actionability by working in multidisciplinary teams [8]. This ensures that WA development is not dominated by NLP experts, but also includes experts in learning and pedagogy like teachers, learning designers, user experience specialists, and cognitive scientists. The constitution of effective WA teams depends on the context in which the WA is expected to be applied, however at a minimum the team needs to include relevant expertise in both NLP and pedagogical domains.

Participatory design has emerged as an important methodology in LA [45] which values the importance of pedagogy by including stakeholders in the design process. Gibson and Lang [23] have also highlighted the importance of pedagogy in the LA research process, recommending a pragmatic inquiry approach that gives priority to the intended practical effects of the analytics, that is, the nature of the effect on learning that is anticipated when the LA is implemented. When applied to WA, both of these methodological approaches can yield meaningful impact on learning [48].

5 LIMITATIONS AND POSSIBILITIES

Despite significant advances in recent years, NLP is still limited to relatively narrow tasks (compared with human processing of language). For WA, this means taking care that NLP technologies are used according to their initial design. For WA designers who are not NLP experts, this means being aware of assumptions that come about from human generalisation of computational processes and ensuring that these are addressed. This may be a non-trivial task as the tendency for computer scientists to co-opt general English language terms for specific computing names can complicate matters. For example, the use of "learning" in the computer science literature is very different to its pedagogical meaning, and assumptions that computers learn like people can be propagated in the WA, resulting in confusion for the user. Similarly, "topic modelling" algorithms do not automatically generate topics in the human form of a subject of interest. Topic models are statistical distributions across a vocabulary and result in a list of words and their corresponding probabilities of belonging to a "topic". These topics can be very useful in WA, but rarely correspond with human interpretation of what the topic might be. Distributional semantics used heavily in NLP aims to detect semantics of words and groups of words based on the words that surround them. However, this is a constrained view in comparison to how humans understand the meaning of words. Humans draw on a much bigger context than the lexical context in which the words are found. When undertaking the task of language understanding, people use prior knowledge and make complex connections that include experiences, emotions, and their physical environment.

Failing to properly comprehend the difference between computational processing of language and human language understanding in WA can have significant pedagogical consequences, as it is possible to design a system that is 'accurate' with respect to a computational analysis of language, but 'useless' with respect to human language understanding. A well-known example of this issue can be found in the simple descriptive analytic of word count. Word-count can correlate highly with quality in some written tasks, but asking a student to improve their writing by writing more words is rarely helpful. NLP limitations are often identified in terms of accuracy in achieving a specific task. However, WA needs to avoid being locked to computer science measures of what is good. Simply because an NLP process is accurate or effective at extracting a textual feature does not mean that it is useful for learning or even necessary for effective writing.

Limitations with NLP, although important to be aware of, do not necessarily translate into limitations in WA. Learning can occur with meaningful design of WA even in the absence of high levels of accuracy [30]. A common example from the teaching of writing underscores this point. Many teachers (over many years) have found that the process of writing drafts is critical to achieving good quality writing for incremental improvement. Often, the reasons for motivating this drafting process are less important than the drafting itself. When WA is concerned with impact on learning, designing WA that encourages writers to write drafts may be more significant than the extent to which the underlying NLP technology is accurate. Accurate NLP is also not equitable with respect to all learners. Many NLP technologies degrade significantly when the language used does not match the norms of usage. Therefore, NLP can perform very poorly on the writing of developing writers and students with language processing difficulties, who don't adhere to the conventions on which the technology depends. Issues of bias can be exacerbated in NLP due to the dominance of development in dominant languages, particularly English. NLP technologies built on English assumptions do not necessarily translate well into other languages, even if software exists. This is particularly the case with machine learning approaches to languages which lack the large corpora on which recent NLP models are trained. Care needs to be taken when designing and implementing WA in contexts of generally good English writers, that success is not assumed for other contexts. The extent to which WA caters for writers of all abilities in all languages could be seen as a measure of the field's maturity, and on this measure at this point in time, there is a long way to go.

The key to maximising the potential of WA despite its limitations, is an inextricable relationship with high quality pedagogy. For WA designers, developers and practitioners, this means working together with educators and holding a clear shared understanding of the practical learning effect that they wish to achieve.

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Chapter 11: Modeling Educational Discourse with Natural Language Processing

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ABSTRACT

The broadening adoption of technology enhanced learning environments has substantially altered the manner in which educational communication takes place, with most people engaging in some form of online asynchronous or synchronous conversation every day. The language and discourse artifacts emerging from these technological environments is a rich source of information into learning processes and outcomes. This chapter describes the current landscape of natural language processing (NLP) tools and approaches available to researchers and practitioners to computationally discern patterns in large quantities of text-based conversations that take place across a variety of educational technology platforms. The capabilities of NLP are particularly important as, in the field of learning analytics, we desire to effectively and efficiently learn about the process of learning by observing learners, and then subsequently use that information to improve learning. We conclude the chapter with a discussion around the emerging applications (i.e., sensing technologies, breakthroughs in AI, and cloud computing) and challenges of NLP tools to educational discourse.

Keywords: Natural Language Processing (NLP), computational linguistics, discourse analysis

The rapid growth of social media, online communities and learning platforms has dramatically changed the manner in which communication takes place. Conversation technologies are omnipresent in today's organizational environment, from email, text messaging, and wikis to more sophisticated knowledge management systems; all of which are leveraged to support social, business, and educational functions. Educational environments in particular have become increasingly reliant on computer-mediated communication, relying on video conferencing, synchronous chats, and asynchronous forums, in both small (with 5–20 learners) and massive (with hundreds or even thousands of learners) environments. These platforms, which are designed to support or even supplant traditional instruction, have become commonplace across all levels of education, and as a result created big data in education [64, 82].

The language and discourse artifacts emerging from these environments is a rich source of information into learning processes. It is important to clarify what we mean by discourse. Our definition of discourse includes both oral and chat-based communication between two or more individuals (e.g., peer-peer, peer-teacher communicative interactions). Indeed, the importance of communication for the learning process has been a consistent narrative in the learning sciences and learning analytics research [112]. The fundamental role of language is represented in the scope of chapters devoted to various language and discourse processes such as social network analysis (cf. chapter X), reading (cf. chapter X), writing (cf. chapter X), a general overview of analysis approaches (cf. chapter X), and multi-party interaction (i.e., peer-peer interactions, peer-agent, or peer-teacher), which is the focus of the current chapter. As evident in these chapters, language provides a powerful and measurable behavioral signal that can be used to capture the semantic, structural and sociocognitive interaction patterns that characterize learning related phenomenon including cognitive, metacognitive, motivational, social and affective dimensions of student engagement [7, 62].

Conventional approaches to quantifying and characterizing language and discourse characteristics have traditionally required human examination (i.e., manual content analysis) [71], which is known to carry biases and other methodological limitations [72]. In particular, the laborious nature of these tasks make them no longer a viable option with the increasing scale of online interaction data (Graesser et al., 2018) [84, 108, 126]. Advances in artificial intelligence methods, such as Natural language Processing (NLP) [63], have made it possible to automatically i) harness vast amounts of communication data being produced in technology-mediated learning environments, ii) quantify aspects of human cognition, affective and social processes in text-based human-to-human and human-to-agent conversations that iii) would otherwise not be possible for human coders to capture, given the multifaceted discourse characteristics of human interaction.

1 ANALYZING CONVERSATIONAL INTERACTIVE DISCOURSE USING NATURAL LANGUAGE PROCESSING

While discourse analysis can involve the analysis of different kinds of data (e.g., video, audio, text), the most widely used techniques for discourse analysis focus on the analysis of written, textual information. Within the field of Text Mining (Aggarwal & Zhai, 2012) and Natural Language Processing [63] there have been many techniques developed which can be used for the analysis of discourse data. In this section we will examine the ways in which techniques from these two fields have been used to analyze educational discourse.

The simplest forms of discourse analysis involve *bag-of-words approaches* [2] and calculation of the N-gram frequencies, which are sequences of consecutive N-words (i.e., unigrams: one word, bigrams: two words, trigrams: three words). Extracted N-gram frequencies are then used as *input features* for the development of various analytical models, such as discourse classification or clustering systems. For instance, Kovanović et al. [68] used unigram, bigram, and trigram counts as features for the classification of discussion messages according to the level of cognitive presence [43], a theoretical construct that captures the development of students' critical thinking. Similar approaches have been used, for example, for detecting student reflection [118], student's knowledge states [80], detection of relevant/irrelevant questions [13], classification of dialogue acts [38], and collaborative problem-solving [108]. In all of these cases, extracted bag-of-words N-gram features were used to represent discourse for the purpose of analytical model development.

While bag-of-words representations (i.e., frequencies of the extracted N-grams) depend on the content of the input data, *dictionary-based approaches* utilize a predefined list of words (or phrases), and represent the input data through frequencies of the different word groups. One of the most widely used dictionary-based tools is LIWC (Linguistic Inquiry and Word Count) [97, 116], which calculates the frequencies of words from over 100 word categories. An important benefit of such approaches is that those categories are empirically validated and representative of important psychological processes, making them easier to interpret and use for research purposes. Within the context of educational research, LIWC has been used, for instance, to assess students' cognitive load [65], predicting student performance and engagement in MOOCs [105, 124, 131] and traditional face-to-face courses [106], cognitive presence detection [61, 92], reflection [45, 69, 76, 78, 119], and social interactions [4, 35, 128].

In addition to simple, word-based representations, there is a whole range of techniques for representing discourse using the different linguistic properties of the input text [84]. Such techniques range from the simple counts of the number of words, sentences or paragraphs to more complex measures of different linguistic properties. In this regard, one of the widely used tools is Coh-Metrix [50, 85], which provides over 200 different linguistic metrics of the input text. In addition to providing simple word, sentence and paragraph counts, Coh-Metrix also provides a wide range of linguistic and coherence indices, including text readability, lexical diversity, use of connective words, syntactic complexity and pattern density, part-of-speech category use, and semantic overlap of input sentences/paragraphs. Coh-metrix has been used in a wide range of studies of educational discourse (see Dowell, Graesser, and Cai [29] for an overview).

Another class of NLP technique for representing discourse focuses on understanding the semantic structure of the input text. Such techniques focus on capturing the meaning of the textual data, and use that semantic information to model the discourse. These techniques typically involve extracting a specific number of hidden, or *latent*, topics in a large collection of textual documents and associating these topics to each of the documents in the collection. The input for such algorithms is the *document-term matrix* (DTM), which is a matrix where rows represent documents, columns represent all words (used across all documents), and values word frequencies in the documents.

One of the earliest and most widely-used semantic analysis techniques is Latent Semantic Analysis (LSA) [74] which is a technique for decomposing DTM into a product of two smaller matrices (document-topic and topic-word matrices) using singular value decomposition (SVD), a simple linear algebra transformation algorithm. Thus, each document represents a combination of latent topics, and each latent topic is characterized through word frequency distribution. LSA has been widely used in education [75], for a wide range of problems from automated essay grading [42], team communication [24], and use of online discussions [14]. LSA is also utilized by Coh-Metrix to calculate the semantic overlap between the sentences and paragraph as a means of assessing cohesiveness of the written text [50].

While LSA has been widely used for semantic analysis of educational discourse, the recent development in statistical machine learning brought several new techniques that often produce results superior to those by LSA. Those include *probabilistic topic modeling algorithms* [8, 115], which derive document-topic and topic-word associations through the use of generative models and Markov-Chain Monte Carlo (MCMC) simulations [47]. The most notable algorithm in this domain is Latent Dirichlet Allocation (LDA) [9], which enables realistic modeling of uneven topic distribution across documents (as often the case in practice). LDA has been widely used in humanities [17] and social sciences [101] including education. Within learning analytics field, LDA and topic modeling have been primarily used for modeling students' online communication [14, 15, 41, 53, 107, 121], and student writings [46, 111], but also for the analysis of student course enrollment data [91].

Recent advancements in artificial neural networks (ANNs) and deep learning resulted in the development of some highly effective techniques for discourse representation. The most notable tool in this area is *Word2vec* [88], which utilises a two-layer shallow neural network to produce *word embeddings*, a vector-based representation of the text which preserves its semantics. Using word2vec, a semantic similarity of two texts can be easily calculated through calculation of the cosine similarity between their respective vectors. Word2vec has been used in learning analytics for a wide range of tasks, including grade predicting through the analysis of student lecture comments [81], short responses [83], and student misconceptions [87].

In addition to the development of more complex and sophisticated discourse representations, there has also been significant focus on capturing and modeling the inherent complexity and temporal dynamics of the learners conversations, such as those that take place in online collaborative learning, problem-solving, and online course forums [18, 52, 55, 104]. In particular, the sociocognitive aspects of learner's interactions reside in and evolve through the semantic connection between individual's utterances over time. As such, researchers have started to use innovative temporally sensitive NLP approaches to assess the socio-cognitive properties of online interactions.

The most representative approach of temporally sensitive NLP tools is *Group Communication Analysis* (GCA) [32], a computational approach for the analysis of multi-party discourse from computer-mediated peer to peer, team, and collaborative group interactions. In contrast with existing computational approaches to text analysis, GCA emphasizes emergent aspects of learner discourse interactions [70]. Temporal emergence of the discourse is integral to the methods behind GCA that capture temporal alignment, sequential ordering and coordination in meaning during human communication [26, 32](Hu et al., 2018).

To this end, GCA combines artificial intelligence methods, such as computational semantic models of cohesion, with temporally sensitive semantic analyses inspired by the cross- and auto-correlation measures from time-series analysis. These semantic space models, which rely on advanced artificial intelligence techniques, may be constructed via Latent Semantic Analysis (LSA) [75], a classic matrix-factorization method, or more current artificial neural network word embedding models such as Skip-gram (i.e. Word2vec, [89]) or Global Vectors of Words (i.e., "GloVe", [98]). Using this approach, GCA allows researchers to quantify discourse as a dynamic and evolving sociocognitive process that resides in the interaction between learner's communicative contributions.

2 CURRENT STATE OF DISCOURSE ANALYTICS

2.1 Small Scale Multi-Party Interactions

One of the most common NLP applications in the context of small-scale multi-party interactions involves examining the word level properties of student's communication. For instance, researchers have used the features from LIWC to explore sentiment [108], transformative discourse [127], and self and socially-shared regulation during collaboration [132]. Similarly, Latent Dirichlet Allocation has proved successful in transforming the topics of texts into values as a basis for representing cognitive information graphically [37]. Grammatical information can also provide valuable insights as shown by Sullivan and Keith's (2019) research [114], which highlights how parts of speech (POS) analysis can be used to uncover student sense-making activity during collaborative learning. Quantifying the occurrence of words in general and across different psychological categories provides information about the precise content of students' communication.

Other tools move beyond the explicit meaning and allow researchers to quantify more latent characteristics of student discourse interactions, such as Coh-Metrix [50, 85], TAALES [73], TAACO [19], and ReaderBench [22]. These systems provide a summative account of learner discourse at the student level (i.e. individual posts or totality of them per person) as well as at the group level (i.e. text of the overall thread transcript) along various text properties, such as cohesion (e.g., [28]), and narrativity [102]. These "bag of words" and more summative NLP methods offer several advantages regarding their simplicity and ability to provide specific information about the content of student discourse during computer-mediated collaborations, such as word level, syntactic, and cohesion properties of texts.

Collaborative interactions are fundamentally defined as a process that occurs over time [103], and characterized by the dynamic, emergent, adaptive, and interdependent nature of joint human communicative actions to produce meaning. However, the above NLP approaches traditionally ignored this character, choosing instead to examine relationships between relatively static input and outcome variables [126]. Temporally sensitive NLP approaches offer significant promise for the conceptualization of the ways in which collaboration unfolds over time and the inherent complexity [49, 51, 103, 104], which could substantially advance our understanding of multi-party collaborative interactions. In this context, Järvelä et al. [58] traced the occurrence of self-regulated learning (SRL) and socially shared regulated learning (SSRL) in the context of CSCL. They used temporal and sequential analysis of chat discussions and log file traces to find evidence of whether the students collaboratively planned regulatory activities were shared in practice. In practice, Järvelä et al. [58] matched each individual's SRL from the log file traces and his or her SSRL from the chat data and composed micro-level examples to demonstrate the interplay between self-regulation and socially shared regulation of learning. The main finding was that collaborating groups engaging in SSRL achieved better learning outcomes when compared with groups that did not.

More recently, GCA has been used to quantify the temporal properties of learners' socio-cognitive processes and communication dynamics in online multi-party interactions. This approach has provided substantial insights on the emergent sociocognitive roles learners occupy during collaborative interactions [30, 32, 34, 33], and deeper understanding of inclusivity and equality in online team interactions [26, 31, 6, 79]. For instance, Dowell and colleagues have uncovered differences in learners' interpersonal interaction patterns across ethnic populations, between male and female students [6], and the influence of gender group composition on equitable interpersonal discourse during STEM interactions [31]. Across these studies, GCA has revealed substantial intra- and interpersonal differences in women and URM's engagement, which could influence their sense of belonging in online STEM environments.

2.2 Scaling of Discourse Analytics

Advances in educational technologies and a desire for increased access to learning, have enabled the development of pedagogical environments at scale, such as Massive Open Online Courses (MOOCs) [62, 120]. Open online courses have the potential to advance education on a global level, by providing the masses with broader access to lifelong learning opportunities. Early research on the MOOC phenomena saw significant investment in understanding the makeup of the learner population, largely through demographic [36], performance, and activity-based measures [66]. The discourse artifacts emerging from these environments were primarily investigated from the network perspective, with Social Network Analysis (SNA; see chapter X for an overview) being a primary means of extrapolating meaning from this data. However, there has been an uptick in the application of NLP tools to understand temporal population trends (e.g., [27]), profiles [34], and various learning phenomena within MOOCs (e.g., engagement, [62]).

Some notable applications include the use of NLP to quantify aspects of learner-generated posts, as well as learners' cognitive, affective, and social processes. Identifying aspects and categories of students posts as enormous value given the scale of student discourse within MOOCs, and the associated teacher effort required. Wise et al. [125] work has focused on bringing order to the chaos in MOOC discussion forums. Their work used a bag of words approach (i.e., unigram and bigram) to classify students' posts into content vs. non-content related posts. Others have used similar approaches in conjunction with tools like LIWC and machine learning models to identify urgent posts that require more immediate teacher attention [3].

A major theme in the literature is the use of NLP for the assessment of learners' psychological processes in MOOCs and broader technology-mediated learning contexts. Interesting applications around affective detection hold significant potential given the important role of emotions in learning (see Graesser [48], Pekrun [96], and Perry and Souza [99] for a review). Sentiment analysis can be used as a first step for identifying complex emotions, such as excitement, frustration or confusion. Sentiment analysis is the process of identifying and classifying learners' opinions from a piece of text into different sentiments-for example, positive, negative, or neutral—or emotions such as happy, sad, angry, or disgusted to determine the user's attitude toward a particular topic or within a context. This can give an insight into how learners feel with the course to be able to perform modifications aimed at increasing learners' engagement and satisfaction, which is very important to ensure the success of the MOOC [90, 100].

Several researchers have highlighted the application of sentiment analysis in the context of scaled learner interactions (e.g., [1, 16, 129]). Some of the earlier work by Wen, Yang, and Rose [123], applied sentiment analysis techniques on student posts on three MOOCs. They observed a negative correlation between the ratio of positive to negative terms and dropout across time. In detecting different confusion states Yang et al. [130] relied on psychologically meaningful categories of words, extracted from online discussions using the LIWC as one of the classification features for retention. Their work highlighted that confusion reduced the likelihood of retention, but this could be reduced with confusion resolution and other supportive interventions. Others have explored student sentiment in scaled environments in relation to performance and student perceptions. For instance, Tucker, Pursel, and Divinsky [117], using word-sentiment lexicon, found that students' affective discourse was negatively related to their average grade. However, this relationship was modest and positively related to their quiz grades. Similar to Yang, Adamopoulos [1] employed AlchemyAPI to extract student sentiment from discussion forum messages and found student sentiment toward course instructors, assignments, and course materials have a positive effect on the course retention.

An emerging trend in research highlights the novel insights that can be gleamed through a combination of complementary analytic techniques, such as SNA and various NLP analytics. The research in this context used systems like Coh-Metrix and LIWC or analytical approaches such as GCA [32] and Epistemic Network Analysis (ENA; [109]) in conjunction with SNA to gain a more holistic understanding of learners discourse [20, 35, 44, 59, 60]. For instance, Coh-Metrix has been involved in pioneering research exploring the potential methodological and theoretical advantages of combining SNA and computational linguistic analyses [35, 59]. Joksimović and colleagues used Coh-Metrix to analyze learners' forum posts in a distributed (Twitter, blogs and Facebook) MOOC. Social Network Analysis was used to determine students' social centrality. Linear mixed-effect modeling was used to reveal the linguistic profiles associated with more centrality located learners. Overall, the results indicated that learners in the MOOC connected easier to individuals who use a more informal, narrative style, but still maintain a deeper cohesive structure to their communication. However, this linguistic profile cannot be immediately interpreted as beneficial for learning. Dowell et al. [35] used a similar methodological design, but also included a measure of student performance in the MOOC. Specifically, students who performed significantly better engaged in more expository style discourse, with surface and deep level cohesive integration, abstract language, and simple syntactic structures. However, linguistic profiles of the centrally positioned learners differed from the high performers. Learners with a more significant and central position in their social network engage using a more narrative style discourse with less overlap between words and ideas, simpler syntactic structures and abstract words [35, 59].

3 CHALLENGES AND FUTURE ADVANCES

Here we have provided a landscape view of computational methods available for researchers to understand and quantify learning related phenomena during computer-mediated communication, and situated these within the context of both small- and large-scale learner interactions. As illustrated by these applied examples, computational linguistic methods are now in full swing within the learning analytics and broader educational community [84]. Thus, as nicely articulated by Wise and Schwarz [126] the substantive question is not if we should embrace computational approaches to understanding multi-party interactions, but how to develop practices and norms around their use that maintain the community's commitment to theory and situational context. Looking forward, we propose it is unlikely that these computational advances and applications will slow, but instead, we are already seeing evidence of future innovations that will have very real implications for both researchers and practitioners, and the relationship between these groups. Below we outline a few of these emerging trends and associated challenges.

Educational discourse research includes both written and auditory discourse analysis, though we focused exclusively on computational methods for computer-mediated text interactions, however, the approaches taken to understanding learner interactions between these registers can differ significantly. Turn taking cues differ heavily between the modalities and shape social aspects of the environment such as power dynamics and inclusion. It is not uncommon for auditory discourse analysis to include these elements, usually through painstaking annotation of text and video transcripts captured from the educational setting. New sensor technologies promise to increase both the recording prevalence and the automation of analysis of technology-mediated speech discourse. Some researchers have already taken a step in this direction by using spoken language to computationally model complex collaboration processes (e.g., construction of shared knowledge, negotiation/coordination, and maintaining team function) [5, 113], effective communication [57], agreeableness [77] and speaker's influence [93]. For instance, Hung and Gatica-Perez connected team cohesion to the audio-visual features within task-oriented groups [54]. This is driven in part by the development of low-cost software and consumer appliances aimed at more natural human computer interaction. For instance, IBM Watson Speech to Text service [56] can aid researchers by generating a transcript from video based multi-party interactions with start and stop times for each utterance spoken by each learner. Similarly, the Amazon Echo Dot, designed for home automation tasks, is a small and inexpensive device which contains an array of seven directional microphones and can capture speaker direction, record audio, and respond to queries based on speech recognition. Depth sensing cameras, popularized by the Microsoft Kinect device but now available from various vendors, form three dimensional maps of a learner based on their physical appearance and have the capability to do facial recognition, detect gaze direction, and detect facial expression.

The implication of such inexpensive yet highly capable sensing technologies rests primarily in the significant opportunity for researchers who study in-person or video based discourse interactions [21, 25]. In addition to potentially lowering manual coding costs and effort (i.e., human annotation of text and video transcripts captured from the educational setting) when categorizing educational discourse processes, the low cost and small size of such devices makes it conceivable that future educational spaces might be built with data analytics in mind [94]. For instance, one could imagine even very large classrooms being outfitted with such technologies which might enable the analysis of (and thus interventions for) active learning approaches. Regardless of whether such equipment becomes ubiquitous in educational spaces or used for research studies alone, it provides an opportunity for educational researchers to rethink data capture and analysis methods, with an eye towards how one might distill large volumes of fine grained data into constructs of interest [10].

Modern computational processing power has created revolutionary advances in NLP. A major player in the field was revealed by Google and is a breakthrough artificial intelligence technology called BERT (Bidirectional Encoder Representations from Transformers; [23], which has garnered significant attention in the Machine Learning community by presenting state-of-the-art results in a wide variety of NLP tasks, including Question Answering, Natural Language Inference, and others. BERT's main technical innovation is applying the bidirectional training of Transformer, a widely used attention model, to language modeling. This is in contrast to previous efforts which examine a text sequence either from left to right or combined for training. Devlin et al. [23] highlight how a language model which is bidirectionally trained can have a deeper sense of language context and flow than single-direction language models. However, this revolutionary AI appears to have a significant issue, as articulated by the NY Times " It could be picking up on biases in the way a child mimics the bad behavior of his parents" [86]. That is, BERT, like many other similar NLP approaches, learns linguistic representations from tons of digitized information, such as old books, Wikipedia entries and news articles. This has created non-trivial issues as these societal artifacts carry decades of biases as well as the current biases within our society [12]. An illustration of the problematic behavior are the recurrently appearing occupational stereotypes that the word *'homemaker'* is related to the word *'woman'* as the word *'programmer'* is to the word *'man'* [11, 122].

Recent studies have aimed to detect, analyze and mitigate gender bias in different NLP tools and applications including word embeddings, but these issues remain and should be carefully thought about when implementing any NLP techniques.

Nonetheless, the advances in the computing domain open up several opportunities for researchers aiming at improving education [64, p.127]. For instance, pervasive sensing and data analytics offer the ability to do real-time capture, inference, and intervention. While the vast majority of current educational discourse analysis is done in a post-hoc fashion, there is a growing trend towards real-time software analytics augmentation [67]. For instance, most learning management systems (LMSs) now have clickstream-style logging of learner interactions which is available instantly to researchers. This native functionality is being integrated by data specification bodies groups such as IMS Global who are now actively engaged in reflecting real-time data interoperability needs in educational data standards. This work has the potential to increase dramatically the number and variety of educational technologies that provide data about learner interactions with systems (including discourse interactions) in an *in-situ* fashion. Those includes the provision of feedback to both students and instructors [67] as well as integration with other real-time analytics systems such as social network analysis [39], epistemic network analysis [44, 107] or Group Communication Analysis [32]. Educational discourse analysis also poses some potentially high challenges for researchers with regard to ethics and privacy preservation [95, 110]. While a discussion of these important issues is beyond the scope of the current work, there have been efforts towards the development of different solutions and frameworks for privacy protection in learning analytics [40].

Educational discourse analysis is a broad research area, and takes place in primary, secondary, higher and emerging education environments. In this Chapter, we have provided an overview of the developing field of educational NLP analysis, and a map of emerging opportunities and challenges educational researchers face with socio-technical advances. As we have outlined, sociotechnical advances have already influenced the scale of discourse data and computational methods used by educational researchers. For instance, the increase in blended, MOOC, and informal educational environments has changed the scale of discourse data, wherein researchers now regularly utilize automated linguistic analysis and machine learning approaches to handle the increasing amount of discourse data produced within these educational environments. As these sociotechnical changes continue, we hope this discussion draws attention not only to future research opportunities immediately available in the field, but also the necessary technical, computational, sociological, and linguistic developments needed to handle the changing nature of discourse, the computational infrastructure resources needed for real-time analysis of educational discourse, and the relationships between educational researchers, institutional educational technologies, and third party vendors, which are imperative to enable next-generation educational NLP scholarly work.

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Chapter 12: Emotional Learning Analytics

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ABSTRACT

This chapter discusses the ubiquity and importance of emotion to learning. It argues substantial progress can be made by coupling discovery-oriented, data-driven, analytic methods of learning analytics and educational data mining with theoretical advances and methodologies from the affective and learning sciences. Core, emerging, and future themes of research at the intersection of these areas are discussed.

Keywords: Affect, affective science, affective computing, educational data mining, learning analytics

At the recommendation of a reviewer of one of my papers [15], I recently sought to learn a statistical method called generalized additive mixed models (GAMMs) [48]. At first, I was mildly *displeased* at the thought of having to do more work on this paper. I downloaded a recommended paper with some eye-catching graphics, which piqued my *curiosity* and motivated me to explore further. This quickly turned into *interest* as I read more, and eventually into *excitement* when I realized the power of the approach. This motivated me to slog through the technical details, which led to *confusion* and *frustration* when things did not make sense, and *delight* when I made progress. When I attempted to apply the method to my data, I felt more *confusion* and *frustration*, interspersed with *hope*, *delight*, and *happiness*. I eventually got it working and wrote the results. When I was done, I felt *contentment*, *relief*, and a bit of *pride*.

As this example illustrates, emotion pervades the learning process. This is not unique to learning as much cognition is tinged with emotion. Emotions are not always consciously experienced [54], but they exist and influence cognition nonetheless. Also, emotions do not occur in a vacuum; they are deeply intertwined within the social fabric of learning. Students experience a range of emotions during learning. Pekrun & Stephens [57] call these "academic emotions" and group them into four categories. *Achievement* emotions are linked to learning activities (homework, taking a test) and outcomes (success, failure). *Topic* emotions are aligned with the learning content (empathy for a protagonist). *Social* emotions such as pride, shame, and jealousy occur because education requires interacting with others. Finally, *epistemic* emotions arise in the course of cognitive processing, such as confusion in the face of an impasse.

Emotions are not merely incidental; they may have evolved to serve specific functions [23, 69]. For example, emotions perform *signaling functions* [66] by highlighting problems with knowledge (confusion), problems with stimulation (boredom), concerns with impending performance (anxiety), and challenges not easily surpassed (frustration). They perform *evaluative functions* by serving as the currency by which people appraise an event in terms of its value, goal relevance, and goal congruence [38]. Emotions perform *modulation functions* by changing cognitive focus; negative emotions engender narrow, bottom-up, and focused processing [8, 66] compared to positive emotions, which facilitate broader, top-down, generative processing [29, 37]. Emotions pervade thought through their effects on memory, problem solving, decision making, and other facets of cognition (see [12] for a review).

What exactly is an emotion? Truth be told, we do not really know, or at least we do not fully agree [38]. This can be readily inferred from recent debates on the psychological underpinnings of emotion. Fortunately, there is general agreement on the following key points. Emotions are conceptual or experienced entities arising from brain–body–environment interactions. However, you won't find them by looking in the brain, body, or environment. Instead, emotions emerge [46] when organism–environment interactions trigger changes across multiple time scales and at multiple levels—neurobiological, physiological, behavioral, and subjective. The emotion is reflected in these changes in a manner modulated by previous experience and the ongoing situational context. The same emotional category (e.g., anxiety) will manifest differently based on a triggering event [69], the specific biological/cognitive/metacognitive processes involved [33, 50], and sociocultural influences [49, 56]. For example, an anxiety-inducing event will trigger distinct "episodes" of anxiety depending on the specific circumstance (public speaking, test taking), the temporal context (one day versus one minute before the speech), the neurobiological system (baseline arousal), and the social context (speaking in front of colleagues versus strangers). This level of variability and ambiguity is expected because humans and their emotions are dynamic and adaptive. Rigid emotions have little evolutionary value as our environment is always changing.

Where do learning analytics (LA) and educational data mining (EDM) fit in? On one hand, given the key role of emotions in learning, attempts to analyze learning without considering emotion will be incomplete. On the other hand, given the ambiguity and complexity of emotional phenomena, attempts to study emotions during learning without the methods of LA and EDM will only yield shallow insights. There is a body of work adopting a data-driven analytic approach to study the incidence and influence of emotions on the processes and products of learning. In this chapter, we highlight some of the core, emerging, and future themes in this interdisciplinary research area.

First, a note on terminology. Emotion is related but not equivalent to motivation, attitudes, preferences, physiology, arousal, and a host of other constructs. Emotions are also distinct from moods and affective traits [62]. Emotion is not the same as a feeling. Hunger is a feeling but is not an emotion. There is some contention as to what constitutes an emotion. Anger is certainly an emotion, but what about confusion? Confusion has affective components (feelings of being confused, characteristic facial expressions; [18], but there is debate as to whether it is an emotion [34, 63]. In the remainder of this chapter, we use the more inclusive term *affective state* rather than the more restrictive term *emotion*.

CORE THEMES

We selected the following themes to highlight the use of LA/EDM methods to study affect during learning. We also deeply review a few exemplary studies within each theme rather than cursorily reviewing many studies. This means many excellent studies go unmentioned, but we leave it to the reader to explore the body of work within each theme. When available, we recommend review papers to facilitate this process.

0.1 Affect Detection from Student Activity Data

Affective states cannot be directly measured because they are conceptual entities. Because they emerge from environment–person interactions and influence action by modulating cognition, it should be possible to infer affect by analyzing context and learner actions. This approach, referred to as "interaction-based," "log-file based," or "sensor-free" affect detection has a decade-long history [1, 16](and was recently reviewed by [7]).

As an example, Pardos, Baker, San Pedro, Gowda, & Gowda [55] developed affect detectors for ASSISTments, an intelligent tutoring system (ITS) for middle- and high-school mathematics [60]. The authors collected training data from 229 students while they used ASSISTments in school computer labs. Human observers recorded affect as students interacted with ASSISTments using the Baker-Rodrigo Observation Method Protocol (BROMP) [52]. According to this protocol, trained observers make live annotations of affect based on observable behavior, including explicit actions towards the software's interface, interactions with peers and teachers, body movements, gestures, and facial expressions. The observers coded four affective states (boredom, frustration, engaged concentration, and confusion) and two behaviors (going off-task and gaming the system[1]). Supervised learning techniques were used to discriminate each affective state from other states (e.g., bored versus others) using features extracted from ASSISTments log files (performance on problems, hint requests, response times). Accuracy for detecting affective states ranged from .632 to .678 (measured with the A-prime metric, similar to AUROC) for affect and .802 to .819 for behaviors. The classifier was validated in a manner ensuring generalizability to new students from the same population by ensuring each student's data appears only in the training or the testing data. Pardos et al. [55] provided preliminary evidence on the predictive validity of their detectors. This was done by applying the detectors on log files from a different set of 1,393 students who interacted with ASSISTments several years earlier. Automatically measured affect and behavior moderately correlated with standardized test scores $(0.09 < |r| < 0.45)$.

Further, San Pedro, Baker, Bowers, & Heffernan [65] attempted to predict college enrollment based on the automatic detectors. They applied the detectors to existing log files from 3,707 students who interacted with ASSISTments from 2004 to 2009. College enrollment information for these students was obtained from the National Student Clearinghouse. Automatically measured affective states were significant predictors of college enrollment several years later, which is a rather impressive finding.

More recently, Hutt, Grafsgaard, & D'Mello [36] developed a sensor-free measure of student engagement with an eye towards scalability. The research was conducted in the context of Algebra Nation, an online math learning platform supporting over 150,000 diverse students studying Algebra 1, Algebra 2, and Geometry. The researchers collected a large-scale dataset of 69,174 students who used Algebra Nation as part of their regular math classes for a semester and used experience sampling to collect 133,966 self-reports of 18 affective states (e.g., boredom, confusion, mind wandering, curiosity) related to engagement. They identified 22 generic activity features (viewing a video, pausing a video, taking a quiz) extracted from Algebra Nation log files in 5-minute windows prior to a self-report survey. These features do not require specialized sensors and are domain- and system-independent. They trained supervised learning models to predict each affective state from the features. Prediction accuracies (Spearman's rho, a correlation coefficient ranging from -1 to 1), were modest and ranged from .08 (for surprise) to .34 (for happiness), with a mean of .25.

The researchers tested the generalizability of the engage-

[1][6] define gaming the system as, "attempting to succeed in an educational environment by exploiting properties of the system rather than by learning the material and trying to use that knowledge to answer correctly" (pp. 1-2)

ment models in several ways. First, they showed the models trained on Algebra students generalized to a different data set of Geometry students (n = 28,458) on the same platform. Jensen, Hutt, & D'Mello [41] demonstrated the models' generalizability to clusters of students based on typical platform use and demographic features. They found models trained on one group performed similarly well when tested on the other groups, although there was a small advantage of training multiple individual subpopulation models compared to a general (all-population) model. These results show the promise of scaling up sensor-free methods to detect engagement on the largest and most heterogeneous student sample to date.

0.2 Affect Detection from Bodily Signals

Affect is an embodied phenomenon in that it activates bodily response systems for action. Signals of these bodily responses should make it possible to infer learner affect (a latent variable) from machine-readable bodily signals (observables). There is a rich body of work on the use of bodily signals to detect affect as discussed in a number of reviews [11, 20, 75]. Research has historically focused on interactions in controlled environments, but researchers have begun to take this work into the real world, specifically computer-enabled classrooms. The study reviewed next reflects one such effort by our research group and collaborators, but the reader is directed to Arroyo et al. [2] for their pioneering work on affect detection in computer-enabled classrooms.

Bosch, D'Mello, Ocumpaugh, Baker, & Shute [10] studied automated detection of affect from facial features in a noisy real-world setting of a computer-enabled classroom. In this study, 137 middle and high school students played a conceptual physics educational game called Physics Playground [67] in small groups for 1.5 to 2 hours across two days as part of their regular physics classes. Trained observers made live annotations of boredom, confusion, frustration, engaged concentration, and delight using the BROMP protocol. The observers also noted when students went off-task.

Videos of students' faces and upper bodies were recorded during game-play and synchronized with the affect annotations. The videos were processed using the FACET computer-vision program [26], which provides estimates of the likelihood of 19 facial action units [25] (e.g., raised brow, tightened lips), head pose, and position (Figure 1). Body movement was also estimated from the videos using motion filtering algorithms [44] (Figure 2). Supervised learning methods were then used to build detectors of each affective state (e.g., bored vs. other states) using both facial expressions and bodily movements. The detectors were moderately successful with accuracies (quantified by AUROC) ranging from .610 to .867 for affect and .816 for off-task behaviors. Follow-up analyses confirmed the affect detectors generalized across students, multiple days, class periods, and across different genders and ethnicities.

One limitation of the face-based affect detectors is they are only applicable when the face can be automatically detected in the video stream. This is not always the case

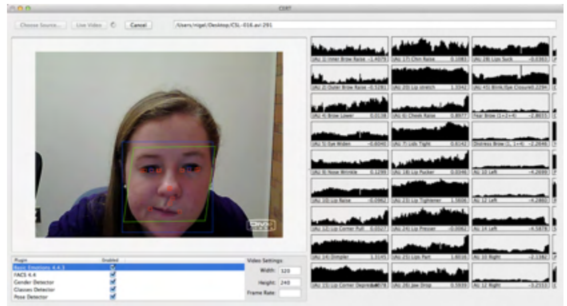

Figure 1: Automatic tracking of facial features using the Computer Expression Recognition Toolbox. The graphs on the right show likelihoods of activation of facial features.

