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Investigating Instructor and Peer Instructional Behaviours in a Large Online Discussion Forum Using Temporal Dynamic Analytics

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Abstract

Online discussion forums are a key data source in STEM education for analyzing student interaction, knowledge construction, and social learning. From a learning analytics perspective, understanding the temporal dynamics of instructional behaviours, for example, the differences between instructors and peers, can offer valuable insights into how instructional support unfolds in online discussions. However, few studies have examined these interactions with attention to their sequential and temporal organization. This study adopts a learning analytics approach to investigate the behavioural dynamics of instructional support in a large-scale online math discussion forum. We analyzed 83,569 posts from Math Nation, a widely used online learning platform supporting K–12 math education in the United States. Instructional behaviours were automatically coded based on a theoretically grounded coding scheme using transformer-based language models, and their temporal patterns were modelled using multilevel vector autoregression. Network visualizations were employed to illustrate the dynamic relationships among instructional strategies. Our findings show that peers posted more frequently than instructors and were more likely to engage in acknowledgement and feedback behaviours. When examining behaviour proportions and temporal transitions within discussion threads, peer interactions were associated with more diverse behavioural sequences, whereas instructor interactions exhibited more focused and directive patterns. In mixed-participant threads, instructors often responded following peer contributions, which was associated with a reduced likelihood of subsequent direct peer interventions. Rather than making claims about instructional effectiveness or learning outcomes, this work contributes to the field of learning analytics by demonstrating how natural language processing (NLP)-based behaviour modelling can be integrated with temporal interaction analysis to characterize role-based instructional support dynamics in asynchronous, discussion-based STEM learning environments.

Notes for Practice

- Peers demonstrate diverse but relatively unstructured instructional behaviour patterns, often lacking the clear scaffolding sequences used by instructors.
- Instructor interventions in mixed discussions reduce peers' likelihood of providing direct answers, suggesting implicit regulation of instructional behaviours.
- Temporal modelling of instructional behaviours can inform real-time support tools that guide peers toward more effective help-giving strategies.

Keywords

instructional behaviours, online discussion forums, temporal dynamics, peer interaction, learning analytics

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1. Introduction

Online discussion forums have become a vital component of contemporary online education, especially in asynchronous learning environments (Farrow et al., 2021; Hecking et al., 2017). These forums offer rich spaces for collaborative engagement, knowledge construction, and self-regulated learning (Rabbany et al., 2014; Huang et al., 2019; Kramarski, 2012). Prior research has emphasized their role in fostering social presence (Lowenthal & Dunlap, 2020; Xu et al., 2023), enabling students to express themselves socially and emotionally (Liu, Xing, Jiao, & Li, 2025), and fostering a sense of community and belonging (Miao & Ma, 2022; Hecking et al., 2017). Importantly, higher levels of behavioural engagement in online forums have been positively associated with academic performance (Lowes et al., 2015; Gasmi, 2022).

In this study, we focus on the instructional behaviours of instructors and students within asynchronous online discussion forums. These behaviours include forms of instructional support such as cognitive scaffolding, feedback, and emotional support, which are widely observed across both classroom and online learning environments (Chi et al., 2001). Rather than defining these interactions as tutoring, which typically refers to a specific instructional delivery structure (e.g., one-on-one or small-group instructional programming; Nickow et al., 2020), we examine how similar instructional behaviours emerge in discussion-based learning contexts. For example, when a student posts a challenging math question, responses may come from instructors using structured pedagogical strategies or from peers who draw on shared learning experiences (Steenkamp & Brink, 2024; De Smet et al., 2008). These interactions reflect diverse forms of instructional support. Distinctions between instructor and peer contributions remain analytically meaningful, as they provide behavioural markers that can be modelled, compared, and interpreted using learning analytics to understand how different forms of instructional support shape interaction patterns.

