From Interaction Categories to Temporal Learning Processes: A Work-in-Progress Proposal for Learning Analytics in LMS

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Abstract

Learning analytics research has traditionally relied on aggregated indicators of student activity in Learning Management Systems, such as frequency of access or number of interactions, to explain or predict academic performance. Although these approaches have produced valuable insights, they often overlook a key aspect of learning processes: their temporal organization. Recent work has proposed theory-grounded classifications of platform interactions based on the learning cycle, improving the interpretability of interaction data and their explanatory power in relation to academic performance. However, the temporal dimension of these categorized interactions remains underexplored. This work-in-progress presents a conceptual and methodological proposal to extend that line of research by explicitly incorporating time into the analysis of interaction data. The study outlines a common analytical framework based on three complementary approaches: process mining, sequence pattern mining, and transition network analysis. Together, these approaches make it possible to examine learning trajectories, recurrent patterns of interaction, and transitions between pedagogically meaningful activity states. Rather than reporting final empirical results, this study explains the rationale, analytical design, and expected educational value of this temporal perspective. The proposed framework aims to advance learning analytics from static representations of activity toward a more process-oriented understanding of learning, contributing to the identification of temporal patterns that may inform future course redesign, monitoring, and decision-making practices.

Keywords

learning analytics, LMS interaction data, temporal analysis, process mining, sequence pattern mining, transition network analysis

1. Introduction

Learning analytics has become a well-established field for the study of digital traces generated by students in educational environments, especially in Learning Management Systems (LMS). In these contexts, interaction data have often been used to explain or predict educational outcomes such as academic performance, persistence, and engagement [1, 2]. However, much of this work still transforms temporally ordered activity into static indicators, which can obscure important aspects of how learning unfolds over time [3, 4].

This limitation is not only technical but conceptual. Learning is not just reflected in how much activity students generate, but also in how that activity is organized over time. Two students may produce similar amounts of interaction in an LMS and still follow very different learning trajectories, engage in different sequences of actions, or regulate their work in different ways. From this perspective, temporality is not an accessory feature of interaction data, but a core dimension of how learning unfolds in digital environments [3]. Recent work has therefore stressed the need to move beyond static or

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aggregated representations and toward process-oriented approaches that preserve order, recurrence, transition, and temporal structure in student behavior [5, 6].

At the same time, the challenge in learning analytics is not only to incorporate time, but to do so in ways that remain educationally meaningful. One of the central tensions in the field concerns the balance between predictive performance and interpretability: data-driven approaches may offer strong predictive results, but they do not always provide transparent or pedagogically grounded explanations of learning processes [7, 8]. In response, theory-driven approaches have sought to classify and interpret LMS interactions through educationally meaningful categories, with past and more recent studies showing that pedagogically grounded categorizations can improve both interpretability and explanatory power in relation to academic performance [9, 10].

This perspective is especially relevant because it adds a pedagogical layer to the interpretation of digital traces. Instead of treating LMS logs as isolated technical events, it becomes possible to relate them to broader functions within the learning process, such as engagement, content access, application, dialogue and sharing, monitoring, or learning process management [10]. Yet, even if such categorizations improve interpretability, an important limitation remains: they do not explain how these interaction states are organized over time. In other words, categorizing interactions helps explain what students do, but not fully how learning processes unfold temporally [3, 6].

This opens a natural next step for research: moving from interpretable categories of interaction to the analysis of temporal learning processes. This shift requires approaches that preserve the order of events, reconstruct trajectories, identify recurrent patterns, and model transitions between states of activity [11, 12]. In this context, three analytical traditions appear to be especially relevant. Process mining supports the reconstruction and comparison of learning trajectories from event logs [13, 14]. Sequence pattern mining helps identify recurrent or discriminative subsequences that may remain hidden in aggregate analyses [15, 16]. Transition network analysis offers a relational view of temporally ordered interactions by modeling them as networks of states and transitions [17, 18]. Although these approaches differ in emphasis, they all contribute to a more process-oriented understanding of learning.

Based on these considerations, this work-in-progress presents a conceptual and methodological proposal for extending theory-based LMS interaction analysis toward a temporal perspective. Rather than reporting final empirical results, we outline a common framework based on process mining, sequence pattern mining, and transition network analysis, and discuss its potential value for the study of learning processes in LMS. The main argument is that moving from interaction categories to temporal learning processes may provide a richer basis for understanding student behavior and, in the future, for informing course redesign, monitoring, and educational decision-making.

The remainder of the paper is organized as follows. The next section reviews previous work on learning analytics, theory-grounded classifications of interaction data, and temporal approaches to the study of learning processes. The review is followed by a presentation of the methodological framework, which explains the complementary role of process mining, sequence pattern mining, and transition network analysis. The research design section then describes the intended data structure, unit of analysis, and analytical procedure. Finally, the study discusses the expected contributions, current limitations, and next steps.

