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-

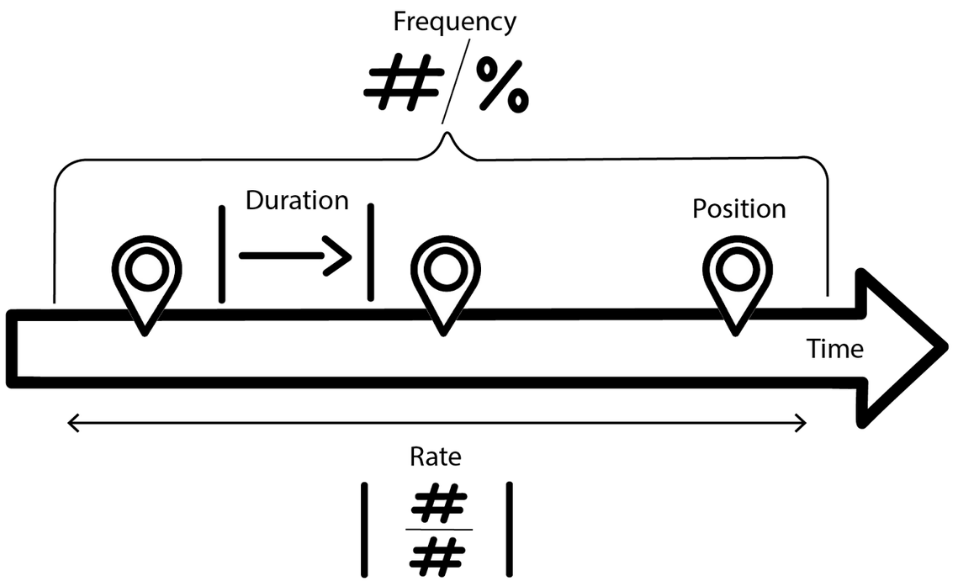

Figure 1: Passage of Time and the metrics.

	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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