From a learning analytics perspective, modelling such instructional behaviours is essential for understanding the quality of interactions and their impact on learning processes and outcomes. However, most prior studies have adopted cross-sectional or static content analysis approaches that fail to capture the temporal progression and evolving nature of these behaviours. For instance, Lee and Recker (2021) employed a mixed-methods content analysis approach, combining manual coding of instructor-initiated discussion prompts with semi-automated text classification of instructor feedback and student posts, using machine learning models trained on hand-labelled data. Similarly, Rodriguez (2014) analyzed forum posts for indicators of cognitive and social presence. However, neither study addressed when behaviours occurred or how they unfolded over time, which are key components of temporal learning analytics.

Recent developments in learning analytics have begun to incorporate sequential and process-oriented methods to capture the dynamics of learning interactions. For example, Saqr and López-Pernas (2023) applied process mining to online problem-based learning forums and found that the sequence of actions was a stronger predictor of learning outcomes than frequency alone. Similarly, Elmoazen and colleagues (2024) conducted a longitudinal analysis of instructional roles using a multilayered approach to visualize the evolving nature of instructional support. These studies demonstrate the value of temporal learning analytics in uncovering patterns that static analyses overlook.

Despite these advances, large-scale investigations of instructional dynamics using learning analytics methods remain limited. A study using statistical discourse analysis analyzed 1,330 asynchronous messages from an online course to examine how individual characteristics and message sequences influence participation (Chiu & Fujita, 2014); however, the analysis was limited by its small sample size and focus on a single course context. The growing availability of educational big data and advances in natural language processing (NLP) provide new opportunities to scale such analyses. In particular, transformer-based language models (e.g., BERT, RoBERTa) have demonstrated strong performance in discourse-level classification tasks and enable fine-grained, automated coding of instructional behaviours at scale (Devlin et al., 2019; Liu et al., 2021; Saqr & López-Pernas, 2023; Song et al., 2024). When combined with multivariate temporal modelling, these techniques can provide powerful insights into how instructional behaviours evolve over time.

This study contributes to the field of learning analytics by analyzing the temporal dynamics of instructional interactions in a large-scale online math discussion forum. Leveraging transformer-based behavioural coding and multilevel vector autoregression (VAR) modelling, we analyze 83,569 discussion posts from Math Nation, a widely used platform supporting K–12 math learners across the United States. We focus on differences between instructor and peer contributions in terms of behavioural patterns, frequencies, and temporal dynamics. Through this work, we aim to advance the application of learning analytics in understanding social interaction processes in online STEM education and inform the development of scalable, data-driven support systems that promote effective and inclusive instructional support.

To guide our investigation, we address the following research questions:

RQ1: How do instructors and peers differ in the frequencies and types of their instructional behaviours?

RQ2: How do the temporal interaction patterns among instructional behaviours vary across instructor-only, peer-only, and mixed-participant discussion contexts?

2. Related Work

2.1 Instructional Behaviours in Online Discussions

This study adopts the lens of instructional behaviours within online discussion–based learning environments, where support is distributed across participants and unfolds through asynchronous interaction. Instructional behaviours in online discussion forums have been widely examined as part of interaction processes that support learners' cognitive, social, and affective engagement in collaborative learning environments. These behaviours are grounded in social constructivist perspectives (Vygotsky, 1978), which emphasize that learning emerges through interaction and shared meaning-making. Within learning analytics, such behaviours provide observable indicators that can be identified and modelled to better understand how support unfolds in digital learning environments.

Scaffolding refers to the ways participants provide guidance that helps learners progress within their zone of proximal development (Vygotsky, 1978). In online discussions, scaffolding is often realized through questioning, prompting, or providing hints that encourage deeper reasoning (Hmelo-Silver, 2007). Direct intervention includes behaviours such as explaining concepts, correcting errors, and guiding problem-solving. These actions shape how learners engage with tasks and have been associated with differences in learning outcomes and interaction quality (Chi, 2009). Feedback, whether confirmatory or corrective, plays a central role in shaping learners' understanding and is widely studied in both educational psychology and learning analytics (Hattie & Timperley, 2007). Emotional support, such as encouragement or helping learners manage frustration, contributes to persistence and affective engagement, which has received increasing attention in multimodal and affect-aware learning analytics research (D'Mello & Graesser, 2012). Managing discussions through organizing dialogue, clarifying questions, or maintaining focus is another important instructional practice. This type of behaviour has been examined in relation to the regulation and orchestration of online discussions, particularly in collaborative learning settings (Wise et al., 2014). In this study, we treat these as categories of instructional behaviours observed in discussion-based learning contexts.