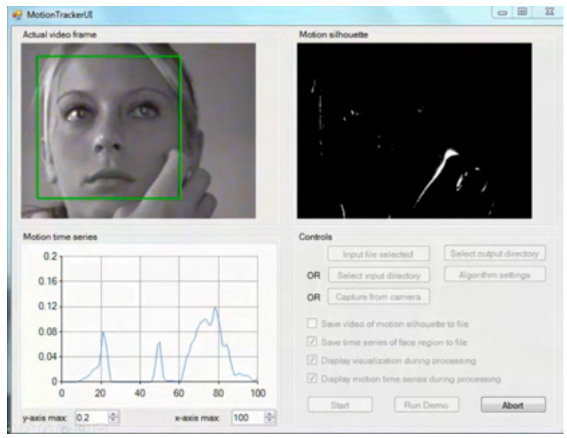

Figure 2: Automatic tracking of body movement from video using motion silhouettes. The image on the right displays the areas of movement from the video playing on the left. The graph on the bottom shows the amount of movement over time.

due to excessive movement, occlusion, poor lighting, and other factors. In fact, the face-based affect detectors were only applicable to 65% of the cases. To address this, Bosch, Chen, D'Mello, Baker, & Shute [9] combined interaction-based and face-based detection via decision-level fusion. The interaction-based detectors were less accurate than the face-based detectors (Kai et al., [42]), but were applicable to almost all of the cases. By combining the two, the detectors could be applied to 98% of the cases, with only a small reduction (<5% difference) in accuracy compared to face-based detection.

0.3 Integrating Affect Models in Affect-Aware Learning Technologies

The interaction- and bodily-based affect detectors just discussed are tangible artifacts that can be instrumented to provide real-time assessments of student affect during interactions with a learning technology. This affords the exciting possibility of closing the loop by dynamically responding to the sensed affect. The aim of such affect-aware learning technologies is to expand the bandwidth of adaptivity of current learning technologies by responding to what students feel in addition to what they think and do (see [22] for a review). Here, we highlight two such systems, the Affective AutoTutor [17] and UNC-ITSPOKE [28].

Affective AutoTutor (see Figure 3) is a modified version of AutoTutor — a conversational ITS that helps students develop mastery on difficult topics in Newtonian physics, computer literacy, and scientific reasoning by holding a mixed-initiative dialog in natural language [31]. The original AutoTutor system has a set of fuzzy production rules sensitive to the cognitive states of the learner. The Affective AutoTutor augments these rules to be sensitive to assessments of learners' changing affective states, specifically boredom, confusion, and frustration. The affective states are sensed by automatically monitoring interaction patterns, gross body movements, and facial features [17]. The Affective AutoTutor responds with empathetic, encouraging, and motivational dialog-moves along with an avatar's emotional displays. For example, the tutor might respond to mild boredom with, "This stuff can be kind of dull sometimes, so I'm gonna try and help you get through it. Let's go." The affective responses are accompanied by appropriate emotional facial expressions and emotionally modulated speech (e.g., synthesized empathy or encouragement).

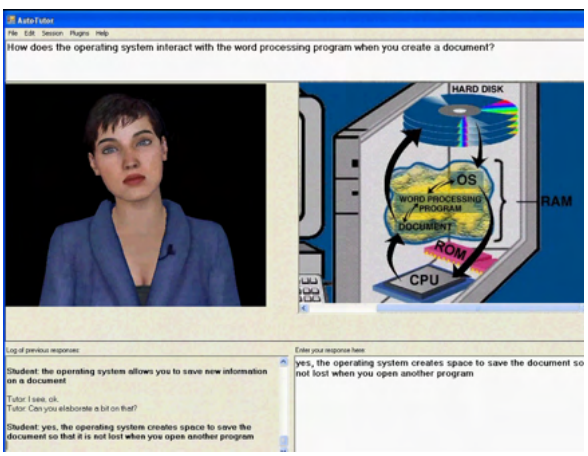

Figure 3: Affective AutoTutor: an ITS with conversational dialogs that automatically detects and responds to learners' boredom, confusion, and frustration.

The effectiveness of Affective AutoTutor over the original non-affective AutoTutor was tested in a between-subjects experiment where 84 learners were randomly assigned to two 30-minute learning sessions with an affective-aware or non-affective tutor [21]. The results indicated the affective tutor helped learning for low-domain knowledge learners during the second 30-minute learning session. The affective tutor was less effective at promoting learning for high-domain knowledge learners and during the first 30-minute session. Importantly, learning gains increased from Session 1 to Session 2 with the affective tutor whereas they plateaued with the non-affective tutor. Learners who interacted with the affective tutor also demonstrated improved performance on a subsequent transfer test. A follow-up analysis indicated learners' perceptions of how closely the computer tutors resembled human tutors increased across learning sessions, related to the quality of tutor feedback, and powerfully predicted learning [19]. The positive change in perceptions was greater for the affective tutor.

As a second example, consider UNC-ITSPOKE [28], a speech-enabled ITS for physics which automatically detects and responds to learners' certainty/uncertainty in addition to the correctness/incorrectness of their spoken responses. Uncertainty detection was performed by extracting and analyzing acoustic-prosodic features in learners' spoken responses along with lexical and dialog-based features. UNC-ITSPOKE responded to uncertainty when the learner was correct but uncertain about the response. The response strategy involved launching explanation-based sub-dialogs that provided added instruction to remediate the uncertainty. This could involve additional follow-up questions (for more difficult content) or simply the assertion of the correct information with elaborated explanations (for easier content).

Forbes-Riley & Litman [28] compared learning outcomes of 72 learners who were randomly assigned to receive adaptive responses to uncertainty (adaptive condition), no responses to uncertainty (non-adaptive control condition), or random responses to uncertainty (random control condition). In this later condition, the added tutorial content from the sub-dialogs was given for a random set of turns to control for the additional tutoring. The results indicated the adaptive condition achieved slightly (but not significantly) higher learning outcomes than the other conditions. The findings revealed it was perhaps not the presence or absence of adaptive responses to uncertainty, but the number of adaptive responses that correlated with learning outcomes.

1 EMERGING THEMES

Research at the intersection of emotions, learning, LA, and EDM, has typically focused on one-on-one learning with an ITS [28, 32, 73], educational games [13, 43, 64], or interfaces that support basic competencies like reading and problem solving [21, 45]. Although these basic lines of research are quite active, recent work has focused on analyzing affect across interaction contexts that more closely reflect the broader sociocultural context surrounding learning. We briefly describe four themes of research to illustrate a few exciting developments.

1.1 Affect-Based Predictors of Engagement and Dropout

Indicators of potential dropout or poor grades and corresponding early intervention systems are some of the "killer apps" of LA and EDM [39]. Most systems in authentic settings focus on academic performance data, demographics, and availability of financial assistance. These factors are undoubtedly important, but there are likely alternate factors that come into play. With this in mind, Tze, Daniels, Buhr, & Le [70] identified affective profiles in a Massive Open Online Course (MOOC). They found these different profiles were associated with varying levels of cognitive, behavioral, and social engagement with the course. For example, profiles with lower levels of boredom and guilt were associated with higher engagement with course content and profiles with high anxiety were associated with higher social engagement. Additionally, Dillon et al. [24] analyzed frequently occurring affective states in a MOOC and found states such as anxiety, confusion, frustration, and hope were positively associated with dropout.

1.2 Sentiment Analysis of Discussion Forums

Language often communicates feelings. Hence, sentiment analysis and opinion mining techniques (Pang & Lee, 2008) have considerable potential for studying how students' thoughts about a learning experience predict relevant behaviors like attrition. In line with this, Wen, Yang, & Rosé [72], applied sentiment analysis techniques to student posts on three MOOCs. They observed a negative correlation between dropout and the ratio of positive to negative posts. More recently, Xing, Tang, & Pei [74] expanded this analysis to specific academic achievement emotions. They found a student's exposure to classmates' negative emotions in discussions was the best predictor of future dropout.

1.3 Classroom Analytics

Recent advances in sensing and signal processing technologies have made it possible to automatically model aspects of students' classroom experience that could previously only be obtained from self-reports and labor intensive human observations (such as BROMP). Hutt, Krasich, et al. [35] used eye-gaze features to predict mind wandering when high-school students used a biology ITS in their regular classroom. Models using eye-gaze data were incorporated into the tutoring system to provide real-time mind wandering estimates for evaluation and to drive interventions. On a different scale, Ramakrishnan, Ottmar, Locasale-crouch, & Whitehill [59] used classroom audio and video to automatically identify positive and negative classroom climate. Finally, Aslan et al. [3] developed a dashboard to alert teachers to student real-time behavioral (on- or off-task) and emotional (bored, satisfied, confused) engagement (Figure 4). By using the interface, teachers could focus on addressing student comprehension rather than discipline; additionally, students showed less increase in boredom over the semester. These analytics can then be used by teachers or students to improve engagement in the classroom, such as reviewing a topic when confusion is detected or redirecting focus when mind wandering occurs.

1.4 Teacher Analytics

Teachers should not be left out of the loop since their practices influence student affect and engagement. Unfortunately, quantifying teacher instructional practices relies on live observations in classrooms (e.g., Nystrand, Gamoran, Kachur, & Prendergast [51]), which makes the research difficult to scale. To address this, researchers are developing methods for automatic analysis of teacher instructional practices. In a pioneering study, Wang, Miller, & Cortina [71] recorded classroom audio in 1st to 3rd grade math classes and developed automatic methods to predict the level of discussions in these classes. This work was recently expanded to analyze specific discourse features in larger samples of middle-school classes in literature and language-arts. Jensen et al. [40] analyzed self-recorded teacher audio to automatically detect seven discourse features (e.g., asking questions, providing feedback), achieving a modest correlation with human-coded labels and demonstrating a robustness to audio quality changes. The next step in this line of work will be to use information on what teachers are doing to contextualize how students are feeling, which in turn influences what the students think, do, and learn.

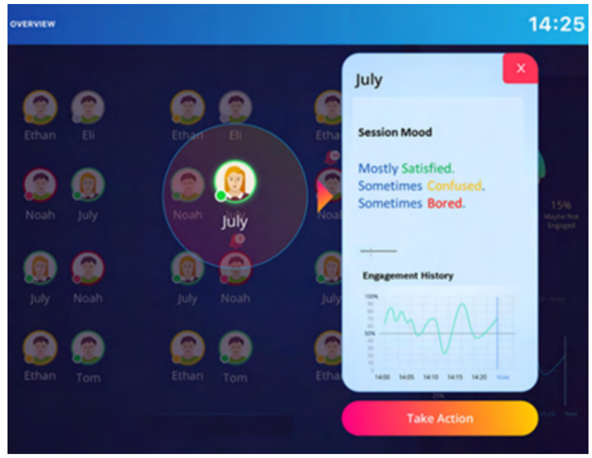

Figure 4: Student view of SEAT interface. Teachers can view overall class and student-specific analytics on engagement.

2 FUTURE THEMES

Let us end by briefly highlighting some potential themes of future research. One promising area of research involves a detailed analysis of the emotional experience of learners and communities of learners across the extended time [35]. A second involves the study of emotion regulation during learning, especially whether LA/EDM methods can be used to identify different regulatory strategies [33], and encourage more beneficial ones (e.g., [5, 58, 68]). A third would jointly consider how emotion arises and shifts alongside attentional states of mindfulness, mind wandering, and flow [14]. A fourth addresses how "non-cognitive" [27] traits like grit, self-control, and diligence modulate learner emotions and regulation (e.g., [30, 47]). A fifth would monitor the occurrence and interaction of emotions of individual learners and the team as a whole during collaborative learning and collaborative problem solving [4, 61] given the importance of collaboration as a critical 21st century skill [53].

Developments in these themes could then be applied to develop interventions that aim to make the learning experience more engaging and effective. This could take the form of redirecting attention, providing tools for emotion regulation, or adjusting instruction to meet student needs (i.e., scaffolding). An important challenge is developing "fail-soft" interventions; that is, if the analysis of a student's current affective state is incorrect, then the resulting intervention will not negatively impact them.

Research to date has mainly focused on the achievement, epistemic, and topic emotions. However, an analysis of learning situated within sociocultural contexts must address the social emotions such as pride, shame, guilt, jealousy, and envy.

3 CONCLUSION

Learning is not a cold intellectual activity; it is nuanced with emotion. Emotions are not merely decorative, they influence our thoughts and behavior. However, emotion is a complex phenomenon with multiple components that dynamically unfold. Despite great strides in the fields of affective sciences and affective neuroscience, we need to know more about emotions, and more about emotions during learning. This does not imply we should refrain from modelling emotion until there is more theoretical clarity; we instead need to be mindful of what we are modelling when we say we are modelling emotion. We also need to embrace, rather than dilute, the complexity and ambiguity inherent in emotion. If anything, the discovery-oriented, data-driven, analytic methods of LA and EDM, especially when applied to data gathered in real-world settings, has the unique potential to advance both the science of learning and the science of emotion. It all begins by incorporating emotion into the analysis of learning.

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Chapter 13: Teacher and Student Facing Learning Analytics

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ABSTRACT

Learning analytics systems are increasingly being designed for and implemented in classroom teaching and learning in K-12 and post-secondary contexts. For analytics to play a constructive role, it is important to consider how they are being used by teachers and students and how they can be designed to enhance and complement human decision making. In this chapter, we first discuss issues that teachers and students face in the sensemaking of learning analytics systems as well as in the subsequent phase of acting on the information provided by such systems. We then discuss the following aspects for teacher facing and then student facing analytics: (a) theoretical models underlying analytics use; (b) ways analytic systems have been designed and implemented; (c) evidence of impact the systems have had on teaching and learning. The chapter ends with an overarching discussion of challenges that concern both teacher and student facing analytics and introduces the possibilities for co-design of analytics systems to address some of these challenges.

Keywords: Student facing analytics, teacher facing analytics, learning analytics systems, learning analytics dashboards, learning analytics use, self-regulated learning, sensemaking, learning analytics design, human-centered learning analytics, participatory design of learning analytics

Much of the work of learning analytics designers and researchers revolves around challenges of how to extract, process, and present data in ways that are useful to educational stakeholders. However, system design alone does not ensure successful uptake [26, 24, 32]: "analytics exist as part of a sociotechnical system where human decision making and consequent actions are as much a part of any successful analytics solution as the technical components" [84, p. 4]. Thus, learning analytics designers and researchers need to attend to the human activity of working with these tools in their various contexts of use. In this chapter, we specifically address the use of learning analytics systems by teachers[1] and students. We first discuss issues in making sense of and acting on information provided by learning analytics systems. We then detail, first for teachers and then for students: (a) theoretical models underlying analytics use, (b) ways systems have been designed and implemented, and (c) evidence of the impact these systems have had on teaching and learning. We conclude with a focus on obstacles and opportunities to the development of effective and adoptable tools.

[1] Throughout this chapter we use the term teacher generally to refer to those holding instructional roles in both K-12 and post-secondary education.

1 IMPORTANT CONSIDERATIONS FOR LEARNING ANALYTICS USE

Using learning analytics effectively involves making sense of the information presented *and* taking action based on it [77, 15]. While analytics are often developed for use across a range of situations, the answer to questions of meaning and action are inherently local. In the case of teachers and students, the design of learning analytics systems needs to be sensitive to the anticipated contexts of use (e.g. daily classroom routines) and potential unintended consequences of use (e.g. taking student metrics as a proxy for teacher competence). Wise and colleagues [96, 95, 93] have pointed to several well-documented issues in using analytics to inform educational decision-making that relate to processes of interpretation and taking action. These considerations must be taken into account by those designing learning analytics systems and those implementing them for use of the systems to be effective.

With respect to interpretation, analytics are abstracted representations of past activity, yet intended to inform concrete future activity. This makes it critical for users to have an understanding of the context, purposes and processes of the learning activity in which the analytics were generated and a means by which to connect this information to possible future action [50, 27]. Most people are aware of the fact that actions in digital spaces leave trace data. The conceptual leap is understanding how the high level representations of learning activity shown in analytic systems are produced from these data. In addition, there is the question of what reference point the data should be compared to (e.g. a pre-determined standard or relative values for peers, [95]). Even when information is understood, it may not be believed as accurate, relevant or useful [42, 96], thus questions of trust and validity present additional consideration for the interpretation of analytics [15, 52]. Another limitation is that analytic systems tend to provide the same kinds of metrics over time; however, different information may be more or less relevant to different parts of the learning process [92]. Finally, students and teachers each have their own goals for learning; thus designers cannot rely on a one-size fits all solution to be relevant for everyone [82]. Students and teachers need to prioritize the relative value they assign to the available analytic feedback.

With respect to taking action, there are two core issues. First, analytics provide a retrospective lens to evaluate past activity, but do not always indicate how to make changes to the situation in the future. For example, a social network diagram can show that a certain student is not receiving replies from their classmate without providing information about what would encourage greater responsiveness. Second, even when desirable action is identified, most change does not occur instantaneously — incremental improvement and intermediate stages of progress are often required. For example in Wise, Zhao and Hausknecht [97] students took multiple cycles of goal-setting and feedback to change their learning behaviors. Action may also be deferred when teachers (or students) are not certain of their interpretation and want to wait for more data to become available [94]. These issues have consequences for analytics design and implementation. To support teachers and students, designers cannot assume that providing data alone is enough. Support is needed to translate information on past activity into future action (and track progress towards this goal) either as part of the analytics system or the surrounding practices with which it is implemented. It also means that when studying use of analytics systems, researchers may need to take a longitudinal approach to reveal changes that happen incrementally over time rather than directly after dashboard use. It is also important to consider the larger culture of trust and transparency around analytics amidst concerns of surveillance. Teachers may fear that their data can be used by administrators to assess performance or compliance with mandated standards [35, 35]. Students are often unaware of how they are being monitored, why, and who can view this data [79]. If data processing prior to analytic presentation is "blackboxed," teachers and students may perceive that the collection of these data is primarily designed for the benefit of the institution and be less likely to trust and use the information provided [78].

2 TEACHER-FACING LEARNING ANALYTICS

Teachers are a natural audience for learning analytics as they are already engaged in examining student learning to inform their practice. While such teacher-inquiry traditionally depended on qualitative methods (e.g. student observations, examination of learning artifacts; [16]), there is increasing interest in the use of quantitative data to inform the process [89]. Analytics can also be a powerful tool to help teachers with other dimensions of their practice, for example identifying and meeting diverse student needs [22]. While the discussion below focuses on cognitive and pedagogical models of use, research suggests that affect also plays a role as teachers may feel encouraged, disheartened or even upset about what the information tells them [94].

2.1 Theoretical Models of Teachers' Learning Analytics Use

One way analytics can support teachers is to inform *learning design*. Learning designs document teachers' pedagogical intentions, providing a conceptual frame for asking questions about learning activities and supporting sense-making of the information provided by the analytics [18]. Data can help teachers understand the effects of a specific instructional approach on student activity and learning [20], which in turn provides feedback to improve the design [65, 60]. Lockyer and colleagues [50] provide a specific model for aligning learning analytics use with learning design that describes how teachers can map the learning processes intended by their design, pre-identify patterns indicating (un)successful student engagement in the processes, and use analytics to track student progression towards the desired state (an absolute reference frame for interpreting the data; [94]). Setting incremental stages to target along the way or using prior activity to judge progress are other comparison strategies that can be employed. In addition to point-in-time judgements, temporal analytics can also be used for dynamic evaluation of learning progress [59].

Another way analytics can support teachers is by providing feedback on activities inside the classroom as they occur [85]. Here the analytics are used in (relatively) real-time as a tool to monitor activity, support the diagnosis of situations needing attention, and prompt teachers to offer support according to the students' needs. These analytics support *classroom orchestration* [69] in which teachers use data as continuous formative assessment to adapt learning at the classroom, small group, or individual level [41]. Several authors have provided descriptive models of how teachers make sense of the information provided and select a pedagogical response [54, 58, 85, 94]. In the first stage, analytics aggregate information for manageable presentation through visualizations comparing students' current activity to prior activity or absolute standards [85, 94]. To arrive at an interpretation of students' activities, teachers triangulate and contextualize the data with other information they have, noticing differences across individuals or groups, to answer goal-oriented, problem-oriented or instructional modification questions [49] . In the second stage, teachers use the information to inform pedagogical responses, which could be scaffolds targeted at the whole class, subgroups of students, or individual students. There is great potential for analytics to support teachers' classroom orchestration by enhancing their insight into the classroom situation, their confidence in this insight, and thus inclination to act [46]. In this way analytics enable teachers to make informed decisions that are aimed at students' needs in-the-moment [58, 85].

2.2 Teaching-Facing Learning Analytics Systems

The most prominent form of learning analytics for teachers thus far are dashboards: visual displays that provide information about students' activities and progress on the task at hand (for recent overviews, see [75, 47]). An important distinction in teacher-facing analytics is the amount of interpretational aid they provide [48]. Some early teacher dashboards left all interpretation to the teacher. For example, Schwarz and Asterhan [73] showed teachers information about students' argumentation in a collaborative learning setting, but did not prescribe when to intervene or what situations might need attention. Similarly, [58] reported on a dashboard that displayed information about individual student performance on mathematics exercises; teachers were free to decide how to interpret and use them for follow up interventions. Other teacher dashboards have gone a step further to provide alerts about the occurrence of problems that specific students or groups might be facing (e.g. [13, 30], or even alerts plus advice regarding what kind of problem students might be facing in a particular situation [86]). Most existing dashboards have focused on supporting teacher sense-making; however many teachers also experience difficulty in determining what action to take in response [75, 86]. While few dashboards have yet to explicitly target the action-taking phase of analytics use, there are some notable exceptions. For example, Olsen, Rummel, & Aleven [63] developed a system which advised the teacher on which students to pair up and when to switch to a different activity. In an earlier example, the Assistant program offered advice to teachers on what feedback to provide to students [14].

Teacher dashboards are a form of *extracted analytics*: data traces of students' learning activity are provided in an interface separate from the learning environment that generated them. An alternative is *embedded analytics*, when the data traces of learning activity are shown directly in the learning environment that generated them [92]. For example, Alavi and Dillenbourg [3] created ambient displays in the form of small lamps placed in the classroom that provided information on whether students had a question for the teacher and how long they had been waiting. In more recent work, Holstein, McLaren, and Aleven [34] developed augmented reality systems that displayed information visible through the teachers' enhanced glasses showing whether students were off-task or stuck on a problem.

Learning analytics can also play a role in supporting teachers by providing information not only about students but also about their own actions. Here the analytics take on a role of stimulating self-reflection, albeit with the same goal of optimizing student learning. For example, Anh et al [2] used small lamps on the tables of collaborating students to display how long the teacher had visited each group, thus providing information to the teachers about their circulation around the classroom. The lamps provided neutral information without enforcing or encouraging teachers to divide their attention equally - that decision remained with the teacher. Despite their potential, systems that advise on specific teacher behaviors are rare and hard to design since the impact of teachers' actions can be very context-specific.

2.3 Use and Impact of Teacher-Facing Learning Analytics Systems

The impact of teacher-facing learning analytics has largely been studied in terms of effects on teaching: teachers' perceptions of usability, their awareness of student activities, and the actions they may take as a result [86]. This is a complex process [93, 86] requiring specific competencies such as data literacy and the ability to integrate knowledge from the analytics with existing teaching knowledge [54]. Multiple studies have found that analytics increase the specificity of teacher diagnoses in their classroom [75, 47]. However, for teacher-facing learning analytics to have an impact on students, teachers need to act on these diagnoses by selecting appropriate response actions. A small number of studies have examined the subsequent actions teachers select based on their interpretation of the analytics. Molenaar and Knoop-van Campen [58] showed that when activating pedagogical knowledge in the sense-making stage, teachers use more diverse types of feedback in the response-stage. Wise and Jung [93] also showed diversity in teachers' responses to learning analytics, including a non-action response of adopting a "wait-and-see" posture. Xhakaj, Aleven, and McLaren [98] found that analytics use influenced teachers' subsequent lesson plannings (e.g. what topics to cover in a class session). Knoop-van Campen, Wise & Molenaar [43] found dashboard consultation led to relatively greater amounts of process feedback and that the difference was especially large for low-ability students.

Going beyond teacher actions, very few studies have yet to follow the prolonged causal chain to examine effects on student activities or learning. In one notable exception, Martinez-Maldonado, Clayphan, Yacef, and Kay [55] report a comparison of impact of two dashboards, one providing information only and one providing information plus alerts. Teacher interventions informed by the system with alerts resulted in an improvement in student learning, those informed by the system with information only did not. This study points to the importance of working towards studies that document the ultimate goal to impact students' learning.

3 STUDENT-FACING LEARNING ANALYTICS

Students are an important audience for analytics use, as their learning is the ultimate goal of educational systems and much of the data collected in learning analytics systems is generated by or about them. There is a presumption that students will benefit from exposure to their own learning data and many argue that students have the right (and responsibility) to review their own data [64]. As such, an increasing number of analytics systems are being designed to provide information about learning directly to students. These both follow and diverge from a long history of educational technologies used to provide feedback to students (e.g., cognitive tutors, [45]; homework practice and assessment tools such as Assistments, [57]; open educational resources such as Kahn Academy, [38]).

Learning analytics dashboards differ from prior feedback systems in a number of ways. First, other systems typically provide feedback about correctness of answers, whereas dashboards often combine performance feedback with information on students' learning processes (e.g., planning, tracking progress). Second, while other systems tend to provide relatively simple static feedback, dashboards offer visual displays which are often complex and/or interactive, allowing students to filter or select specific information. In addition, prior feedback systems typically provided information to students *after* they had finished a problem, activity or assignment, whereas dashboard information can be available on-demand, so students have flexibility and control of when they consult this information. Third, while many feedback systems benchmark using normative standards, in dashboards student performance is often also visualized in relation to that of local peers. Sometimes, students are also provided with information specifically in the context of "students like them" [40]. Finally, in cognitive tutors and similar systems, the computer is in control, whereas dashboards offer information to students, who decide on any possible follow-up actions. These dashboards are quickly becoming a standard feature in applications aimed at personalizing learning, such as Learning Management Systems, as well as in newer applications for personalizing learning like gameful approaches to pedagogy (e.g. Gradecraft [1]) and as part of tailored messaging systems (e.g. eCoach; [36]).

3.1 Theoretical Models of Students' Learning Analytics Use

Student-facing learning analytics aim to support students in conscious attention to and improvement of their own learning processes [93]. Feedback is provided in the context of dynamic cognitive processing whereby students select, adapt and generate tactics and strategies for learning and monitoring their learning [12]. Affective considerations come into play as well as how students use analytics depends not only on what the information helps them know, but also how it makes them feel [92, 42]. Although there have been calls for student facing learning analytics to be theoretically grounded with respect to pedagogy and learning (e.g. [74, 6, 7, 37]), most system designs are still driven primarily by available data. When theory does drive system design, models of Self-Regulated Learning (SRL) are commonly employed [56].

Zimmerman [100, p. 4] described self-regulated learning as students that are "metacognitively, motivationally, and behaviorally active participants in their own learning". This includes planning, monitoring, and evaluation of one's own learning, and using these strategies to achieve academic goals. As a positive relationship exists between self-regulation and learning performance [10, 90], SRL is seen as a promising way for learning analytics to support students by making these processes more explicit and allowing students to see and assess their own learning. Drawing on SRL theory, Wise [97] proposed a specific model of student learning analytics use involving goal-setting, action and reflection. These engendered four principles for pedagogical practice to support students' analytics use, with initial empirical validation in Wise et al. [96]: Integration, Agency, Reference Frame, and Dialogue. Later work by Klein et al. [42] validated the central importance of Agency in shaping students' relationships to analytics and offered four additional factors to consider in their sense-making: Accuracy, Relevancy, Trust and Relationships.

While SRL has been the dominant theoretical paradigm thus far, several other theoretical frameworks could also contribute to the system design for student-facing analytics. Expectancy Value Theory (EVT; e.g., [25]) posits students are motivated based on their expectancy of success, value, and cost of their options to accomplish learning goals. Investigation of dashboard use under EVT could reveal in which contexts students consider dashboards to have lower utility, and thus lower value, such as students taking a course to fulfill a requirement versus those who want to perform well (e.g [42]). Self-Determination Theory (SDT: e.g. [68]) posits that motivation is primarily based on the satisfaction of three needs: autonomy, relatedness, and competence. Based on SDT, dashboard design and evaluation could be oriented toward how effectively they contribute to students' need satisfaction. For example, students' motivation to engage with a dashboard may depend on their belief that it provides (a) a sense of control over their ability to accomplish course goals, (b) a greater sense of belonging within the course or discipline, and/or (c) information that increases their competence in meeting course requirements. Students who experience a higher level of control in the learning process are more likely to be intrinsically motivated and improve their performance [19] and dashboards may be an excellent avenue to provide students with a greater sense of agency and autonomy.

3.2 Student-Facing Learning Analytics Systems

Fritz [28] conducted one of the first wide-scale deployments of a dashboard specifically aimed at students, called Check My Activity (CMA), that allowed university students to compare their LMS activity and grades against their classmates. Student focus on grade views has been observed repeatedly, including Young's [99] analysis of students using a commercial LMS (Blackboard). Following Blackboard's design, Corrin and de Barba [17] created a dashboard with data on students' formative and summative assessment scores and their LMS engagement. Students were able to articulate and interpret feedback presented through a dashboard, but there was little evidence of students' ability to understand the connection between feedback and their current learning strategies. Wise and colleagues [92] implemented an analytics-enhanced discussion forum called Starburst that incorporated goal-setting and reflective prompts to encourage analytics use as part of an SRL cycle. Students' use of the analytics showed that comparison with peers played an influential — though not always positive —role on changes in behaviour, and students' mistrust in how some analytics were computed may have dampened use [96]. Khan and Pardo [39] implemented Data2U, a system providing students with feedback about their interactions with the online resources. They characterized different types of student dashboard use, providing insight into when different students utilize the dashboard (i.e. beginning, middle or end of a study session). However, there was no statistically significant relationship between students' use of the dashboard and their academic performance. Taking a participatory approach to analytics with a critical lens, Knox [44] developed the Learning Analytics Report Card (LARC) to give students choices about what data to include and exclude in the reports it generated. Most recently, Kia et al. [40] implemented a student dashboard into their campus' LMS, and found that students' SRL behaviors and academic achievement influenced how students used the dashboards.

3.3 Use and Impact of Student-Facing Learning Analytics Systems

There has been limited research exploring how students interpret and act on learning analytics and the resulting effects on their motivation, behavior, knowledge and skills [6, 74, 87]. This problem is not unique to learning analytics, however. Regarding the broad research on the effectiveness of feedback, Winstone [91, p. 227] points out "there are very few examples where researchers explore the use of feedback on a behavioral level, and even fewer examples where researchers collect data to follow up and see how students' engagement influences them later in time". With the notable exception of collaborative learning analytics (particularly group awareness tools, e.g. [5]), existing research on student-facing learning analytics systems has concentrated more on dashboard usability and usefulness, rather than an understanding how they support educational practices in the wild [29].

When *how* students use analytics is studied in authentic educational settings, their interactions with technology (e.g., counting views, files accessed, time on task) are usually the main marker of impact. For example, Wise [92] found the most common change that students made after the introduction of the analytics-enhanced Starburst tool was to increase the percentage of their peers' posts that they read. This is a behavior thought to contribute to learning theoretically (through increasing the diversity of ideas to which a student is exposed), but direct evidence of learning outcomes gains was not available. Further, only a few recent studies have investigated differences in how students use dashboard information [4, 33, 40], such as the particular tactics and strategies they take to work with the information [29], that may have important effects on subsequent outcomes. From these studies it is clear that the use and impact of student-facing analytics is a crucial topic for future research to understand how, when, and to which students we should provide these systems. In the preceding sections we described teacher- and student-facing learning analytics systems independently. However, there are important issues that bridge across these categories.

A central question for teacher- and student-facing learning analytics is what kinds of information is most useful to distribute across which parts of the overall system at different points in time. What support should analytics offer to students directly, which information is best passed to the teacher first, and which decisions can effectively be made by the analytics system autonomously? One example is suggested by Rummel, Walker, and Aleven [70] as they describe an "utopian" vision of adaptive support for collaborative learning in which the analytic system nudges a student directly to engage more with her partner during a learning task, supports her review and reflection on her engagement once the task is complete, and provides information and suggestions to the teacher for assigning her a subsequent collaborative partner and task. They also consider what analytic systems can learn from teachers and students to help them provide more useful information and/or guidance. This represents a move towards considering hybrid teacher-analytic and student-analytic systems as part of the classroom ecology.

In addition, the triangular interplay between teachers, students and analytic tools is a growing area of focus and research. Two particular issues to consider are symmetry (to what extent do students and teachers have access to the same kinds of information) and transparency (to what extent do students know what teachers can see). In situations where teachers and students are able to work with data jointly to improve learning processes, analytics can be seen to act as a third "voice" in the conversation between teacher and student [92]. For example, in two recent studies of teacher-facing dashboards at the university level, teachers expressed the desire to have a deidentified view of the analytics so they could show their students evidence about why they were concerned about their performance in the class [48, 94]. Analytics can also act as a mediational object for interactions between teachers and students as seen in Tan, Koh, Jonathan, and Tay [81] who documented a 9th grade school teacher sharing visualizations of her students' online discussion comment types and interaction network with them as an object to support collective reflection about the quality of their collaboration. Similarly, Lonn, Aguilar, and Teasley [51] described how when a dashboard designed specifically for academic advisors was shared in an advising session, it became a tool for advisors and students to talk about the student's academic progress. With the introduction of this third voice, a recalibration of student and teacher classroom roles is needed.

For students, analytics offer the opportunity to be explicitly prompted and supported to monitor and reflect on their learning, allowing them to develop metacognitive skills and take responsibility for their own learning. Research has shown that some students arrive in the classroom better equipped to make use of analytic information than others [53]; thus there is often a need to develop data literacy and self-regulation skills in tandem with analytics use. However, there is also a risk that providing too much information, automation or guidance (whether from the learning analytics systems or by the teacher) may create dependency, robbing students of the opportunity to display agency in their own learning. Educators worry about the rise of "helicopter analytics" where institutional tools and processes assume a decision-making role for students that many parents have been criticized for playing [35]. On the whole, a balance is needed to provide guidance that both helps students make better-informed choices in the short-term [62] and increases their ability to be independent learners over the long-term [9].

For teachers, analytics can provide essential insights to enhance their practice through optimizing learning design or improving on-the-spot decision making. Analytics should be designed to process information from many students at the same time and solve lower-level issues such as selecting appropriate follow-up tasks for a student. Doing so frees up valuable time that the teacher can spend on addressing higher-level support needs such as providing elaborate explanations or modelling effective collaborative behavior [72, 80]. Designing analytics to empower teachers will also mitigate concerns that the technology will undermine their role and responsibility in the classroom and cause them to feel forced to defend their own worth [86]. Goos [31] describes how teachers' professional identity includes their mode of working with technology (e.g. analytics) where it may be conceptualized as a partner, servant or enemy. Several authors have therefore argued for promoting teacher use of analytics as a *collaborative relationship*, leveraging the strengths of both teachers and technology [72].

4 CO-DESIGN OF LEARNING ANALYTICS AS A WAY FORWARD

One powerful route to addressing these challenges is to involve students and teachers in the design of learning analytics systems. Processes of co-design (or participatory design) address concerns that technologies might not meet the actual needs, context, and practices of the intended end-users [61, 8]. The shift can be described as a move from "designing *for*" to "designing *with*" [21] that generally involves multiple iterative cycles of ideation, development and testing. Adoption of co-design practices to develop learning analytics tools [87] is part of a recent shift towards human-centered learning analytics [76]. Co-design of learning analytics can involve users in decisions about the content of the analytics (what information is provided) and/or the visualization of the analytics (how the information is provided). When co-design is employed, it has most often involved teachers (e.g. [2, 23, 34, 55, 83, 84, 88]). Recent efforts have started to engage students in the process of analytics design as well (e.g. [67, 66, 71]).

The potential benefits of co-design are substantial: by giving teachers and students a role in the creation of learning analytics we are not only better able to design tools that fit their contexts and needs, but also allow them to surface their hopes and fears related to the use of analytics. There is a long tradition of work in HCI that can inform our processes of co-design (e.g. [21]); however there are also challenges specific to learning analytics, particularly varying levels of data literacy and asymmetric power dynamics. These issues may also intensify existing tensions in co-design for learning between what users want and what others want for them. Techniques from established co-design methodologies are being adapted for learning analytics to address such challenges [34, 66, 71]. A basic tenet of learning analytics is to provide information that is actionable by its users. Adopting co-design practices along with established learning theory makes it more likely that designers can discover what teachers and students need to do, and to provide them with information that helps them accomplish those goals. This is an important area for further development in support of adoptable, actionable and impactful teacher and student facing learning analytics.

In conclusion, for mainstream adoption of teacher and student facing learning analytics to become a reality [11], it is critical to establish a level of transparency and trust between developers and users of analytics. In addition, to be efficacious, analytics must be designed to fit with real world educational contexts and be validated through testing of use and impact in them. By engaging in practice-informed design and careful consideration of users' concerns as part of our research, we move towards the creation of learning analytics systems that truly impact teaching and learning.

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Chapter 14: Professional Learning Analytics

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ABSTRACT

Professional learning is an important component of productivity in contemporary work environments characterised by continual change. Learning for work takes various forms, from formal training to informal learning through work activities. In many work settings professionals collaborate via networked environments leaving various forms of digital traces and 'clickstream' data. These data can be exploited through learning analytics to make both formal and informal learning processes traceable and visible to support professionals with their learning. This chapter examines the state-of-the-art in professional learning analytics by considering the different ways professionals learn. As learning analytics techniques advance, the modelling techniques that underpin these methods become increasingly complex and the assumptions that underpin the analytics become ever-more embedded within the system. This chapter questions these assumptions and calls for a new, refreshed vision of professional learning analytics for the future which is based on how professionals learn. There is a need to broaden our thinking about the purpose of learning analytics build systems that effectively to address affective and motivational learning issues as well as technical and practical expertise; intelligently align individual learning activities with organisational learning goals and to be wary of attempts to embed professional expertise in code written by software developers, rather than by the professionals themselves. There are also ethical concerns about the degree of surveillance on learners as they work and learn with anxieties about whether people understand the (potentially serious) consequences [19]. Finally, learning analytics generally are developed for formal learning contexts, in schools, colleges and universities, missing opportunities to provide the support professionals need as they learn through everyday work.

Keywords: Professional learning, work, training

Contemporary work is characterised by the accelerated integration of technology within the professions [38, Chapter 1]. This change often is symbolised as 'jobs being replaced by technology systems', with reports suggesting millions of jobs will be lost over the next decade. For example, a BBC report [51] estimates that up to 20 million factory jobs could be lost by 2030 as tasks are automated.

1 THE INTEGRATION OF TECHNOLOGY WITH WORK

There is evidence that some jobs already are already disappearing. Telesales and service staff are being replaced by 'chatbots', computer-based communication systems designed to interact with humans via the internet [60]. Hotel reception staff are being superseded by automated check-in systems [46]. Paralegal tasks are being carried out by document checking systems that search for and recommend documents specific to each legal case and similar systems are gathering together news items around specific topics, replacing some journalist positions [6]. However, some of the most profound changes in employment are not where humans are replaced by machines, but where digital systems are automating routine tasks, rather than replacing humans.

Computational systems tend to be good at specific tasks that are difficult for humans, such as identifying patterns in large datasets and completing computational analysis extremely quickly. For over a decade, cancers have been spotted using computational systems that compare large datasets and identify patterns that lead to diagnosis [59]. Automating routine work means that Oncologists have more time to focus on more complex tasks, leaving doctors to focus on recommending treatment plans. The finance sector has been reshaped by 'Fintech' systems that identify trading patterns and carry out transactions in micro seconds, much faster than any human [18]. This semi-automation of trading frees Traders to consider and research future investment areas. Thus, the integration of technology with work continually changes what professionals do, dynamically changing work practice and creating a need for professionals continually to learn new ways of working [38, Chapter 1].

For some years now employers have been aware that the digitisation of work offers opportunities to capitalise on the data generated as a by-product of learning in digital systems. Data mining and analytics techniques can be used to support and enhance work and learning. Learning analytics systems were first developed for use in university education to provide learners, teachers and managers with information [53]. Many of these early learning analytics systems were based on predictive models that analyse individual learner profiles to forecast whether a learner is 'at risk of dropping out' [66]. These data usually are presented to learners or teachers using a variety of dashboards to inform students of their likely progress, with recommendations for remedial action; teachers were given information about likely learner outcomes; university managers were provided data to plan for future income, costs and impact [45, 53].

