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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