2.2 Instructor and Peer Roles in Online Discussions

A substantial body of research has examined differences between instructor and peer contributions in online discussion forums, without framing these roles as formal tutoring relationships. Instructors, typically teachers or designated moderators, often possess domain expertise and pedagogical experience, enabling them to provide structured guidance and metacognitive support. In contrast, peers contribute based on shared learning experiences and often engage in more informal and socially oriented interactions. These roles are conceptualized as participation roles within discussion-based environments rather than formal tutoring roles.

Prior research has identified systematic differences between these groups. Peers tend to participate more frequently but may provide support that is less structured or less cognitively demanding (De Smet et al., 2008). Their contributions often emphasize knowledge sharing and social interaction, particularly in voluntary or loosely structured environments (Asterhan & Schwarz, 2007). Instructors, by contrast, are more likely to provide structured explanations, regulate discussion flow, and guide learners toward conceptual understanding (Garrison et al., 2000; Xie & Ke, 2011).

Mixed-participant discussions, where both instructors and peers contribute, provide opportunities to examine how different forms of support interact and complement each other (Wise et al., 2014; Xia et al., 2022). However, most prior studies have relied on descriptive or frequency-based analyses. Few studies have examined how instructional behaviours evolve over time or how interactions between participant roles shape these dynamics. Our study addresses this gap by comparing instructor-only, peer-only, and mixed-participant contexts using behavioural coding and temporal modelling.

2.3 Modelling Instructional Behaviours in Online Forums: A Learning Analytics Perspective

Learning analytics has increasingly been used to examine how discourse and interaction data in online discussion forums can be captured and analyzed to understand learning processes. Prior research has demonstrated the potential of machine learning and NLP approaches to classify forum discourse and enable large-scale analysis of interaction patterns (Du & Xing, 2023). More recent work has extended this line of research by modelling behavioural and temporal dynamics in learning environments (Liu, Xing, Ngo, et al., 2025; Oh et al., 2025).

Instructional interactions in online discussions have been conceptualized as multidimensional processes involving cognitive, metacognitive, and socio-emotional dimensions (Smet et al., 2010). Early work on computer-mediated communication emphasized the importance of meaningful interaction and knowledge construction in online learning (Salmon, 2012). Models such as Salmon's Five-Stage Model describe how learners progress from initial social engagement to deeper knowledge construction over time, providing a useful lens for understanding the evolution of instructional behaviours. From a learning analytics perspective, these frameworks enable the operationalization of pedagogical constructs into observable indicators. Behaviours such as questioning, explaining, and providing feedback can be computationally modelled to uncover patterns of participation and engagement at scale. At the same time, the dynamic and context-sensitive nature of interaction has led to increasing interest in temporal modelling approaches (Ghadirian et al., 2016).

Despite these advances, most prior work has focused on static representations of behaviour, such as frequency counts or aggregated features. Relatively few studies have modelled the temporal organization and interdependence of instructional behaviours in large-scale online discussion data. Our study addresses this gap by applying temporal modelling techniques to examine how instructional behaviours unfold and interact across different participation contexts.

3. Method

3.1 Study Context

This study draws on discussion data from Math Nation[1], a large-scale online mathematics learning platform designed for middle and high school students in the United States. Math Nation supports students' mathematics learning through multiple integrated components, including instructional videos, practice problems, assessments, and an online discussion forum referred to as the *wall* (Math Nation, 2020).

The wall functions as an asynchronous, text-based question-and-answer forum. Students initiate discussion threads by posting math-related questions, and responses are contributed over time by peer students, instructors (designated platform experts), or both (see an example in Figure 1). All primary users of the platform are student learners enrolled in mathematics-related courses. Instructors are designated platform experts or trained content moderators officially affiliated with Math Nation. Their responsibilities include providing accurate explanations, correcting misconceptions, and maintaining the quality and focus of discussions. In contrast, peers are students who voluntarily respond to others' questions, often drawing on their own problem-solving experiences to provide explanations, hints, or encouragement.