These systems are also being applied to Professional Learning, particularly when professionals sign up for formal qualifications at universities or through online learning organisations. There have been fewer attempts to situate professional learning analytics within workplaces, whether inside organisations or in virtual spaces where sole workers gather together, such as crowd-work platforms. Some of the systems that have been developed have been based around organisational administration and competency mapping. For example, some organisations use systems that map data about current and future job roles with data on the current competencies of employees to help companies train and recruit people with the skill-sets needed [8]. However, these systems are based on a competency supply chain model, rather than supporting professionals as they work and learn.

Applying data analytics techniques to complex learning contexts is complicated; it is difficult to know what data to gather, analyse and what conclusions can be drawn from learning analytics [19]. This chapter examines the evolution of professional learning analytics. The chapter begins by tracing the progression of learning analytics systems, followed by an analysis of different forms of professional learning. The chapter then maps learning analytics systems and techniques within a typology of professional learning, considering whether and how different analytics techniques that support the various ways professionals learn. The chapter concludes by putting forward a vision for professional learning analytics, drawing attention to areas that require attention from all those involved in the future development of learning analytics.

2 LEARNING ANALYTICS

Learning analytics is a methodological research area aimed at "the measurement, collection, analysis and reporting of data about learners and their contexts, for the purposes of understanding and optimising learning and the environments in which it occurs" [58, 55]. Learning analytics aims to be multi-disciplinary, using ideas from learning science, computer science, information science, educational data mining, knowledge management and, more recently, Artificial Intelligence [22, 40]. Learning analytics uses computational systems to leverage the massive amounts of data generated as a by-product of digital learning and work activity to support learners in achieving their goals [3, 4]. Examples include systems that track learner progress and predict outcomes, recommending remedial action; facial recognition or skin conductivity systems that gather data that are used to interpret learners' emotions and how these relate to learning; location indicators that track the position of a learner and infer moments of interaction with others (see [68]).

AI scientists have been building on approaches in machine learning, computer modelling and statistics used in the business sector to support education [40]. Some Learning platforms use Artificial Intelligence (AI), a range of analytic methods used to harvest, structure and analyse computationally large data sets to reveal patterns, trends, and associations [45]. One branch of AI is based on 'machine learning' where large amounts of data are gathered and fed into an 'engine', which uses statistical algorithms to identify patterns and to make decisions based on the trends identified. The system is considered 'intelligent' because, as data is fed into the engine, it 'learns' to make more informed decisions about individual cases.

AI techniques are based on the use of 'Big Data' which are "information assets characterized by such a high volume, velocity and variety of data to require specific technology and analytical methods for its transformation into value" [41, p. 103]. The volume of data available is increasing as people work using digital systems. As they work, people leave various forms of digital traces and large amounts of data, generally known as 'Big Data' [39]. Analysis of these data potentially provides a means of improving operational effectiveness by enhancing and supporting the various ways professionals work, learn and adapt. The velocity with which these data are generated is escalating rapidly as more data becomes available via different computational systems people use for work. These systems draw upon and use a diverse variety of data. Data sets gathered and used for analysis involve multiple data types including behavioural data (how often a learner accesses a site), discourse data (what learners say or type), learner disposition data (key characteristics associated with each learner, such as how they prefer to learn) and biometrics data (including [58]).

Techniques used in learning analytics include discourse analysis, where learners discussions and actions provide opportunity for helpful interventions [22]; semantic analysis, tracing the relationship between learners and learning [67], learner disposition analytics, identifying affective characteristics associated with learning [55] and content analytics, including recommender systems that filter and deliver content based on tags and ratings supplied by learners. These techniques are useful in encapsulating the complex factors that influence how professionals learn.

The application of LA and AI to support professional learning largely has been focused on conventional approaches to online education, where students access learning materials and submit assessment or assignment materials to demonstrate they have achieved a set of pre-defined competencies. Examples of learning analytics include combining learner profiles with online behavioural data (the number of times a student accesses a Virtual Learning Environment) to predict the likelihood of a student dropping out of a course or being admitted to a program, to offer timely support or to provide feedback and guidance [31, 68].

These examples of learning analytics are designed to support formal education, where learning is structured and the outcomes of learning are pre-defined. However, there is ample evidence that professional learning takes different forms in different contexts and often achieved through engaging in everyday work tasks, rather than through formal, accredited learning [17].

3 PROFESSIONAL LEARNING

Keeping skills and knowledge up-to-date is crucial for all professionals, whether experienced workers or novices, and is also important for organisations to remain competitive. This means that professional learning tends to be driven by the demands of work tasks and is interwoven with work processes [16]. Professional learning is much broader than formal education, since formal learning alone does not provide all the knowledge needed for work [62]. Professional learning includes "the activities people engage in to stimulate their thinking and professional knowledge, to improve work performance and to ensure that practice is informed and up-to-date" [38].

However, when professionals are asked about how they learn, they tend to think of formal training, where learning is focused on assessment, learner outcomes and explicit pedagogical models [17]. Examples include workshop training, professional courses (such as certificated programs or postgraduate degrees) which are intentionally structured and some are assessed around pre-defines outcomes. Intentional learning may be pre-planned and structured as formal learning for example degree programs, classroom training, practical workshops, coaching or mentoring [62]. Other forms of intentional learning tend to be less well defined and structured, such as coaching, mentoring or questioning a more expert colleague. Although these types of learning are intentional, they are loosely structured and more difficult for professionals to recognize as 'learning'.

There is evidence that professionals do much of their learning through engaging in everyday work tasks, which is termed 'non-formal learning' [14, 17, 20]. Learning through work tends not to be planned, assessed or accredited. This makes it difficult for professionals to recognise it as a form of learning, without being prompted to reflect on particular types of experience or specific changes in their capabilities [17]. For example, professionals may learn new ways of working when they move to a new location or team [37]. People may be unaware of they are learning, because their practice evolves over time [37]. Nevertheless, learning through work is a critical component of ongoing improvement and innovation and the adoption of new practices in the workplace [37]. These different forms of professional learning are illustrated in Figure 1:

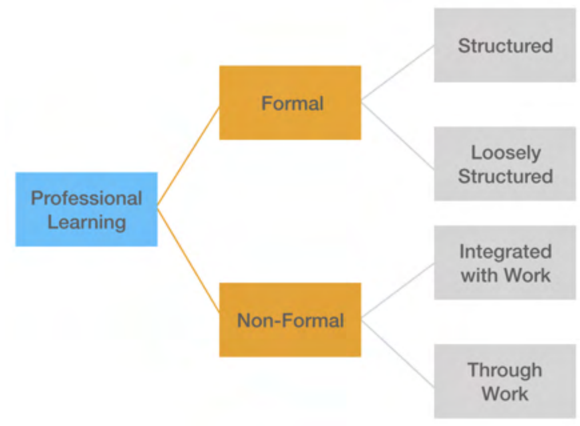

Figure 1: Typology of professional learning, informed by [16, 14]

These different forms of learning facilitate development of diverse types of knowledge [63, 37]. Structured education and training tend to focus on learning theoretical and practical knowledge, while more loosely structured coaching and mentoring allow opportunities to learn other types of knowledge, such as socio-cultural and self-regulative knowledge. All these knowledge types are critical for the adoption of new practices for work. Change in practice requires the construction of conceptual and practical knowledge as well as the development of socio-cultural and self-regulative knowledge [15]. Construction of multiple types of knowledge is most readily achieved through a combination of intentional learning opportunities with on-the-job learning [24]. As such, workplace learning operates as a reciprocal process [5] shaped by the affordances of a specific workplace, together with an individual's ability and motivation to engage with what is afforded [5, 20].

There is a tight relationship between the workplace context and learning when people learn at work. There is a growing body of evidence that professional learning is more effective when integrated with work tasks (see for example [10, 62, 20, 14]. However, it is difficult to distinguish unintended, on-the-job learning from everyday work tasks, so it is difficult to recognise when professionals learn through work [2, 13].

Professional learning is influenced by the learner's internal motivation, personal agency and work tasks [37]. These three critical components need to be taken into consideration when designing computational systems to support work and learning. To ensure personal agency, professionals have to be able adapt and self-regulate their learning. To trigger motivation, learning should be integrated with, rather than separate from, work practices. These important factors have not always been taken into consideration when designing analytics systems. The next section explores these gaps by examining how learning analytics techniques and systems have been applied within professional learning contexts.

4 PROFESSIONAL LEARNING ANALYTICS

Professional learning analytics provides an opportunity to make both formal and non-formal learning processes traceable and more explicit in order to support individuals and teams to work and learn [39, 35]. This vision of professional learning analytics is based on a system of mutual support through which each professional both connects with, draw from and contributes back to the collective knowledge [43]. In theory these actions create a common capital via the selective accumulation of shared by-products of individual work activities, initially motivated by personal utility [23, p.15]. These actions would be supported by a set of algorithms, data mining mechanisms and analytics that create a "common capital through re-usable knowledge via the selective accumulation of shared by-products of individual activities motivated, initially, by personal utility" [23, p.15].

4.1 Analytics for Formal learning

Early attempts to apply learning analytics to professional learning contexts involved the transfer of techniques from formal education, such as university education, to professional learning contexts. In formal education, students tend to follow a learning pathway with predefined objectives and regular assessments. This sequenced developmental path is similar to forms of training and formal learning for professionals. Key applications of learning analytics in formal education include learner profiling and prediction of outcomes [68].

One of the most common applications of learning analytics is learner profiling and prediction of outcomes using predictive analytics techniques. One example is 'OU Analyse', a system developed by The Open University, UK to provide early prediction of 'at-risk' students. The system is predicated on the idea that each student follows a linear learning pathway and that every few weeks they engage in a 'Tutor Marked Assessment'. Learners are profiled by gathering demographic data about each student's age, gender, place of residence and prior qualifications. These data are combined with data related to observed activity within the university's Virtual Learning Environment (Moodle). Each individual's data is analysed in relation to data from prior cohorts of students to predict the likelihood of passing the next Tutor Marked Assessment. These predictions are visualised for course tutors as a course overview dashboard where they can view the progress of individual students (see [34]). Progress is illustrated using a 'traffic light' system, to show whether a student is likely to pass their next tutor-marked assessment, based on their previous actions, grades and those of previous students. The system then uses the data to make a decision whether remedial action is needed and recommends to the tutor or student what the learner should do next. Predictive analytics systems are helpful in suggesting remedial action to students at risk of not passing an assessment. However, there are significant concerns for learners in predicting future learning outcomes based on past activity. The system can (inadvertently) create unseen problems for learners and teachers. The system can create 'sound clouds' that normalise specific behaviours of learners and misinterpret others, so learners have to follow 'normal behaviours' to be accepted by the system [37]. By relaying on a computational system, rather than their own professional judgement, to assess learner progress, teachers can become 'deskilled' [19]. Predictive analytics systems require large amounts of data (so-called "Big Data') including personal data about learners. Large-scale collection and analysis of personal data are of concern to human-rights advocates, who have called and continue to call for stronger data protection legislation and implementation (see for example [64, 65, 48]). Yet there are few analyses of the likely impact of AI in education on workers freedoms and fundamental rights.

Pre-defined, structured courses often are not helpful for people who work in highly specialised roles. Early analytics systems to provide personalised *adaptive system* support were based on intelligent tutoring systems that provide immediate, customised content or feedback to learners, usually without intervention from a human teacher or expert. More recent adaptive systems for Professional Learning bring learning and work together by embedding professional learning with work practice so people learn as they work. Many organisations recognise that training is not effective if professionals learn a new process then do not use their new knowledge and embed it within their practice. Recognising the importance of enabling people to learn new expertise at the point of need, organisations have been seeking ways to capture and disseminate expertise. These work-integrated systems include *augmented reality systems* that are used to support professionals to learn about their work environment by providing just-in-time information for professionals as they carry out their work. Augmented reality involves overlaying layers of digitally-generated information on top of the work environment, using location sensors to detect where the worker is located. These layers of information are made visible using Wearable Technology, such as augmented reality spectacles or observing real-world objects via a smartphone screen. For example Wearable Technology headsets can be used to capture data and information as an experienced professional works, and then disseminate this information to less experienced colleagues at the point of need to help them learn. The headset video records how an aerospace technician dismantles a valve in an aircraft engine and carries out a repair. The video has audio commentary and metadata added. When a novice technician carries out the same task, the video information is transmitted via an augmented visual interface, allowing the novice to learn in detail how to triage and repair the valve.

One example of an augmented reality system is *Wearable Experience for Knowledge Intensive Training* (WEKIT), which was designed and built as part of an EU funded project which commenced in 2015 [11]. WEKIT aims to make informal learning processes traceable and recognisable so that novices can develop expertise in an agile way. The system is based on a three-stage process: mapping skill development pathways, capturing and codifying expertise, making the expertise available to novices at the point of need. In the first stage a community of professionals and stakeholders (the WEKIT.club) map out recognised skill development pathways for industry. In the second stage a group of software developers use the pathway templates to develop technology tools to support novices in learning new procedural knowledge - for example how to turn on (or off) a specialist valve. Finally, the expertise is transmitted to the novice via the augmented visual interface. Head-mounted digital displays allow the novice to see the valve overlaid with instructions on how to safely switch it on. Through wearable and visual devices, the system directs each professional's attention to where it is most needed, based on an analysis of user needs.

These three key steps in the transfer of expertise in the WEKIT methodology all have risks associated with them. First, expertise development pathways are difficult to model. Experts are involved in building the pathways and algorithms to support expertise development in an attempt to capture and codify the expertise accurately. However, it is difficult for an expert to understand the optimal learning pathway that will enable each novice's expertise development, since this depends on the novice's prior experience. Second, not all expertise can be codified. Augmented visual interfaces and collaborative digital interfaces can help with some aspects of expertise development. However, professionals draw on explicit and tacit knowledge as they carry out tasks. Tacit expertise, such as the 'gut feeling' that a piece of equipment is operating optimally, takes time to be developed. Thirdly, the novice has to be actively involved in learning new expertise, with the scaffolding being reduced as they become more expert. Otherwise there is a risk they will simply follow instruction, rather than learn. In the future smart systems might not only draw the learner's attention to a specific task, but could record how the novice carries out the task and compare this with how the expert carries out the repair. This would require additional analytics that compares visual recorded data with the expert video data and interacts with the novice, offering dialogue of how to improve his or her work.

While these examples structure professional learning around *competency frameworks*, other professional learning analytics systems provide *personalization through adaptive systems*. These systems are based on the idea of each professional developing a personalised learning pathway, with learning goals aligned with their work tasks. Early examples of personalised professional learning were based on the idea that people with specific job roles or expertise would benefit from bespoke learning pathways that brought them into contact with specific content. When a high degree of specialism is needed, professionals themselves are best placed to decide on their learning needs and the unique combination of expertise they require [32]. One example is the ROLE system (Responsive Open Learning Environments role-project.eu) [28] where individuals define specific concepts and practices they need to learn, then browse and select a set of web-based resources and tools that support their learning. The analytics method uses a recommender system to combine the web-based content resources in different ways to support specific job roles. The web-based resources are sets of learning materials that the professionals sequence and tailor for their own use. The more the system is used, the better it 'learns' specific combinations of content appropriate for specific job roles. These resources can be reproduced and adapted to support other people with similar roles. The system uses demographic data to provides appropriate content that is sequenced and structured in a bespoke way.

Some analytics systems are based on the assumption that people might learn more effectively by using strategies that have been effective for other people in similar roles [39]. One of these systems is LearnB, which has been trialled in the automotive industry [57]. The tool is designed around a self-regulated learning framework which gathers data on factors that have been shown to influence learning at work [56]. These factors include the specific learning and development goals that workers plan and the range of activities they engage in to learn. Learn B collects and analyse these data to identify and connect people with similar learning goals [57, 25]. Common goals are identified and analysed using semantic analysis techniques. These data are fed into social technology systems that recommend topics people might benefit from learning and different learning strategies they might adopt, based on the learning patterns of others. The system uses the organization's Performance Review systems to guide professionals in documenting their learning experiences. The system then makes these experiences available for others who might benefit from learning in a similar way in the future. In theory, by documenting learning experiences, it is possible to analyse and compare experiences and performance and map these against organisational benchmarks. It might be useful, for example, to know that a new skill can be learned in a few hours [56](. On the other hand it may be reassuring for professionals to know that it takes an average of six months experience to become competent in a new procedure (Ibid). The system evaluation provided evidence that professionals benefited from updates about their social context – knowing, for example, what resources other people used and how long they took to learn specific concepts and practices [56]. Supporting self-regulation and other forms of metacognition encourages professionals to take an active approach to their learning. However, in the LearnB trial professionals were operating within a traditional organisational culture with a 'top down' competence system. The problem with this system is that the organization pre-determines the competencies needed for each job role and recommends the ways people demonstrate how they learn these capabilities [9].

These sequenced and (relatively) linear developmental pathways in formal learning are different from the non-formal learning most professionals engage in, which require good self-regulation ability [17, 37].

4.2 Analytics for Informal Learning

There are a growing number of applications of AI and learning analytics systems in non-formal settings. Some of these applications have come from groupwork or projects in higher education, while others have been pioneered in industry settings. These approaches include use of intelligent agents, natural language processing, learning through sensory modality. These sit alongside semantic analytics systems that connect professionals with the people and knowledge they need to learn new tasks.

The development of *intelligent conversational agents* opens up opportunity for dynamic support for professionals as they carry out their work. The initial application of conversational agents in work contexts was to help workers with administrative tasks, such as using computer applications, scheduling meetings or managing to-do lists [21]. A number analytics systems use intelligent conversational agents to stimulate and monitor the effects of professionals practices for individuals and within teams. In some cases, these have been embedded into established forms of practice already used in industry. For example, intelligent agents have been used to stimulate reflective practice, which plays an important role in learning at work [7]. Performance is said to improve through appreciation of the causal mechanisms behind actions and outcomes which increases certainty in the ability to complete a task [69]. This meta-level understanding can be stimulated through reflection, yet, despite its importance, reflection can be overlooked as a purposeful practice. Particularly in stressful work situations when (ironically) reflection is most needed. An EU funded project, 'MIRROR – Reflective learning at work', provided a platform for experimentation to identify whether and how a range of computer applications (Apps) might stimulate and monitor the effect of reflection on work. Apps can encourage reflection on a range of factors, such as mood (are you stressed or worried?), team-work (is the team working well?) or progress (are you working effectively?) [50]. In some cases quantitative data is gathered, for example 'mood' can be traced by asking people to indicate how they feel during work tasks by selecting relevant emoji. Work progress can be monitored through qualitative data gathering using online diaries. These data can be analysed and reflection stimulated through group-work with human agents (for example colleagues or mentors) or with intelligent agents (for example chatbots).

Mirror [49] is an analytics-based system that supports professionals in learning from their own and others experiences. Reflection is a significant component of self-regulated learning which may improve learning and performance through motivational and affective factors [37]. The Mirror system is based on a set of applications ('Mirror' apps) designed to facilitate informal learning during work [33]. These apps were used in Health settings to support analysis of individual and team actions. These reflections allowed both individuals and teams to learn which practices had the most impact within their organisation. For example, the 'Talk Reflection App', was developed to support physicians treating patients suffering from acute strokes and other neurological emergencies in learning how to interact better with patients and their relatives [47]. The App tool prompts individual doctors to reflect on specific work situations by answering questions, such as how they felt. Each individual can share answers with colleagues (human agents), who document their own experiences, and can learn through reading the responses of others or talking with them. Evaluation studies of the MIRROR Apps found a clear link between individual and team learning and organisational learning (linked to Human Resource procedures, rewards and promotions) [29]. However, for computational systems to be effective in changing work practice, the technology tools have to be adopted into everyday work to effect change. This can only be achieved if end users (workers) are involved in the design and implementation of a system from the outset. Some systems use multi-modal conversational agents that use chat and voice modalities to support reflection. For example, Roberta is a system that supports individual and team reflection as teams work together via an online teamwork platform, Slack [30]. The conversational agent, Roberta, prompts individuals or teams to log and reflect on their daily progress and outcomes. This triggers reflection, prompting workers to identify at a meta-level what actions they might take to improve how they work. When chat (text based interaction) and voice modes were trialled, chat was considered easier to review, but slightly less personal compared with voice [30]. These Apps are being used by individual workers to reflect on and improve their practice. Evaluation studies provide evidence that these Apps work well only when professionals appreciate the value of reflection and adopt this into their everyday work practice [30].

Attempts to embed computational systems within everyday work practice have focused on replicating existing practices online. For example, Sankaranarayanan et al. [52] developed a computational system to simulate 'Mob Programming' practices in an online environment. Mob Programming is an approach used in software development where a team simultaneously work on the same output, at the same time, in the same environment. The benefits of this approach range from facilitated knowledge sharing and learning to the use of distributed knowledge [27]. During Mob Programming team members swap roles to facilitate learning, disseminate knowledge and to make sure no single person dominates the output. In the computational system, a human team facilitator is substituted for an Intelligent Conversational Agent. The Agent gathers data from an online chat system and monitors code edits and highlights examples that participants can emulate. The Agent also analyses these data and indicates when people should swap roles to keep the activity progressing. Data analysis can identify whether work is carried out evenly across the team and can monitor whether the chat is related to project activity. From this analysis, the Agent can draw conclusions about different factors such as team dynamics and learning potential. The Agent can reassign the tasks and monitor the effects. This type of system potentially provides a powerful way to embed professional learning within day-to-day work tasks.

However, there are ethical questions around the continual monitoring of professionals.

By exploiting organisational and professional networks, professionals can, in theory, achieve agile learning in ways that support immediate work problems [9]. This type of self governing, bottom-up approach to professional learning requires an understanding of how and where professionals interact and exchange ideas about their work. Analytics techniques have been used in attempts to visualise informal organisational and professional networks. de Laat and Schreurs [35] developed and piloted Network Awareness Tool (NAT) - a tool that uses Social Network Analysis techniques - within a school to identify online teacher networks. The tool visualised multiple, isolated networks of teachers within the organisation. This sort of tool could be used to support teachers in reflecting on how networks could be exploited or restructured. However, to achieve effective networking it is important to understand how people interact in both online and physical networks. Endedijk traced and visualised networks of care workers in a physical HealthCare setting using wearable tracking devices [12]. These devices gathered geospatial data (e.g. the location, proximity and direction) of each care worker and analysed these data to identify how professional networks were dynamically formed. The study provided evidence of limited connections within and across the professional network. These data can be used by the organisation, team managers and the professionals themselves to reflect on ways they can improve their networking in ways that exploits the human capital within each team [12]. The idea of supporting professional learning through informal networks is powerful, particularly when it allows consideration of information flow through informal networks. However, information flow in itself does not indicate learning, so these techniques have to be supplemented by other methods to test the underlying assumptions.

Another technique being used to assess team cohesion and teamwork is *Natural Language Processing* (NLP). NLP techniques are being incorporated into learning analytics systems as a promising way to support non-formal learning. These systems process and analyse dialogue to trace learning and development by comparing how different groups, for examples novices and experts, express concepts and ideas or by tracing discourse development over time. The development of linguistic cues is an important signifier of social identity and expertise development within communities of practice [36]. Analysis of social media narratives over time could identify whether, while using web based learning resources, whether novices were moving towards using expert language. Yan, Naik and Rose [67] carried out novel research where they analyse natural language. The researchers examined the use of natural language within Reddit – a social media platform used to aggregate stories within online communities. They used a natural language processing analysis technique, Content word filtering and Speaker preferences Model (CSM) to detect how the use of language develops within online communities. By extracting 'functional story schemas', they identified schematic structures that characterise specific sub-narratives within the community. These schemas serve as lenses that reveal 'community norms' within Reddit sub-communities. The NLP analytics techniques can detect and make visible when teams work coherently, or where there are structural problems. These techniques can be used to compare the ways experts and novices work, allowing support to be tailored. However, there are assumptions around behaviours built into the system. These assumptions become foundational 'norms' that are difficult to change; the more the system 'learns' the more these conventions become assimilated. Future techniques have to find ways for systems to become more intelligent through being able to 'learn' and 'unlearn', rather than setting up 'sound clouds and 'stereotypes'.

For decades robots and humans have worked together collaboratively through direct physical interaction, for example in automotive assembly lines [1]. As robots co-work with professionals, there is opportunity to exploit learning through sensory modality. Humans learn by interacting with their environment through touch, which helps to build an understanding of objects and events. For example, robots can teach people how to move their arm during rehabilitation after an accident [44]. By providing smooth, strong virtual surfaces and other haptic effects the robot can turn a shared workspace into a learning space. Haptic technologies have been used effectively in professional learning settings, particularly in medicine and dentistry, where 'touch' is important for sensory learning [61]. The computational systems that drive the robots harvest data through various sensors: touch, geo-location, visual and so on. These data can be combined and analysed to provide feedback to the learner. For example, a dentist can learn a new technique by sensing the 'feel' of drill while working on a virtual patient before carrying out the procedure on a human [61].

These forms of informal learning need to be evaluated using innovative forms of assessment and accreditation.

4.3 Assessment and accreditation

Professionals could have competency in their everyday work recognised and accredited using automated forms of assessment. For example, when operations staff in a manufacturing plant learn how to operate equipment and carry out a range of tasks to a specific level of competence under supervision before they full fill their probationary period and are allowed to work unsupervised. Supervisors verify when they reach the competency level by observing, questioning and then verifying the learner has reached a level of competence and computational systems are being used to gather and store information on learner progress using blockchain technology [42]. Blockchain technologies have been proposed as a way to ensure the authenticity of the data, allowing an audit trail of activity that is useful for documenting learning progress [26]. A blockchain is a distributed record of online activities, or digital events, which has a consensus method to agree whether a new 'block' is legitimate [54]. This system allows formation of a permanent, distributed record of intellectual effort and reputational reward. A central claim is that blockchain 'democratises' education by opening up records of achievement beyond traditional forms of certification in ways that allow employers to view a wide range of achievements. Computational systems are not simply records of achievement.

5 CONCLUDING REMARKS: FUTURE PROFESSIONAL LEARNING ANALYTICS

Although in its infancy, professional learning analytics is set to form a foundation for future learning and work. Learning analytics are already supporting professionals in improving their performance. Analysis of these approaches point to the need to develop systems that support professionals as they learn through everyday work, rather than only focusing on analytics systems for professional courses or work-based training.

Several approaches use machine-based analytics to augment human intelligence. However, the connection between the system and the human is a point of risk for a number of reasons. First, professionals have to be able to identify and act upon their learning needs, therefore the ability to self-regulate learning is critical to the success of many analytics techniques. Second, without a parallel shift in the culture and the mindsets of people within the organisation, learning systems based on analytics will have limited impact. This is particularly relevant in work settings where task outcomes are difficult to predict. Learning in these situations is most effective when integrated with work tasks. Professional learning analytics can be more powerful when incorporated into work-integrated systems: platforms that support experts and novices in co-working, smart systems or augmented reality environments, such as those described earlier. Future implementation of approaches to learning analytics should consider these human elements.

Finally, there are a range of ethical considerations that need to be embedded not only within the use of analytics systems, but to inform their development. By contributing their data to a system, professionals can benefit from analytics systems that help them to connect with information, knowledge and people that can help them learn or carry out a new task [37]. However, there needs to be better transparency around how these data are combined with other datasets and used. If professional learning analytics is considered as a race, we are still in the starting blocks.

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Chapter 15: Game Learning Analytics

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ABSTRACT

Games are a pervasive cultural phenomenon with intriguing connections to learning, and the use of learning analytics can inform our understanding of learning in the context of games. In this chapter we identify four principles that are fundamental to both compelling gameplay and meaningful learning – **agency**, **engagement**, **growth**, and **social connection**. Agency in learners helps them grow and feel safe to fail, persist, and feel ownership of their learning. Engagement, both as great interest and active involvement, is essential to learning, and digital games can be very engaging. Growth involves increases in ability that are developed through effort, perseverance, trying alternative strategies, and seeking help from others. Social connection with other players both within and outside of games facilitates learning. We propose that these four principles serve as an entry point for understanding and conducting game learning analytics work. For each principle we provide examples of evidence-based approaches to the design, measurement, and analysis of learning in game-based contexts to guide thinking and work in the nascent field of game learning analytics. This chapter is intended to be useful not only to game learning analytics practitioners but also to people working in LA-adjacent domains, such as game design, classroom learning, data security, and educational policy. We suggest that designers, practitioners, educators, and learners could all benefit from the translation of academic GLA work into a form that is useful to this broader constituency.

Keywords: Digital games, learning, analytics, agency, engagement, assessment, collaborative learning, social learning

Games have been played within all cultures, over millennia, in myriad contexts, for varying reasons. This ancient form of human interaction, used to convey and stabilize cultural norms, has also long been both a source of enjoyment and an instrument of teaching and learning. Even some of the oldest known games – from the 6th century B.C. sport Polo, which taught war skills [17], to the 11th century A.D. board game, Rithmomachia, which taught number theory [77] – facilitated learning. Using games to support learning is now an established practice, and the use of digital learning games, from Oregon Trail to Minecraft to America's Army, propels an ever-growing interest in evaluating the impact of gameplay on learning [80].

Game Learning Analytics (GLA) is the application of learning analytics (LA) methods to gain insight about learning in the context of digital gameplay. Across many definitions of 'game', we find Salen and Zimmerman's [73, p. 80] most concise and effective: "A system in which players engage in an artificial conflict, defined by rules, that results in a quantifiable outcome." Game data are different from other LA data, since they comprise detailed information about players' frequent decision making and actions in a media-rich world. Additionally, learner actions tied to the specifics of the game world context enable GLA to be more contextualized than other dense, open ended data streams (such as emotional LA).

Since the purpose of educational games is to positively impact learning, it is important for learning game designers, educators, as well as learners themselves to understand if, how, and to what extent learning happens. Game learning analytics affords a unique perspective on learning impact, as it provides a look at learning over a broader time period, by finer-grained measures, and at a larger scale than other learning game research methods. GLA is a key tool in an ecosystem of design and evaluation, since it can provide analytical insight into exactly which aspects of games do or do not support learning, in a way that other research methods, like pre-post assessment of learning, cannot. GLA can enable data-informed game design and inform feedback to learners, educators, and others who work to support learning. Additionally, GLA methods can transfer to LA work in non-game contexts, such as highly interactive learning (e.g., sensor-equipped spaces providing dense data streams) or highly contextualized learning (e.g., makerspaces and project-based classrooms, where the learners' actions are contextualized in the pursuit of long-term goals but involve many individual sub-tasks).

Game learning analytics is a young field, without a lot of standards, and practitioners need to be nimble and scrappy. In this chapter we identify four key principles that are shared by games and learning that we propose can serve as a toolkit for approaching game learning analytics work. It is our hope that this framework serves as a helpful guide to practitioners as they identify what they value in games for learning and the questions they want to answer. For each of these four principles we provide evidence-based approaches and examples to guide practitioners' design, research, and analysis of game-based learning.

1 FOUR PRINCIPLES OF GAME-BASED LEARNING

We propose that there are four fundamental principles that are essential to *both* compelling gameplay and meaningful learning: **agency**, **engagement**, **growth**, and **social connection**. These four principles correspond roughly to the four "pillars of learning" that Hirsh-Pasek et al. [35] derived from learning sciences research, but we have adapted them specifically to address game-based learning. Understanding the critical role of agency, engagement, growth, and social connection in both games and learning provides insight into designing learning games, shapes how we measure and analyze learning using GLA, and illuminates why and how games can be valuable learning tools. Each of these factors alone fuels successful gameplay and learning experiences; combined they provide even more powerful effects.

1.1 Agency

In good games, players feel and act with agency. Games both enable decision-making that shapes and reflects players' active sensemaking and help players formulate and express personal ideas and desires. Like ritual and play, games occur in circumscribed spaces, "temporary worlds within the ordinary world" [38], an idea later popularized as the "magic circle" [73]. The magic circle supports agency by providing players a "psychosocial moratorium," a developmental concept introduced by Erikson [29] and applied to video game contexts by Gee [32]. Within the magic circle, players craft a personalized narrative in dialogue with the game's design [7], assume temporary power, experiment with identities or roles, and explore their sense of ethics and morals with reduced risk versus real-world exploration of such ideas.

Agency is foundational in a constructivist view of learning. The **constructivist** theory of cognitive development [59] maintains that children actively construct their own knowledge by exploring, developing and testing theories, and internalizing the results of their actions. Learning games embody this philosophy by providing environments in which players explore and experiment, providing a "Rich Environment for Active Learning" [33].

1.1.1 Design For Agency

The design of games and GLA can support the development of agency in learners – helping them grow, feel safe to fail, persist, and feel ownership of their learning. Agency is closely tied to concepts of self-efficacy, active learning, and meaningful learning.

Bandura's concept of **self-efficacy** [3] suggests that the more people believe they can succeed, the more likely they are to engage and the more effort they will invest. Game design can support players' self-efficacy by ensuring that even beginning players are able to succeed and then raising the bar for continued demonstration of competence as mastery grows.

Active learners take control of their own learning process by monitoring their understanding, seeking out opportunities to experiment and explore, and applying what they discover to shape their own knowledge. Well-designed games provide players with rich environments to explore, a system for keeping track of their discoveries, and a degree of control that enables them to progress at their own pace.

Meaningful learning involves connecting new information with what you already know and with your relevant real-life personal experience [11]. One example of games that hold special promise for meaningful learning is those using augmented reality, since they incorporate elements of the player's actual real-life environment. To optimize meaningful learning, game design should incorporate player interests and preferences and enable players to actively reconstruct the game world alongside their broader, real-world experiences [19]. As a result, it is critical for designers, researchers, and educators to be aware of the influence of learners' background (sociocultural factors, gaming experience, personal connection with content and theme, etc.) on their sense of agency in a game.

Two design approaches that aim to ensure active, meaningful learning and self-efficacy for all players are Human Centered Design (HCD) and Universal Design for Learning (UDL). HCD is based on understanding the needs of users, involving users in iterative design, and adapting technology based on user feedback [83]. UDL provides recommendations and methods for including diverse learning needs, goals, and abilities to better support all learners [71] and improves learning processes for a diverse population of students [14].

1.1.2 Measurement and Analysis of Agency

Agency, operationalized in self-efficacy, active and meaningful learning, is reflected within gameplay through the goals player-learners set for themselves and styles of play that they choose. Analyzing these behaviors sheds light on how they adopt different roles and perspectives, and enables **player categorization**.

GLA work related to agency is primarily focused on categorization of player behavior (often called **player models**) by examining actions in pursuit of goals like character customization, game badges and achievements, or competing with other players. LA work on player modeling focuses on assessing player agency by recognizing learners' play styles and identifying goals or plans that players are pursuing, and then eventually supporting their agency by adapting the game to suit a particular player's gameplay style.

In the field of video game studies, there are many ways to categorize and identify **play styles**. This work originates with four archetypal player types proposed by Bartle [5]: achievers, explorers, socialisers, and killers – which has since been critiqued and extended using qualitative and quantitative analyses of gameplay and survey data [34].

The field of learning games extends this categorization work. Player-learner models are built from a mix of gameplay data and theory-based cognitive models. GLA methods are used to generate groupings of player-learners, like identifying players who play by rapid guesswork versus those using slower strategic moves, which provides insight on players' prior domain knowledge [46]. For a systematic review of GLA player-learner modeling work see Hooshyar, Yousefi, and Lim [37]. Player-learner models can be used to adapt games to different learner preferences, competencies, and understandings. For instance, procedural content generation (PCG) is a productive way to practice data-driven adaptive game design. In PCG, the game "terrain" (the space, components, and obstacles in a challenge) is dynamically generated to suit a player's experience and inferred preferences [92]. Games and GLA can be designed and developed to identify learners' preferences and current understanding, as well as scale enemy difficulty, puzzle complexity, and other factors to support productive learning pathways.

There is a lack of GLA work examining player categories through the lens of equity. Qualitative analyses help us understand how to support richer participation and engagement by diverse sets of participants; for instance, characters, themes, and narratives that reflect the experiences of under-represented groups (particularly along gender, race, and ethnicity lines) help support agency in gameplay [66]. Future work in GLA should similarly address issues of equity and justice, and better address the range of players' physical and learning abilities. GLA analyses can also examine the interaction of personal values and preferences with game design elements (like theme and narrative) to engage players on a more personal level and to support fuller personal expression by learners, especially those minoritized in game cultures.

Since all of this work involves sensitive information about players, it is critical that game designers, developers, and educators advance and implement ethical LA (Chapter ??, this volume) and ensure learner privacy, data security, and transparency for learners about how data is collected, interpreted, and used.

1.2 Engagement

Engagement, both as great interest and active involvement, is critical to learning. If you are not interested and not doing anything, you will not learn! Games can enhance players' motivation to learn as well as persist beyond failure. In games, failure is normalized, pleasurable, and even celebrated [39]. Games can also teach us, with low stakes, things we need to know in real life, and this type of learning can feel enjoyable – pushing the limits of pattern mastery and sensemaking can be fun!

It's a commonplace assertion that digital games can be very engaging. The concept of engagement, however, is ill-defined and complex at best [9], so designing for, measuring and analyzing engagement are not straightforward endeavors. Engagement includes cognitive, behavioral, and affective components [31]. One of the challenges to developing and understanding GLA regarding engagement is that game designers typically focus on addressing the cognitive and affective components of engagement, while researchers tend to measure and analyze behavioral components. Resolving this discrepancy is an important area of opportunity for future design and GLA work.

1.2.1 Design for Engagement

Given the ill-defined nature of the concept of engagement, it's not surprising that researchers operationalize engagement with digital games in many potentially overlapping and/or contradictory ways. These include intrinsic motivation [60], attention, immersion, involvement, presence, flow [8], memory, motor speed and control, persistence, and positive and negative affect [22]. Likewise, design features that are suggested to support engagement include factors as diverse as role-playing, narrative arcs, challenges, interactive choices and interaction with other players [25], leveling up [57], and adaptivity [13]. **Intrinsic motivation** is the most well-researched of these constructs, and ties together many of these features, so we explore that concept in more depth.

What makes digital games engaging, fun, or intrinsically motivating? Why do people want to play them with no encouragement, prompting, or external motivation? Deci [23] argues that some activities provide their own inherent reward, independent of any kind of extrinsic rewards. Well-designed digital games exemplify this type of activity. Malone and Lepper [47] propose a taxonomy of intrinsic motivation factors that make learning games fun, including individual motivations such as challenge, curiosity, control, and fantasy, and interpersonal motivations like cooperation, competition, and recognition. Intrinsic motivation, so common in gameplay, is also linked to school success [1]. As a result, researchers have investigated the integration of intrinsically motivating games into the classroom [25].

Student perceptions of the concept of intelligence also impact school success, and learners with a growth view of intelligence (malleable via effort) are more likely to take risks, try new approaches, and persist at challenging tasks [28]. Moreover, praise for effort or progress is more likely to encourage a **growth mindset** than praise for task performance or ability, which has important implications for the wording of instructional and reward messaging in learning games. The growth mindset approach has been effectively applied to game incentive structures that identify and reward effort, strategy use, and gradual progress [49, 50].

1.2.2 Measurement and Analysis of Engagement

To quantify engagement, GLA work starts with characterizing behavioral engagement via amount of gameplay – for instance, number of players, means and variance in gameplay time, play time per session, and numbers of play sessions – but we can get a deeper understanding of the cognitive and affective components of engagement through observational and qualitative measures, sensor-based data, and more detailed gameplay data.