2. Literature review

2.1. Learning analytics and LMS interaction data

In LMS, student activity is recorded as event logs that capture actions such as accessing resources, submitting assignments, completing assessments, or participating in communication spaces [4, 19]. These logs provide a detailed trace of students' activity, but they are not immediately equivalent to educationally meaningful indicators. Raw event names are often platform-specific, heterogeneous in granularity, and difficult to interpret without additional theoretical or pedagogical framing [9].

A central issue in learning analytics is therefore how interaction data are transformed into variables or categories that can support meaningful analysis. Aggregated indicators, such as access frequency, total number of interactions, or time spent on the platform, are easy to compute and have been widely used in descriptive and predictive models [5, 20, 21]. However, they provide only a partial representation of learning activity because they abstract away from the educational function of actions and from the order in which those actions occur [3, 4].

Alongside this line of work, increasing attention has been paid to approaches that improve the interpretability of LMS interaction data. Rather than treating all logged events as equally meaningful, these approaches classify interactions according to their educational role. A relevant example is the learning-cycle-based categorization proposed by [10], which organizes LMS actions into categories such as engagement, content, application, dialogue and sharing, track/review, and learning process management. This type of classification makes it easier to relate digital traces to broader learning functions instead of relying only on technical event names or ad hoc groupings.

2.2. The temporal dimension of learning processes

Although theory-based classifications improve the interpretation of LMS interaction data, they do not address the temporal organization of learning by themselves. Learning is not simply a set of actions, but a process in which events occur in a particular order, at specific moments, and with different levels of recurrence and continuity. From this perspective, time is not only a timestamp attached to each event, but a central dimension of how learning unfolds in digital environments [3].

This view is consistent with broader educational theory. Learning-cycle models describe learning as a structured and evolving process in which different phases are interconnected rather than isolated. Research on self-regulated learning similarly emphasizes that students move through iterative processes of planning, execution, monitoring, and adaptation over time, which cannot be fully captured through static indicators alone [22]. These perspectives suggest that the temporal organization of activity is essential for understanding learning processes in LMS.

In learning analytics, this issue has gained increasing attention in recent years. In [3], the authors distinguish between analyses focused on the passage of time—e.g., duration, rates—and analyses centred on temporal order, arguing that both are useful, but that order-based approaches are especially important for understanding how learning develops step by step. Similarly, [6] argue that the sequence matters because the meaning of an action depends on its position within a broader trajectory. From this perspective, studying temporality means moving beyond measures of activity volume to the analysis of processes, trajectories, and transitions.

2.3. Temporal approaches in learning analytics

Several methodological approaches have been used to capture the temporal organization of the learning activity. One of the most established is process mining, which analyzes event logs as processes and makes it possible to reconstruct activity flows, identify variants, and detect deviations or bottlenecks [13]. In educational contexts, process mining has been used to reconstruct learning trajectories, analyze quiz-taking behavior, identify self-regulated learning patterns, and support process-oriented interpretations of student behavior [4, 11, 23].

A second line of work is sequence pattern mining, which focuses on identifying recurrent subsequences in temporally ordered data. Unlike approaches that aim to reconstruct a full process model, sequence mining is especially useful for detecting repeated behavioral motifs, or patterns, without imposing a predefined global structure on the data. Recent studies have shown its value for identifying sequential patterns related to self-regulation, distinguishing between groups of students, and revealing patterns that may be associated with higher or lower academic performance [15, 16].

The third line is the analysis of temporal networks and transition structures. In this perspective, learning is represented as a system of states and transitions, where activities become nodes and temporal relations become directed links. This approach preserves sequencing while also making it possible to study structural features such as central states, recurring cycles, and paths through the network

[17, 24]. Recent work on Transition Network Analysis has highlighted its potential to combine sequence, transition, and structure within a single analytical representation [18].

Viewed as a whole, these approaches show that temporality can be examined in different but complementary ways. Process mining focuses on trajectories and variants, sequence pattern mining on recurrent subsequences, and transition network analysis on the structure of transitions between states. This complementarity is especially relevant when the aim is not only to detect temporal patterns but also to interpret them in ways that remain educationally meaningful.

3. Methodological Framework

This study proposes a framework for analyzing LMS interaction data from a temporal perspective while keeping the analysis educationally meaningful. The starting point is that student activity in digital learning environments should not be understood only through aggregated indicators or isolated events, but through ordered sequences of interaction categories. Building on theory-grounded interaction categories, the framework combines three complementary temporal approaches: process mining, sequence pattern mining, and transition network analysis.