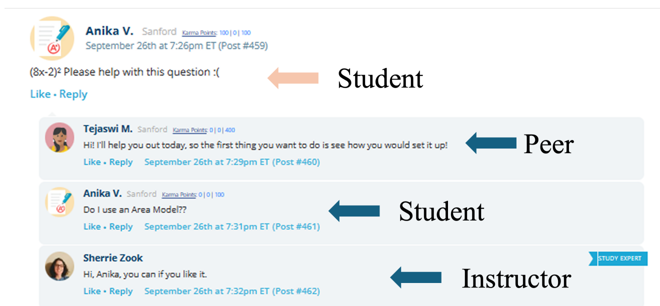

Figure 1. A discussion thread involving a student, a peer participant, and an instructor from Math Nation.

Platform interaction logs indicate that the time interval between consecutive posts within a thread typically ranges from several minutes to multiple hours, and in some cases extends across days. This asynchronous structure provides sufficient temporal separation between instructional behaviours for modelling sequential and temporal dynamics of instructional support within discussion threads.

For this study, we focused specifically on discussion threads in which students sought help on mathematics problems and received responses from peers, instructors, or both. All discussion data were de-identified prior to analysis in accordance with the platform's data use policy. This study was approved by University of Florida Institutional Review Board (IRB No. IRB202201770).

3.2 Dataset Description

The original dataset contains 2,493,472 discussion posts collected from Math Nation between 2016 and 2024. From this corpus, we first identified student-initiated discussion threads that received at least five posts, resulting in a pool of threads comprising more than 400,000 posts. From this pool, we then applied additional inclusion criteria (e.g., complete interaction sequences, identifiable instructional behaviours, and suitability for temporal analysis), yielding a final analytic dataset of 2,288 threads with 83,569 posts, which is the dataset used for all subsequent analyses (see summary in Table 1). Each thread represents a coherent help-seeking episode initiated by a student (original poster, OP) and sustained through responses from peers, instructors, or both.

To examine differences in instructional behaviours between instructors and peers (RQ1), we compared posts from instructors and peers across the entire analytic corpus. This comparison was conducted at the post level to capture differences in behavioural tendencies independent of thread composition.

To address RQ2, which concerns whether and how different interaction configurations exhibit distinct temporal patterns, we categorized threads into three interaction contexts: peer-only threads, instructor-only threads, and mixed threads involving

[1] https://stem.acceleratelearning.com/mathnation/

Table 1. Number of threads, posts, and participants in peer-only, instructor-only, and mixed discussion threads.

	Both experts and peers	Peers only	Experts only
Total number of threads	776	751	761
Total number of posts	41,785	28,045	13,739
Total number of participants	1,634	1,572	61

both peer and instructor participation. Temporal dynamics were then modelled separately within each context, allowing us to examine how instructional behaviours unfold sequentially under comparable asynchronous discussion conditions.

3.3 Coding Scheme

To analyze instructional support strategies enacted by instructors and peers, we annotated instructional behaviours within online discussion threads. We developed the coding scheme using a combination of top-down and bottom-up approaches. First, an initial coding framework was derived from prior literature on instructional support, facilitation, and scaffolding behaviours. Subsequently, two PhD researchers applied the constant comparative method (Glaser & Strauss, 1967) to iteratively refine the scheme by identifying additional constructs that emerged from the data but were not explicitly represented in prior work. Through continual comparison across codes, conceptually similar behaviours were clustered into broader categories, consistent with established qualitative analysis procedures (Glaser & Strauss, 1967).

Ultimately, seven main categories and 17 subcategories were identified as concrete and operational indicators of instructional support behaviours. Table 2 presents the finalized coding scheme along with representative examples. The coding scheme captures instructional behaviours at the discourse level rather than complete instructional episodes. Each coded unit reflects an instructional function (e.g., scaffolding, feedback, or direct intervention) enacted through an individual post. This design is well suited to asynchronous discussion forums, where instructional support is distributed across time and participants and does not follow the structure of real-time, dyadic interactions.