Using observational and qualitative measures, engagement in games has been examined through the lens of **flow** [42] – the immersive, deep engagement that is maintained by an appropriate amount of challenge of a problem at hand [20]. In addition to using time on task and flow, one can layer in a variety of behavioral, cognitive, and affective perspectives to understand engagement in learning games [58].

Detailed gameplay data can provide insight on engagement in a variety of ways. For example, progression through different sections of the game – levels, obstacles, or terrains – are indicators of where players spend time and where they succeed or fail. One way to quantify game progress is by using heatmaps to identify where players proceed or get stuck [61]. Other LA techniques, including clustering and state network diagrams can be used to measure engagement [52]. These two papers also provide examples of how these analyses can inform game design.

In addition to documenting player agency, player categorization can be used to help keep players engaged. Predictions of engagement and gameplay dropout are often part of player models [37]. Dynamic difficulty adjustment is a popular data-driven technique that uses player models to maintain an appropriate level of challenge to keep learners interested [96]. For instance, the Hamlet system [15] describes how to model a player-learner's current and upcoming state of progress or struggle using their play data. Then enemy difficulty level in the game is adjusted to match players' skill and understanding level, thus keeping them engaged in the learning aspects of gameplay.

Note that some engagement data can be misleading with respect to learning. For example, games may entice players to spend time in activities that don't lead to productive outcomes. Game design elements with questionable purpose have been described as dark design patterns [94]. Mismeasurement is especially likely with educational games, since engaging features may not address learning goals [43]. Thus, it is the responsibility of learning-game designers and researchers to make principled use of design elements and measurements of engagement to ensure that they are used in the service of learning.

1.3 Growth

Agency makes people feel they can learn and engagement motivates them to want to learn. How can we design learning games to support, use data to measure, and conduct meaningful analysis regarding learners' growth of skills (what learners can do) and performance (how they demonstrate skills)?

Growth involves increases in ability that are gained through effort, perseverance, trying alternative strategies, and seeking help from others [28]. Cognitive, behavioral, and affective growth can be achieved through learning. In good games, growth of skills and performance advance game play and make playing games challenging and fun.

The effectiveness of games in supporting learning is still debated. While some educational games are documented to be effective learning instruments, findings can be inconsistent [74]. Further, while GLA can help clarify and elaborate on the extent to which games can support learning in various domains, contexts, and for diverse groups of learners, there is mixed data around the degree to which players are able to **transfer** skills, extending learning in one context to other contexts, particularly skills learned within games into non-game contexts [4].

1.3.1 Design for Growth

Games effectively promote learning when they integrate cognitive engagement with playfulness, and when content engagement is linked to game action [41]. Games that blend these factors can serve as personally meaningful "objects-to-think-with" [53, 36].

Successful learning games reflect evidence-informed game design principles, which incorporate the best available efficacy evidence from research, content experts, practitioners, local context, and users [21]. One productive approach to designing learning games is employing **design-based research**, in which prototype versions of a game are tested iteratively with users to inform further design [63]. Design-based research involves understanding learning processes in authentic contexts, such as schools, homes, or museums, and working to improve game-based learning outcomes within those contexts [78].

As a learner explores a game, mentors or digital agents can support learning through the use of scaffolding techniques. **Scaffolding** provides learners with as much or as little support as they need to succeed on a task and reduces this support as the learner becomes more capable [88]. Designing scaffolding into digital gameplay is a particularly useful technique for supporting learners of varying skill levels playing the same game [54, 65].

Guided play experiences, which combine the approaches of constructivism and scaffolding, are optimal for learning [30]. Guided play combines elements of free exploration with elements of mentorship, to ensure that exploration and hypothesis testing is structured and systematic. Guided play provides a natural opportunity for playful conversation, and a prime context for learning [90]. With the introduction of artificial intelligence in games, the design of interactive, social, intelligent agents [12] might be able to effectively guide game-based learning, eventually providing something approximating the kind of scaffolding that a human play partner provides [86].

Building algorithms into learning games that enable them to adapt to address individual learner's skill levels holds special promise for learning outcomes. Research regarding the design of adaptive level progressions that optimize engagement and learning is ongoing [13]. In-game, real-time, individualized response to success and failure is another critical game feature that supports learning [64]. For feedback to be effective it should be scaffolded, encouraging, and incremental. With regard to failure, a wrong answer is a learning moment. If you don't get anything wrong, you aren't learning – your performance is evidence that you were already competent in the content before playing the game!

1.3.2 Measurement and Analysis of Growth

Measuring growth involves examining how players develop competence and understanding. GLA can be used to measure growth by assessing users' success on in-game tasks and the ways in which scaffolding, feedback, and challenge affect learners' patterns of experimentation, strategies, and success.

Data visualizations and learner-action classification using Bayesian network analyses, clustering methods, or Markov models, are a few commonly used data mining methods to depict and measure growth of skills in educational games [16, 51]. Here, we describe three examples of analyses that span a variety of game types and learning contexts.

First, Bayesian networks can be used to identify learner progress by analyzing gameplay data signifying player actions, successes, and failures [75]. This work leverages the Stealth Assessment Framework [76], which involves developing learner models that describe what learners know, competence models that articulate the learning domain, and evidence models that map player game actions to learning. The **Stealth Assessment Framework** proposes a design and analytic framework for embedding assessment activities in engaging game tasks, with the goal of blurring the distinction between assessment and learning in gameplay.

Next, cluster analyses of gameplay data can be used to identify different learning phases such as Exploration, Tinkering, and Refinement, as described in the EXTIRE framework [6]. This framework was developed based on a constructionist programming game played in classrooms, and presents methods enabling automated identification of the learning phases via game actions and tasks.

Finally, Hidden Markov Models (HMMs) can be used to identify productive and unproductive progress in gameplay [85]. Tissenbaum et al. [85] use HMMs on museum-based gameplay data to identify productive player actions (for instance, remembering successful approaches or trying out novel approaches) as well as unproductive player actions (like repeating the same successful approach with no change). Since productive actions indicate learner growth and unproductive actions often correlate with visitors leaving the exhibit, identifying these patterns helps in understanding and supporting growth of skills and performance.

These measurements of learner growth are useful in communicating with different participants in the learning environment, including parents [68], teachers [62], and docents [44]. These participants have access to real-world interactions not easily accessible in GLA data – which makes integrating GLA with their contextually informed intervention particularly valuable. Developing platforms to convey this information, typically through dashboards, is extensively discussed in Chapter ??, this volume.

1.4 Social Connection

Almost all of human learning takes place in social contexts. Games have traditionally played a critical role in enshrining social practices like rituals and etiquette [18], which in turn provide valuable kinds of sociocultural learning [69]. Digital games offer a spectrum of social opportunities, from in-classroom social interactions where learners express and build identity through avatars [40], to experiencing apprenticeship, mastery, and real world (meatspace) community through massively multiplayer role-playing game cultures [81].

1.4.1 Design for Social Connection

Social connection with other people facilitates learning. Human brains have evolved to learn in social contexts with other people, and designing games that support social learning can build on this brain-based human tendency [48]. Examples of design features that support collaborative play and learning include creating a common goal for the group [95], providing common ground for shared understandings among players of different ages and experience levels [2], including explicit role assignments for different players [10], providing collaborative interfaces and tools [82], structuring guidance for both individual and collective action [87], and designing intelligent agents to interact with players in a social way to capitalize on parasocial relationships [45].

Social connection with other players outside of games also facilitates learning. Minecraft players participate in social communities through tutorials they make for each other [55]. Minecraft and other social games can also provide inroads for socialization for children with autism [67]. Remarkably, players of complex, multiplayer online games achieve reading levels almost three grade levels higher when socially engaging with other players on discussion boards [79]. Salen [72] further describes many kinds of rich, productive social activities learners engage in while playing or communicating about games – including working and solving *in-game* problems with physically collocated family; discussing, cooperating and competing with classmates and friends in games; and engaging in creative and interactive online communities where players learn from each other and participate in rich communities around their games.

1.4.2 Measurement and Analysis of Social Connection

There is a dearth of GLA work on social connection in gameplay. Measuring social connection involves recognizing dynamics such as role enactment, collaboration and competition, collective and individual guidance, social sharing, and parasocial connection. However, some of these interactions take place off-screen, and are hard to capture completely through gameplay data. Thus, they are often assessed in concert with qualitative analyses of observational data, and multimodal LA based on motion tracking, wearable, and/or other sensor data.

There is a rich body of qualitative work examining social configurations through digital games in different learning environments. Social interactions within and around games in classrooms can involve sensitive topics of representation, inclusion and identity [84, 40]. Hybrid physical and digital game activities can also be designed to support social interactions and collective understanding through physical movement around digital games. Games, like BeeSims [56], can connect embodied physical movement with digital simulations of complex phenomena and are able to support different kinds of roles and collaborations [24]. Hybrid games have also been used in LA analyses of collaboration through methods discussed in Chapter ??, this volume.

Social game play has been measured using a variety of data analytics methods. For example, players' demonstration of collaborative strategies and expertises can be identified through methods like social network analyses, networked engagement metrics, and other measures of communication coupled with game progress – especially in online multiplayer game environments like World of Warcraft [27, 93]. As the development and adoption of online multiplayer games in classrooms and other learning environments rises, this work will become more and more applicable to learning settings [70].

Within GLA, gameplay data has been used to identify different kinds of social learning. Models of social learning behavior can be built by conducting qualitative research on the game, the physical space that it is situated in, and user interaction patterns typical of players in the game's context. These models can be mapped to patterns in gameplay data, and then used in future studies to recognize instances of social interaction and learning, without needing to rely on further qualitative visual observation. This is exemplified in the analysis of data from a museum game where visitors can play on an interactive digital tabletop in a way that facilitates individual play, talking to other players, seeing others' work, and working collaboratively or competitively [85]. These different kinds of social play and learning, even when occurring outside of game interactions, can be identified through patterns in gameplay data – for instance, people who looked at others' work and talked to others have distinctive sequences of repeating and modifying their own and others' strategies.

There is a pressing need for LA work on **computer-supported collaborative learning** [91]. Work in this space has the potential to expand GLA for social connection, which is particularly important given the proliferation of social learning games [89]. Fostering social connections through inclusive social networks can help address issues of equity in games. For example, gender-equitable communities with strict moderation around all forms of harassment and trolling have proven popular across gender and ethnicity groups [66]. Developing LA methods to identify and support productive social connection in such spaces is a key opportunity to enhance the creation of more equitable game-based learning experiences.

2 OPPORTUNITIES

Game learning analytics is a nascent field. To provide some structure to GLA thinking and work, we have proposed the four principles of **agency**, **engagement**, **growth**, and **social connection** as an organizing framework, but there are additional issues to be addressed.

Standardizing the assessment of efficacy in learning games is a prime opportunity in GLA. Doing so will require multidisciplinary collaboration among those working in LA with those in adjacent domains like curriculum design, game design, educational research, data security, and educational policy. This work can build on existing standardization frameworks in the video game industry [26] and could also enable the evaluation of learning across multiple games and contexts.

Standardization of GLA can also inform transfer, which is a central issue in learning sciences. Standardized inter-game GLA has potential to illuminate near transfer from game to game and also pave the way for identifying far transfer to different activities when integrated with other school and activity data.

GLA also has potential benefits for a broader range of stakeholders than its current primary use in academia. The aim of this chapter is to be informative not just to LA practitioners but to anyone working with games for learning, including those who design games, select and integrate games for classroom use, assess the effectiveness of games, manage data to help kids play safely, and set guidelines for healthy play. Our hope is that GLA will evolve to be transparent, digestible, controlled by, and empowering for all involved participants – teachers, parents, and (in particular) learners themselves.

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Chapter 16: Analytics for Informal Learning in Social Media

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ABSTRACT

Social media reaches billions of people on a daily basis, with many interactions and sites helping individuals learn and participate in learning discussions. Much of the research in learning analytics has focused on understanding practices in formal educational settings, with limited examination of learning in open, online forums. Yet, the prevalence of open, online learning suggests including learning in and through social media is a relevant area of study for learning analytics. This chapter addresses how learning in social media aligns with informal learning as, learner-led and conversation-based; how participation is essential, but also nuanced, including stages of learning how to join the community, and partial participation as each medium complements learning in an overall personal network; and how conversational interaction builds the social learning network. Conversation analysis and social network analysis are highlighted as analytical techniques, as the former defines the ties that build the network, with analysis of social media postings revealing discussion relating to subject matter, persuasion and explanation, career advice, socializing, and reinforcement of in-network rules and norms.

Keywords: Informal learning, social media, social learning, online learning, social networks, learning networks

The reach of social media, online sites, discussion forums, and communities is vast, with recent estimates of monthly active users of 2.4 to 1.1 billion per platform: Facebook, 2.4 billion; WeChat, 1.1 billion; Twitter, 330 million; Reddit, 330 million; and Stack Overflow, 50 million (as of October 2019) [54, 70, 69]. Within these social media platforms, features and subsections are emerging that focus intentionally on learning, setting the expectation of learning about a subject area of interest while also enacting a forum for discussion. How can learning analytics address these sites? What are we learning about these sites that can support design, knowledge sharing, and learning on and through social media?

This chapter addresses analytics for open, online learning environments on social media. Such online sites support a variety of collective approaches to information seeking, learning, discussion, and sharing of knowledge and life experiences. Social media sites are of interest not only for their wide reach, but also for how learning processes are determined by appropriation of technical features and in-group regulation and management, and how this creates and sustains learning communities. Neither formal nor non-formal, social media sites enact a form on informal learning dependent on networked interaction, conversation, and community in support of knowledge exchange and community. Examining how learning happens in these sites opens up exploration of what supports and signifies successful individual and community learning, and knowledge development in open, online initiatives.

This chapter first situates learning in social media within the frame of formal, non-formal and informal learning, arguing that such learning represents a new form of informal learning. Features of this new form include: a self-organizing structure for the discussion of subject matter, norms of interaction, role definition, and expert validation; the necessity of visible participation through conversation; the record of the *persistent conversation* that forms in-network social capital; and the challenges of an open, fluid membership. The chapter then addresses analytics for informal, open, online learning in social media through conversational analysis and social network connectivity.

Informal Learning in Social Media

Informal learning is distinguished from formal and non-formal learning by practice outside institutions. While formal learning is associated with educational institutions, and non-formal learning with institutions such as community and recreation centers, museums, and libraries, informal learning is associated with more ad hoc learning, and includes acquisition of attitudes, values, skills, beliefs, and knowledge from sources such as family, friends, work colleagues, media, etc. In formal and non-formal learning, experts organize and oversee the learning. In informal learning, the expert is seen as an agent who is able to identify and respond to opportunities to engage learners in any aspect of knowledge [17, 13, 68, 37].

While *informal learning* is sometimes used as a catch-all for learning not classifiable as formal or non-formal, its value is in responsive to learner interests, in spontaneous, unplanned, conversationally-based interaction. "Informal education can be viewed as being driven by conversation and, hence, unpredictable. Informal educators do not know where conversation might lead. They have to catch the moment, to try to say or do something to deepen people's thinking or to put others in touch with their feelings." This kind of informal learning: "Works through, and is driven by, conversation. Involves exploring and enlarging experience. Can take place in any setting" [68].

A view of learning as "driven by conversation" situates informal learning in the tradition of *social learning theory*, with its emphasis on observation of behavior and its imitation (or not) based on the observed reaction to behaviors [2]. Following this tradition, Buckingham Shum and Ferguson [9, p. 5] describe the social, interactive aspect of this kind of learning and engagement online as "either interacting directly with others (for example, messaging, friending or following), or using platforms in which their activity traces will be experienced by others (for example, publishing, searching, tagging or rating)".

Working with these definitions, the structure of learning in social media aligns well with informal learning, particularly in terms of the focus on learner-directed question and answer effected through conversation. Yet, the open context and peer learning associated with social media sites differentiates it from non-school, informal learning associated with family or workplace settings. In particular, the *self-organizing structures* that emerge in open, online communities are different from the acquired structures of family and workplace. In creating these structures, participants collaborate to define and reinforce practices that support their collective learning goals [63]. Conversation, of various types and forms, provides the connective structures for the learning network. Examining conversational interaction thus provides a window into normative and emergent practices that support learning.

Within the wide range of attributes that could be analyzed for informal learning in social media, this chapter concentrates on the conversational aspects and how this supports a learning network. Discussion begins with the crucial element of participation, as it is only through some critical mass of participation that learning via social media can happen.

PARTICIPATION IN SUPPORT OF SELF-ORGANIZING PRACTICES

Self-organizing structures define and maintain the subject matter of interest, norms of interaction, membership practices, role definition, and expert validation. Yet, they depend on participation. As such, how individuals participate, and what motivates, maintains and drives participation, are key factors in assessing informal learning in social media. Such participation must be visible. Through social media and other forms of computer-mediated communication, where there is no face-to-face or institutional co-location, social presence is only measurable through visible contributions. While communications may include many modes of text, image, photo, video, audio, etc., these all must be accessible through the social medium, and contribute to an ongoing conversation.

Early research on computer-mediated communication and virtual communities wrestled with the need to build *critical mass* to start and maintain functional conversations via interactive media, and thereby build and sustain online community (e.g. [49, 12, 56]). Encouraging participation has been a major area of concern for online classes, communities, peer productions, citizen science, and knowledge sharing environments (e.g., [3, 38, 14, 62]). From an analytics perspective, participation can be assessed in a multiple ways: raw counts of activity, number of participants contributing at all or above a particular threshold, reciprocity in discussion, centrality in the network of contributions, churn in membership, longevity of the forum, affect demonstrated in posts, topics discussed, sanctions applied, and more. To determine appropriate measures, it helps to explore what is known about why people do or do not contribute, how they learn to contribute, and what is needed to sustain a viable learning community.

From Lurking to Posting

Conversation is seen as a major contributor to learning, whether informal or formal [43]. Thus, it is not surprising to find that lurking, i.e., reading and not posting, has been seen as a liability for online learning communities. On Stack Overflow, a site for learning and sharing knowledge about computer programmers, non-participants cited a number of reasons for their behavior, including doubts about personal reputation and a lack of a safe environment:

> "Over 20% of respondents said they have never participated on Stack Overflow, and we asked them why in a free text question. Many respondents said their questions already had answers, so they felt no need. Others shared different factors, though, including lack of English proficiency, the time commitment involved, and not having enough reputation to contribute the way they want. A few participants perceive the community or site mechanics as too strict or toxic for them to feel safe interacting here." [54]

Creating the *safe space/* for contribution has been a focus of collaborative learning, another area of learning that requires contribution [7]. The safeness of a space depends on conversational style, discourse, and norms accepted and practiced in the learning environment, and how this motivates (or not) potential contributors. Safe spaces encourage expression of opinion, asking questions and potentially revealing a lack of knowledge. FAQs repositories can provide initial help on norms, but it is the actual live practice, and others' response to that practice, that matters most.

In online spaces, part of what makes a space safe is knowing how to engage in the conversation; this requires learning how to contribute in open forums [33]. Recognition of this learning has given new emphasis to lurking as *legitimate peripheral participation*, allowing newcomers the time and space to observe and learn how to participate [44, 57]. At the same time, this space to learn must eventually turn to participation or critical mass will not be maintained and the community will dissipate. An equal concern about online communication has been that the dominance of a small set of voices can mitigate against wide-spread contribution, and thus fail when central individuals leave the forum [6, 24].

Participation also requires knowing how to engage with others, i.e., how to be a member of the community. This is well-taught and well-learned for the traditional classroom, but a barrier when engagement in online environments is new. Engagement is a collective effort; how others respond to posts greatly affects whether participation continues. A post with no answer can be discouraging. For example, Bornfeld and Rafaeli [5] found about 50 percent of contributors to Stack Exchange Q&A sites dropped out after posting a single answer, but positive feedback, in up-votes and comments, was correlated with further contribution.

Not all participation is, or needs to be equal. Participation can change over time, as newcomers join the community, and others move on to other interests or forums [39, 36]. With more participation, and more commitment to the site, many individuals choose to take on more prominent roles in the community [8], e.g., as moderators, specialists, or experts; as gatekeepers bridging between multiple similar communities; and in-network *librarians* who bring attention to frequently asked or answered questions. Collectively, these commitments define the roles that support membership across the whole community. From the not-quite-ready to post lurker, to the tentative novice poster, to the fully engaged advanced participant who are likely to contribute more than they receive for their effort.

Commitment to the site may also be only partial. Participation in sites is no longer all-or-none. and learners may engage in *legitimate partial participation*. Multiple sites can provide resources. The networked individual and connectivist learner pick and choose across various sites and sources to find their ideal knowledge set [59, 67]. Participation in one site may be single threaded, e.g., seeking just the answer to a question, but multi-threaded in another, e.g., seeking and providing information on the topic, career advice, social and learning support. This shows two aspects of connectivity. First, that the combined set of threads – single for some actors, multiple for other – reveals the full nature of the social network connections that define each community (with caveats against selecting just a few members as exemplary of the site). Second, that sites with adequate participation can sustain individuals in partial participation modes, e.g., as lurker, newcomer, novice; a critical mass of participation can sustain a wider range of onlookers.

Individual motivations greatly affect participation, but, there are motivations also beyond the personal. The networked individual is often motivated by personal as well as community wide goals. Raymond [60] first noted the 'personal but shared need' associated with contribution to open source projects, which highlights dual motivations relating to personal knowledge, and contribution to a wider community. Following this idea, Budhathoki and Haythornthwaite [10] found contributors to the open source, crowdsourcing project OpenStreetMap were motivated both by personal interest associated with career or individual learning, and a wider orientation to making mapping information free to all via an open source platform. Participation may thus depend on what the site is supporting, as much as for individual learning objectives.

An In-House Library of Informal Resources

While learning engagement happens through conversation, one of the features of open, online discussion is the record of interaction that remains. Although this is not true of all social media, on platforms were online conversation is recorded and retrievable, it becomes *persistent conversation*. As defined by Tom Erickson and Susan Herring (e.g., [19]), the "transposition of ordinarily ephemeral conversation into the potentially persistent digital medium. ... Such communication is persistent in that it leaves a digital trace, and the trace in turn affords new uses. It permits conversations to be saved, visualized, browsed, searched, replayed, and restructured." (`http://www.tomeri.org/HICSS_PC.html`).

In social media, the resulting library of opinion pieces, speculations, questions and answers, becomes a resource for new learners entering the domain (supporting learning both content and conduct). The use of this library of resources has given rise to a newly identified role of the *FAQ Finder* (Frequently Asked Questions finder). These *site librarians* research and pull together resources from within the site to streamline community knowledge exchange. The resources themselves challenge traditional information gatekeeping mechanisms, e.g., of approved texts and authorities. They provide a new kind of resource that is a history of informal inquiry, argumentation, and answer construction.

While Reddit has formally identified the site librarian role with an FAQ Finder *flair*, other communities similarly build and recognize in-site knowledge. For example, Preston [58] found participants in an online professional development community for teachers created new artifacts by braiding together texts from across the community and outside. These texts were further validated by community interaction and comment and remained a resource for use inside and outside the community. In this way, stored online discussion becomes a tangible asset of the community – its *social capital* – embodied in the questions, answers, comments, arguments, dialogue, interaction patterns, actors and roles that constitute the collective resource. While these features are familiar to epistemic communities, e.g., in academic domains comprised of publications, scholarly meetings, and a range of scholarly actors, they are not features that are normally associated with ephemeral social media, nor with analytics of the learning community.

ANALYTICS OF LEARNING IN SOCIAL MEDIA

Social structures, participation, and persistent conversations, together build the social capital of these networks. These in-network structures hold both accessible and mobile social capital, through network actors and accumulated resources [47]: accessible through conversational Q&A with peers and in-network experts, and through records of conversation; mobile through communal response to questions, and searchable conversational records. While analytics might focus on one aspect of structures, participation, capital, etc., the learning community is a net result of their multiple interactions, and as such may best be examined as a collective set of elements leading to a particular learning community outcome. This places examination of social media learning in the traditions of ecological analyses (e.g., [53]), activity theory [18], and multi-dimensional statistical analyses.

Another method is social network analysis, taking the network configuration as the outcome, as built through conversation. This method combines examination of actors, conversation, and community, with communications between actors as the relations and ties that form the social network [71, 72, 51, 34]. The following sections discuss two complementary approaches to learning analytics for social media based on a social network perspective: *conversation analysis* and textitnetworked connectivity. These approaches provide a beginning to exploring the vastness of open, online learning, and suggest some starting points for analysis and further study.

CONVERSATION ANALYSIS

What people talk about creates the ties that support the learning community and the emergent network; thus analysis of online conversations is a key part of analyzing open, online learning networks and communities [74, 55]. Analyses have explored how arguments are formed [73, 15], how people are persuaded to adopt a different perspective [41], and what constitutes community communication online [34].

A number of efforts have used content analysis and automated coding to identify the underlying relations that create the learning communities. Gruzd, Haythornthwaite and colleagues studied postings in Reddit using content analysis to explore conversational patterns in four "Ask" subreddits (AskScience, Ask_Politics, AskAcademia, and AskHistorians; [42, 34]), and later to evaluate the application of the coding to Twitter and test an automated coding process [26]. The coding process built on earlier studies of interaction analysis [28] and exploratory dialogue [50], and was framed by the community of inquiry framework [20, 21] and analytics approaches to social learning, social networks, and online community [9, 30, 56, 25, 27].

Three rounds of coding resulted in a set of eight major types of conversation in these subreddits that are the basis of the learning network: explanation, with (1) disagreement, (2) agreement or (3) neutral presentations; socialization, with (4) negative or (5) positive intent; (6) information seeking; (7) providing resources; and (8) rules and norms. These codes show not just argumentation, but also the practices of a self-organizing community, e.g., managing in-network norms, and the non-topic based socializing that form the safe (or not safe) space for learning. Moreover, this analysis was able to show differences across subreddits, e.g., that Ask_Politics has more explanation with disagreement (18% in the study sample) than the other forums (6-9%).

Similar studies have examined other platforms. Comparing history learning communities on Twitter and Reddit, Gruzd et al. [26] found the eight codes held, but more posts with the #Twitterstorians tag fit with the code of "providing resources" than did posts in #AskHistorians. This suggests differences in conversation in response to the affordance of the two platforms – short vs longer text. Looking at postings about computer programming on Stack Overflow revealed a similar array of conversational exchange [65]: postings about computer programming that offer (1) code only (2) explanation only (3) code and explanation (4) improvements of posted code or explanation (5) alternative solutions (6) limitations to offered solutions; postings that include (7) affect, from frustration at a problem to thanks for suggestions; (8) references and/or in-network links; and (8) moderator comments relating to site norms.

Coding in this way shows how conversation effects informational exchanges and learning in open, online forums. The coded texts represent that connections – social network relations and ties – that form the community and its norms, and build the sustaining basis for each social network. In these media, the *learning conversation* first enacts a space for learning through the practice of seeking information by asking questions and responding with answers; knowledge is then refined through dialogue, explanation, and disagreement; verification is provided through use of references to outside resources or to previously posted answers.

These are just a few studies of learning in social media, but similar conversational coding efforts can show how an open learning site comes to be define by the participation of its members, enacting *community* through the conversational types, tone and responsiveness, and the management of norms. As an open site, community practice can be observed by newcomers, allowing time to act as legitimate peripheral participants before joining the conversation. In Reddit, as in other online learning spaces, questions and answers can be voted up or down according to approval or interest, providing an observer with evidence of what is a good (or appropriate) post versus a poor (inappropriate, non-relevant, etc.) post. Norms within the community are maintained by other participants in ways that conform to site use, e.g., by asking for references to support an explanation (#AskHistorians), or by moderators keeping conversation on topic and with appropriate tone [23].

NETWORKED CONNECTIVITY

Where conversation can show the ties among actors, the next step is to see how the many different relations support the overall networks. Two complementary perspectives stand out for approaching analysis of learning networks: an *egocentric* approach examining *personal learning environments* and a *whole network* approach examining *learning networks*.

In a connectivist manner [67], analytics may address the way self-directed individuals create their own *personal learning network*, pulling learning together across multiple platforms, drawing on multiple sources, in real or asynchronous time, conversing online with a variety of others, and creating their own space for learning [61, 16, 48, 67, 35, 45, 53, 64]. This highly individualist, *egocentric* network approach allows aggregation in a way that provides a picture of typical multi-site media use for learning, reaching both multiple resources and multiple actors. It allows insight into the *media multiplexity* [29, 31, 46] associated with networked individualism [59], and how multiple media (including face-to-face communication) are used to build a personal learning space, in what combination, and to what effect.

An alternative, but complementary view, is to put the focus on the collective with a *whole network* approach, considering how a particular learning site is structured, how members interact with each other, and how the open, online forums support knowledge exchange and co-construction. Looking at the network reveals patterns of conversational interaction – who talks to whom about what – that sustains the ties and roles that support learning. For example, in a study of a Twitter group dedicated to learning about social media use in healthcare (#hcsmca), a network analysis showed how site members communicate as a whole, rather than in separate cliques, and how communication crossed work roles (nurse, health communication specialists, doctors, other health professionals; [24]; see also [22]).

Keeping the egocentric and whole network approaches in mind, there are further opportunities for understanding open learning that could be explored, e.g., understanding a *collective learning space* and the set of media and resources that collectively support their goals; or looking at how multiple collectives build a knowledge infrastructure supporting a particular area of inquiry – what one might call *disciplinary learning environments*. Taking a sociocultural and sociotechnical perspective, mappings of online ecologies can show how knowledge is distributed across online spaces, and how the different participants and technologies support knowledge construction (e.g., [4, 66, 1]).

One more aspect of ecologies can be found with a network perspective – the roles and positions that support the network structure. Roles emerge as actors take on specific patterns of topic, social, and/or conversational interaction (e.g., the questioner, answerer, joker, social support provider, norms manager, administrator), and/or occupy certain important positions in the network (e.g., central actors who receive a lot of questions or provide a lot of answers; [11]). Somewhat different in open, online environments is the way roles can swap regularly – each new question defines a learner, whether this is their first question or their 100th. Similarly, each answer defines a teacher, particularly as they adjust explanation to craft the appropriate response for the question.

How and what *roles* emerge in open, online learning has not yet received a systematic analysis in the context of open learning environments. Yet, many different kinds of roles are emerging and identifiable in online learning environments. In a formal online learning setting, Montague [52] identified *learner-leaders* who take information, experiences, and opinions from inside and outside the learning context in an iterative process of learning and leading; in a community of practice for teachers, Preston [58] identified *braiders* who weave together others' posts to create a synthesis. *Moderators* are identified and invited based on in-network participation and given technical privileges to manage adherence to norms and site content [23]. In some sites, *experts* are identified based on their contributions, including those who provide good answers to questions (e.g., earning points in Stack Overflow, karma in Reddit), and researching in-group conversations to find previous answers (e.g., the FAQ finder in Reddit). In social networks, roles appear as patterns of common relations, and network analysis may identify roles before they are formally recognized. Further study can examine what roles are emerging and how these specifically support learning goals.

The two network perspectives discussed above are synergistic, each addressing different aspects of open, online learning: the egocentric view of personal learning and knowledge networks, the whole network view of group interaction and community practice, and the networked view of the collective or disciplinary space. The emphasis of a social network approach is to examine what patterns and roles are present, rather than those designated on an organization chart. Thus, this method responds well to finding the 'unpredictable' in informal learning. It is well suited to observing what kinds of relations and ties build network structures, where roles emerge, and where established roles no longer follow or need to follow traditional practice. (For more on applying a social network perspective to online learning and learning analytics, see [32, 40]).

SUMMARY

The increasing reach of social media, and its support of sites for learning opens up questions of how learning happens in these open, online spaces. Approaching open, online learning as a form of informal learning highlights the role of conversation in creating and maintaining the self-organizing structure of learning sites. This paper addressed the importance of participation through conversation as an essential element of online learning spaces, and how participation has different stages and extent depending on individual status in the site, and the relevance of the site to individual's personal learning networks. Attention to conversation leads to applying techniques such as content analysis and automated coding as means of identifying and evaluating the range of interactions that sustain learning in different communities. Conversational topics represent the network relations and ties that support a network of users, and build structures and roles that support persistent communities. While many social media provide ephemeral, just-in-time answers to questions, recorded interaction permits searching within site history to support the process of knowledge exchange and authentication. There is much yet to understand in how and why individuals choose to participate and collectively address knowledge spaces, and this chapter has introduced just a few ideas on how to begin addressing informal learning in social media.

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Chapter 17: Institutional Implementation of Learning Analytics - Current State, Challenges, and Guiding Frameworks

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ABSTRACT

Since its emergence, the field of learning analytics has proposed that educational institutions can and should make better use of learner data to optimize learning and learning environments. A range of social, political and economic forces have also encouraged educational institutions to consider system-wide implementations of learning analytics. In spite of a decade of optimism and interest, however, very few examples of effective institutional LA implementation exist, and evidence of positive impact on learning is sparse. This chapter provides an updated summary of the growing body of literature exploring the challenges of making systemic change with LA in complex educational contexts. Proposed frameworks for guiding institutional LA implementations are reviewed, and work describing use of the most promising – the SHEILA framework – is outlined in more detail. The need for attention to complexity leadership and institutional logics is noted as a focus of recent work, and emerging issues are highlighted: a critical need to expand the literature documenting evidence of real impact on learning, a need for institutions to make use of reliable LA evaluation strategies, and the need for critical consideration of how and if LA can also benefit learners beyond the traditional higher education contexts of the wealthy North.

Keywords: Learning analytics, implementation, institutional, evaluation, complexity

Over the past decade, researchers, analysts and theorists have increasingly argued that higher education should harness the data exhaust from educational technologies with analytics, in order to better understand and optimize learning and learning environments across many dimensions [47]. Learning analytics (LA) is focused on the learner and on learning environments. Its many approaches make use of data from learning management and student information systems, as well as a wide range of additional tools and technologies that may be employed in teaching and learning. It explores learner choices and behaviors in a variety of learning contexts, and its measures of 'success' are educational: student success is typically represented by metrics of 'improved learning' (or improved 'achievement'). Table 1 summarizes what are believed to be the core affordances of learning analytics, illustrating the range of educational stakeholders and purposes that different approaches to learning analytics may serve.

1 BACKGROUND: THE LEARNING ANALYTICS IMPERATIVE

In principle, then, learning analytics offers institutions new approaches to understanding the activities, choices and behaviors associated with effective learning, and ideally can indicate ways of leveraging this new knowledge to optimize educational systems [6, 10].

As Ferguson [21] and others have outlined, an array of forces have coalesced in recent years that have pushed educational institutions to think about system-wide implementations of learning analytics, including pressure to 'do better' for their diverse learners (often with reduced resources), and some evidence that learning analytics may feasibly support these goals. Technological advances have made the generation, capture, storage and analysis of 'big data' faster and easier. Shifts in both educational approach and educational needs (for example, increasingly diverse learner audiences) have prompted greater integration of data-generating technologies into teaching and learning. National and regional governments are increasingly concerned about the quality of their educational systems, both in relation to their own economic development, and also to the extent that it influences their standing on the global

Table 1: Affordance of learning analytics for educational institutions (adapted and updated from [49]).

Increased formative feedback to instructors. LA can help close the instructional loop [13] by allowing instructors to identify components of their courses – online or in class – where students are struggling or failing to grasp key concepts. Realtime feedback can allow just-in-time teaching (see for example, [17]; slower reflective feedback can allow cycles of improved learning design (see for example, [46].
Empowerment of students. Giving students metrics about their own progress and their progress relative to peers can assist in development of self-directed learning skills [17] and metacognition [75], improve motivation, and help them identify areas for improvement (see for example, [24].
Illumination of curriculum connectivity. We sometimes think of courses/modules as stand-alone units. LA can help departments and committees better understand their programs and support effective learning by, for example, mapping prerequisites or common routes leading to different majors specializations [32, 58].
Improved curriculum alignment. Programs and institutions are increasingly being challenged to ensure that courses (assessments, learning outcomes) align constructively with desired graduate attributes/competencies [61]. Emerging analytics methods can map and track student progression through courses in pursuit of identified graduate attributes (see for example, [33])
Improved assessment of learning. Considerable evidence supports the argument that end-of-term summative assessments are a poor approach to measuring actual learning. LA supports a range of alternate and complementary assessment practices – practices that make better use of the rich array of educational data now available – that may well offer more effective approaches to improving learning, especially processes that reveal development of student understanding over time [51].
Improved evaluation of teaching. Garrison, Anderson, and Archer [26] identified 'teacher presence' as a critical component of high quality learning environments in their 'Community of Inquiry' model – a model of high quality learning environments now well-supported by empirical studies [27]. Clearly, teaching forms part of the 'environment in which learning occurs' [47], and yet, we have only poor metrics for evaluating teaching. LA, used sensitively and carefully, may help educational leaders understand the quality of teaching in their courses.
Evidence to inform academic planning. Which programs show potential for growth? Which appear to be in decline? Can we identify new trends and patterns revealing new areas of learner interest or new career pathways? Predictive analytics can assist with many areas of planning, from faculty recruitment and curriculum development, to student recruitment and facilities management.
Development of 'early alert' systems. Which students are at risk of failure? An increasing body of evidence indicates that predictive models developed using data from LMSs and other learning technologies, in combination with student academic history and demographic data, can indicate, earlier, which students may be in need of additional academic support [8].

stage. Meanwhile, sectors such as marketing, sports, retail, health and technology have embraced analytic methods and demonstrated their potential to enhance systems and outcomes [54]. These latter authors have argued that, "[i]n a big data world, a competitor that fails to sufficiently develop its capabilities will be left behind...Early movers that secure access to the data necessary to create value are likely to reap the most benefit" (p. 6).

The sense of urgency is palpable. LA are proposed to offer new, far-reaching and sophisticated insights into teaching, learning, the learner experience, and educational management activities that were previously unimaginable [3]. In this New (Educational) World context of increasingly constrained education budgets and increased focus on quality and accountability [50], it is perhaps not surprising that institutions are starting to see learning analytics as not just a 'nice to have' option, but, rather, a pragmatic and ethical imperative, and that some are embracing Slade and Prinsloo's [69] assertion that "[i]gnoring information that might actively help to pursue an institution's goals seems shortsighted to the extreme" (p. 1521).

1.1 INSTITUTIONAL IMPLEMENTATIONS: CURRENT STATE

Against this backdrop, every Horizon Report [1] published since 2012 - an annual publication that seeks to identify key educational technology trends and developments - has optimistically listed LA as an emerging technology on the 'mid-term time-to-adoption horizon' (3-5 years or less until adoption). And yet, education still lags behind other sectors in harnessing the power of analytics [54] or demonstrating impact. Very few well-developed examples of LA deployment at scale across educational institutions exist, and even fewer credible studies can be found in the peer-reviewed learning analytics literature of demonstrated impact on learning or student success at scale [22, 73].

Table 2 offers a selection from the small number of available case studies of institutional LA implementations in higher education, though it should be noted that their inclusion here does not necessarily indicate that empirical evidence exists to demonstrate positive impact on learning or learner success, or that the implementation is still in use.

The few examples of institutional learning analytics implementation that do exist – and the early benefits they reported (see, for example, [2, 44]) – are regularly held up as models to follow, making colleges and universities worldwide increasingly anxious to embrace the LA wave. By 2012 up to 70 percent of EDUCAUSE member institutions reported that learning analytics implementation was viewed as a major priority by at least some departments, units, or programs; 28% reported that analytics was a major priority for their entire institution [5]. However, regular surveys have found that in spite of these ambitious goals, most institutions remain mired at "Stage 1" of a five-stage implementation process: "Extraction and reporting of transaction-level data" [31]. Yanosky & Arroway's 2015 [76] analysis of 'analytics maturity' in US higher education institutions demonstrated that little had changed since 2012, and that institutions were still struggling to realize the potential of LA. And as Gasevic, Tsai, Dawson, and Pardo [28] have described, even in institutions who have reported successful LA adoption, "achievements tended to be short-term victories, such as experience-gain, cultural change, infrastructural upgrade and a better understanding of legal and ethical implications."