The rationale for combining these approaches is that temporality can be represented at different analytical levels. Process mining addresses the trajectory level, sequence pattern mining addresses the motif/pattern level, and transition network analysis addresses the structural level. These levels are not treated as competing alternatives, but as complementary views of the same phenomenon: the temporal organization of learning processes in LMS.

- At the trajectory level, process mining provides a representation of how students move through categorized interaction states over time. Its role in the framework is to make visible the main paths and variants of student activity, especially when comparing different course contexts or delivery modes [4, 11, 13].
- At the motif/pattern level, sequence pattern mining is used to identify recurrent or discriminative subsequences within students' trajectories. Its role is not to model the whole learning process, but to detect shorter behavioral configurations that may be associated with different ways of engaging with course activities [6, 15, 16].
- At the structural level, transition network analysis represents categorized interactions as states and transitions. Its role is to examine how interaction states are connected, which states occupy central or bridging positions, and whether recurrent cycles emerge in the temporal organization of student activity [17, 24, 18].

The contribution of the framework therefore lies in organizing these three approaches around a shared pedagogical representation of LMS activity. The same categorized event sequences can be examined as trajectories, as recurrent subsequences, and as networks of transitions. This common basis allows the temporal analysis to remain interpretable, while also capturing different aspects of how learning activity unfolds over time.

4. Research design

This study is conceived as a work in progress. Its aim is not to report final empirical findings, but to define a clear analytical design for studying temporal learning processes in LMS data.

4.1. Context and data sources

The framework will be explored in two contrasting educational contexts. One corresponds to a technology-enhanced course with a strong practical and collaborative component. The other corresponds to a fully online Moodle-based course, where student progression is more directly reflected in the platform traces. This contrast is useful because previous work has shown that the value of LMS interaction data depends on the design of the course and the mode of delivery [9, 10, 25]. In courses where much of the learning takes place outside the LMS, logs may only capture part of the process. In fully online courses, they are more likely to reflect students' progression in more detail.

In both contexts, the analysis starts with pedagogically meaningful interaction categories derived from prior work on LMS interaction classification [10]. Rather than analyzing raw event names in isolation, the design assumes that logged actions can be interpreted through categories linked to stages or functions of the learning process. This provides a common basis for the temporal analyses and makes it possible to compare patterns across contexts while preserving interpretability.

4.2. Unit of analysis and temporal representation

The main unit of analysis is not the isolated event, but the ordered sequence of categorized interactions generated by each student over time. This means preserving the timestamp of each event and using it to reconstruct the succession of interaction states. At a general level, each event needs at least three elements: a case identifier, an interaction category, and a timestamp. This structure is consistent with the requirements of temporal approaches such as process mining [13], and also supports sequence-based and transition-based analyses by preserving order and allowing the extraction of subsequences or transition pairs.

A further issue is the temporal segmentation. Previous work has shown that decisions about time scale and segmentation are methodologically important, as different learning phenomena become visible at different temporal resolutions [3, 6, 26]. For this reason, segmentation is treated here as an analytical decision, rather than as a purely technical preprocessing step. Depending on the context, sequences can be examined at the level of whole course trajectories or at the level of bounded study sessions.

4.3. Analytical procedure

The analytical procedure comprises five stages. First, raw interaction data are extracted from the learning platform and organized as event logs. Records not associated with student activity, or not interpretable within the learning process, are excluded. The retained events include at least a student identifier, an event name, and a timestamp.

Second, raw events are mapped onto pedagogically meaningful interaction categories derived from learning-cycle-based classifications [10]. This mapping is treated as a theoretical abstraction process. For example, actions related to accessing course materials are assigned to content, submission or quiz-related actions to application, forum contributions to dialogue and sharing, grade or feedback consultation to track/review, and calendar or preference-related actions to learning process management.

Third, categorized events are ordered chronologically for each student to construct individual sequences of interaction states. These sequences may represent whole-course trajectories or—most likely—bounded study sessions, depending on the analytical objective. Session segmentation is then treated as a methodological decision, since different temporal resolutions may reveal different aspects of the learning process.

Fourth, the three temporal approaches are applied to the same categorized sequences. Process mining examines trajectory-level organization, sequence pattern mining identifies recurrent or discriminative motifs/patterns, and transition network analysis represents the structure of transitions between interaction states.

Fifth, the outputs are interpreted comparatively. The aim is not to determine which technique performs best, but to examine what each one contributes to the understanding of temporality in LMS interaction data. Process models provide a global view of activity paths, sequential patterns reveal recurring behavioral configurations, and transition networks show how pedagogically meaningful states are connected over time.

4.4. Scope and current status of the study

The present study does not report completed empirical results, but the conceptual rationale and analytical design of an ongoing line of work. Its main contribution therefore lies in defining a temporal perspective grounded in pedagogically meaningful interaction categories and in identifying three complementary techniques through which that perspective can be explored.