To establish annotation reliability, two researchers independently coded an initial set of 100 discussion posts and calculated inter-rater reliability using Cohen's Kappa. The initial Kappa value was 0.605. After discussing discrepancies and refining code definitions, the same two researchers independently coded an additional set of 100 posts. Cohen's Kappa for the second round increased to 0.822, indicating substantial agreement (Landis & Koch, 1977). To provide greater transparency regarding reliability across the coding scheme, we also examined agreement at the level of individual behaviour categories in the second round of coding. Cohen's Kappa values across individual instructional behaviour codes ranged from 0.79 (Scaffolding) to 1.00 (Direct Intervention), with the majority of codes demonstrating moderate to substantial agreement. Consistent with recommendations in content analysis research (Lombard et al., 2010; Krippendorff, 2013), we report an overall aggregated Kappa value as a stable indicator of coding reliability, particularly given that several categories occurred infrequently. After reaching consensus, one researcher manually annotated an additional 800 posts following the finalized coding scheme.

Table 3 provides a concrete example of how individual discussion posts were coded, illustrating how different instructional functions may alternate within a single asynchronous help-seeking episode.

3.4 Text Classification

Text classification models can automatically label large datasets using machine learning algorithms trained on labelled data (Xing, Pei, et al., 2025; Du & Xing, 2023). We first split the labelled dataset into training ($n = 750$) and evaluation ($n = 250$) sets. Then, we used four different models to classify the text data into the aforementioned coding scheme: BERT-based (Devlin et al., 2019), RoBERTa-based (Liu et al., 2021), XLNet-based (Z. Yang et al., 2019), and random forest (Breiman, 2001).

The choice of these models was motivated by their strong performance in various NLP tasks, including text classification. For example, BERT, RoBERTa, and XLNet are transformer-based models, which have been shown to be robust few-shot learners (i.e., achieving competitive accuracy with limited training samples; Brown et al., 2020). BERT and XLNet differ in their training and prediction assumptions (bidirectional vs. unidirectional), which can lead to different results depending on the context (see the review by Acheampong et al., 2021). RoBERTa is a variant of BERT and has been reported to achieve better performance than its counterpart (Liu et al., 2021). Finally, random forest (Breiman, 2001), as one of the most robust traditional machine learning models due to its ensemble structure, served as a benchmark to establish a lower-bound classification performance.

In response to recent advancements in educational data mining using transformer-based models, we applied BERT (Xing, Li, et al., 2025), RoBERTa, and XLNet using raw text as input without additional preprocessing. These models can capture contextual information from input text, making them suitable for this task. We fine-tuned each transformer model on the labelled dataset. For the random forest model, we experimented with three text representations: bag of words, term frequency–inverse document frequency (TF-IDF) (Manning et al., 2008), and GloVe embeddings (Pennington et al., 2014). Bag-of-words

Table 2. Coding scheme for instructional behaviours in online discussion forums.

Code	Instructional category	Description	Examples
Scaffolding Vygotsky (1978)	Questioning Eloff et al. (2006) Hmelo-Silver et al. (2006) K. J. Topping et al. (2011)	Asking questions that provoke thoughts and constructive scaffolding	What is the value of the y-intercept?
	Providing further references Martin et al. (2020)	Providing information sources related to the topic for references	Also try looking at Section 4 Topics 3 and 4 if you don't understand.
	Asking for elaboration	Asking the student to provide an elaboration on their thoughts or solutions	Can you be more clear with what you mean here?
Direct intervention	Giving explanations Eloff et al. (2006) Chi et al. (2001)	Explaining the related concepts and principles, providing additional information	Don't get confused with the different variables. They all mean the same. Just matter where they are placed.
	Guiding Chi et al. (2001)	Decomposing a complex task into simpler ones and giving them step-by-step guide	Let's take this step by step. What 2 points do you want to take?
	Correcting	Correcting errors in students' problem-solving process	You are missing your 'x' variable
	Giving instruction Eloff et al. (2006) Graesser and Person (1994)	Giving direction to students	You then take half of 1 and square that.
	Giving answers	Directly giving answers to the question	I believe A is the most reasonable answer here!
Feedback Chi et al. (2001)	Confirmatory feedback Chi et al. (2001)	Giving confirmatory feedback on the answer	Yes, that is correct.
	Negative feedback Chi et al. (2001)	Giving negative feedback on the answer	Not quite.
Emotional support	Praising and encouraging K. J. Topping et al. (2011)	Giving praise for tutees' success and encourage them to keep their work	That is correct! Way to go!!! :)
	Managing frustration Wood et al. (1976)	Helping students manage negative feelings and frustration	[name], please be patient. You have several people helping you. Please do not be rude.
Managing discussions	Managing discussions Molenaar et al. (2011)	Managing and adjusting questions and answers, not related to the math question itself, but to the discussion	Do you need any more help?
Peer interaction support	Encouraging peer interaction	Encouraging (other) students' interactions	That's a great idea [peer's name].
	Guiding peer interaction	Giving feedback on (other) students' peer interactions	[Peer's name], let's please make sure that we aren't posting any answers.
Acknowledging issues	Correcting oneself	Correcting their own utterances	You are correct. My mistake.
	Showing uncertainty	Expressing confusion or uncertainty about their own utterances	I think so I don't know hopefully you are right.