It appears, then, that bridging the gap between LA vision and reality is a challenge for most educational institutions. What is holding us back?

2 CHALLENGES AND BARRIERS: NUMBERS ARE NOT ENOUGH

In an early study, Macfadyen and Dawson [50] undertook a case study of LA impact in a large research-intensive university. The authors had hoped that LA provided to decision-makers would "provide compelling data that would generate the sense of urgency necessary to motivate broad scale institutional change associated with learning, teaching and technology" (p. 151). Instead, they discovered that simple provision of analytics was insufficient to inspire and motivate innovation and institutional change – a realization that prompted a deeper investigation into the challenges of systemic adoption of an innovation like LA.

Surprisingly, the challenge of moving from evidence of good educational practice to effective action is not new. As early as 1979, McIntosh bemoaned the inability of her education research unit (at the UK Open University) to have any impact on major problem areas [56], even after providing educational leaders with detailed findings drawn from research that should have usefully informed decision-making. A growing number of studies have explored this challenge in the LA era, and have examined and enumerated a wide range of barriers and challenges to the implementation of institutional analytics [15, 23, 48, 51, 68, 72]. Table 3 below summarizes barriers to learning analytics adoption identified in the literature.

3 TAKING INSTITUTIONAL CULTURE INTO ACCOUNT

As this growing list of recognized barriers makes clear, effective institution-wide adoption of LA calls for more than just increased technical and analytic capacity, and required attention to the many social and organizational elements of institutional culture in an educational institution [18]. Klein [43] quotes Thornton, Ocasio, and Lounsbury [70] to explain that institutional logics represent "the socially constructed, historical patterns of cultural symbols and material practices, including assumptions, values, beliefs, by which individuals and organizations provide meaning to their daily activity, organize time and space, and reproduce their lives and experiences" (p. 2). These logics or

[1] Educause. https://www.educause.edu/

Table 2: Selected institutional LA implementations in higher education.

Institutional LA Project	References
OU Analyse, The Open University, UK	[23, 39, 38]
Course Signals, Purdue University, USA	[2, 67]
Check My Activity (CMA), University of Baltimore, Maryland Campus	[24, 25]
Electronic Expert (E2Coach), The University of Michigan, USA	[40, 57]
Degree Compass, Austin Peay State University, USA (acquired by the Desire2Learn/Brightspace LMS software company in 2013)	[19, 74]
LATHEE, University of Cuenca, Ecuador, KU Leuven, Belgium	[9]

conceptualizations of LA shape how (and how effectively) LA are implemented and taken up by stakeholders. Recently, three significant studies undertaken in Australia [15], Europe [72] and the United States [43] have tended to confirm and extend this compilation of barriers and challenges, and highlight the significance and impact of diverging institutional contexts and logics.

In Australia, Colvin et al. [15] interviewed senior leaders from 32 of 40 universities about the implementation of LA in their institutions, and identified two distinct LA implementation profiles. Institutions clustered in the first profile, characterized as 'instrumentalist', typically identify LA as a technical solution to address a specific institutional challenge (such as student retention)and have typically employed a top-down leadership model to implement LA [18]. Their rapid LA implementations have quickly leveraged existing technical infrastructure, and made 'tools' available, but have given little or no attention to stakeholder engagement or capacity building. As a result, buy-in from learners and academic staff has been poor or non-existent. Institutions clustered under the second institutional implementation profile, characterized as 'emergent innovators', see LA as a process that may bring understanding to learning and teaching practices, and inform a continuous, iterative, dynamic and sustainable improvement of teaching and learning. Typically, institutions in this group have fostered a 'bottom-up' approach to LA adoption [18] and have sponsored more complex and localized implementations, and engagement with a greater diversity of stakeholders.

Tsai et al. [72] surveyed LA implementation in European higher education, interviewing and surveying senior managers in 83 institutions across 24 European countries. Similar to the Australian findings, these authors report two apparent 'clusters' of motivations underpinning institutional LA implementation: 'improving institutional performance or management' or 'enhancement of teaching and learning support'.

Finally, in the US context, Klein's [43] preliminary work has focused on elucidating the 'institutional logic' of LA use in higher education in relation to LA, with the goal of better understanding how LA may be shaping not just student learning, but also the structures, interactions, and goals of higher education. Klein conducted 55 interviews with members of state oversight agencies, technology vendors, and higher education organizations within a single state university system. Open coding of these interviews revealed three dominant logics – 'technocratic, managerial, and success' – which appear to align meaningfully with the two broad clusters of LA motivation/conceptualization identified in the Australian and European HE contexts.

While regional and contextual details vary, then, this collection of studies should alert us to the reality that institutional cultures, contexts and logics are critical forces that will shape the scope, nature, speed, scale, uptake and effectiveness of institutional LA implementation. All three highlight the continuing "tensions between innovation and operation" [72](p. 2842) that educational institutions must manage in the current era.

4 WHERE TO START? FRAMEWORKS AND GUIDELINES FOR INSTITUTIONAL IMPLEMENTATION

Surveying the barriers listed in Table 3 and the range of possible institutional conceptualizations of LA discussed above, it is clear that successful institutional adoption of learning analytics demands comprehensive development and implementation of strategies and policies to address challenges of learning design, leadership, institutional culture, data access and security, data privacy and ethical dilemmas, technology infrastructure, and a demonstrable gap in institutional LA skills and capacity [51]. It is not surprising, then, that even educators, managers, administrators and researchers convinced by the potential of implementing learning analytics are asking "Where should we start?" [28].

In the 1st edition of the Handbook of Learning Analytics, Colvin et al. [14] usefully surveyed existing models and frameworks proposed or developed to guide institutional LA implementation efforts. Table 4 now summarizes and updates this compilation.

Colvin, Dawson, Wade, and Gašević [14] characterized most of these frameworks as either 'input' or 'output' models. They are primarily descriptive, and highlight a focus on either assessing institutional 'current state of readiness' for LA implementation, or progress through proposed states of LA 'maturity'. The dimensions and themes they introduce are largely conceptual, and not backed up by empirical research. Most critically, the majority of these models offer little pragmatic guidance for institutional leaders, and little or no evidence is available

Table 3: Challenges to Institutional learning analytics projects (adapted and updated from [49])

Pedagogical	• Weak pedagogical grounding of LA technologies and implementation design [42]. • Disagreement about or inexperience with learning design • Divergent use of learning technologies or use of technologies with limited or inaccessible data • Differing beliefs about the virtues (or not) of educational technologies • Institutional commitments to academic freedom with regards to teaching practice that preclude data gathering or 'evaluation' • Lack of standardization in relation to learner assessment and evaluation • Fundamental philosophical disputes about the virtues of quantitative vs. qualitative approaches to understanding 'learning' or 'learner success'
Technological	• Use of learning technologies with limited or inaccessible data • Institutional data sets silo-ed in mutually incompatible databases and formats • Interoperability standards not implemented • Technological challenges relating to development of integrated reporting systems or data stores • Lack of awareness of limitations of data commonly used in learning analytics [28]
Interface	• Poor data literacy at all levels of an institution [72] • Non-intuitive, highly complex, or inaccessible analytic tools • Presentation of simplistic 'dashboards' that obscure or misrepresent nuanced meaning [30, 41] • Lack of necessary contextualization and customization of data [29]
Evaluation & assessment	• Heterogeneous definitions of "student success" • Focus on 'final grade' or 'graduation' as the only available/accessible outcome measures of 'learning.' (Some researchers propose that learning analytics offers potentially new approaches to assessment and evaluation – a not uncontroversial proposition. For further discussion see, [51])
Leadership	• No established institutional data governance structure (data quality, data management, data policies, business process management, and risk management surrounding the handling of data in an institution) • A long history of educational decision-making based on anecdote and tradition • Researchers and decision-makers may speak "different languages" • Decision-makers may lack familiarity with statistical and analytic methods and interpretation • No analytics champions at the senior leadership level • A need for complexity leadership [18]

Resource Support	• Costs associated with technological and human resources [5, 14, 72] • Missing human skills and resources across the highly interdisciplinary educational analytics domain. Demand for "deep analytical talent" may outstrip supply by 50% by the end of the decade [54] a demonstrable gap exists in institutional capacity for analytics [5]
Ethical	• No established institutional policies for ethical use of student data in the LA era • Inattention to key ethical questions and dilemmas surrounding collection and use of data about learners [69] – Purpose (and transparency) (Why is data being collected? To what end?) – Data ownership – Issues of consent, privacy, de-identification – Data handling and protection processes – The potential obligation to act on new knowledge
Institutional culture	• Institutional structures can limit progress with learning analytics as different units and teams defend their 'turf': processes, data and power • Lack of attention to institutional culture within higher education, lack of understanding of the degree to which individuals, and cultures resist innovation and change, and lack of understanding of approaches to motivating social and cultural change can seriously hinder innovation. For extended discussion see [50] • Insufficient engagement with all stakeholders, resulting in mistrust and lack of buy-in [20, 71] • Lack of recognition of the divergent institutional logics (motivations, conceptualizations) underpinning institutional LA implementation projects [15, 43]

Table 4: Frameworks and instruments designed/proposed to usefully guide institutional LA implementation

Framework	Purpose	References
Analytics Framework	Presents analytics capacity as a process of maturation from basic data querying through to predictive modelling.	[16]
Learning Analytics Framework	A generic design framework proposed to guide establishment of LA services.	[34]
ECAR Analytics Maturity Index	Allows institutions to assess maturity, readiness, and capacity for LA; Measures analytics maturity on six dimensions: process, culture, expertise, investment, governance/infrastructure, and data/reporting/tools.	[5]
Learning Analytics Sophistication Model	A five-stage model of institutional LA maturity that integrated analytic capability and systems deployment.	[68]
Organizational Capacity Analytics Framework	Maps actual institutional initiatives against a framework of seven action categories; Proposed to indicate migration paths for future practice.	[60]
Learning Analytics Readiness Instrument (LARI)	A diagnostic instrument that provides an institutional profile with readiness indicators for LA success; Can help determine strengths and weaknesses before a large-scale LA initiative is undertaken.	[1]
Model of Strategic Capability	Represents institutional dimensions as complex, dynamically interconnected and temporal. Provides empirical insights into the relationships between institutional contextual features and the outcomes of their learning analytics implementations.	[15]
ROMA Outcome Mapping Approach	Developed to support policy and strategy processes in complex contexts; A seven-step model focused on evidence-based policy change. Designed to be used iteratively, and to allow refinement and adaptation of policy goals and the resulting strategic plans over time and as contexts change.	[23, 51]
SHEILA Framework	Builds on and further elaborates the ROMA approach; Revised model can inform strategic planning and policies for LA adoption.	[71]
LALA Framework	Developed in Latin America; adapts the ROMA approach and provides detailed steps to identify the needs of different stakeholders, design, implement, and evaluate LA tools.	[64]
Barton & Court Model of Transformation	A model that builds on the pragmatic dimensions considered in earlier models, and considers actions required to develop a data-informed culture and bring about institutional transformation.	[4]

in the literature to detail their operationalization, adoption or effectiveness. The single current exception appears to be the 'process model(s)' [14] that have evolved from the ROMA model originally proposed by Ferguson et al. [23], discussed below.

5 THE SHEILA FRAMEWORK: A MODEL FOR INFORMING INSTITUTIONAL LA STRATEGIES AND POLICY PROCESSES

The SHEILA framework has emerged from the basic realization that educational institutions are complex adaptive systems [12, 35, 52, 59]. Like all complex systems, they are resilient, resistant to change, and tend to maintain their organizational structure and processes [11]. Change strategies aimed at only one or a few of their subsystems are unlikely to succeed. The wide-ranging and interconnected nature of challenges to institutional implementation of LA emphasizes that a systems perspective is critical for successful institutional implementation of LA (or indeed of any educational innovation).

In 2009, development scholars outlined the Rapid Outcome Mapping Approach (ROMA) [77] to help leaders bring about evidence-based change in complex contexts. Ferguson et al. [23] proposed that an adapted version of the ROMA model could act as a pragmatic, iterative and operationalizable framework to support and guide institutional LA implementation. [71] have subsequently taken up, refined and validated this framework under the auspices of a European research project: SHEILA (Supporting Higher Education to Integrate Learning Analytics) [2]. In their major study, this project team used the ROMA model to code and analyze interviews from interviews with senior managers from 51 European higher education institutions, to uncover the diverse challenges associated with each of the original 'ROMA dimensions' that institutions experienced, and to identify strategic approaches (key actions) that facilitated LA adoption. The renamed 'SHEILA Framework' (structure shown in Figure 1) now consists of "a comprehensive list of adoption actions, relevant challenges and policy prompts, framed in the six ROMA dimensions" (p. 9), and can be used to evaluate institutional readiness and initiate strategic and policy planning for early-stage adopters.

Moreover, while Ferguson et al. [23] outlined two successful case studies of institutional LA implementation that appeared to have evolved using a ROMA-like systemic approach, Tsai et al. [72] have now detailed a diverse set of European higher education case studies to illustrate the utility of the ROMA/SHEILA framework as an iterative analytic tool for examining existing LA practices, refining strategies and updating policies. At time of writing, The SHEILA Project team has developed and launched a web-based SHEILA Framework web tool [3] and associated tools and materials to allow educational institutions to build a custom framework for their own context, and a

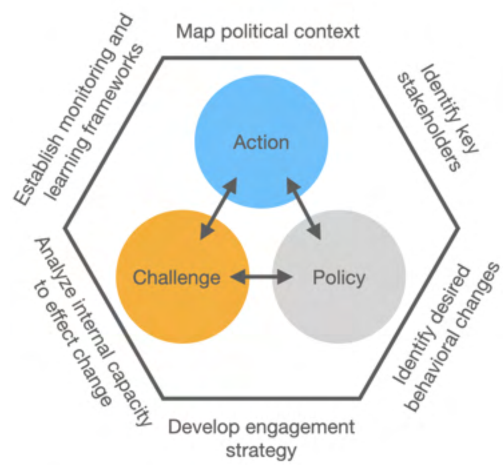

Figure 1: The SHEILA framework structure [71]

MOOC [4] has been launched to train educational leaders in its use. A number of SHEILA Framework institutional use cases describing the application or value of the framework have now appeared in the LA literature [9, 36]. And a multinational and multi-institutional team of researchers has initiated Project LALA [5] whose goal is to adapt the SHEILA Framework for use in the context of Latin American Higher Education Institutions (HEIs) [53].

At present, then, it appears that ongoing and published work emerging from the recognition of the need for a systemic approach and the development, implementation and adaptation of the ROMA/SHEILA Framework may be starting to address the lack of empirical studies of LA implementation, and helping to bridge the persistent gap between LA research and practice.

6 NEXT STEPS? PERSISTENT CHALLENGES, EMERGING THEMES

6.1 The Importance of Complexity Leadership

While earlier studies and frameworks have emphasized the need for, and importance of, committed and knowledgeable senior leadership who can champion institutional LA transitions, some more recent research has begun to explore the need for 'complexity leadership' [37] or 'distributed leadership' [7] models in such complex contexts. Recognizing the systemic complexity of educational institutions, Dawson et al. [18] and Gašević et al. [28] have explored approaches to leadership that may better support both 'instrumental/top-down' and 'emergent innovator' approaches to LA implementation. Dawson et al. [18] argue that new models of educational leadership, informed by complexity leadership theory, are needed in the LA era, to help institutions "move on from small-scale course/program levels to a more holistic and complex or-

[2] http://sheilaproject.eu
[3] https://sheilaproject.eu/sheila-framework/create-your-framework/
[4] Learning Analytics in Higher Education, https://edge.edx.org/courses/course-v1:UC3Mx+IT.2x+3T2019/about
[5] https://www.lalaproject.org/

ganizational level" (p. 236) of LA implementation. These authors argue that effective complexity leadership is critically important in supporting integrations of innovations such as LA into the social system of an organization that will lead to acceptance and action.

6.2 The Need for Evidence of Impact

Numerous authors across the decade have pointed to the persistent lack of 'evidence of impact' of LA on learning and learner success – especially at the whole-institution level; several of the large-scale studies discussed in this chapter have reported 'lack of evidence' as a critical barrier to buy-in and institutional adoption of LA (see for example, [72]). Ferguson & Clow [22] have investigated this challenge in detail and highlight that as yet little evidence of positive LA impact exists. Evidence that is available appears to be significantly skewed towards the positive, suffers from a variety of other weaknesses, and likely does not represent the full range of findings within the discipline. These authors point to the Evidence Hub [6] of the Learning Analytics Community Exchange (LACE) (now a SoLAR SIG) as a venue and project around which the LA community might organize to share evidence from countries and sectors that are under-represented, and identify gaps in the current evidence. They characterize the need for more and better empirical evidence as a moral and scientific imperative that is absolutely critical for validating the field of LA as a whole.

6.3 How Can We Evaluate LA Implementation?

At present, even institutions that self-report some adoption of LA typically have no monitoring or evaluation strategy in place [72]. The challenge of how to evaluate impact of institutional LA adoption is not insignificant in complex and diverse educational contexts and systems. Scheffel's Evaluation framework for learning analytics (EFLA) [65, 66] was developed with the goal of standardizing the evaluation of learning analytics tools. It appears to offer an approach to measurement and comparison the impact of learning analytics on educational practices, and contribute to the evidentiary literature in the field.

6.4 Integration Beyond Higher Education

The current LA research and implementation literature is overwhelmingly focused on higher education, with very limited focus on schools, workplace, informal, or other learning contexts [22]. Starting in 2018, SoLAR's annual international conference (Learning Analytics and Knowledge, LAK) has hosted an Analytics in Schools workshop [7], with the goal of building interest and community in the compulsory/K-12 education sector. Mazziotti, Kovanović, Dawson, & Siemens [55] report the launch of a new project to investigate LA implementation in schools and develop a theory-based and data-driven framework for guiding LA implementation in school contexts.

6.5 LA Implementation Beyond the Global North

As Pelánek [62] notes, most LA research currently takes place in the United States or other rich countries, placing this research in a specific context which unquestionably shapes both the research and its findings. One 2018 compilation [45] invited reflections on the potential for and value of LA implementation in 'The Global South', and included responses from scholars in South Africa, Mainland China, and developing countries in Southeast Asia and Latin America. To date, preliminary work from the LALA Project [53] appears to be the only literature available detailing efforts to implement LA for the benefit of learners in Latin American contexts. Prinsloo [63] cautions us, however, to give attention to uncritical assumptions that data use in the Global South is 'necessary for development', and the attendant risks of data colonialism, as LA providers increasingly focus their attention on 'new markets' in the South. We must as a field remain alert to the social, cultural, economic, methodological, technical, institutional, ethical and communal aspects that shape the complex educational systems of the many countries of the Global South, and expand our awareness that LA "should not promote one size fits all" [29] to acknowledge this global reality.

7 CONCLUSION

In summary, then, we might conclude that learning analytics remains a field that offers great potential to support educational development, but that the barriers to sustainable, impactful and ethical system-wide integrations are extensive and complex. Some selected examples highlight possible strategies for success: attention to institutional logics and cultures, use of effective process models to guide strategy and policy across multiple dimensions, and appointment of leaders who are demonstrably effective in complex contexts. As efforts to harness the power of LA evolve in the next decade, it will be critical to expand our literature to include rich descriptions of LA successes and failures [22], to focus more attention on investigating and documenting evidence of real impact on learning, to adopt reliable LA evaluation strategies, and to carefully and critically consider how and if LA can also support improved learning out comes beyond higher education contexts of the wealthy North

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[6] https://www.lalaproject.org/

[7] See for example: https://lak20.solaresearch.org/la-for-schools

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SECTION 3

Use & Systems

Chapter 18: Learning Analytics and Learning at Scale

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ABSTRACT

Learning at scale – an interdisciplinary field at the intersection of learning science and computer science – investigates learning environments with many, many learners and few experts to guide them. In recent decades, new large-scale learning environments have been announced with much fanfare about their potential to transform or "disrupt" traditional systems of formal schooling. This disruption has not occurred. Rather, new technologies are put to use in limited ways in specific niches of the existing education system, and the growth in their adoption is more steady and linear than abrupt or exponential. Though the societal impact of learning at scale has been uneven and incremental, the best hope for making the most of new large-scale technologies is through a continuous process of research and improvement. (The ideas in this chapter are expanded on in [24]).

Keywords: Learning at scale, learning analytics, peer learning, adaptive tutors, massive open online courses, design-based research, experimental research

INTRODUCTION

Many hoped that the massive volumes of fine-grained, global-scale learning tracking data, when combined with new forms of computational analysis, would lead to data-driven breakthroughs in learning science or instructional design (See for instance, [15]). This dream has not come to fruition. To date, learning at scale research has led to some useful insights on what might be called "educational policy analytics" – studies of how learners from different life circumstances use learning technologies differently – and "education behavior analytics"—how people click and act in online learning platforms. But research insights about learning—about changes in human cognition or capacity – from studies of large-scale technologies have been far more limited. The most promising possible future for learning analytics in learning at scale will not come from accumulating larger or more fine-grained troves of user data, but from research studies that use design-based or experimental methods to study systematic variation in competing approaches to effective design of large-scale learning [26].

In what follows, I address four questions, 1) What is learning at scale? 2) How has learning at scale changed the nature of education? 3) What has learning analytics and related research revealed about learning at scale? And 4) What are the possible futures for design and research in learning at scale?

1 WHAT IS LEARNING AT SCALE?

The ACM Learning@Scale 2020 conference home page offers a useful summary of the field:

> L@S investigates large-scale, technology-mediated learning environments that typically have many active learners and few experts on hand to guide their progress or respond to individual needs. Modern learning at scale typically draws on data at scale, collected from current learners and previous cohorts of learners over time. Large-scale learning environments are very diverse. Formal institutional education in K-16 and campus-based courses in popular fields involve many learners, relative to the number of teaching staff, and leverage varying forms of data collection and automated support. Evolving forms of massive open online courses, mobile learning applications, intelligent tutoring systems, open courseware, learning games, citizen science communities, collaborative programming communities (e.g. Scratch), community tutorial systems (e.g. StackOverflow), shared critique communities (e.g. DeviantArt), and countless informal communities of learners (e.g. the Explain It Like I'm Five sub-Reddit) are all examples of learning at scale. All share a common purpose to increase human potential, leveraging data collection, data analysis, human

interaction, and varying forms of computational assessment, adaptation and guidance.

The diverse learning environments described above can be categorized into three genres defined by the question, "Who sets the sequence of learning activities?" These sequences can be created by instructors – as in the case of MOOCs, by algorithms – as in the case of adaptive tutoring software, or by peers – as in the case of distributed learning networks. Each of these genres of instructor-guided, algorithm-guided, and peer-guided large-scale learning technologies has a history, a research literature, and a track record of success and failures in formal educational institutions. Each genre also uses a common set of core technologies, and they reenact pedagogical debates that have deep roots in the history of education. Figure 1 summarizes the three genres, and then I discuss the genres, their technologies, and their pedagogical roots below.

The massive open online courses (MOOCS) created by elite universities are examples of instructor-driven learning experiences [10]. Instructors design or select lectures, readings, and activities that form a knowledge base for student learning. Learners are assessed by tools and systems designed by instructors, that can range from simple multiple-choice questions to complex systems for evaluating computer programming assignments. The learning experiences in the course are arranged in a particular order, from the Shang Dynasty to the Era of Mao or from "Hello World" to recursive algorithms, that are selected by the instructor. A student may be free to traverse this material in her own way, and she might help a peer along the path, most students generally proceed along the main path laid out by instructors.

Adaptive, large-scale learning environments are those where each item in a learning sequence is selected by an algorithm or other system on the basis of student performance in previous parts of a learning sequence. These kinds of learning experiences are often called adaptive tutors or computer-assisted instruction, and Khan Academy offers a useful example. While Khan Academy is best known for Khan's video lectures, when Khan Academy is used in schools, students spend 85% of their time doing practice problems [21]. These problems will be familiar to anyone who has ever completed a worksheet in mathematics class. They pose a question, and students have to provide a correct answer by inputting an equation, selecting a point on a Cartesian plane, ordering a series of numbers in line, selecting from a list of multiple-choice options, and so forth. The problems are organized into topics, such as dividing fractions or solve quadratic equations.

Unlike a paper worksheet however, the order of problems that a student encounters depends upon her performance on each problem. Within a class of problems – such as multiplying fractions – some problems are easier (multiplying by ½) and some are harder (multiplying by 1/13). Students are given an initial problem, and if the student gets a problem right, an algorithm assigns a more difficult problem. If she gets it wrong, the system assigns an easier problem, perhaps along with some form of remediation, like a hint or link to an explanation. These systems are often called adaptive, since they can increase or decrease in difficulty and provide specific remediation based on the performance of the student. In nearly all MOOCs from edX or Coursera, every student receives the same number of problems and assignments which are presented in the same order. Students using Khan Academy and other adaptive tutors are offered a set of assignments that are dynamically adjusted for the individual student.

Peer-driven learning environments – like those proposed by Sugata Mitra in the School in the Cloud – are where participants can offer instruction, examples, comments and feedback, and users can follow each other, and form subgroups and networks. Mitra argued that if learners were organized into small groups, with access to the learning resources of the internet and some minimal on-demand mentoring and coaching (he proposed using a network of British pensioners in his trials), then students could learn any topic of any complexity [2, 20]. The original Connectivist-inspired MOOCs, provide another example of a peer-guided large-scale learning community. Participants created their own blogs, social media accounts, and other sites on the open web where they responded to course prompts and to each other. Instructors used the course home page and other technologies to aggregate copies of these diverse contributions into one central location, but at their most successful, peer interactions were the driving force of cMOOCs [19].

The most prominent peer-driven learning environment in K-12 schools is the community organized around the Scratch programming language, developed by the Lifelong Kindergarten Lab at MIT [29]. Scratch is a block-based programming language where the young and young-at-heart can learn to program by dragging "blocks" with executable code instructions into place with other blocks, rather than by writing programming syntax with specifications for spacing, semi-colons, variable names and so forth. By default, all Scratch programs exist as projects, all projects are publicly viewable and openly-licensed, and all projects can be forked and remixed as new projects, so that sharing and community are integral parts of the experience of using the Scratch programming language. In these communities there are designers and leaders—Mitch Resnick, Natalie Rusk, and many others in the Lifelong Kindergarten Lab create the environment for Scratchers to work and learn, they highlight projects on the Scratch website and social media, and cultivate community. This community then creates a wide array of projects, tutorials, guides, and other sub-communities, and learners in the Scratch community then choose for themselves how they navigate this web of opportunities for practice and learning.

The three genres of learning at scale – instructor, algorithm, and peer-guided – typically draw on different technologies, different pedagogies, and different research traditions. Instructor- and algorithm-guided large-scale learning environments typically depend upon some form of autograder to evaluate learner performance; by contrast

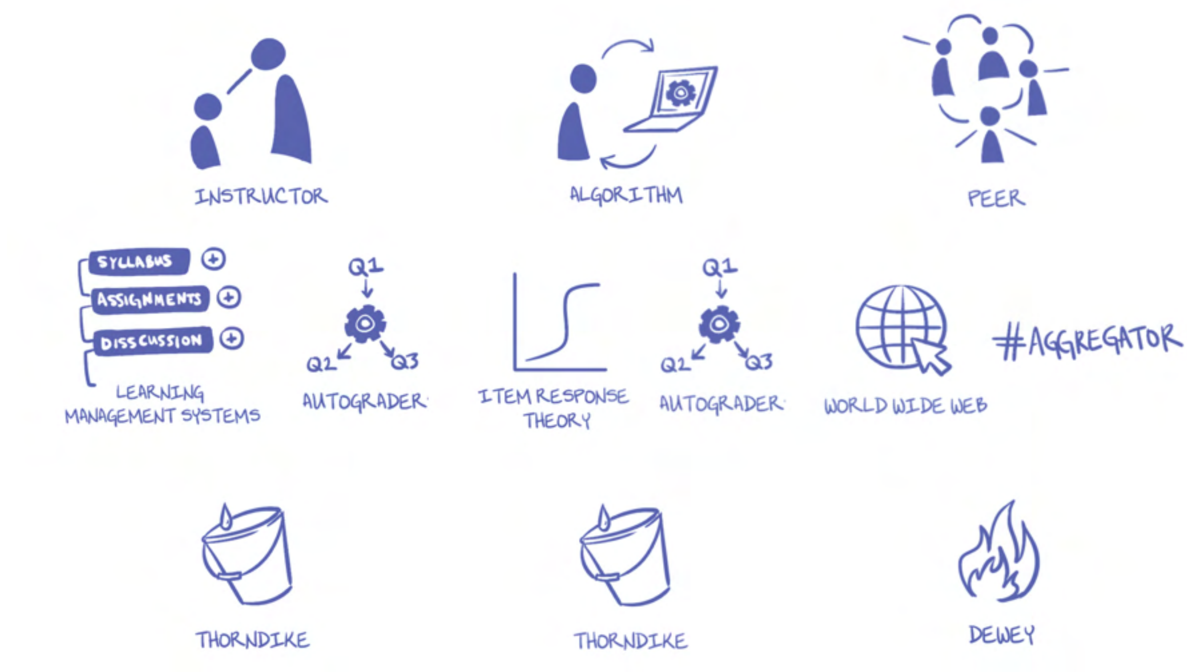

Figure 1: Genres of learning at scale.

peer-guided learning environments typically eschew formal assessment and focus on discourse and peer feedback. Instructor- and algorithm-guided genres typically take pedagogical inspiration from instructionist approaches to pedagogy, in the tradition of Thorndike [34] or more recently [33] where experts disseminate knowledge to be absorbed by novices. In the peer-guided genre, design is more often inspired by pedagogical philosophies emphasizing learner discovery and apprenticeship, like the Constructionism [6] at the heart of the Scratch programming community or the Connectivist [32] ideas that inspired the earliest massive open online courses. The three genres are also often studied by different research communities: scholars interested in adaptive tutors attend the International Conference on Artificial Intelligence and Adaptive Education or Educational Data Mining conference; those interested in instructor-guided learning at scale attend eMOOCs or Learning with MOOCs; and researchers studying peer-guided learning communities attend the Connected Learning Summit or the Constructionism conference.

Despite these differences, the three genres share much in common: they face a similar set of challenges in adoption in formal learning environments, and a common underlying data structure to track the activities of learners.

1.1 How has learning at scale changed the nature of education?

For those with access to global online networks, it is the greatest time in world history to be a learner. Never before have learners had such incredible access to resources, courses and communities of tutors and apprentices. Whether you want to learn to play guitar, brew beer, identify birds, translate Cicero, throw a javelin, intubate a trauma victim, integrate a function, detonate a bomb, program in Javascript, or become a better teacher, there are online classes, tutorials, forums, and networks full of people who are excited to teach and excited to learn. If you've ever signed up for an online class, downloaded an educational app, or watched a video about how to unclog a toilet, you are part of that network.

Yet, despite the extraordinary growth of informal online learning, changes to formal educational systems remain modest and targeted. Over the last twenty years, education technology advocates have promised dramatic changes in education systems. In 2008, Harvard Business School professor Clayton Christensen, with colleagues Curtis Johnson and Michael Horn [4], wrote a book called Disrupting Class about online learning and the future of K-12 schools. They predicted that in ten years – by 2019 – half of all middle and high school courses would be replaced by adaptive, self-paced online courses, and "the cost will be one-third of today's costs, and the courses will be much better." Udacity founder Sebastian Thrun argued that in 50 years, "there will be only 10 institutions in the world delivering higher education and Udacity has a shot at being one of them" [17]. Sugata Mitra went further to argue that in an internet-connected world, schools weren't even necessary:

> "Thirteen years of experiments in children's education takes us through a series of startling results – children can self organise their own learning, they can achieve educational objectives on their own, can read by themselves. Finally, the

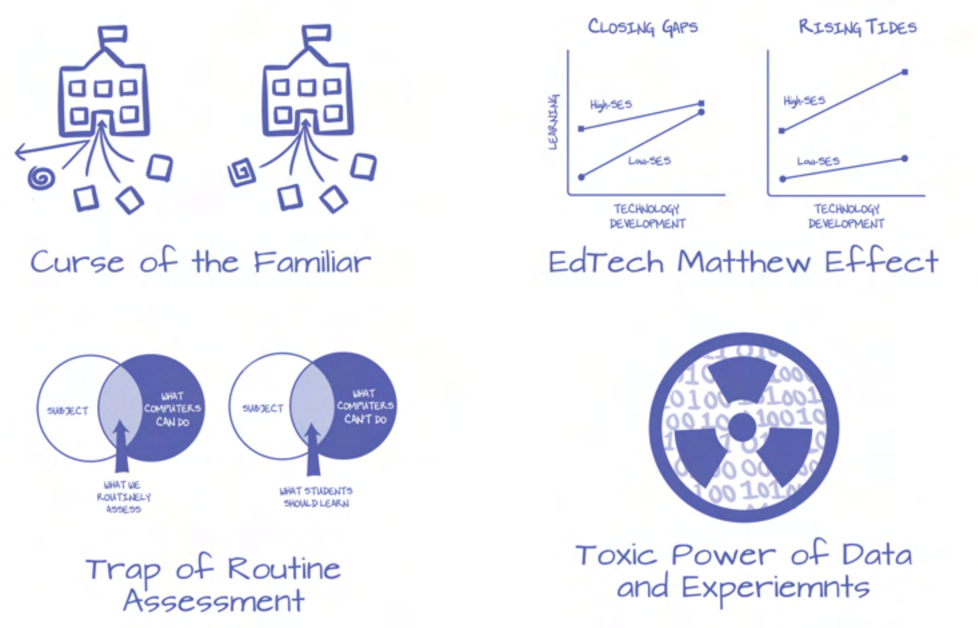

Figure 2: Four "As-Yet Intractable Dilemmas in Learning at Scale.

> most startling of them all: Groups of children with access to the Internet can learn anything by themselves" [20]

None of these predictions have come true, nor will they. The core misconception behind these predictions is that new technologies can disrupt, transform, or brush aside existing educational systems. This rarely, perhaps never, happens. Far more commonly, our complex, conservative educational systems domesticate new technologies, embedding them in existing routines in specific niches of the ecology of education.

One challenge to educational transformation is the "Curse of the Familiar" [23]. Educational systems can only readily adopt technologies that extend existing school practices. One of the most widely used educational websites in the world is Quizlet, which provides digital flashcards [8]. Tens of millions American students use Quizlet every year, but digitizing flashcards doesn't change routines in schools. Things which digitize existing practices can be readily adopted, but they provoke minimal changes in learning routines. By contrast, things which propose dramatic changes in learning routines are difficult to adopt. Early forms of Connectivist MOOCs offered a striking reinterpretation of learning practices in higher education, but many learners and instructors found their distributed, networked approaches to learning to be confusing [16].

Moreover, new technologies are typically only useful in specific subjects or disciplines. Both instructor-guided and algorithm-guided learning at scale technologies depend on autograders to computationally assess learner performance. Autograding technology, however is limited by what I call the "Trap of Routine Assessment." Computers are good at assessing the kinds of routine tasks that computers are good at doing, that we no longer need humans to do in the work force [27]. Autograders are good at assessing things with one right answer, or when a correct answer can be strictly defined by a set of decision rules. These are also the kinds of routine tasks that computers and robots can be programmed to accomplish. In math we have good autograders for computation, but not for explaining the reasoning behind computation strategies. In computer science, we have good autograders. In language arts, we have good autograders for the basics of decoding and pronunciation, but not for evaluating intrepretations of literature or poetry. The unevenness of our autograding technologies explains why large-scale learning technologies are more commonly found in some fields – STEM, computer science, early language acquisition – and not in others.

Like other education technologies, large-scale learning technologies typically disproportionately benefit the affluent. The "EdTech Matthew Effect" argues that like many sociological phenomenon, new technologies often accrue advantages to the already-advantaged [35, 28]. Morgan Ames [1] studied the roll out of One Laptop Per Child devices in Paraguay, and found that students who most deeply immersed themselves in the learning opportunities afforded by Scratch or Turtle Writer were those who had parents and families that had already introduced their children to learning opportunities with computers. MOOC researchers have consistently found that instructor-guided, large-scale learning depends on a well-developed set of self-regulated learning skills [11]. Already-affluent, already-educated learners are most likely to have had the opportunities to develop these skills, so MOOCs have not democratized education, but rather have accrued the bulk of their advantages to those who already had educational opportunities.

These common challenges help explain why the predictions of disruption and transformation from learning at scale have generally fallen flat. School systems are complex, technologies are uneven, opportunities are distributed inequitably in a highly-stratified society. Instead of dramatic transformations, we see specific technologies in specific disciplines used to the benefit of particular groups of users. If you are hoping that new technologies will be able to radically accelerate human development, the conclusion that change happens incrementally is probably a disappointment. But if you think that global human development is a game of inches – a slow, complex, maddening, plodding process with two steps back for every three steps forward – then the field of learning at scale offers one avenue for taking some of those forward steps.

1.2 What has learning analytics and related research revealed about learning at scale?

Across instructor-, algorithm-, and peer-guided learning environments, one of the unifying features of large-scale learning environments are the data and data structures that underlie these systems. At any given moment, a large-scale learning system needs to have a model of all possible actions that a learner can take – a model of the system – and a model of a student's state within this system. In Scratch, this might be all of the blocks assembled into a Scratcher's program at this particular moment; in a MOOC, this might mean tracking every assignment a student has completed to date and every assignment that is currently available but not yet completed. All of this data can be harnessed to create a complete record of what every learner has ever done within the system: a longitudinal record collected keystroke by keystroke and click by click, for millions of learners around the world. Large-scale learning environments are generating datasets that are orders of magnitude larger than what educational researchers have traditionally studied.

Coursera founder Daphne Koller [15] argued that these new sources would "turn the study of human learning from the hypothesis-driven mode to the data-driven mode, a transformation that, for example, has revolutionized biology." Since the founding of MOOCs, hundreds of millions of dollars have been spent on new courses, new platforms, and research efforts lead by some of the world's most accomplished computer scientists and learning scientists. Despite these efforts, Koller's prediction has not come to pass.

Researchers studying the vast new datasets from MOOCs have uncovered some useful findings about the demographics and behaviors of MOOC participants. For instance, despite an early rhetoric claiming that MOOCs could "democratize education," a number of studies have shown that people from more affluent countries and neighborhoods are more likely to register for MOOCs and once enrolled, more likely to complete them [9, 12]. Alongside these kinds of "educational policy analytics," much of the early research in MOOCs focused on correlations among behavioral measures. Deboer, Ho, Stump and Breslow [7] showed that a wide variety of learner inputs (videos viewed, problems answered, actions taken) correlated with each other and with outcomes like grade and earning a certification. Many studies published similar results, and I jokingly have described this line of inquiry as proving "Reich's Law," that students who do stuff do other stuff, and students who do stuff, do better than students who don't do stuff.

Two findings that go a step beyond Reich's law involve self-regulated learning, and the "doer" effect. Several MOOC studies found that successful learners showed evidence of proficiency with self-regulated learning, as measured by actions like reviewing prior material in the course [18, 11]. Given the very low levels of human supports available in MOOCs, these researchers theorize that proficiency with self-regulated learning is a prerequisite to success in MOOCs. Koedinger and colleagues [13, 14] at CMU showed in several studies that MOOC participants who engaged in problems and watched videos had better learning outcomes than students who only watched videos – a phenomenon they describe as the "doer effect." These are useful initial findings – that learners in courses without teachers need to be good students, and good students do problems and don't just watch videos—but they perhaps offer robust evidence for common sense, rather than new directions for the field of learning science. It turns out that researchers can collect terabytes of data about what people click without generating much new additional understanding of what's happening inside their heads.