This positioning is important for two reasons. First, it keeps our proposal methodologically transparent about its current stage and avoids overstating results that are still under development. Second, it allows us to foreground the main contribution of the study, which should not be seen as a finished comparison of methods, but as a coherent framework for moving from static representations of LMS activity toward the analysis of temporal learning processes. In this sense, the research design becomes a central part of the argument of the proposal.

5. Expected Contributions

The expected contribution of this study lies in extending the analysis of LMS interaction data from static representations of activity toward a more process-oriented understanding of learning. More specifically, we aim to contribute at three connected levels: conceptual, methodological, and educational.

At a conceptual level, the study reinforces a growing argument in learning analytics: interaction data should not be reduced to cumulative indicators alone, because these indicators often obscure the temporal logic of student behavior [3, 4]. By focusing on trajectories, subsequences, and transitions, the proposed framework treats time as a central dimension of learning processes, rather than as a secondary attribute of event logs. In this sense, this work helps connect theory-based interaction analysis with broader calls to study learning as a dynamic and temporally structured phenomenon [5, 6, 12].

At a methodological level, the study contributes by bringing together three approaches that are often discussed separately in the literature. Process mining, sequence pattern mining, and transition network analysis have all been used to study temporally ordered educational data, but they are usually framed within different methodological traditions or applied to different types of questions [11, 15, 18]. The framework proposed here shows how they can be organized around a shared objective: the analysis of temporal learning processes based on educationally interpretable interaction categories. This is useful because it creates a common analytical structure in which trajectories, recurring motifs/patterns, and transition structures are treated as complementary dimensions of the same phenomenon.

A further methodological contribution concerns interpretability. One of the strengths of the proposed design is that temporality is not introduced only over raw event names, but over a semantically meaningful representation of LMS activity grounded in the learning cycle [10]. This matters because it preserves the educational readability of the outputs. Instead of producing purely technical descriptions of behavior, the framework is expected to generate process models, sequential patterns, and transition structures that can be interpreted in relation to recognizable functions of learning activity. This makes the proposal potentially more useful for educational inquiry than approaches that preserve temporal order but do not incorporate a pedagogical layer of interpretation.

At an educational level, the framework is expected to support a more nuanced understanding of how students engage with digital learning environments. By examining categorized interaction data at the levels of trajectories, recurrent patterns, and transition structures, the framework may reveal forms of temporal organization that remain hidden in aggregate indicators. These outputs may help identify dominant pathways, repeated behavioral configurations, central interaction states, bridging transitions, and recurring cycles within the learning process. In other word, by combining the insights offered by the three approaches, they may improve our understanding of how temporal organization shapes student behavior in LMS.

This also has practical implications. If temporal approaches make it possible to identify meaningful trajectories, repeated patterns, or structurally important transitions, they may later inform decisions related to course redesign, sequencing of activities, monitoring strategies, and pedagogically grounded interventions [13, 27]. At the current stage, this work does not claim that such interventions can yet be derived directly from the study. Its contribution is more modest and more realistic: to define a clear basis for future analyses that may support those decisions.

Finally, the study contributes by opening a research agenda rather than closing one. As a work-in-progress contribution, its value lies not in presenting definitive results, but in establishing continuity between prior work on interaction categories and future work on temporal learning processes. That continuity may be especially relevant for learning analytics research seeking to combine interpretability, methodological rigor, and educational usefulness.

6. Conclusions

This work-in-progress has presented a framework for moving from theory-grounded interaction categories to temporal learning processes in LMS. The central argument is that, although pedagogically meaningful classifications improve the interpretability of platform data, they remain limited if the temporal organization of interactions is ignored. Learning unfolds through ordered actions, recurrent patterns, transitions, and trajectories, and these features need to be preserved if learning analytics is to provide a richer understanding of student behavior.

The proposed framework combines process mining, sequence pattern mining, and transition network analysis as complementary approaches organized around a shared pedagogical representation of interaction data. Rather than treating these techniques as competing alternatives, the paper positions them as different analytical views of the same categorized event sequences.

At the same time, the proposal has several limitations. First, it does not yet report empirical findings, so its value lies in the coherence of the analytical design rather than in demonstrated results. Second, the usefulness of the framework will depend on the quality of the event logs, the validity of the mapping between raw events and pedagogical categories, and the extent to which platform traces capture the actual learning process. Third, methodological decisions such as temporal segmentation, session definition, and level of granularity may substantially affect the patterns identified.

The next step is to implement the framework empirically in contrasting educational contexts and examine what each temporal approach reveals about student activity. This future work will also need to assess how stable, interpretable, and educationally useful the identified temporal patterns are for course redesign, monitoring, and decision-making.

Declaration on Generative AI

During the preparation of this work, the authors used ChatGPT 5.4 for grammar and spelling checks and content restructuring. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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