Table 3. Example of coded discussion posts illustrating instructional support behaviours.

Turn	Role	Post Text	Assigned Code
1	Student (OP)	I need help with y = 150 + 155x. Where y represents the total cost.	–
2	Peer	So first, what would the y-intercept represent?	Scaffolding – Questioning
3	Student (OP)	The total cost.	–
4	Peer	Not quite. Think of the "one-time evaluation fee."	Direct Intervention – Giving Instruction
5	Peer	The y-intercept is when x = 0. What is the cost before anything else happens?	Scaffolding – Questioning
6	Peer	Also, try looking at Section 4, Topics 3 and 4, if you don't understand.	Scaffolding – Providing Further References
7	Peer	The one-time evaluation fee would be the first fee. What would that be considered?	Scaffolding – Questioning
8	Student (OP)	x	–
9	Instructor	Think y = mx + b. Here, b is the y-intercept and m is the slope.	Direct Intervention – Giving Explanations
10	Student (OP)	I'm still confused.	–
11	Peer	What are you confused about?	Scaffolding – Questioning
12	Instructor	Guys, let's wait for anonymized name.	Managing Discussions

and TF-IDF were selected for their simplicity and interpretability, while GloVe embeddings were used to capture semantic information. Random forest models were trained separately on each representation.

To evaluate model performance, we trained each model on the training set and evaluated it on the held-out evaluation set. The evaluation metrics included accuracy, F1-score, Matthews correlation coefficient (MCC), and Cohen's Kappa. These metrics provide a comprehensive assessment of both overall correctness and class-specific performance. Given that the manually labelled dataset was inherently imbalanced across instructional behaviour categories (see Table 4), MCC and Cohen's Kappa were used to complement F1-score due to their robustness to skewed class distributions (Boughorbel et al., 2017).

Table 4. Distribution of the coded dataset.

Label	Count	Percentage (%)
Direct intervention	445	44.5
Scaffolding	234	23.4
Feedback	118	11.8
Managing discussions	67	6.7
Emotional support	67	6.7
Acknowledging issues	36	3.6
Peer interaction support	33	3.3

Table 5 summarizes the performance of all models. Based on these results, BERT was selected to annotate the remaining posts. While the best-performing model, BERT, achieved an overall accuracy of 0.80, classification performance varied across instructional behaviour categories. In particular, category-level accuracy ranged from 0.66 for *Peer Interaction Support*, the least frequent category, to 0.92 for *Managing Discussions*.

3.5 Temporal Dynamics

The multilevel VAR model is a statistical technique that integrates multilevel modelling with VAR to analyze how multiple behaviours evolve and influence one another over time within nested interaction structures. In this study, the multilevel VAR framework is used to model temporal dependencies among instructional support behaviours within discussion threads. Specifically, the VAR component captures lagged, directional relationships between behaviours across successive time periods, while the multilevel structure accounts for variability across discussion threads.

The VAR model predicts the value of multiple variables at a given time point t based on their values at the immediately preceding time point $t-1$ (Bringmann et al., 2013). Here, each variable corresponds to the frequency of a specific instructional

Table 5. Results of automatic text analysis models.