Analytics researchers have also found it relatively straightforward to predict learner outcomes based on only a few initial weeks of user participation data [30, 38, 37]. Predicting who will drop out and succeed, however, is only useful to the extent that instructional designers can use that information to provide additional supports to struggling learners. To date, little research has shown how these predictions can be leveraged to improve student outcomes. Neil Heffernan, the principal investigator for the ASSISTments platform, an adaptive, math homework practice platform, once declared, "I now tell my students that no one is allowed to make a prediction without having some intervention planned to address the results of the prediction" [25]. Learning analytics without a linked intention to improve learning runs the risk of aimless fiddling.

1.3 What are the possible futures for research and design in learning at scale?

In his admonition to students, Heffernan anticipates one of the two sea changes in learning analytics research necessary for the field of learning at scale to advance. First, the case that learning science can be advanced by the passive, observational, cross-sectional study of massive datasets using advanced computational techniques thus far appears weak. Researchers need to be involved in designing studies that systematically introduce variation in instructional design to test the theory and practice of learning. In quantitative research traditions, this might look like randomized controlled trials that evaluate and compare differing instructional approaches. In qualitative research traditions, this might look more like iterative design-based research [31]. The massive, granular datasets collected by large-scale learning environments might prove especially useful in illuminating the mechanisms by which competing instructional designs might lead to better learning outcomes, but these large datasets need to be put in the service of design-based and experimental approaches, rather than more passive, observational, cross-sectional studies.

Second, the study of learning requires measures of learning. Most studies of large-scale learning platforms use measures and indicators derived from platform data, many of which are not well designed for tracking and evaluating learning. Studies of MOOCs use grades and certifications as proxies for learning, but many of these studies lack rigorous pre-test data (so it's not clear how much students are actually learning versus certifying pre-existing competencies) and many of the assessments that under-gird these grades and certificates are not well designed. In peer-guided learning environments, the open-ended nature of learning environments provides another kind of assessment challenge – what does it mean to measure learning across Scratch projects if the point of Scratch is for young people to create whatever they want? Clever manipulation of the underlying activity data is no substitute for attention to these challenging issues of measurement. (Colvin and colleagues [5] offer one model of studying learning with well-validated measures in several physics courses).

Similarly, many studies of large-scale learning are bound entirely within a single platform, but one of the core purposes of learning is to transfer skills into new domains. Studying this transfer, therefore, is vital to understanding the potential and limits of learning at scale. A few studies have investigated transfer of learning "beyond the MOOC." To evaluate the impact of a Functional Programming MOOC, Chen, Davis, Hauff, and Houben [3] examined GitHub log data requests to find evidence of MOOC participants (using the same usernames across platforms) deploying programming skills from the MOOC in projects. To evaluate the impact of a course on learning analytics, Wang, Baker, and Pacquette [36] evaluated how MOOC participants joined scholarly societies and submitted papers in the field. Napier, Huttner-Loan, and Reich [22] studied how teachers adopted skills and practices from a MOOC about leading educational change. If one point of learning is to build human capacity to flexibly tackle future challenges, learning analytics will have to study students beyond learning platforms.

Contrary to predictions from the early days of MOOCs, the data collected by large-scale learning will not magically lead to a data-driven revolution in education science, but it still has potential to be a valuable resource in advancing learning science. The most promising future of learning analytics in large-scale learning will be interdisciplinary ventures conducted by joint teams of experts in substantive domains, in measurement and assessment, in design-based or experimental research, and in analyzing the granular data generated by large-scale platforms.

These efforts will not lead to the disruptive transformation of educational systems, but rather to steady, incremental progress in the field. Peer-guided learning technologies will be beloved platforms for devoted hobbyists – many, many children will get a brief introduction to computational creativity through Scratch, and a tiny handful will fall in love with the possibilities of the platform and blossom as programmers. Adaptive tutors will continue to find uses in educational systems in fields where human performance is amenable to evaluation by autograders, in fields like early language acquisition, mathematics, and computer science. Many students using adaptive tutors will learn a little more than they would have otherwise. MOOCs and other instructor-guided learning environments will primarily benefit those with the self-regulated learning skills to persevere through online learning with minimal supports; unfortunately most of the people who fall into this category are already-affluent, already-educated learners pursuing additional advanced credentials. In the status quo, large-scale learning is more likely to exacerbate educational inequality rather than to democratize education.

Learning analytics, learning at scale, and learning science as fields could all play a role in shifting this trajectory in a more positive, more equitable, and more promising direction. Such a shift would require embracing interdisciplinary research that recognizes the enormous complexity of iteratively improving systems that support learning at scale. It would require research that follows learners beyond online platforms and into the classrooms and workplaces where the transfer of skills can be observed and supported. It would require resisting the siren song of massive datasets and elegant, sophisticated post-hoc analysis, and reimagining large-scale learning analytics research in the service of more ambitious approaches to design-based and experimental research.

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Chapter 19: Data Literacy and Learning Analytics

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ABSTRACT

Data use, whether through traditional methods in education or more sophisticated techniques such as learning analytics and educational data mining, has emerged as an important part of educational practice. Foundational to the use of data is data literacy; that is, educators' ability to use data effectively and responsibly. A construct called data literacy for teachers has been operationalized and differs from assessment literacy to include the many diverse sources of data that educators now encounter. However, an issue, even with traditional data use is the extent to which educators have sufficient data literacy. The introduction of learning analytics presents the need for even more sophisticated data use capacity that may or may not be practical in most K-12 educational settings. This chapter explores the intersection of data literacy and learning analytics, and in doing so draws parallels between data use in the K-12 and post-secondary education settings, where data-driven decision making and learning analytics have traditionally been positioned. It provides a review of data literacy and the technologies that support data use. It discusses the practical challenges and constraints to transforming more traditional data use to include learning analytic strategies and how data literacy applies. The chapter then looks toward the opportunities and possibilities made possible by the sophisticated data use in learning analytics.

Keywords: Data literacy, accountability, continuous improvement, practical implications, challenges, opportunities

This chapter provides a link between data literacy and learning analytics (LA). It is our perspective that data literacy is fundamental to LA and educational practice, with LA being a sophisticated form of data-driven decision making (DDDM). The chapter provides a brief introduction to DDDM and data literacy and then a link to LA. It outlines the technology that supports DDDM, including implementation issues and challenges. It concludes with opportunities for DDDM and LA for research and practical next steps.

We first provide a foundation for the chapter by defining three key concepts.

- DDDM – the systematic collection and analysis of different types of data to inform decisions that will enhance students and schools [18].
- Data literacy or data literacy for teachers (DLFT) – "is the ability to transform information into actionable instructional knowledge and practices by collecting,, analyzing, and interpreting all types of data (assessment, school climate, behavioral, snapshot, longitudinal, moment-to- moment, etc.) to help determine instructional steps. It combines an understanding of data with standards, disciplinary knowledge and practices, curricular knowledge, pedagogical content knowledge, and an understanding of how children learn" [17, p.2].
- LA – the use of measurement, data collection, analysis, and reporting to understand student learning and the learning environment through digital learning tools and technologies, intelligent data, and analytic models [3, 24].

Much has been written about DDDM, especially data use for accountability for schools and districts to measure progress as mandated by state and federal agencies. More recently the focus of DDDM has been on continuous improvement, although critics view accountability inextricably linked to data use. The purposes of DDDM is to provide an evidentiary base from which educators can make factual decisions to inform practice. Regardless of purpose, it is essential that educators have the skills and knowledge to use data effectively and responsibly; that is, they must be data literate [28, 29, 30]. Mandinach and Gummer developed a construct, DLFT that defines the skills, knowledge, and dispositions educators need to be data literate.

It is our position that data literacy must become a foundational skill set for all educators (and students too) to be able to use the plethora of data that inundates educators today to inform their practice. With the introduction of LA, the DLFT construct needs to generalize to many educational roles and to extend to more sophisticated data use which may or may not be practical and realistic in most educational settings. This chapter explores this possible expansion of DLFT to more sophisticated data use, beyond what Mandinach and Gummer [29, 30] and Beck and Nunnaley [5] envision for a continuum of data expertise. This extension reflects recent writings about DDDM in relation to LA [3, 7, 41] where the authors note some differences, intersections, and requisite skill sets. There are salient components applicable to data literacy and its potential extension to the K-12 environment. First, these concepts do not pertain to the typical educator, especially not teachers, and peripherally to administrators. Bowers et al. [6] and Bowers [7] discuss educational quantitative analysts, research specialists, data scientists, and to a lesser degree, practicing administrators, all of whom need advanced data analytical skills and statistical literacy. These classifications also interface with sophisticated data technologies that are likely to be more advanced than what is typically available in most schools.

Second, even the inquiry cycle, or as [3] call it, the data analytics model in education, is more advanced than those described in the DDDM literature [17, 18, 29, 30, 37]. LA relies on historical data, predictive modeling and mathematical algorithms, going beyond descriptive statistics to construct data visualizations. Therefore, there is a need to develop new forms of expertise with increased sophistication. In typical education settings, there is a continuum that transforms data into information and then to actionable knowledge with a feedback loop [31]. The inquiry processes are similar. The cycle of Means el al. contains the following components: plan, reflect, implement, assess, and analyze data, reflect [37]. The Hamilton et al. [18] cycle contains: collect and prepare student learning data; interpret data, develop hypotheses to improve student performance; and modify instruction to test hypotheses. Mandinach and Gummer's [29] inquiry cycle specifies the skills and knowledge needed in the five following components: identify a problem of practice, use data, transform data into information, transform information into a decision, and evaluate the outcome of the decision. In contrast, Agasisti and Bowers [3] LA model involves: data collection and acquisition, storage, cleaning, integration, analysis, representation and visualization, and action(s). Figure 1 illustrates some of the differences between the inquiry model in DDDM and the LA approach. The Figure represents an amalgam of models that exist so that they capture the essence of the many existing processes. However, the standard DDDM model infers that the impetus of the DDDM process is identifying an issue or posing an educational question. Although many of these steps can be found in DLFT, they are focused on high-level data skills and predictive models, and less so on the translation into just-in-time interpretations, actions, and decision-making.

Third, and by extrapolation, the statistical and technical skills needed for DDDM and LA differ as well as their level of complexity. Bowers [7] defines general categories of skills and topics for four job categories. There is little overlap with the traditional skills, even for administrators whose preparation involve more applied quantitative methods courses [7]. Although there has been no specific definition of the data skills for leadership in the DDDM literature, one can extrapolate from DLFT by modifying the fourth component, which focuses on pedagogical action to create administrative actions instead. The focus then would be on the decision-making skills, not research methods. Take for example what Bowers calls the data scientist, the focus is on educational data mining, LA, programming, design-based research, and technology and instruction. Only the last category, instruction, overlaps with DLFT. It is safe to say that data literacy in DDDM differs in how it is viewed and emphasized in LA and therefore leaves open opportunities for future research and development.

Fourth, DDDM and LA differ in a heavy reliance on technologies. The kind of analyses required in LA necessitates sophisticated technologies. Educational settings do have technologies [32, 50] such as learning management systems (LMS), data warehouses, assessment systems, data dashboards, and early warning indicator systems, but for many schools, even these technologies are too big, too expensive, or not practical. There is a push toward personalized learning environments that do have many technologies but again, this is impractical for many schools [9, 14] (Pane et al., 2017).

REVIEW

We documented central differences between LA and DDDM. This section reviews areas common to LA and DLFT practices to examine the extent to which LA theory and practice can be applied to and extend current DDDM and DLFT strategies.

Shared Purpose

LA and DDDM focus on the learner and learning. They share similar purposes to apply analytic strategies to improve learning. In LA, "analytics" refers to "software tools, machine learning techniques, and algorithms used for capturing, processing, indexing, storing, analyzing, and visualizing data" with the aim of improving learning and the learning environment [11, p.19]. Fundamental to DDDM is the use of diverse data, including achievement and behavior, to inform decisions about instruction to improve student outcomes. LA and DDDM function at the teaching and learner level to improve student outcomes. Both can involve decisions at all system levels [25]. For example, typical DDDM practices also can address: identifying student learning challenges; determining appropriate instructional responses; using parent and climate survey data to identify service needs; examining attendance, behavioral, and academic data to identify students at risk of being retained; and examining student course requests to refine instructional program offerings; [2, 33]. In this regard, the application of DDDM to multiple system levels

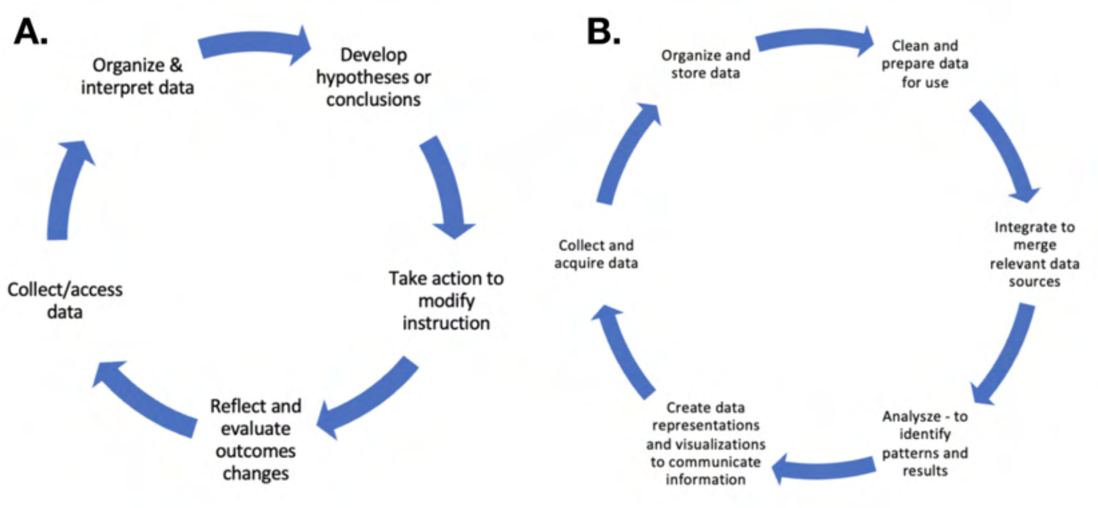

Figure 1: Comparison of the Standard DDDM Inquiry Model (A) and LA Model of Inquiry (B) [3].

integrates LA with academic analytics and institutional analytics [11, 24]. LA and DDDM are intended to guide action to achieve the desired effect on student learning but also inform policies and decisions at the systems level.

Reliance on Data Management Systems

Both LA and DDDM rely on the use of data systems to support the analytic process. LMS collect and house information about student learning activities that are central to LA. The widespread implementation of course management tools provides a range of information about student learning. These data often serve as a proxy for student engagement. LMSs also include test results, discussion board postings, group interaction, frequency and duration of access, and overall progress in a course. These data are used to understand learners' behaviors, engagement, and needs to improve student learning. Macfadyen [24] describes the benefits resulting from LA, including increased feedback to learning, enhanced student agency, better instructional coherence across courses; greater curriculum alignment, improved assessment of learning, and evaluation of teaching.

Likewise, the use of integrated data systems is common in K-12 settings. These systems enable educators to develop and administer assessments of student learning aligned with their instructional goals and content standards. Additional functionality can vary across school systems to include longitudinal data and predict future performance [52]. Data systems provide immediate feedback to teachers about student performance at grade, classroom, student levels according to overall or subgroup characteristics. Results can be used to support varied uses including identifying students' strengths and weaknesses, grouping students according to ability levels, and determining appropriate remediation or re-teaching strategies [38, 44]. According to Farley-Ripple et al. [16], the DDDM literature organizes educator responses along conceptual and functional approaches.

Implementation Issues

Implementing LA and DDDM practices often requires shifts in resource allocation, increased capacity, and institutional cultures that promote inquiry-focused mindsets. The LA and DDDM literatures suggest that similar issues and potential barriers exist. Both require the investment of considerable human and infrastructure resources. First, technology and software tools are required to capture student learning data, administer assessments, and support the varying statistical analyses. Training is needed to learn how to use the systems to support data-informed instruction. Staff need increased capacity and technical skills to analyze, interpret, and apply information to learning issues. These technical skills are coupled with the need to develop in-depth understanding of data and time to engage in this work. These challenges are well-documented [10, 19, 23, 29].

Developing human capacity is a key component in DDDM [22, 42, 51]. Daniel [11] notes the lack of capacity and need for professional development in higher education that addresses both the technical and pedagogical knowledge needed to support different LA stakeholder groups. Daniel extends this discussion to the importance of institutional culture in ways that address potential resistance and privacy concerns about LA practices.

The cultural shifts required at large, post-secondary institutions are also necessary in K-12 settings. The DDDM literature documents the importance of context and school administration in encouraging effective data use. Supportive administrative actions include articulating clear and shared goals, establishing cultures and environments that value inquiry, and structuring time for discussing and analyzing data [36, 42, 51]. Institutional messaging about DDDM can have a powerful influence on the extent to which educators can realize its potential. For example, in schools and districts with a heightened focus on accountability, learning and improvement becomes lost. This fundamental dichotomy in how educators approach DDDM is characterized by key differences in culture - improvement versus compliance [1]. DDDM in compliance-based cultures is frequently highly prescriptive, involves the identification of students often on the cusp of passing (e.g., bubble kids) or located in a specific performance range, may be rife with inappropriate data use, and reflects superficial forms of inquiry, often detached from instructional practice. Alternatively, DDDM in settings with improvement or inquiry-focused cultures is closely tied to teaching, embedded in instructional planning conversations, and is related to professional mindsets concentrated on improvement and learners [37].

CHALLENGES AND COMPLEXITIES

This section explores the challenges and complexities of DDDM in classrooms and schools, providing a reality check to implementation and the data literacy needed for effective data use. We explore several relevant topics including the data needed for DDDM, data displays, the constraints of real-world educational settings and link each topic to data literacy and applications to LA.

Data

When most educators think of data, they think of test results. These are quantifiable measures that can reside in technologies. However, data are much more diverse than test scores. Educational data can be qualitative or quantitative and they extend beyond student performance. Mandinach and Gummer [29] have advocated for a broad definition of data that extends to demographics, socio-emotional, motivation, behavior, health, justice, special status (i.e., homelessness, foster care, military family, language learner, disability), to understand the whole child. With an increasing emphasis on data use and equity, Datnow and Park [12] have stressed the need to adopt an asset model that is based on understanding students' strengths, interests, and contextual background, rather than a deficit model aligned with accountability. The whole child perspective not only broadens the notion of data but impacts how data are collected and where they are stored and accessed.

The broad perspective on data closely aligns with a foundational principle of data literacy, to use multiple sources of data to inform decisions. Educators must understand the importance of not just data triangulation but the need to examine contextual data to gain a comprehensive understanding of the student. According to the DLFT construct [29], data skills are informed by other sources of knowledge which include knowledge of learner and knowledge of context [46, 45], essential to understanding the whole child.

The use of multiple data sources is one area where DDDM practices lag behind the application and promise of LA. The LA literature includes a number of existing systems (learning management systems, student information systems) and tools that rely on and capture a wide range of student data, including demographic, behavioral, and academic information. Different tools have been developed that integrate with LMS to support students' academic progress. For example, the Degree Compass system (Austin Peay State University) can assist in course planning) other technologies provide learners with feedback on their use of the LMS relative to peers according to class performance (University of Maryland Baltimore County, Check My Activity tool), and receive feedback about course performance, including alerts signaling a potential risk of failure. The latter is based on the Purdue University's Course Signals system. Signals was frequently cited as an example of learning analytics. This "early alert system" relied on a predictive algorithm that included pre- and post- college admission data: high school grade point average, standardized test scores, socio-economic status, college course grades, frequency of advising appointments, and student use of the LMS to produce an indicator of risk, or potential, for failing a course [4, 24]. The system then alerted instructors and students as a form of early intervention. Even though initial outcomes of the Signals were promising, additional evaluation efforts revealed mixed impacts on student outcomes that when combined with implementation challenges lead to the closing of the program. A case study of Signals identified a number of factors important to future implementation of similar technologies including the: need for capacity and infrastructure to support timely integration of data; clarity of messages across courses and instructors; attention to timing and frequency of communications and impact on student motivation and learning outcomes; and the role of different institutional departments in education focused systems implementation and deployment [43].

Data Displays

More sophisticated technologies to support DDDM continue to emerge and have a long history [48, 49, 50, 53]. They are apparent in personalized learning environments [14, 39]. However, one concern raised is that there is little integration among the technologies that make the triangulation of data difficult for educators [34, 39]. Teachers have a difficult enough time with the data overload and triangulation [18], and personalized learning presents a larger challenge.

In contrast to the plethora of data from personalized learning, a recent trend is the creation of data dashboards and early warning indicator systems that present to educators targeted data [13]. Instead of bombarding educators with too much data, these systems streamline the data being presented to make them more readily interpretable.

To further complicate matters, there are critics of data systems more generally, commenting that the typical presentation format dumbs down the interpretation process and thereby misrepresents the data (Penuel & Shepard in [34]). The criticism is that many systems display data as a stop light with red indicating failure, yellow as cautionary, and green as passing and that this format distorts the meaning of the data that educators interpret the data in a cursory manner, and fail to be grounded in a theory of learning.

In terms of data literacy, understanding how to use data technologies and the ability to understand trends and patterns are part of DLFT. But DLFT, even in taking the skill set to the most expert, does not likely extend to the level of sophistication required in LA [5].

Constraints

Many constraints exist in extending data use to the sophisticated level required of LA in terms of data literacy and educational realities. We raise several, but each deserves its own chapter. Thus, our goal is to raise the issues and accompanying questions. There are no easy answers.

First, what do we do with non-quantifiable data that do not readily fit into data systems, given the need for diverse data sources and how can LA accommodate such complexities? For example, how are data observed from the formative assessment process collected? How do we teach educators and data scientists to effectively use such data in their practice? Because of the need for diverse data sources, how can the firewalls across data silos for justice and health be overcome? What are the implications for the acquisition and protection of data from virtual learning environments?

Second, what can the field do to address interoperability issues and technology more generally? LA requires sophisticated data systems, whereas in most classrooms, such applications are not feasible. Cost is an issue. There is a knowledge barrier. The sophisticated skills and knowledge required of LA are not part of traditional educator preparation. Without denigrating educators, the more complex systems that exist in schools today may be beyond the grasp of many practitioners. Introducing the kinds of systems required by LA is even more of a stretch.

Third, how should the field handle the institutional diversity, considering that many districts can barely afford simple technologies, especially those that are small, rural, and charters? These schools must rely on more simplistic and cost-effective solutions.

Fourth, how can we attain a sufficient level of data literacy among educators? As the National Forum on Educational Statistics [13] notes, educators need to know how to examine learner profiles, gain detailed knowledge of their students, and use diverse data sources with real-time, not just static data to understand student progress. They need to understand structured and unstructured data. Educators need to understand what data are needed for what purposes. Educators need to know how to discern trends and how to use the technologies to support data use. According to Bowers [7], educators need statistical knowledge, empirical reasoning, applied quantitative methods, and data visualization to personalize learning, and analyze performance patterns. Although some statistics are part of DLFT, most educators do not have the statistical literacy required of complex analytics. This is a major impediment. One could argue that data literacy is role dependent and that some educators may instead need to be good consumers of information, rather than hands-on with data. What is a sufficient level of data literacy? Should the field strive toward the level of expertise required of classifications Agasisti and Bowers [3] outline? And if so, from where will the training come, given the dearth of DDDM being addressed in colleges of education [27] and the different foci from the best professional development providers, even with the emergence of data science courses at some universities there are fundamental questions around capacity building at both the pre-service and in-service levels, as well as the priorities of districts, given funding limitations.

Fifth, there are other general issues that exist in schools that may create challenges, what Jimerson et al. [21, 20] refer to as the enablers and challenges. Teacher time is an issue. Many think that DDDM is an add-on, not an integrated part of practice. DDDM requires too much time that could be devoted elsewhere. Educators need to be convinced of the value-added of DDDM and that it may not be just another passing fad. Thus, teacher beliefs play a role [15, 40]. Enculturation is important. Does a school have a data team and a data coach? Is data practice enculturated? Is there strong leadership that supports DDDM? Is there dedicated time for data work? All these factors make a difference [18].

Sixth, what are the ethical issues that surround the use of LA in DDDM and how do we prepare educators to use the data responsibly? With the large amounts of data and the technologies that support the data, there are ethical issues and threats to privacy that must be addressed. Wang [47] raises ethical issues around the use of artificial intelligence in DDDM that include unintended bias, a lack of humanism in decision-making, and moral values such as equity. Wang implicitly argues for the need for balance between the accuracy and efficiency of AI and the human considerations.

Finally, will educators use LA or know how to use it? How will the sophistication of LA translate to actual practice? Will educators know how to transform these data into decisions? This brings the issue of data literacy full circle. How do we prepare educators to use such data in a way that can effectively impact their practice?

These constrains are not trivial and should be considered thoughtfully about the implications for development and practice. Additional research is needed with full consideration for the state of current practice but with an eye to the potentials for future practice.

OPPORTUNITIES

Mandinach [26] discussed the challenges and opportunities (CHOPs) to DDDM in which the challenges far outnumber the opportunities but the opportunities far outweigh the challenges. The same situation should apply to data literacy and LA. We conclude with a forward-looking examination of the opportunities and consideration of what is possible in terms of building data literacy capacity for LA. We play off the challenges enumerated above and lead with specific topics.

How to Enhance Data Literacy

Data literacy will continue to be an issue for current and future educators. Capacity building is a highly systemic issue [28, 29], one that must be addressed by professional organizations, educator preparation programs, professional development providers, and local and state education agencies. The accumulation of data literacy skills, knowledge, and dispositions should be an ongoing process across the entire trajectory of educators' careers, beginning during pre-service and reinforced through professional development, in-service training, and graduate courses. Data literacy, both basic and more advanced for LA, provides several kinds of opportunities. For colleges of education, it provides an opportunity to integrate DLFT into their courses, and perhaps in LA and data science. For professional development providers, it creates new opportunities for trainings. For professional organizations, it provides opportunities to reconsider the skills sets that are necessary parts of educators' repertoires. For research and development staff, there is a need to create materials that can be used to build capacity, something for which the first author has advocated for years [35].

A Vision for Better Data Displays and More Effective LA

As Bowers et al. note [8], there is not only a need to build research and analytic capacity around data use in schools, but also to develop innovative data products that can help educators extract meaning from data displays and interpret data. LA requires sophisticated data displays. They must go beyond the stop light form of presentation and incorporate the diverse data sources we have discussed. They must make the data easily accessible, understandable, analyzable, and interpretable and provide reports that can be implemented and readily translated into actionable steps to inform practice. These characteristics require thoughtful design considerations that make the technologies attractive to and useable for educators, without sacrificing complexity. Such design constraints provide opportunities for the development of both sophisticated and easy to use technologies that will facilitate effective use of data.

How to Capitalize on Diverse Data Sources

Educators need rich and diverse data to address the complexities of the whole child. As noted above, interoperability and cost are issues. Systems need to adapt to both qualitative and quantitative data. We advocate for the broadest possible use of the diverse data. Such rich data provide untold opportunities for educators to gain a more comprehensive understanding of their students and educational situations. The diverse data also provide the means of moving the needle from a strict accountability focus to one that focuses on the whole child, continuous improvement, and understanding context beyond the school walls that impact students. If LA can provide the expertise to explore the full range of data sources, it would benefit the field.

A Challenge to the Field

According to Bowers [7], LA is a sophisticated form of DDDM that can enhance the use of evidence in education. The question remains whether the level of sophistication required in terms of data literacy, the needed technologies, and other skill sets such as statistical literacy, are realistic in educational settings. Mandinach [26] questioned, what is the least amount of data literacy that is acceptable for educators. The discussion at hand falls at the far end of the continuum of expertise in terms of whether educators should aspire to the data expertise required of LA and the roles and responsibilities of such individuals in typical educational settings. With increasing complexities come certain risks, over-analysis, and potential ethical and moral problems, as noted by Wang [47]. The challenge for the LA and DDDM fields is how to harness the potential value of LA and ensure that educators not only know how to access, analyze, and interpret complex data, but more importantly, how to transform those data into actionable educational practices. This is the essence of data literacy. Fundamental questions remain, whether all educators need to have a high level of sophistication, and what are the practicalities of adopting LA approaches in DDDM educational practice.

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Chapter 20: An Introduction to Fairness, Absence of Bias, and Equity in Learning Analytics

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ABSTRACT

In this chapter, we examine the ways educational justice has been and may be taken up in learning analytics research. To do so, we first outline how we see equity as playing a necessary role in the future development of the learning analytics community. Next, we review how equity has been explored in this area heretofore, focusing on notions of algorithmic fairness and absence of bias. Then, we turn to newer political approaches to the study of learning that are emerging in the learning sciences. We summarize trends in this research's conceptualizations of equity and the political dimensions of learning. Finally, we connect these related ways of thinking about social justice with respect to learning analytics, and examine the tensions and possibilities at their intersection. We close with some recommendations for the learning analytics field to ensure that it contributes to positive educational change moving into the future.

Keywords: Equity, educational justice, fairness, bias

Broadly speaking, an equity orientation to education recognizes that people in general and children in particular have a fundamental right to education [43, 42]. It acknowledges that there are massive disparities in people's experiences of educational environments (including, but not limited to, in educational outcomes). These disparities are often related to learners' race, gender, sexual orientation, ability status, and/or economic status (in the United States, see for example [13, 34]). Ameliorating these inequities—and offering alternatives that empower learners and challenge oppressive social structures—is a primary goal of equity-forward educational research.

When it comes to learning analytics, we focus our attention on equity with respect to researching, designing, and enacting learning environments. Elsewhere in this volume, authors discuss learning analytics as they relate to ethics (Prinsloo et al., this volume), scale (Reich et al., this volume), and policy (Scheffel et al., this volume). Each of these is an important part of designing for equity. Therefore, we embrace a relatively narrow scope in discussing equity, which for the purposes of this chapter focuses on when and how learning analytics can be culturally, socially, and politically responsive to a diverse array of students. Importantly, we address this chapter to readers with a desire to improve education, recognizing that equity is a central concern in such a goal.

Undoubtedly, algorithmic approaches, complex computations, and machine learning are not a priori helpful, just, ethical or likely to increase quality of life for many. They are not even neutral in this regard [45]. Rather, countless examples detail how an uncritical perspective on these analytics and their uses has had just the opposite effect, leading to what Eubanks [21] refers to as *automating inequality* and what Noble [44] has called *technological redlining*. Indeed, without a critical perspective, learning analytics are not only unlikely to deliver on promises of bringing about positive educational change; worse, they are likely to reinscribe and make more efficient existing systemic discriminatory practices.

We do not think it is a foregone conclusion that learning analytics will play such a role moving into the future. On the contrary, we see great potential in the advanced approaches being taken by this community for improving students' educational experiences. However, we understand that potential to be most probably realized if the learning analytics community is proactive in taking on critical, political, and nuanced approaches to equity.

In this chapter, we begin by reviewing how the learning analytics community, to date, has approached issues of equity. In general, this has been through the notions of algorithmic fairness and absence of bias. Next, we turn to how scholars in the learning sciences have recently begun to theorize the political dimensions of learning to advance a more justice-centered perspective on learning. We recognize that the learning sciences is only one of a wide variety of fields that contribute to learning analytics insights. Furthermore, relative to fields like ethnic studies and qualitative methodology, the learning sciences is at the outset of its thinking about equity, and its conceptions of equity are informed by these fields. Nonetheless, it is in this space that some of the strongest thinking connecting justice projects to learning processes is taking place. Furthermore, many have argued that the learning analytics and learning sciences communities are well positioned to learn from and contribute to one another [56, 62]. We conclude by exploring tensions and possibilities at the intersection of these communities' ways of taking up equity, drawing from critical technology studies to close with some recommendations.

FAIRNESS AND ABSENCE OF BIAS: CURRENT VIEWS FROM LEARNING ANALYTICS

Issues of equity in learning analytics are an extension of observed problems in algorithm-informed decision making. As Safiya Noble indicates in *Algorithms of Oppression* [44], the development of an algorithmic or analytic process can easily incorporate the biases of those who design it, and employing such biased algorithms enforces unjust perceptions, policies, and practices of oppressing marginalized communities. For example, word association algorithms, such as GloVe (Global Vectors for Word Representations) can embed into their associations problematic racial and gendered stereotypes, in turn propagating problematic decision making in the tool's application for hiring or admission processes [9]. Such issues entail a precarious dilemma within learning analytics since decisions made from learning analytic processes can directly impact learner experiences and participation in terms of what is represented and enabled through these systems. Given the principle importance of education as a means to participate in larger social systems, it is not surprising that the scholarship within learning analytics has begun to discuss what constitutes equitable practices of algorithm informed decision making for teaching and learning.

Indeed, such concerns have been a pertinent debate in learning analytics at the end of the decade. Niel Selwyn's provocative considerations in his LAK'18 keynote challenged scholars to consider the ways in which existing learning analytics practices can hinder access and decision making (see [60]). Direct replies to Selwyn's concerns illustrate the constraints of analytics for making equitable and fair decisions for processes of teaching and learning (see [7, 20, 22, 51, 57]). In order to address these concerns, however, a larger perspective on the state of the field in terms of equitable or fair practices is necessary.

Similar to broader concerns about the application of predictive algorithms (see [54]), the dangers of classification or predictive algorithms to determine who gets support, resources, and opportunities to participate in educational systems have long been a concern [52, 55]. Papers from the inaugural FairLAK workshop at LAK'19 exhibited responses to these concerns primarily through the lens of algorithmic fairness. We define algorithmic fairness as a property of a computational process wherein equivalent outcomes exist between a baseline and target group (e.g., 18-24 years old vs. 25-34 years old), though we recognize that the criteria and metric by which this is determined is an open discussion and multiple definitions have been proposed (see [24]). For example, Gardner et al. [25] used slicing analysis to compare disproportionate results in models. They showed that these comparisons can provide insight into model performance across populations and therefore potentially lead to more accurate predictive tools. Similarly, Doroudi and Brunskill [16] examined the fairness of knowledge tracing algorithms in terms of the susceptibility of these processes to inappropriately aggregate input training data or make incorrect assumptions about students' learning. They found that simulations of learners with different characteristics (e.g., "slow" vs. "fast" learners) revealed disproportionate outcomes for these learners in Bayesian knowledge tracing algorithms. These two approaches provide examples in using fairness as an evaluative component in the development of learning analytic models.

Fairness (and, by extension, absence of bias) entail examining issues of inappropriate discriminations made by an algorithm or its use. Both of the previously discussed instances sought quantitative measures of fairness in terms of the outcome of a model as a test or classification of a learner or group of learners. Fairness and absence of bias in learning analytic algorithms are therefore fundamentally intertwined in whether an algorithmic process produces proportionally equal outcomes across demographic dimensions.[1] These instances present an additional challenge, however, in whether "bias" is best understood as a property of the algorithmic process or a property of the decisions made from the *use of* these tools. This wider set of issues is one of the interaction of social and technical systems as producing biased or unfair practices. In our view, bias in learning analytics results from the intersection of what is represented within data and how these representations are employed in practice. Meaney and Fikes [37], for example, illustrate this nexus in their articulation of building systems based off of a group of early completers of tasks to detect issues across a course population, and the consequent challenges other stakeholders faced in embedding outputs from this system in their practice. Specifically, the use of early completers of a task to construct a model ignores potential relevant differences in their participation compared to other learners, especially experiential and culturally-relevant differences that may not be represented in the task or the data produced from it. This allows for further embeddings of practices that may not support all learners, since the application of results is based on students who least need assistance and thus ignores those who may benefit most from more attention. The use of an analytic, then, is fundamentally situated and bound in the social functions it is intended to serve. Such uses are present in the use of machine learning tools in any social, and therefore value-laden, context (see [59]),

[1] Alongside "fairness," we tend to use the term "absence of bias" (rather than simply "bias") to indicate that fairness and bias's absence are both desired properties.

of which education certainly qualifies.

Paths to mitigate these sources of inequitable decision making are an emerging area of research in learning analytics. Jones and McKay [30], for example, emphasized the need to involve practitioners in learning analytics and educational data science communities more directly in the design of analytic systems through reflection on ethical issues within the design of the tool before they manifest. This approach reflects broader efforts detailed at the intersection of learning analytics and human computer interaction design processes (i.e., human-centered learning analytics; see [7]) and focusing on the different valuations (social, cultural, and political) embedded within a community and its tools (see [10] for a review and application of value-centered design in learning analytics).

It has further proven useful to consider learning analytics from a more critical, power-centric perspective. Drawing from the sociologically-informed discussions of critical data studies (see [3]) as well as emerging critical studies in the information sciences (such as the newly-formed *International Journal of Information, Diversity, & Inclusion*), this family of approaches attempts to consider learning analytics and the decisions made from them in terms of power and politics. Perrotta and Williamson [48], for example, articulated the role of valuations and decision making in the construction and execution of a clustering algorithm, thereby revealing hidden social and political assumptions in its implementation. Namely, the output from clustering algorithms applied to educational data describes a complex network of situated social, technical, and political choices, and this contextual attunement may be lost when algorithm results are implied to describe instrumental, transferable relations that can be unproblematically transferred across learning contexts. Prinsloo [50] expands these discussions in considering data and the analytics thereof as constructed actors within the larger social, political, cultural, and technical systems and therefore entailing a set of social values and designs. The broader aims of this more critical approach, then, are to articulate the functions of use of analytics for teaching and learning in terms of how such metrics impact and are impacted by practices in a larger array of social, cultural, and political values. Naturally, this strand has much to offer in terms of what constitutes equitable processes and practices with learning analytics in larger social and political contexts, but has yet to fully be taken up in the development of analytics to assess the fairness of algorithms (as discussed in [25]).

Fairness, absence of bias, and ultimately equitable analytic-based decision making in learning and education represent an emergent, multifaceted challenge that substantively shifts in meaning and value depending on the affordances and constraints of the social and technical systems in which these tools are developed and deployed. Fundamentally, the determination of whether a learning analytic process is fair or free from bias must connect to the circumstances of the data quality available within an educational context and the literacy of those in a position to make decisions from such tools. Learning analytics as a path to promoting more agentic learning and thus disrupting existing barriers in participation in education must contend with these issues or risk producing no disruption at best or inimical changes at worst [63]. As such, the development of fair and equitable learning analytic practices represent fundamental questions for: (1) the use of algorithms that have been shown to not inappropriately discriminate across populations; (2) the integration and use of data systems that do not exclude or misrepresent groups in education, and; (3) the facilitation of literacy and development of learning analytic tools in and across contexts as a design process in and of itself. In this regard, the extension of learning analytics into the related design intensive research of the learning sciences towards equitable learning environments is needed.

POLITICAL APPROACHES AND EQUITY: NEW PERSPECTIVES FROM THE LEARNING SCIENCES

In recent years, the learning sciences has also increased its attention to equity (e.g., [18, 49, 33]). While we recognize that the learning sciences is but one of many fields that inform learning analytics, we see immense opportunity for connection between these fields [56, 62, 70]. Given the particularly rich conversations in the learning sciences around issues of culture and equity as they relate to learning processes, in this section we turn to how notions of equity have been taken up in the learning sciences community. Note that while we ascribe these views to the learning sciences, the scholarship discussed next is best understood as working across a number of perspectives, including critical social theory, curriculum studies, and cultural psychology.

To begin, it is necessary to acknowledge that disparities exist in people's experiences of educational environments, participation practices, and learning outcomes (conceptualized broadly). While oftentimes these disparities exist along racial, gendered, classed, or other visible lines, acknowledging disparities in education does not imply that minoritized students' backgrounds are *deficits* that need to be overcome for learning to take place. However, such a deficit perspective has been a dominant perspective in educational research historically and persists still today [46]. Sociocultural learning theorists position culture as central in the study of learning [12, 27]. From an asset-based perspective of learners, students' cultural backgrounds are often rich, and in an equitable learning space, people's cultural backgrounds offer funds of knowledge that can productively contribute to learning [26, 38]. Culturally-responsive pedagogy [32] and culturally-sustaining pedagogy [46] emerged as researchers and educators saw a need to position minoritized students' backgrounds in this resource-based way. This need was driven by a sense that such pedagogies would improve educational outcomes, but also that they offered students—particularly minoritized students—a more just and dignifying educational experience. Importantly, these critical cultural perspectives recognize that identity groups are not monolithic. In fact, they understand race (and many other social categorizations) to be a social construction rather than a biological reality [39]. Rather than treating culture as a static demographic variable, therefore, it is more appropriate to focus on students' prior cultural *repertoires of practice* to understand and design at the intersection of culture and learning [27].

From this perspective, there has been deep attention to unpacking culture as it relates to identity (e.g., [40, 28]). This necessitates investigating how culture relates to race, gender, sexuality, and other identity categories, and to power, privilege, and oppression as it surrounds these categories [41, 36, 18]. While from a sociocultural perspective learning is often about taking on new identities, identity is a joint accomplishment between learners and learning environments [28]. Students contend with racial and cultural storylines about who they can and cannot be [61]. In other words, identity and learning constrain together. This has led some scholars to center equitable disciplinary identification, focusing not only on how individuals navigate (usually STEM) disciplines, but also how such disciplines and communities function to become hostile to particular learners (e.g., [4, 35]).

In conversation with these trends, some learning scientists have argued that all learning has a political dimension which requires consideration by learning researchers [5, 6, 33]. Foregrounding this political dimension necessitates asking questions like "for whom," "with whom," and "to what ends" do people learn [49]? To really think through these questions, it is necessary to acknowledge that racism, heterosexism, sexism, genderism, ablism, settler-colonialism, and other systematic forms of discrimination not only exist, but that these systemic discriminations are highly consequential for learners' educative experiences and their lives [18]. Indeed, these historical inequities have compounded in a way that Ladson-Billings [31] argues creates an *educational debt* that is owed to minoritized—and specifically in the United States, Black and Indigenous—people. Equity-focused learning scientists have also highlighted that heterogeneity in people and ideas is fundamental to learning [58] and productively expands the long-term projects of research disciplines like science [38]. Importantly, centering the political reminds us that the societal purposes of education and learning cannot be disregarded in research and design. Some argue that learning and education are most powerful when they center on the critical analysis and positive transformation of social circumstances [14, 23, 68]. Indeed, this learning must center the fundamental dignity of humans [17, 19] and more-than-humans [2, 67].

Together, these sociocultural and sociopolitical attunements in learning theory and design research build on the sociocultural shift of focus from individual learning experiences (such as how a person's race affects their learning) to the design of learning environments (such as how an environment might enact, reify, or combat racism). They offer the potential to make or keep research relevant to everyday educational practice and to life improvement. They also advance learning theory by building our understanding of factors that affect where, when, and how people learn that have historically been understudied in the learning sciences, learning analytics, and educational psychology communities. Uttamchandani [64] summarized these trends as comprising four equity pathways: (1) Consider the goals of an equity-oriented framework for learning; (2) Theoretically draw on existing critical social theory; (3) Methodologically, focus on collaborative change-making, and; (4) Support heterogeneity in knowing and doing (i.e., in design). In these ways, we see equity and learning as having productive orientations to the historical, cultural, and political that can be more explicitly brought to bear in learning analytics research. Clearly, culture cannot be reduced to one (or, arguably, even many) algorithmic variable(s) in studying its relevance for learners. However, there is still great promise for how equity, politics, culture, and cultural responsiveness can be meaningfully taken up at the intersection of these perspectives and existing learning analytics traditions.

CONNECTING THE DOTS: FUTURE DIRECTIONS FOR EQUITABLE LEARNING ANALYTICS

Looking across fairness and absence of bias (predominant views in learning analytics) and educational equity and justice (emerging views in the learning sciences), we conclude by exploring how the learning analytics community might take up these views to avoid furthering social inequality and instead offer powerful and scalable new ways to contribute to educational justice. We assert that it is impossible to discuss fairness, absence of bias, or equity in any meaningful way without discussing that which makes things unfair, biased, or inequitable: systemic racism, heterosexism, sexism, genderism, ableism, nationalism, classism, religious discrimination, settler-colonialism, and other dehumanizations that have been built into our day-to-day lives through legislation, politics, and broadly accepted but problematic social norms. Insofar as learning analytics work offers new ways to conceptualize systems of learning, it must be cautious that these new learning systems do not absorb these surrounding oppressions, but rather actively combat them. At first glance, it may appear that fairness and absence of bias in learning analytics is quite unlike politicized approaches to the learning sciences. However, we argue that there is immense potential at the intersection of these two communities. Given its scope and potential to scale, learning analytics can positively contribute to brighter social futures. For example, equity analytics [53] can be used to better understand students' participation and thus lead to the identification of structures that produce inequitable experiences and outcomes—and new designs to combat such structures. To conclude this chapter, we offer some considerations we think are worth exploring at this intersection.

Firstly, we argue that algorithmic fairness and absence of bias are an incomplete subset of equity orientations to learning analytics. While we agree that, at minimum, algorithms should be fair and unbiased, we also point to the fact that the "equity computation" being done in learning analytics must be sociohistorically situated. In other words, one cannot compute their way to a more equitable society, and it is incumbent on learning analytics researchers to conceptualize the fairness of their designs in terms of their ramifications for larger oppressive or emancipatory systems. This entails a highly critical perspective on "harmful data regimes" [11] and technology's promises to revolutionize education [69], especially when these promises are made in the absence of serious considerations of social justice (see Cifor et al.'s "Feminist Data Manifest-no" for more on what is entailed in ethical relationships with information and data [11]).

Secondly, equitable learning analytics require detailed attention to the circumstances in which a tool has been developed and is deployed. In this regard, there exist several relevant traditions such as human-centered design and participatory design, in which a diverse array of perspectives from those who may ultimately use a tool are foregrounded in the design of that tool and its contexts of use (see [15] for a helpful discussion of these and related terms). As Buckingham Shum et al. [7] indicated, more participatory strategies in the design of learning analytics can lead to greater insight in representing and interpreting learning through learning analytics. Such design processes also bring attention to the perspectives of different stakeholders and their circumstances. We contend these perspectives will also provide insight in fairness and bias in learning analytics. Further, these situated perspectives necessarily impact the tool and its capacity to be used in different circumstances over time and in different environments. Recognition of these constraints and their amelioration and emergence within an educational environment is therefore a necessary challenge in scaling the function of an equitable learning analytics tool. Equity, fairness, and absence of bias of learning analytics therefore represents an ongoing design process that require continual (re)evaluation.

Building on this, we argue that to effectively incorporate issues of equity, a more participatory approach to design and analysis is necessary [1]. Vakil, McKinney de Royston, Nasir, & Kirshner [66] argued that equitable learning research and design centering race and power is advanced when participants and researchers share *politicized trust*, trust that "requires not only a personal working relationship but also a political or racial solidarity" (p. 200). Designing effectively in this participatory way will require increasing methodological heterogeneity (see [29]). In particular, introducing rich qualitative analyses, such as qualitative language-based methodologies, into learning analytics work can add important contour to the larger studies of how people experience the environments being researched and designed through learning analytics (e.g., [47, 65]). Qualitative data and analysis may be helpful both for building into tools and for critically examining how they are used in situ. As Wise and Cui pointed out, at minimum, "Representative examples from the underlying data should be presented to help draw connections between the learning events as they occurred and their computational representations" [70, p. 1806]. Fine qualitative attunement to such examples can be a useful tool for helping learning analytics attend to political issues in learning. In particular, we would advocate for more inclusion of learner participation in the design and evaluation of the fairness and efficacy of a learning analytics tool throughout and even after the design process. Learner participation can lead to broader representations of learning and have, largely, been an excluded voice in learning analytics research and practice [8].

In sum, we see several ways in which learning analytics researchers can attune to educational justice meaningfully:

- Take a critical perspective to learning analytics. Such a perspective does not assume that learning analytics can solve every educational equity problem, but rather asks "Does learning analytics have a role to play in addressing this problem, and if so, how?"
- Remember that educational data often represents the real, lived experiences of people. Learning analytics must always foreground the well-being of the learners involved.
- In general, aim for fairness and limited bias in the design of algorithms.
- Recognize that learning analytics interventions are part of educational systems, so a foundational question for researchers and practitioners is how these interventions reinforce or challenge the oppression of minoritized groups in the context of those systems. In other words, "less biased" designs are not the same as "neutral" designs since learning analytics interventions always take a position as supporting or opposing particular ways of participating in educational systems.
- Involve a range of diverse perspectives throughout the design, implementation, and evaluation of learning analytics research and practice.
- As discussed in the introduction, other chapters in this volume examine policy, ethics, and scale as they relate to learning analytics. In addition to the above recommendations, each of these areas (and their intersections) are also places where learning analytics researchers and practitioners can contribute to educational equity. Further, taking an equity lens by critically examining how policy, ethics, and scale can work towards the goal of educational justice is foundational to ensuring that scholarship in these areas has a positive impact for a wide variety of learners.

Finally, we argue that equity must be positioned as a central concern in learning analytics. This will come with new challenges and require the development of new tools. However, centering equity will help ensure that learning analytics fulfills the promise of improving education, rather than making the existing inequitable structures of education function more efficiently. As the learning analytics field continues to evolve, we hope to see more empirical work with an explicit equity orientation be advanced.

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Chapter 21: Human-Centered Approaches to Data-Informed Feedback

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ABSTRACT

Learning analytics seeks to support and enhance learning through data-informed feedback practices. As learning analytics emphasizes an iterative loop from learner to data, metrics, and interventions, it is imperative that both teachers and learners play *active roles* in this process and contribute to the design and evaluation of enabling technologies. A key question that concerns us is: *How can learning analytics tools enhance learners' agency in the feedback process?* We argue that the design and deployment of learning analytics need to recognize feedback as a dialogic process. In doing so, we emphasize that effective feedback is not just about providing *information* relevant to learning, but also about the practices of the *people* who carry out evaluations and produce or interpret information based on such evaluations. A human-centered approach is thus critical to the effectiveness of data-informed feedback. In this chapter we discuss key elements of feedback, current approaches to data-informed feedback and associated challenges; and propose a human-centered approach which facilitates collaborative learning and continuous learning among a network of actors and highlights the importance of developing data-informed feedback literacy among learners.

Keywords: Feedback, co-design, learning analytics, human-centered, data

The emphasis on data-informed decision-making in the learning space has grown rapidly in recent years (Wise, 2019). This is notably influencing feedback practices in the education sector with the emergence of analytics technology, also known as learning analytics [39]. The ability of learning analytics (LA) to collect and analyze data about learners and their learning activities at a large scale can enable educational institutions to explore opportunities to enhance learners' experience and teaching quality. This is a key factor of the increasing prominence of LA in providing timely and personalized feedback to learners at scale [71]. For example, in blended-learning scenarios, the immediacy of information produced by learning analytics can enable teachers to adjust teaching prior to or during a teaching session to tackle areas that learners may seem to struggle with [62]. In scenarios where classes have large enrolments, learning analytics can leverage the efforts of the teacher by personalizing feedback at scale [50]. As LA emphasizes an iterative loop from learner to data, metrics, and interventions [15], teachers and learners need to play active roles in assessing the impact of LA-based feedback on learning strategies and outcomes [9]. In addition, the design process of data-informed educational practices and technologies should also enable teachers and students to voice their needs and expectations [54].

Traditionally, feedback has been broadly defined as any *information* provided to learners to enable comparisons between actual performance and set standards [33]. This view has influenced many early instructional digital systems which considered feedback as anything displayed back to learners through the 'user interface' in response to their actions [72]. In this way, feedback provision is considered an uni-directional process in which the teacher or an algorithmic agent is an authoritative figure who provides comments and/or a score to learners [12, 16], using written or spoken language, non-verbal cues, example solutions or corrections on learners' artefacts [63]. Learners are arguably positioned as passive recipients of such feedback.

By contrast, contemporary agentic perspectives of feedback consider feedback as a dialogical process in which learners make sense of information to enhance their work and learning strategies [6, 11, 19, 28]. Henderson et al. (2019) explained that for¬ this process to effectively support learning, learners need to become active agents knowing how to use feedback, educators need to design and assess the effectiveness of feedback purposefully, and the whole process needs to be tailored to meet the different needs of learners. In other words, effective feedback is not just about *information*, but also the *agents* that carry out evaluations and produce or interpret information based on the evaluations. Building on these principles, LA requires human-centered methodologies to engage key stakeholders in the design of LA systems and practice, including educators, learners, learning designers, tool developers, educational managers and so on.

The agentic perspective of feedback can be observed in recent attempts within the LA community to automatically support feedback processes by providing contextualized and personalized information to provoke learners' reflection and enhance self-regulated learning [39, 49, 50]. However, personalized feedback demands high involvement of teaching expertise, not only in the production process but also the evaluation of the validity, utility or interpretability of data-intensive technological tools [46]. Thus, a human-centered design approach is crucial to ensure a deep understanding of current teaching and learning practices, authentic assessment and feedback, and best ways to curate and present data. In the LA community, human-centered approaches have recently attracted increasing attention [8, 70]. In particular, participatory and co-design practices have shown promising potential to enable teachers and learners to become active agents in data-informed feedback practices and design [55, 21, 22, 29, 54, 53].

In this chapter we discuss key elements of feedback, current approaches to data-informed feedback and challenges, and propose a human-centered approach to enhance the effectiveness of LA in the feedback process.

1 FEEDBACK AS A DIALOGIC PROCESS

Feedback can be understood as both a product and an evaluation process of the relationship between a set goal and the existing state of learning or performance. Hattie and Timperley [27, p. 81] define feedback as:

> Information provided by an agent (e.g., teacher, peer, book, parent, self, experience) regarding aspects of one's performance or understanding.... Feedback thus is a 'consequence' of performance.

Here, feedback is perceived as a 'product' of the judgement of the discrepancies between the current performance and the expected standards. By contrast, Butler and Winne [9] highlight feedback as an evaluation process that can prompt self-regulated activities. In their model of self-regulated learning, feedback comes in two forms – internal and external. Internal feedback is generated in the learner's cognitive system where learners self-monitor a path from interpreting given tasks to setting goals, strategies, and creating mental (affective and cognitive) or behavior products. These products can lead to observable performance, which can be evaluated based on the set standards of the given task, thereby generating external feedback. In this sense, feedback is not simply a piece of information, but a continuous activity that involves both the affective and cognitive systems to close the gap between a desired goal and the current state.

The view of feedback as an inherent element of a process to develop self-regulated learning has influenced many scholars after Butler and Winne [9]. For example, Nicol and Macfarlane-Dick [48, p. 205] argue that a good feedback practice is "anything that might strengthen the students' capacity to self-regulate their own performance" . They propose principles to support the development of self-regulated learning skills, emphasizing the dynamic interactions between teachers, feedback, and students. Boud and Molloy [6] suggest that the sustainability of feedback depends on what learners bring and what the curriculum promotes. In addition to a deliberate planning for feedback to be a central part of the course design, students need to see themselves as an agent of change. In other words, student ability to seek, interpret and use feedback to bring about change needs to be cultivated. Similarly, Tchounikine [66, p. 246] argues that "learners are not to be seen as passive beneficiaries of a superior control entity". If LA is to fulfil its promise of 'optimizing learning' [43] the system design and deployment strategies should purposefully create opportunities for learners to exercise agency in decision-making, instead of assuming that all adaptive technologies automatically enhance learner agency [65, 69]. This emancipatory view of learners as active agents in successful learning requires learners to develop a certain level of feedback literacy; that is, the capacity to involve themselves productively in the feedback process [11]. Thus, a critical question for researchers and practitioners is: *How can LA tools enhance learners' agency in the feedback process?* We will return to this question at the end of the chapter.

2 CURRENT APPROACHES TO DATA-INFORMED FEEDBACK

There are at least three broad approaches to facilitate data-informed feedback processes in LA, and in many cases more than one approach is adopted: dashboards, human augmentation tools, and automated agents/systems.

2.1 Dashboards and visualizations

The first approach emphasizes visualized displays of data-informed feedback, often presenting learning activities and performance of individual students or/and of a course-wide cohort. An early example is Purdue Course Signals, an Early Warning System, which utilizes traffic light signals to flag the likelihood of a student to pass a course (green being highly likely, yellow being potentially problematic, and red being at risk) so as to prompt instructors to implement support [3]. In the context of pre-tertiary education, the study by Molenaar and Campen [47] demonstrates that LA dashboards can notably inform feedback provision to support learners on the task at hand and to reflect on their learning processes. Other examples of dashboards that focus on developing self-regulated learning skills include the LASSI dashboard, which present comparison data between individuals and the cohort regarding student time- management, motivation, concentration, test strategies and failure anxiety using unit-chart visualization [7], and a dashboard developed at Keel University to help students identify motivators of studies and visualize student progress to attain each of the motivator [55]. Although positive results of dashboards on learners' motivation, engagement, satisfaction, and academic performance have been reported in the studies above, there are still no widely accepted principles for the design and evaluation of LA dashboards [25].

2.2 Human augmentation tools

The second approach promotes teaching augmentation [2]). Pardo [49] used the metaphor of conceptual exoskeletons to describe how LA tools can augment teachers' capabilities to support students at scale. Pardo proposed a data-supported feedback model where LA collects and integrates multiple sources of evidence showing learning engagement or achievements. Such evidence is subsequently measured by both automatic and human agents according to the set standards of a task or a learning goal, either alone or with additional sources of data (e.g., student characteristics) to produce information that can be used for feedback. Based on this feedback model, a semi-automated tool, OnTask, was developed to enable teachers to construct personalized emails efficiently. Research has shown positive impacts of OnTask on learners' perceptions of feedback quality, academic achievement, and self-regulated learning [38, 50]. Inspired by this model, Martinez-Maldonado et al. [44] enabled teachers to define rules, based on their pedagogical intentions, to interrogate different types of data collected in nursing simulations (e.g., actions, time responsiveness, positioning) and create *data stories*: a combination of enhanced visuals and narratives reflecting the kind of feedback a teacher would communicate to students directly.

2.3 Automated agents and algorithms

The third approach generates personalized recommendations to learners using algorithms and agents that can fully automate the process. This approach has been explored extensively over the last two decades in the forms of Intelligent Tutoring Systems (e.g., [1]) and recommender systems (see review by [64]. Edna (2013) argued that several of these systems had the purpose of confirming learners' existing knowledge or prompting learners to adjust their beliefs and knowledge based on the analysis of previous answers to practice or test questions. Although this approach is rooted in the traditional perception of feedback as uni-directional information transferred from a digital agent to learners, a number of conversational agents have been proposed

with the purpose of facilitating interactions with students (e.g., [20, 37]). Using automated agents (e.g., chatbots) and algorithms to facilitate a dialogical, adaptive process between a digital agent and the learner has also recently been explored in the context of MOOCs [10].

3 CHALLENGES FOR DATA-INFORMED FEEDBACK PROVISION

Although LA has opened up rich opportunities to enhance feedback processes with data-informed insights, research has frequently reported ineffective use of LA notably due to 1) the lack of actionable information, 2) weak grounding in learning sciences, 3) limitations in user capability, and 4) distrust in data.

According to Hattie and Timperley [27], effective feedback needs to feed up (clarify set goals), feed back (assess the gap between a learning output and the expected standards), and feed forward (inform the next steps to further learning). However, learning analytics-based feedback tends to focus more on where learners currently are or where they are likely to be (if predictive modelling is used), but less on what to do to move towards or beyond an expected standard of a task [58]. For example, a study conducted by Cha and Park [13] shows that while dashboards may help learners monitor their learning progress and time management, learners desire prescriptive tips and recommendations to help them achieve learning goals. The lack of actional information in LA-based feedback has also been partly attributed to the disconnect with learning design.

Although the observation of misalignments between LA and learning sciences is not new [24] research continues to identify this issue and its threat to effective use of LA in feedback practice [45, 59, 61]. For example, Jivet et al. [31] found that little attention was paid to supporting the management of learner-set goals in the design of LA dashboards. In another study, the same authors found that evaluations of LA dashboards often focus on assessing the usability and impact on behavioral competence, neglecting the cognitive and emotional development in learners during feedback practice [32]. The authors thus conclude that the development of learning analytics dashboards is predominantly driven by the desire to leverage available data, rather than a clear pedagogical intent to support and improve learning. The same observations were reported in another study [45] where the authors also identified the lack of 'self-regulation level' feedback provided by existing LA dashboards [27]; that is, how to improve learning strategies. The importance of instructional alignment (Cohen, 2016) and constructive alignment [5] in learning design underscores the need to choose metrics based on demand rather than the availability of data [38, 45, 59].

Moreover, while dashboards are meant to help instructors and learners monitor learning progress and engagement more efficiently, studies have reported gaps in the feedback loop, such as the difficulty to comprehend visual representations [51] and learners' struggle to translate feedback into learning strategies [17]. In light of unequal levels of visual and data literacy among users, researchers have argued for the need for textual feedback [56], explanatory interfaces that combine text and visualizations (Echeverria et al., 2018), and training to assist users in the sense-making process [38, 51]. Importantly, as feedback research has also shown, the awareness of the function of feedback, the comprehension of the information, the motivation to act on feedback, and the perception of one's agency to enable changes all impact the effectiveness of feedback for learners [73]. Conversations around LA adoption in feedback practice need to go beyond characteristics of the feedback sender (human or machine agent) and content to consider feedback literacy among learners [30].

Related to user capability, there is a culture of distrust in data rooted in various ethics concerns. A notable one is the paradox between the need to present numbers in an objective manner and the reductionist nature of this practice that inevitably requires interpretations that may introduce biases or fail to consider the context where the data is generated [52]. The distrust in data is also observed in areas where LA conflicts with educational values, such as equity of treatment and the diminishment of learner agency in an unequal power relationship between data subjects and algorithms [69]. Studies have thus highlighted the importance of adaptability of LA tools in terms of customizing feedback to meet the needs of different learners [4, 34, 67] and providing users with certain control over what is to be included or excluded [57].

The issues discussed above need to be addressed with the involvement of key actors in LA-based feedback practice, particularly instructors, learners, and technologists. We discuss the role of each actor and the contributions they bring to a data-informed adaptive feedback practice in the next section.

4 A HUMAN-CENTERED APPROACH TO DATA-INFORMED FEEDBACK

A learning analytics feedback system cannot address authentic learning needs effectively without involving teachers and students, nor can design ideas be realized without inputs from technical developers. As identified previously, LA-based feedback struggles to fulfil its potential due to 1) an absence of actionable information, 2) discounted learning theories, 3) unscaled user capability, and 4) distrust in data. For these challenges to be addressed and for LA innovations to be operationalized in an educational system, collective efforts from different stakeholders are required. A relational process is especially important here as feedback is a two-way process. The interpretation of LA-based feedback relies on pedagogical and data expertise in addition to the internal and contextual knowledge of the data subjects. This relational process highlights the importance of a human-centered approach that seeks to define functions, meanings and opportunities of LA based on the values that matter to key users [8, 14] and values that are created during the process of using LA (e.g., experience and personalization) [21].

From a pedagogical point of view, understanding 'how' students interact with knowledge and the world is more important than knowing 'how much' they do so [41]. As the designer for learning, teachers are best placed to determine if the observed learning patterns match with pedagogical intents, and identify indicators meaningful to an instructional setting [18, 42, 40, 49]. On the other hand, students are best positioned to judge the representation of learning in data (e.g., precision and completeness) and fill in the missing gaps from uncaptured data. Moreover, the experience of being in the learning process places learners in the best position to describe learning needs and struggles [60]. For learning analytics to be accepted, adopted, and integrated with learning and teaching practice, it is believed that both teachers and students need to be given a voice in shaping the development of a learning analytics feedback system [29]. The role of technological developers and LA specialists is equally important in exploring contextual design elements with teachers and students, and turning ideas into prototypes [29, 68].

A number of co-design models have been proposed to facilitate the development and implementation of LA [14, 21, 29, 53, 54]. Among these models, the one proposed by Prieto-Alvarez et al. [54] emphasizes continuous collaboration among teachers, learners, researchers, and developers during the phase of implementation, which is crucial to enhance and sustain the impact of LA-based feedback loops. The model extends a three-phase process of design thinking, *understand, create, and deliver* [23], with a support phase where key stakeholders are supported and involved in a continuous process of evaluation. Here, we highlight the initial (understand) and final (support) phases where all the above-mentioned stakeholders need to interact dynamically.

The main goal of the understand phase is to define design problems in order to identify appropriate tools to address the needs of key users in the next phase (create). This initial phase is crucial to the acceptance of LA among teachers and students as it serves to align technological design with the needs of users and values held by them [53, 74]. In a design meeting, the understand phase can take a significant amount of time for different stakeholders to understand the design context, identify a common language and design problems, and determine tools or approaches to address the problems [68]. Research has frequently highlighted that the difficulty to understand complex algorithms can hinder full engagement of stakeholders [21, 29], and the lack of an authoritative voices can lead to student disengagement [8]. During this process, design trade-offs are necessary when translating human values into algorithmic choices [14]. In a similar vein, when aligning technological design with pedagogical values, it may be necessary to embrace imperfection in computational accuracy [35]. The negotiation and trade-off decisions need to be made collaboratively to cultivate a common vision and consequently produce a sense of ownership. This is especially important to shape the intention to act on feedback, as research has demonstrated the role of feedback appreciation on feedback effectiveness [73].

The support phase is especially important in the context of feedback practice, as feedback essentially involves multiple phases of sense-making. Based on the data-supported feedback model by Pardo [49], learners first need to interpret a given task and the desired standards to identify suitable strategies and approaches to carry out the task. The outputs (e.g., behavior and performance) are then analyzed and interpreted by an agent represented by instructors, experts, peers, and algorithms. The evaluated results are then delivered back to learners who will interpret the feedback relying on existing knowledge, beliefs and attitudes and in turn updating them. When algorithms are employed, this final phase of sense-making involves semantic translation between the computational epistemic domain and the psychological epistemic domain [26]; that is, learners relating the computational representation of their learning to the psychological construct of *self*—what they believe and know about themselves. It is in this relational process that the values held by learners, teachers, and technological developers need to join together harmoniously to bridge the epistemic boundary between the computational and the psychological domains.

Following this rationale, the development of data literacy and capability to turn data into meaningful action is crucial in the support phase of a LA feedback system. Firstly, a consensus between technological experts and pedagogical experts in the *understand* phase regarding the threshold of imperfection tolerance of computational inaccuracy will allow opportunities in the *support* phase to cultivate critical awareness of the use of data in its best capacity to support learning; i.e., acknowledging limitations of LA and setting expectations of its uses [35]. Thus, the development of data literacy and feedback literacy among learners also needs to raise the critical awareness of the inherent imperfection of LA feedback systems [35] and the symbolic elements of computational representations of learning [26].

Secondly, translating data-based information to action requires cross-checking the epistemic beliefs embodied in LA-based feedback [36]. With teacher-facing feedback systems, it is only possible for teachers to act on the feedback if the epistemological assumptions (conceptualization of knowledge) built into the feedback system apply to a given instructional setting and design. For example, a teacher who takes an apprenticeship pedagogical approach to learning design would be interested in data about learners' social interaction with each other and are likely to refine the design of activities to facilitate desired interactions among learners based on LA feedback. Similarly, with student-facing feedback systems, learners are likely to act on feedback about their social interaction with peers only if they share the same epistemic belief; that is, knowledge can be obtained through social interaction. In the support phase, seeking learner and teacher opinions on the feedback generated through a LA system is important to make technological improvement continuously. Importantly, when evaluating the impact of LA on learning, all the relevant stakeholders should examine the degree to which LA generated feedback has contributed to any form of learning gain, whether the feedback presented to users make sense to them, and what might be the gap between linking data to past and future action.

LA seeks to support and enhance learning with data-informed feedback. A key question that concerns us is: *How can LA tools enhance learners' agency in the feedback process?* We argue that the design and deployment of LA need to recognize feedback as a dialogic process. That is to say, LA should aim to prompt *internal* and *external* dialogue. *Internal dialogue* is essential to a reflective process when learners make sense of the computational representation of their learning, draw connections to their internal knowledge and beliefs, and devise strategies to move towards desired learning goals [9, 26, 49]. For teachers, LA needs to be able to prompt /internal dialogue/ that helps them to identify when and how to support students, which may include adjusting teaching design or contacting students directly in forms such as email reminders or feedback. LA should also aim to encourage /external dialogue/ between students and teachers or among students, for example by providing evidence-based (peer) feedback or seeking support. Importantly, there needs to be continuous and comprehensive dialogue among key stakeholders, in particular teachers, students, developers, and LA specialists, throughout the process of understanding, creating, delivering, and supporting LA [54]. In other words, the involvement of multi-stakeholders should be throughout the lifecycle of LA – from design to continuous improvement of the deployment. Building on the co-design model proposed by Prieto-Alvarez et al. [54], we argue that it is crucial to develop data-informed feedback literacy in the *support* phase; that is, *the ability to make sense of data-informed feedback critically and productively*. Critical sense making involves an understanding of the context where the data is generated and the limitations of LA, whereas productive sense-making requires a process of psychological construction or reconstruction of *self* based on feedback [9, 26], which may result in updating one's belief or knowledge or taking further action. A human-centered approach to designing and implementing data-informed feedback emphasizes collaborative learning and continuous learning among a network of actors, in particular teachers, students, developers, and LA specialists.

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Chapter 22: Global Perspectives on Learning Analytics in K12 Education

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ABSTRACT

Learning analytics within schools has been a rising interest both with K12 education practitioners and within the research community. Although LA has its roots in higher education, the spread of technology-enabled data collection has been a phenomena across all sectors of the education system. Analytics are routinely offered as part of education technology software offerings [23] and the LA research community has dedicated workshops at the Learning Analytics & Knowledge Conference in 2018 and 2019 and a forthcoming special issue of the Journal of Learning Analytics on the topic of LA in schools. Although this work is in its infancy, what is clear is that the adoption of LA within K12 education represents a complex endeavor. School systems are highly heterogeneous in their cultures, practices and attitudes toward technology and data and they occupy a politically charged position within society. Due to this heterogeneity, rather than attempt to summarize what LA in K12 education is in its totality, the following chapter provides a snapshot of the opportunities and issues associated with LA from the perspective of six researchers who are currently working in the space in different geographies: China, Finland, South Africa, Uruguay and the United States of America.

Keywords: K12 education, school, policy, international education

Learning analytics within schools has been a rising interest both with K12 education practitioners and within the research community. Although LA has its roots in higher education, the spread of technology-enabled data collection has been a phenomena across all sectors of the education system. Analytics are routinely offered as part of education technology software offerings [23] and the LA research community has dedicated workshops at the Learning Analytics & Knowledge Conference in 2018 and 2019 and a forthcoming special issue of the Journal of Learning Analytics specifically to the topic of LA in schools. Although this work is in its infancy, what is clear is that the adoption of LA within K12 education represents a substantially more complex endeavor than has been observed in individual universities or even university systems . School systems are highly heterogeneous in their cultures, practices and attitudes toward technology and data and they occupy a politically charged position within society. Due to this heterogeneity, rather than attempt to summarize what LA in K12 education is in its totality, the following chapter provides a snapshot of the benefits and issues associated with LA from the perspective of six researchers who are currently working in the space in different geographies: China, Finland, South Africa, Uruguay and the United States of America.

1 CHINA: GROWTH IN BIG DATA OUTPACES REGULATION & TRAINING

As the country with the largest population in the world, China could also "be the largest personal data pool and the biggest application market for big data" [60, p. 783]. By 2018, China had more than 230 million K-12 students [13]. Moreover, Chinese households pay great attention to their children's education and are willing to make significant investments. Therefore, K-12 education in China generates an enormous amount of educational data.

In the Chinese educational context, the term "big data analysis" (BDA) is more commonly used than "educational data mining" (EDM) or "learning analytics" (LA). An analysis of 546 studies from China National Knowledge Infrastructure (CNKI) revealed that Chinese researchers had an increasing interest in BDA in K-12 education since 2014 (Figure 1).

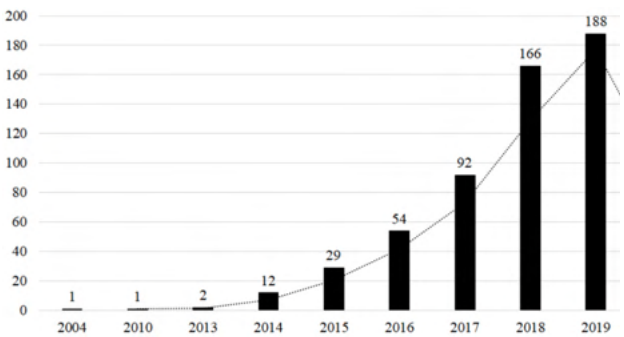

Figure 1: Published articles on BDA, EDM and LA in Chinese K-12 education (by year) .

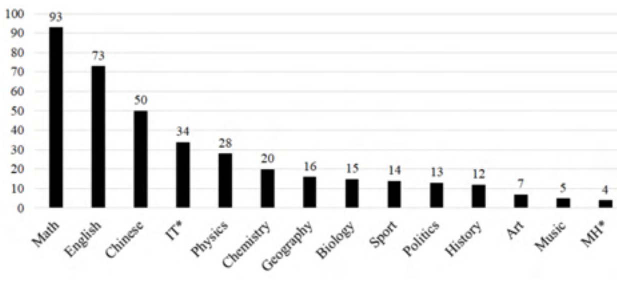

Figure 2: The frequency of subjects mentioned based on 546 studies. IT = Information Technology, MH = Mental Health

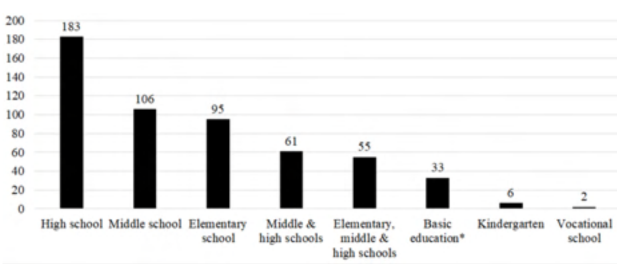

Figure 3: The number of schools that adopted BDA based on 546 studies. In China, "basic education" refers to the education across the stages of kindergarten, elementary school, middle school, and high school.

BDA techniques are most commonly utilized across three subject areas: Chinese, English, and math, but documented use exists in other subjects including chemistry, physics, biology, geography, politics, history, information technology, art, music, sport, and mental health (Figure 2). BDA techniques are used for learning behavior analysis, learners' weakness analysis, learning prediction and evaluation, instructional design, the configuration of educational resources, the management of teacher resources, and teachers' professional training [29]. These research studies and application practices are widely conducted across elementary schools, middle schools, and high schools in different areas of China (Figure 3).

Additionally, researchers have classified five types of educational big data applications in the basic education in China: question pool, homework support, language learning, classroom teaching, and adaptive learning [37]. With the development of artificial intelligence (AI) newer techniques are also being applied. For example, question pools are built using image recognition, optical character recognition (OCR), and natural language processing (NLP) to grab question items from paper-based resources, analyze these items, and generate knowledge graphs.

Homework support includes several types of applications such as photo answering and intelligent marking-up, which enable a student to take a photo of the question or her answer to the question, upload it to the internet, learn how the question should be answered or whether her answer is correct. This application is supported upon question pools. Successful examples are Homework Gang and Ape Counseling. In language learning, oral language evaluation and situational dialogues are major applications. Automatic speech recognition (ASR) and NLP are two major AI techniques that are being widely used. Successful products include Liulishuo and Microsoft Xiaoying. Classroom teaching, either online or face-to-face, generates substantial amounts of data through systematic teaching and learning evaluation systems. For example, by using the speech emotion recognition, ASR and NLP, the teaching quality is evaluated and the interaction between teachers and students is analyzed. By using the knowledge graph, teaching resources are integrated into classes. Adaptive learning depicts the learning path, analyzes the students' learning weaknesses, and pushes appropriate learning content and materials. It considers multidimensional learning elements (emotional factors, interest, motivation, etc.), and adopts the knowledge graph and deep learning techniques. A representative company in China is Squirrel AI, which offers intelligent adaptive learning.

Several issues or challenges exist in the application of BDA in Chinese K-12 education. On a macro level, firstly, China still needs a safe and unified mode to apply big data technologies in K-12 education [61], a national guideline of how to wisely and ethically develop and apply big data technologies in K-12 education. Secondly, data security, privacy, and ethics are important challenges [61]. Thirdly, more educational big data talents are needed [26].

On a micro level, the application of big data technologies in Chinese K-12 schools might be challenged for various reasons. For example, teachers and administrators may fear using new technology, or may not want to burden themselves with big data technologies by learning these new technologies and adjusting or changing their teaching methods [38].

In conclusion, the application and research of big data technology in K-12 education in China are increasing. However, challenges and issues co-exist. For example, the

COVID-19 pandemic and the "Double-Reduction" policy released by the Chinese Ministry of Education in July 2021 may significantly affect EDM and LA applications in K-12 education in China. Future researchers may explore or investigate the long-term impact caused by these changes. Additional attention should be paid to the development and release of a national guideline or norm of how to use big data in K-12 education wisely, safely, and ethically. Meanwhile, more talents with appropriate knowledge and skills of EDM or LA should be cultivated and hired. Moreover, teachers and administrators at schools may need to adapt their instruction and educational management to big data technology.

2 FINLAND: TOWARDS A NATIONWIDE TEACHING AND LEARNING ECOSYSTEM

In Finland, the Digivision 2030 program [48] emphasises the enhancement of the Higher Education sector with learning analytics being one of the key focal points. The goal of this program is to utilise learners' data in order to provide personalised educational experiences with the ultimate goal of improving society as a whole. In view of this effort, a learning analytics special interest group has been formed — under the supervision of the Ministry of Culture and Education — with the responsibility to develop frameworks and guidelines for the evolution and integration of learning analytics practices in K12 education in Finland as well.

The Finnish National Agency (EDUFI) is a key stakeholder in the field of education. The main responsibilities of EDUFI range from the formation of the curricula to providing resources for the adoption of new teaching methods and the integration of novel educational technologies in the school context (K12) as well as funding professional development programs for in service teachers. One of the latest focus areas of the currently funded programs concerns the utilisation of educational data. EDUFI is also responsible for developing the KOSKI-system [15]; a national data warehouse in which individuals' educational data (e.g., study records, study rights) will be stored. KOSKI serves many governing bodies including the Social Insurance Institution (Kela) and the Statistics Finland (StatFin). EDUFI is also responsible for maintaining the mPassId-solution [16]; a national identification system that provides individuals with a unique identifier, which can be utilized to access different web services (e.g., student registry system, learning management and e-assessment systems). To date, many content providers have integrated their eLearning solutions with the mPassId. Nevertheless, in K12 education the information is still scattered across various systems. Although learners can access the different services with the same (unique) identifier, each system is storing and maintaining its own data, and this data is not shared between the systems.

Each city and municipality has the freedom to choose the web services (eLearning solutions) that will be integrated in the school context whereas, teachers maintain the autonomy to adopt solutions as per their learners' needs. However, the above make the collection of learning data a challenging task; an issue, which is currently highlighted, also in the international literature. Typical questions that govern this problem range from "How can we collect data systematically (i.e., on a weekly basis)?", "How can we unleash the promise of Learning Analytics to identify and prevent learning losses due to a pandemic?", or "How can we create research-based interventions to overcome such losses on a nation-wide level?".