Models	Accuracy	Macro F1	Weighted F1	MCC	Kappa
BERT	0.80	0.76	0.80	0.75	0.73
RoBERTa	0.78	0.74	0.78	0.73	0.70
XLNet	0.77	0.72	0.76	0.72	0.69
Random Forest + BOW (Bag of Words)	0.66	0.58	0.64	0.58	0.54
Random Forest + TF-IDF	0.66	0.57	0.64	0.58	0.54
Random Forest + Embeddings	0.62	0.52	0.59	0.53	0.48

behaviour (e.g., scaffolding, feedback, direct intervention) observed within a discussion thread during a defined time interval. Thus, the model estimates how the occurrence of one instructional behaviour in an earlier phase of a thread predicts the likelihood of the same or different behaviours emerging in the subsequent phase.

To construct comparable temporal representations across discussion threads of varying lengths, we divided each thread into 10 equal sequential segments based on post order. Specifically, each discussion thread was partitioned into 10 consecutive segments, each containing an approximately equal number of posts, thereby preserving the relative progression of the discussion regardless of absolute posting times. We did not use timestamps to define temporal segments, as interactions on the platform are asynchronous and the elapsed time between posts varies substantially across threads, making clock time–based segmentation less meaningful for modelling behavioural dynamics. These segments therefore represent relative interaction phases within a thread rather than absolute time intervals, allowing us to model how instructional behaviours evolve as discussions unfold. The choice of 10 segments reflects a trade-off between temporal resolution and data sparsity. Using fewer segments would obscure fine-grained behavioural transitions, whereas dividing threads into more segments would lead to sparse observations within segments, particularly for less frequent instructional behaviours. Ten segments provided sufficient temporal granularity while maintaining stable frequency estimates across behaviours. To ensure a meaningful temporal structure, threads with fewer than 10 posts were excluded from the analysis ($n = 136$), as they could not be reliably segmented into 10 sequential phases. After this filtering step, each thread contributed 10 segment-level observations, and the resulting segment-by-thread units constituted the analytic time-series data used in the temporal network analysis.

We predicted the frequency Y of a particular instructional behaviour i at time point t for each discussion thread d, conditional on the frequencies of all instructional behaviours at the previous time point $t-1$, as specified in the following equation:

$$\begin{aligned} Y_{djt} = a_{0di} &+ \omega_{1di} \cdot \mathit{DirectIntervention}_{d,t-1} + \omega_{2di} \cdot \mathit{PeerInteractionSupport}_{d,t-1} \\ &+ \omega_{3di} \cdot \mathit{ManagingDiscussion}_{d,t-1} + \omega_{4di} \cdot \mathit{EmotionalSupport}_{d,t-1} \\ &+ \omega_{5di} \cdot \mathit{AcknowledgingIssues}_{d,t-1} + \omega_{6di} \cdot \mathit{Feedback}_{d,t-1} \\ &+ \omega_{7di} \cdot \mathit{Scaffolding}_{d,t-1} + \varepsilon_{dit}, \end{aligned} \tag{1}$$

$$\begin{aligned} \text{where } i \in \{&\text{DirectIntervention}, \text{PeerInteractionSupport}, \text{ManagingDiscussion}, \text{EmotionalSupport}, \\ &\text{AcknowledgingIssues}, \text{Feedback}, \text{Scaffolding}\}, \\ t \in \{&1,2,\ldots,10\}, \quad d \in \{1,2,\ldots,2152\}. \end{aligned}$$

There are seven distinct instructional behaviours; therefore, the multilevel VAR model can be compactly expressed as

$$\begin{aligned} Y(t) = \alpha &+ \omega_1 \cdot \text{DirectIntervention}(t-1) + \omega_2 \cdot \text{PeerInteractionSupport}(t-1) \\ &+ \omega_3 \cdot \text{ManagingDiscussion}(t-1) + \omega_4 \cdot \text{EmotionalSupport}(t-1) \\ &+ \omega_5 \cdot \text{AcknowledgingIssues}(t-1) + \omega_6 \cdot \text{Feedback}(t-1) \\ &+ \omega_7 \cdot \text{Scaffolding}(t-1) + \varepsilon. \end{aligned} \tag{2}$$

In this formulation, $Y(t)$ denotes a vector of instructional behaviour frequencies at time t, and each coefficient ω_k represents the estimated lagged influence of one behaviour on another in the subsequent interaction phase.