The Centre for Learning Analytics (University of Turku), in cooperation with national authorities, has been investigating and dealing with such issues since the early 2000s. Over the course of this time, a unique teaching and learning ecosystem for Finland has been developed; ViLLE – the collaborative education environment [34]. The platform has received various awards with the latest one being from UNESCO [58]. In addition, the "From Teachers to Teachers" initiative has led to the adoption of the platform by 60% of Finnish schools with hundreds-of-millions of completed tasks with immediate assessment and feedback being performed on an annual basis. This ecosystem enables data decision support systems from the classroom to the national level and further enables researchers to conduct mass scale multidisciplinary studies, while also offering the opportunity for teachers to take immediate actions based on the learners' performance behavior.

3 SOUTH AFRICA: THE SHADOW OF DIGITAL COLONIALISM

In 2015, the Presidency in South Africa, headed by Jacob Zuma, announced Operation Phakisa in Education (OPE) – a project to fast-track the delivery of computer devices to all 23,000 public school learners[21] based on a methodology first developed in Malaysia. The initiative is designed to transform – rather than reform – the basic education sector (Grades R-12) through the digitization of education. OPE also has a second core aim: to bridge the digital divide through the delivery of digital tech to the poor black majority [32, pp. 69–70].

The policy was announced against the backdrop of deep inequality and educational crisis. Despite twenty-five years of formal democratic governance, neoliberal policies have perpetuated poverty, inequality, and unemployment throughout the country [42, 41]. Public schools are failing despite high rates of government spending: as of 2016, 78% of Grade 4 learners could not read for meaning, an outcome heavily concentrated in poor black communities [47]. The failure to deliver basic levels of literacy imperils educational development and compounds inequality, as students who cannot read cannot acquire an understanding of more advanced concepts essential to democratic citizenship and high-paying skilled labor.

To help fix the educational crisis, OPE intends to upgrade the education system using computers and the internet. A computer-based solution for education is nothing new, however. In 2004, the Department of Education[1] pub-

[1] The Department of Education has since split into the Department of

lished the first e-education policy, the White Paper on e-Education [17]. As with OPE, the paper envisioned the delivery of information and communication technologies (ICTs) to public schools as a way to improve educational outcomes and bridge the digital divide. Yet the White Paper on e-Education failed to deliver at scale, as few schools ever received equipment.

The government has stated that OPE is based on the White Paper on e-Education, and they have advertised that a four-week Lab, held at the Birchwood Hotel in Johannesburg, focused on five "work streams": connectivity, devices, teacher professional development, digital content development and distribution, and e-Administration [14]. Statements made by government officials, tech corporations, and non-profits in attendance revealed that the government is planning a one device per child roll-out based on technologies and concepts developed in the Global North. In particular, the government would like to deploy blended learning, flipped classrooms, and adaptive learning techniques in the classroom, as well as US-based technology products and Big Data surveillance for pedagogical and administrative activity [31, pp. 148–178].

The e-education program violates official commitments to democratic governance. The DBE subscribes to the Batho Pele principles, which require governments to consult with citizens on matters to do with their needs, provide them with accurate information, and be open and transparent decisions made by government [50]. Additionally, the Phakisa methodology mandates the sharing of Lab findings with the public to incorporate their feedback and the production of a roadmap to inform citizens of a plan of action. DBE officials have yet to publish a report following the 2015 Lab but they [31, pp. 259–264]. Moreover, in 2007, the Department of Public Service and Administration passed a Free and Open Source Software (FOSS) policy preference which stipulated that FOSS would be given preference for use in the public sector [51]. Based on several documents commissioned in the early 2000s, the government was concerned that Big Tech transnationals like Microsoft would colonize the tech ecosystem, making South Africa dependent upon foreign corporations that would use proprietary software to dictate how computer experiences work while extracting rent from intellectual property monopolies. FOSS was to replace proprietary software in the public sector, including schools, to prevent neo-colonial domination [31, 33].

Eight of the nine provinces have discarded the FOSS policy preference, without providing a motivation, in favor of proprietary software solutions from Microsoft and Google. This is despite the government's own concerns that a mass deployment of US-based corporate infrastructure threatens to lock South Africa into subservience and monopoly rents through the process of digital colonialism – the political, economic, and social domination of another territory achieved principally through the ownership and control of the digital ecosystem [32].

While adoption of ICTs in schools has been slow to date, the South African government's choice to deploy Silicon Valley tech in schools reflects their self-imposed commitments to the so-called Fourth Industrial Revolution agenda coined by Klaus Schwab of the World Economic Forum. Ultimately, the African National Congress (ANC) is preparing South Africa to "restructure the economy" for the North's system of digital capitalism. To prepare for the tech-driven "future of jobs and skills", the ANC seeks to shape the education system according to a technocratic imperative that would "[produce] skills that are required at the correct time and in correct numbers" [12].

The government has yet to deploy OPE on the national scale, and it is not too late to change direction through democratic engagement and debate. An alternative vision for education technology, People's Tech for People's Power [31] – a nod to the People's Education for People's Power movement launched in the 1980s – could mandate the use of Free and Open Source Software, strong privacy protections for education participants, and internet decentralization technologies like FreedomBox and the Fediverse in all public schools [33, 31]. The use of such technologies and policies fulfills government policy and is consistent with human rights and equality in education and society.

4 URUGUAY: STATE FUNDED, STAKEHOLDER INCLUSIVE RESEARCH

Uruguay stands out in Latin America for its high income per capita[2], low level of inequality, and low level of poverty. Despite recent progress, several structural constraints to growth remain, in particular in the area of education, which may obstruct the progress towards sustainable development [55]. Uruguayan education is free and compulsory from pre-primary to upper secondary. Primary education is universal. Secondary education, however, faces serious challenges of student enrollment and retention. Only 40% of Uruguayans between 20 and 24 years completed secondary education, way below the average for Latin American countries (60%) [28].

Learning analytics (LA) is not a silver bullet to solve education problems but, because of the high level of digitized education in Uruguay, it can become an effective tool to better understand and tackle fundamental problems in the Uruguayan education system. Since 2007, Plan Ceibal[3](a government agency) has provided a laptop or tablet for every student in public primary (covering 85% of Uruguayan children) and lower secondary school in Uruguay. It also provides Internet access in schools and a wide variety of digital tools (e.g., LMS, math ITS, online library). These platforms are a great source of educational data which, given the nearly universal implementation of the program within the country, offers an excellent opportunity to conduct LA research in the K12 system. During the first two years of the COVID-19 pandemic, Plan Ceibal's infrastructure allowed to assess students'

Basic Education (covering grades R-12) and the Department of Higher Education.

[2]Uruguay GDP per capita for 2018 was $17.278, `https://www.macrotrends.net/countries/URY/uruguay/gdp-per-capita`

[3]https://www.ceibal.edu.uy/en/institucional

learning processes and to track their outcomes, supporting learning continuity at a national scale during school closures and beyond. This way, the Uruguayan education system was able to make decisions in real time and to provide suitable assistance to students that were offline.

Plan Ceibal is in advanced stages of the deployment of a Big Data platform for LA [6, 2], an initiative focused on data collection and integration to enable advanced analytics to support the education system. It is therefore responsible for the crucial and challenging tasks of protecting user privacy, guaranteeing quality and an ethical use of the data generated by 85% of the children in the country. A privacy committee is responsible for ensuring user privacy whereas an inter-institutional ethics committee is in charge of establishing the ethical guidelines that govern educational research. Moreover, it created an educational behavioral laboratory in 2022. This unit has a strong emphasis on carrying out experiments, using user-centered data analytics and applying behavioral science principles from a multidisciplinary perspective.

In 2015, Plan Ceibal created the Center for Research Ceibal Foundation[4] to support and promote research in education and technology. Both institutions have conducted numerous LA research projects [53, 1, 3, 43, 4, 49]. For instance, analyzing how should online teachers of English as a foreign language write feedback to secondary school students to encourage participation in discussion forums. How complex should teachers' feedback be? Results suggest that students participate more when feedback is adapted to their English proficiency level, neither too simple nor too complex [1]. In [4], a quasi-experimental study analyzes how learners' engagement with online educational resources is affected by receiving a new computer, an important question when implementing a large-scale educational computing initiative such as Plan Ceibal.

What can LA tell a primary school teacher, who spends long hours with her students and gets to know them very well, about her students that she doesn't know already? High quality research on topics that are relevant to stakeholders, is crucial for LA to have an impact on learning. This requires a strong collaboration between educators, policy makers and academia so as to understand the problems that are noteworthy, to include the stakeholders' know-how and to develop tools that they are willing and capable of using in their daily practice.

In the last few years the local LA research community has seen its capacities and its relationship with education stakeholders strengthened, resulting in the successful development of various national K12 LA initiatives [40, 19, 46]. For instance, high student dropout and grade retention problems motivated the development of a national LA initiative focused on tracking the trajectories of Uruguayan students during upper secondary education [40, 39]. Results show how students' performance at specific timepoints, as well as in specific subjects, predict student promotion or failure. Positive feedback was received from policy makers, as these results are useful to help at-risk students and to define new countrywide policies, such as implementing summer programs focused on the most problematic subjects [40]. This is a clear example of a fruitful collaboration between local institutions, national and foreign universities, where the joint work has generated concrete results and strategic recommendations for policy makers and educators.

[4]https://fundacionceibal.edu.uy/en/

Uruguay is giving its first steps towards realizing the benefits of LA in K12, but there is still a long way to go. In addition to deepening the paths already started, it is necessary to address crucial points, such as to promote data literacy among stakeholders and to be able to make pertinent interventions based on LA findings. Uruguay has made a permanent effort to build a high quality infrastructure and solid institutions capable of addressing the use and protection of students' data in a rigorous way, and the first LA developments have already yielded useful results. This, together with the fact that Uruguay is a small country with high enrollment in public education, puts it in a privileged position to conduct research in K12 supporting the national education system and contributing to the international LA research community.

5 USA: PERSISTENT INEQUITIES DESPITE THRIVING ED TECH

There has been no comprehensive empirical assessment of the use of learning analytics in schools within the United States and so it is difficult to say with any precision how many schools and to what extent they are utilizing new forms of data to impact learning. Yet, there are some claims that we can make with a high degree of confidence. Namely, that a) the study of learning analytics within K12 education in the US lags behind the study of LA within higher education and b) that, much like other aspects of the US education system, utilization of learning analytics is mediated by access to resources which vary considerably between schools across the country.

The study of learning analytics in schools has not had the same proliferation of reports and articles that have occurred within higher education [35, 57]. For many reasons, universities provide more fertile ground for the study of LA, they are closed data systems with defined populations and the expertise on staff to implement data intensive research. Conducting research within schools in the US is often more logistically complex, especially within public school systems that typically involve negotiating several layers of bureaucracy [20]. This is not to say that LA research has not occurred in schools in the United States, there are many examples (I.E. through better understanding of student learning pathways utilizing learning management systems and learning platforms [45, 8, 7]), but there is certainly less in comparison to higher education.

Despite the lack of empirical work, there have been multiple attempts to impress upon schools nationally the value of data and specific practices that purport to facilitate LA. Most recently, the work of Digital Promise lays out a detailed framework for embedding sound data processes and LA research into teaching practice [30]. It should be noted that such global frameworks for data informed instruction have been proposed before with limited success [52, 54]. The failure for such frameworks to be utilized at scale is likely related to the previous point, the decentralization of the United States school system and its vast heterogeneity with respect to teaching cultures, practices, bureaucracies and particularly resources.

Resource access can differ along many dimensions within the United States school system, including private vs. public schools, by school district, or demographic make-up of the school. These differences can be pronounced even within the same geographic area due to the decentralized nature of the US educational system and the dominant public school funding model, where schools are funded from local taxes [44]. The technological infrastructure that provides the raw material for analytic interventions such as dashboards and automation is subject to these funding discrepancies. So even before data can be utilized, there is substantial variability in which schools generate that data. It is unlikely that learning analytics in and of itself will provide the means to disrupt this pattern. When success has been attained, such as 99% of schools now having access to broadband internet on campus, it has been through long term political and policy negotiations with many stumbling blocks on the way [36].

In the United States, LA currently has limited ascertainable impact in K12 education. As such, LA is an emerging field in K12 schools that is prime for new research opportunities.. Two positive trends that support such opportunities are the growth of supra-district technology and data sharing organizations, and direct partnerships between schools and technology companies. Boards of Cooperative Educational Services (BOCES) or Educational Cooperatives in several states including New York, California, Kentucky and Colorado have a 70 year history in spreading capacity and access to technology across districts and have recently made progress in expanding the use of analytics in their associated schools through Regional Information Centers (RICs) [10, 56]. These centers have a mandate to spread the capacity to utilize data from technological sources across districts including sharing training and the development of data infrastructure.

At the same time, there is little doubt that the United States has one of the most active education technology sectors in the world [11]. Many companies offer learning analytics services to schools such as dashboards and prediction algorithms, and post-pandemic uptake of these tools is at record highs [5]. At the same time, startups are working with schools to conduct learning analytics research through government funding mechanisms such as the Small Business Innovation Research Program, a program designed to aid product development [22]. There are also well documented studies of specific platforms within schools including [27, 59, 18]. In the previous decade these tended to be correlational studies only though, concluding that students who performed better on state tests tend to also perform better within platforms. There is currently a renewed push however to move toward understanding the causal mechanisms between platforms and learning. Strategies involve pooling data across platforms and opening up platforms to researchers [24, 62]

There has also been growth in partnerships by the ed tech sector and school districts. Such partnerships have had mixed success from both a learning and political sense though. The Summit Learning Program, a personalization platform that has been funded by philanthropic monies from the Chan-Zuckerberg and the Gates Foundations, has been widely criticised for its attempt to automate learning using big data [9]. However, the partnership between Khan Academy and the Long Beach Unified School District, which has produced some interesting though small effects in research trials [25], has experienced more success. These partnerships tend to be treated with suspicion for several reasons: 1) key questions about conflict of interest and the ethics of utilizing student data to improve products have not reached consensus and 2) the school districts are under-resourced. These types of partnerships offer a double-edged sword in which districts gain access to technology, but at the expense of their students becoming research subjects.

Overall, learning analytics in the United States faces similar issues that all educational practice within the country faces. Large, multi-factor discrepancies between schools with respect to resources and practices hamper all systematic change efforts. Learning analytics could theoretically identify discrepancies in order to help ameliorate issues but requires substantial resources to be implemented before that vision can be realized.

6 CONCLUSION

The following descriptions of the state of learning analytics in five countries paints a picture of both substantial differences but also different approaches to similar problems. Two key concerns appear to be a) that data utilization is a task of far greater complexity than data collection and that b) that governments are playing catch up with respect to understanding how analytics are being used in K12 education. There are a range of approaches to both these problems. With respect to the first problem, Uruguay and South Africa have attempted to partner with non-governmental organizations, while Finland is keeping a lot of the work within national government entities and the United States and China have substantial private sector involvement. The second issue is a central problem for the learning analytics enterprise - the ability to understand how LA is being utilized is a central concern for the field as a whole. There is little debate across these country descriptions that LA is happening, but the concern remains that it is happening in a way that research will be unable to characterize. We see centrally controlled approaches to LA in Uruguay and Finland that may allow for a more complete picture of the state of LA in the future for those countries while South Africa, the United States and China have heterogeneous systems and implementation and, in the case of China, the sheer size of the educational system, may make the comprehensive characterization of LA difficult.

In this chapter the authors are cautiously optimistic that analytics can serve a useful purpose in the advancement of education and positive change in their respective societies. They argue for reasonable goals in harnessing LA, that take into account issues technical, ethical and pedagogical that can arise and are specific to the school context. All authors call for the need to coordinate efforts to better understand the consequences and opportunities that LA presents so that we are better placed globally to create more robust and equitable school systems.

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Chapter 23: Learning Analytics Policies

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ABSTRACT

More and more higher education institutions have been making use of learning analytics in the last few years. But despite an increased funding and more research in the learning analytics domain, there is still a lack of systematic and large-scale implementations of learning analytics. In order to improve learning analytics adoption and to establish it sustainably, higher education institutions need to align learning analytics-related activities with their goals and visions. Their making us of data requires a set of guidelines and principles, i.e. a policy, that fits their context and speaks to all involved stakeholders. Only then can the effective and responsible use of learning analytics be ensured and will higher education institutions be truly able to establish learning analytics in a sustainable way.

Keywords: Learning analytics, policy, adoption, impact

Learning analytics has emerged as an interdisciplinary field that brings together research and practice in education, psychology, and data science. It collects, measures, analyses, and reports data about learners in order to improve learning as well as the environments where it occurs [23]. Over the years, the NMC and EDUCAUSE Horizon Reports have seen learning analytics as an important factor when it comes to educational technology in higher education and it has been voted a key issue every year since 2011. In the 2019 EDUCAUSE Horizon Report [1], "analytics technologies" in general are put on the one year or less time-to-adoption line. Learning analytics specifically, however, is associated with "adaptive technology" which has fallen out of the priority due to limited impact observed so far. It is argued that this may be due to the elusiveness of learning analytics for many campus leaders and faculty because in many cases the skill to distinguish between types of learner data available is not developed enough yet. The report therefore stresses that higher education institutions "will need to develop these advanced analytic capabilities through innovative leadership, new computational technologies and systems, and a highly skilled workforce equipped for understanding and effectively sharing and using large and complex data resources" [1, p.23] and that analytics need to move from static and descriptive analyses to dynamic and personalized ones. The 2020 EDUCAUSE Horizon Report [9] does not follow the forecasting time-to-adoption structure anymore and instead focuses on current trends and portraying possible futures. For the technological trend category, "analytics and privacy questions" are seen as a trend and "analytics for student success" are deemed as one of six emerging technologies and practices that are believed to be having a significant impact on the future of higher education teaching and learning.

The question thus is how higher education institutions (HEIs) can be supported in employing and implementing LA to increase the quality of teaching and learning? What are the barriers that prevent data from being used systematically and effectively? How can the effective and responsible use of learning analytics be ensured? In order to address issues such as data quality, ownership, access, organizational culture, and expertise available to implement LA [7]and to tackle LA-associated challenges such as technical, cultural and social aspects [39], an institutionally wide strategy (i.e. a plan of action to achieve goals and objectives) is needed to build analytics mindsets, capabilities, and capacity for LA. But despite increased funding opportunities for LA as well as a rising number of research activities in the LA domain, there is still a lack of systematic and large-scale implementations of LA in higher education [16, 47, 46]. For HEIs to establish LA in a sustainable way, it is imperative that they align the adoption of LA with their institutional vision and goals [39]. Strategic planning processes are needed to overcome institutional resistance to innovation and change [24]. Ultimately, the harvesting, use, and dissemination of data requires an institutional policy (a set of guidelines and principles) that aligns with national and international legislative frameworks, so as to ensure an enabling environment for LA [33]). It is important to establish principles to guide stakeholders and encourage ethical use of data within an educational system where power is unequally distributed among different stakeholders [46].

1 CHALLENGES OF LA DEPLOYMENT

In the global landscape, the USA can clearly be identified as a leader in research publications about LA, followed by Spain, the UK, Australia, Germany, Canada, India, the Netherlands, Japan, and China [48]. Review studies have looked into the trends and perspectives of educational technology on a national level in five countries around the world (China, Germany, Japan, Italy, and the USA) [26] as well as the efforts for data-driven improvement of education in seven European countries (Austria, Denmark, Finland, Germany, Norway, Spain, and Sweden) [28]. While some studies have investigated a nation-wide LA deployment, e.g. the USA [3], Australia [10], New Zealand [25], and the UK [27, 38], the systematic adoption of LA in higher education is embryonic [47].

Institutional adoption of LA is influenced and can thus also be hampered by interactions of technical, social and cultural factors. Most cases of deployment of LA at HEIs are at one of the first three stages of the LA sophistication model [39] that in total consists of five stages, i.e. awareness, experimentation, implementation, organizational transformation, and sector transformation. So far, no large-scale systemic adoption has yet been reported. This is echoed by studies that describe the field of LA deployment as thriving but yet to mature [11, 43] and that stress the need for verification of LA's potential with more empirical evidence [15]. In a review of over 25 publications about the adoption of LA in higher education, only 6% of the studies were deemed scalable [47]. This complements the findings of a study examining over 520 publications where the majority focused on small-scale projects or independent courses [11].

Generally, the problems of institutional LA deployment in higher education can be narrowed down to four challenges [45]:

1. Stakeholder engagement and buy-in: barriers to LA adoption can be due to unequal engagement with or inclusion of key stakeholders during the planning and implementation stages leading to institutional resistance and unwillingness to change.
2. Weak pedagogical grounding: very often, learning data is collected and visualized simply because it is available, instead of considering pedagogical practices and educational theories to meet the stakeholders needs and basing design.
3. Resource demand: the success of LA deployment does not only depend on financial resources, but instead also needs to take technological as well as human resources into account as infrastructures need to be setup and maintained, expertise needs to feed into the design and model making, and staff and students need to be informed and trained.
4. Ethics and privacy: questions about privacy and ethics of data use, of what can and cannot be done, and which legal guidelines and laws have to be followed often make the deployment of LA difficult as the lack of examples in practice has left much space for interpretations of legal frameworks in different local contexts.

Over the years, a number of models and frameworks have been proposed to assist HEIs in their learning analytics adoption and to tackle the challenges associated with it. While some focus on the setting-up processes of learning analytics, others are geared towards ethics and privacy aspects, and still others address leadership and management or specifically promote stakeholder engagement.

For example, the generic Learning Analytics Framework by Greller and Drachsler [17] provides six dimensions to look into when developing learning analytics: stakeholders, internal limitations, external limitations, instruments, data, and objectives. Supporting HEIs to identify and evaluate their strengths and weaknesses when implementing learning analytics, the Learning Analytics Readiness Instrument [2, 29] focuses on the five components including ability, data, culture and process, governance and infrastructure, and overall readiness perception. Pardo and Siemens [30] gathered four principles (transparency, student control over data, right of access / security, and accountability and assessment) that can help HEIs to assess their current level of compliance in order to then possibly improve privacy-related issues. The ethical framework for HEIs by Slade and Prinsloo [40] consists of six principles: LA as moral practice, students as agents, student identity and performance are temporal dynamic constructs, student success is a complex and multidimensional phenomenon, transparency, and higher education cannot afford to not use data. Similarly, the eight-point DELICATE checklist (determination, explain, legitimate, involve, consent, anonymize, technical, external) by Drachsler and Greller [17] can be applied to facilitate trusted implementation of learning analytics.

In order to steer the adoption of learning analytics in HEIs when it comes to institutional management and leadership, Colvin et al. [10] highlight strategic capabilities (leadership, strategy, institutional readiness) and operational capabilities (capacity and infrastructure) as primary forces while Gašević et al. [13] break down systemic adoption into three areas: data and its limitations, models used for processing and analyzing data, and institutional transformation. Stressing the role of dialogue among different stakeholders, the framework by West et al.[49] is meant to structure and systematize discussion about learning analytics implementation and adoption. Similarly, OrLA by Prieto et al. [32] offers a communication tool to guide and support decision making about adoption and implementation of learning analytics. The work by Herodotou et al. [19] provides seven guidelines on how to overcome academic resistance: provide evidence, propose student support interventions, promote communication across stakeholders, use predictive analytics to inform decisions, mitigate teachers' resistance, allocate managerial time, and complement the teaching practice.

From all of these works, HEIs can draw much inspiration and support on how to face, tackle and overcome challenges of learning analytics deployment. However, these frameworks and models often only focus on some aspects or provide general principles for a wide range of situations. In order for HEIs to be able to actually use all of these in a systematic and sustainable way, they need to adapt the principles, guidelines and models to their context.

2 CONTEXTUALISING LEARNING ANALYTICS POLICIES

The institutionalization of LA needs to be examined from micro, meso, and macro levels [34]). The macro level considers the habitus [42], i.e. a combination of experiences, perceptions, assumptions, values, and belief that shapes the worldviews of people in a particular social group, of an institution, which is influenced by institutional leaders as well as the national context. The habitus shapes people's perceptions and interpretations of data. It also defines a fiduciary and moral duty of educational institutions regarding the use of student data for LA. The meso level inspects the capacity of an institution in terms of its resource capacity to provide and sustain support for learners. At this level, the distribution of power in a complex social system can shape intentions and (in)actions of individuals in the institution. The micro level drills down to factors that affect learning motivations and outcomes. For example, the quality and relevance of data are crucial to the representation of learning, the psychological attributes and social interactions of individuals both contribute to successful learning, and the structural elements in a society may constrain learner agency and self-efficacy. Thus, the success of LA can depend on the interplay of factors on the macro, meso, and micro levels of an institutional context.

The impact of contextual factors on LA adoption and success cannot be overlooked when developing institutional strategy and policy. Macfadyen et al. [24] point out that HE is an interconnected system and any new change introduced to one area of the system can trigger unanticipated consequences in the other areas, and an institution's resistance to change is usually a result of a mix of political, social, cultural, and technical norms. Therefore, to cultivate an adaptive attitude and positive thinking about the changes that accompany LA, institutions need to ensure that wicked issues (as discussed in the earlier section) with LA are addressed in a policy that reflects the institutional goals. Importantly, the policy needs to be 'sensitive' to an institutional context in order to guide decision making and ensure desirable and accountable outcomes of LA.

In a complex social system, people are arguably the most crucial factors to consider when moving innovations from the lab context to operation at scale. The readiness of an institution for LA is not only determined by the availability of technological resources and data, but also by a culture of using data to inform decisions, the capability of making sense of data and taking action accordingly, the awareness of ethics and pedagogical implications, and leadership to facilitate collaboration among different stakeholders [2, 17, 29, 46]. As LA implementation involves a wide range of stakeholders including professional staff (e.g., IT, student advisors, and legal representatives), academics, managers, students, and external parties (e.g., service providers), the development of LA policies especially requires careful consultation across stakeholders so as to cultivate a shared vision. As Dollinger and Lodge [12] argue, inclusivity in the process of LA adoption may balance the unequal distribution of power in an institution and that primary stakeholders (students and teachers) are more likely to generate trust and empathy towards the institution. It is especially important to understand the interests and concerns of different stakeholders.

The concept of habitus [42] can be used to understand the differences in perceptions of LA among different stakeholders; that is, expectations are shaped by personal experiences in the institution. A study by Hilliger and others [20] shows that interest in LA is influenced by people's expectations of each other in the institution. While managers, teachers, and students expressed unanimous agreement that LA can enhance the quality of feedback for students, teachers mentioned the benefit of helping students develop study skills more frequently than the other stakeholders. In contrast, students commented on the use of LA to improve teaching skills more frequently than the other stakeholders, and managers talked about using LA to evaluate teaching performance and the effectiveness of interventions much more frequently than the other stakeholders.

Although there is shared interest in using LA to enhance learning, stakeholders tend to perceive the usefulness and disadvantage of LA based on their roles and responsibilities in the institution. Thus, it is not surprising that managers are particularly driven by key performance indicators (KPIs) such as student retention and success [4, 46] and that their approach may vary between solely focusing on monitoring and measuring student progress [51] and connecting the observed phenomenon with teaching, learning and student experience factors [10]. From the perspective of teachers, interest in LA focuses on improving teaching effectiveness and support for learning. The approaches for teachers include identifying connections between course design and learning patterns [21, 44, 46], providing timely and personalized feedback [31], and identifying opportunities for interventions [5]. From the student point of view, interest in LA focuses on enhancing learning experience and outcomes. Perceived benefits include receiving support that addresses gaps between learners due to different academic, cultural and socioeconomic backgrounds [46], developing personalized relationship and a sense of belonging through receiving customized messages about their learning [35], and improving self-regulated learning skills by monitoring their own learning progress more closely [31, 35, 50]. However, it is worth noting that different student populations, e.g., campus and online cohorts, have distinct needs for and interest in LA [31, 50]. A LA policy needs to reflect the interests of key stakeholders to establish a common vision and a sense of ownership.

Importantly, the principles and guidelines in a LA policy need to address concerns and risks perceived by different stakeholders. While managers are generally concerned about institutional capacity (e.g., available funding, relevant expertise, data culture and literacy, technological infrastructure, and competing priorities) and legal obligations [3, 46], teachers frequently express worries about inadvertent impact on students (e.g., demotivations, stereotypes, agency compromise, unequal treatment, and privacy invasion) and impact on themselves (e.g., workload, responsibilities, and performance monitoring) [21, 31]. Similarly, students share concerns about the potential negative impact on them and highlight the need for informed consent [35] and secure processing of data [50]. The variations of these concerns show the influence of personal experience and beliefs on perceptions of LA. It is thus important to consult relevant stakeholders and incorporate their views into a LA policy.

An example approach to creating policy in HEIs for LA considering factors of contexts and stakeholders is the one taken by Tsai et al. [44] in Europe. Building on the RAPID Outcome Mapping Approach [16, 24, 52], Tsai and others [46] developed the SHEILA policy framework [1] based on a series of consultation with LA experts and key stakeholders including managers, teachers, and students from over 20 European countries. The framework contains a repository of LA adoption experiences in Europe, organized by lists of key actions, prominent challenges, and policy considerations in accordance to key dimensions of policy development: 1) map political context, 2) identify key stakeholders, 3) identify desired behavior changes, 4) develop engagement strategy, 5) analyze internal capacity to effect change, and 6) establish monitoring and learning frameworks. The same approach has also been applied in the Latin American context to identify needs and directions for policy development in higher education [36].

It is worth noting the role of communication with key stakeholders not only during the process of developing a policy, but also after the process to ensure shared understanding and to review the relevance of the policy. A study on LA experts' views towards essential elements of a LA policy shows that while privacy and transparency are rated as the most important elements, they are also considered the easiest to implement in the policy context, e.g., describing data protection measures clearly [37]. The SHEILA framework thus emphasizes the need to solicit feedback on the implementation of a written policy to bridge gaps between conceptual guidelines and practical implementation. Other studies have also argued the importance of two-way communications to avoid equating transparency with understanding [46] and address a prevailing phenomenon of privacy paradox (individuals' action contradicts their protective views of personal data) among students when it comes to sharing data for LA [41, 50].

[1] The SHEILA framework web tool: https://sheilaproject.eu/sheila-framework/

3 LA POLICY CASES IN HIGHER EDUCATION

A review done in 2016 was able to identify only four HEIs that had developed their own institutional policy for learning analytics [43]. Apart from categorizing these policies according to different aspects such as strategy, obligations, privacy protection and data management, the authors identified six challenges of LA adoption in higher education: leadership involvement, LA-specific policies, communication between stakeholders, pedagogy-based approaches, skills for learning analytics, and evidence of effectiveness. The analysis showed that these policies "have not given enough considerations to the establishment of two-way communication channels and pedagogical approaches. Most policies lack guidance for the development of data literacy among end-users and for evaluation of the impact and effectiveness of LA" [43, p.241]. Since then, other HEIs have developed their own institutional policy or are currently in the process of doing so. Often, these policies make use of the SHEILA framework and also try to address the issues that were previously not taken into account enough.

The University of Edinburgh, for example, had been observing the Jisc Code of Practice [22] for LA related practices until a decision was made in 2016 to develop an institutional policy [2] that would meet the needs of key stakeholders within the University. A task group was then established to undertake a wide range of communication and engagement activities, including discussion at Senate, discussion at the Senate Learning and Teaching Committee (LTC) and Knowledge Strategy Committee (KSC), meetings with Schools, Colleges, and other stakeholders. Moreover, a sample-based student survey and a staff survey, and focus groups with staff and students were conducted to understand interest and concerns about LA among primary stakeholders using the same instruments adopted to develop the SHEILA framework. Considering the feedback received from the consultation, the task group developed a set of policy principles and purposes [3] in 2017. The seven principles reflect interests of multi-stakeholders highlighted in the SHEILA framework, including stating the vision to support students through human interventions, acknowledging limitations of data and potential negative impacts of LA, affirming ethical conducts and support resources, and promising not to monitor staff performance.

Similarly, and inspired by many international examples [22, 14, 6] a German consortium consisting of the University of Frankfurt, the Technical University of Darmstadt, and the DIPF | Leibniz Institute for Research and Information in Education aimed at adopting Learning Analytics according to the SHEILA framework [44]. The consortium initiated in 2018 the DELTA project [4] (Towards Digital Ed-

[2] https://www.ed.ac.uk/academic-services/policies-regulations/learning-and-assessment/learning-analytics

[3] https://www.ed.ac.uk/files/atoms/files/learninganalyticsprinciples.pdf

[4] https://www.dipf.de/en/research/current-projects/towards-digital-education-with-modern-learning-technologies-and-assessment-approaches

ucation with modern Learning Technologies and Assessment approaches), that aims to gather empirical insights for the adoption of digital learning and learning analytics according to the SHEILA framework. In this context the DELTA project interviewed students of all faculties about the opportunities and challenges for Learning Analytics and other digital tools on the campus. Among this qualitative approach, the consortium also gathered quantitative data with a Group Concept Mapping study with all stakeholders of the University (students, faculty staff, administrators, teachers, professors) [8]. Furthermore, the SELAQ survey from the SHEILA project [50] is being applied to investigate the expectations of the students at the local campus as well as broadly in Germany. Results will then be compared to those from international students. Based on these qualitative and quantitative insights the consortium developed a first code of conduct on learning analytics in Germany [18].

Monash University started its institutional adoption in 2018 by creating a Working Group that was approved by the University Learning and Teaching Committee and the Academic Council to oversee the process. The group reviewed existing work in LA and decided to follow the SHEILA framework. To bootstrap the adoption of LA and enable the launch of several institutional projects, the working group defined the principles and purposes for LA by following the model of the LA policy of the University of Edinburgh. These projects were part of other institutional strategies - digital learning and student retention. As part of the process, Monash University adopted the tools and instruments of the SHEILA framework to engage students. The university has developed a novel instrument to assess expectations and requirements from academic and professional staff about LA. The instrument, created in the form of vignettes, solicits the participants' functional, ethical, privacy, and other expectations. This approach will enable the institution to identify both the priorities to be set by the university, and outline the specific details of both the institutional strategy and policy. This example emphasizes the need to closely tie the work on the policy and strategy development together with implementation of specific tools and uses of LA in a HEI.

These examples show that HEIs can actively formulate their policies in a context-based way, i.e. fitting their institution (or set of institutions) specifically. The leadership is strongly and actively involved in the set-up of the policy as well as its application. Also, stakeholder-driven development is seen as an important issue as communication between stakeholders is endorsed and improvement of student experience and learning processes are the targeted goals. Transparent data collection and usage as well as human control are core principles in addition to the HEIs' commitment of providing opportunities of skill development to staff and students. Guidance for measuring and evaluating the impact and effectiveness of learning analytics are addressed, i.e. the need for validation of the benefits for chosen approaches is stressed.

CONCLUSION

Looking at it from afar, one might get the impression that not too much has changed in the last few years when it comes to learning analytics adoption and that the same issues, challenges and problems that had to be tackled five or even ten years ago are still the same. While this does hold true in some regards, e.g. as many HEIs are still piloting learning analytics on a small scale and no large-scale systemic adoption of learning analytics has yet been reported, HEIs can now draw inspiration and support overcome challenges of learning analytics adoption and implementation from works and best practices of others.

Learning analytics is now more and more geared towards improving students' success as well as teaching and learning processes instead of analytics on an institutional level. The need for leadership support and collaboration among all stakeholders involved has been recognized in order to formulate contextualized strategies, principles, guidelines and ultimately policies. HEIs thus need to reflect on the needs unique to their situational contexts to identify goals and objectives for LA, and ensure that LA deployment is governed by a comprehensive policy that speaks to all relevant stakeholders. Only then can they make decisions on what to do and what not, i.e. they need to find their own learning analytics strategy and create their own, personalized institutional learning analytics policy. Only then can the effective and responsible use of learning analytics be ensured and will HEIs be truly able to establish learning analytics in a sustainable way.

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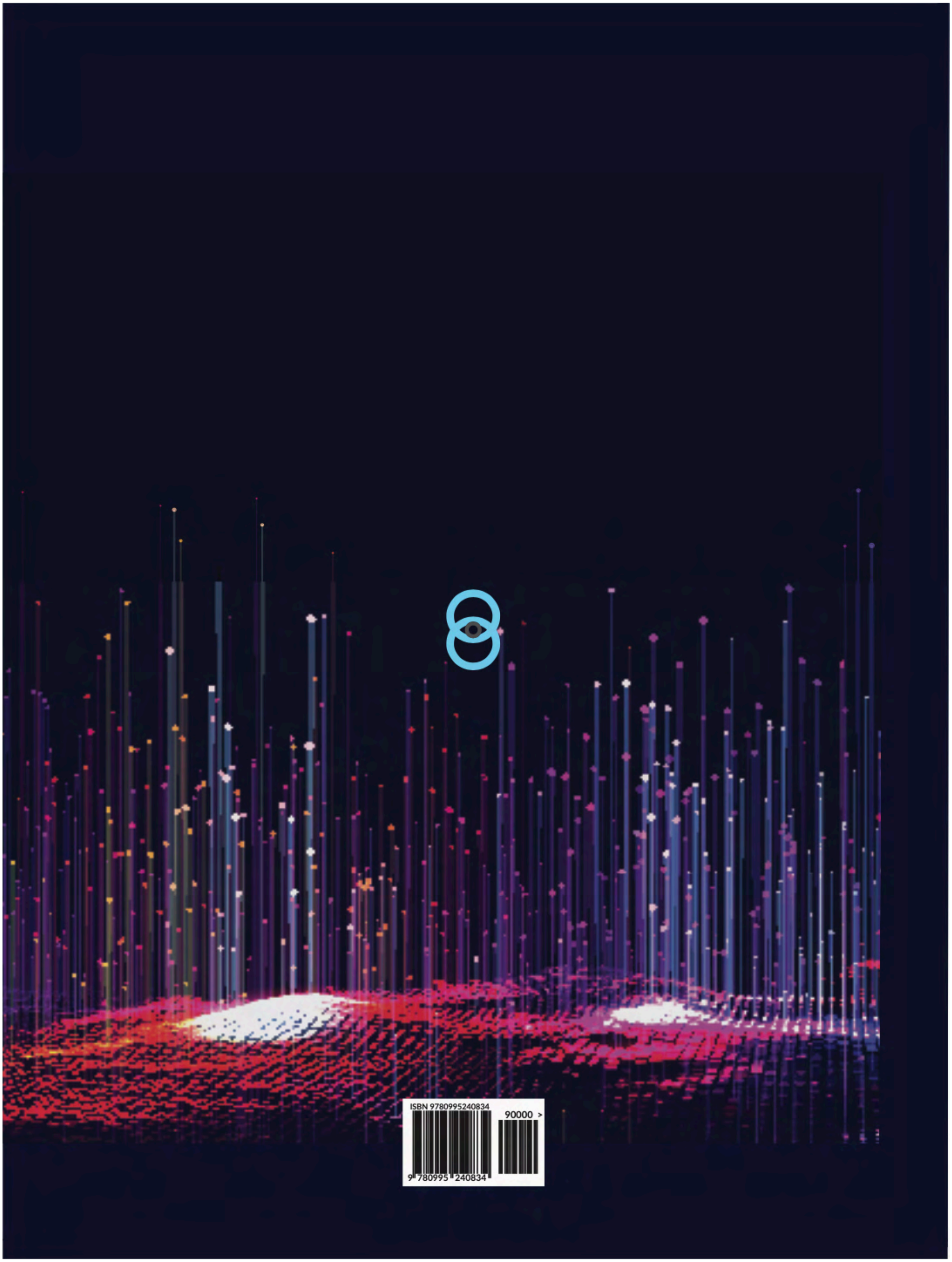

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