From a network perspective, ω_1 is a set of weight values whose edges originate from the seven instructional behaviour nodes and point to the node *DirectIntervention*. In this way, we construct a directed, weighted network consisting of seven nodes, each representing an instructional behaviour. The edge weights indicate the strength and direction of temporal influence between behaviours across successive phases of a discussion thread. This network representation enables visualization and comparison of how instructional behaviours dynamically interact over time. To investigate differences across interaction configurations, we estimated three separate models: one using all threads, one using peer-only threads, and one using instructor-only threads.

Several alternative approaches exist for analyzing temporal interaction data, including epistemic network analysis (ENA) and frequent sequence pattern mining. ENA is effective for modelling co-occurrence structures among discourse codes and has been widely used to study epistemic framing and collaborative learning processes (Shaffer et al., 2016). However, ENA does not explicitly model time-lagged or directional dependencies between behaviours across successive interaction phases. Likewise, frequent sequence pattern mining techniques are useful for identifying recurring behavioural patterns in educational interaction data (Romero & Ventura, 2010). However, these approaches are primarily descriptive and do not estimate the strength, directionality, or statistical significance of temporal dependencies among behaviours. In contrast, the multilevel VAR approach adopted in this study is specifically designed to model directional, time-lagged influences among multiple instructional behaviours while accounting for the nested structure of longitudinal interaction data (Bringmann et al., 2013). This makes it particularly suitable for addressing research questions concerned with how instructional behaviours dynamically influence one another over time, rather than simply identifying common co-occurrences or frequent sequences.

4. Results

4.1 Response to RQ1

To compare instructional behaviours between peers and instructors, we annotated discussion posts with seven instructional behaviour categories (see *Code* column of Table 2). Peers contributed a substantially larger average number of posts per thread (37.3 posts/thread) than did instructors (18.1 posts/thread). In general, peers and instructors exhibited significantly different distributions of instructional behaviours $X^2(6, N = 41784) = 1333.5, p < 0.01$. The analyses were conducted using instructional behaviour proportions at the thread level, thereby reducing the influence of unequal posting volumes between peers and instructors.

Table 6 shows the mean proportion of each instructional behaviour category per thread for peers and instructors. Overall, all instructional behaviour categories differed significantly between the two groups. It is noteworthy that the effect sizes for feedback and acknowledging issues were both larger than 0.8, indicating large effects. Direct intervention and emotional support exhibited a medium effect size (Cohen's d is about 0.5), while the remaining categories showed small effect sizes (Cohen's $d < 0.5$).

Table 6. Univariate tests of the dependent variables for peers and instructors. *Note*: Mean was calculated by instructional behaviour proportion per thread. All t-test results are statistically significant. Cohen's d measures effect size.

	Participant role	**Mean** (%)	**SD** (%)	**T-statistic**	**Cohen's *d***
Scaffolding	Peer	13.60	8.08	7.16	0.37
	Expert	10.20	10.10		
Direct intervention	Peer	27.70	13.30	12.57	0.65
	Expert	15.00	13.70		
Feedback	Peer	10.80	7.21	22.97	1.18
	Expert	3.66	4.56		
Emotional support	Peer	4.95	4.81	9.15	0.47
	Expert	3.02	3.22		
Managing discussions	Peer	4.61	5.12	5.42	0.28
	Expert	3.38	3.56		
Peer interaction support	Peer	1.67	2.76	3.68	0.19
	Expert	1.22	1.92		
Acknowledging issues	Peer	6.05	6.27	22.28	1.15
	Expert	0.78	1.67		

4.2 Response to RQ2

To identify patterns of interaction among instructional behaviours, we conducted temporal dynamics analysis and visualized the resulting interaction structures. Figure 2 presents the interaction networks of the temporal dynamics of instructional behaviours across peer-only, instructor-only, and mixed-participant discussion threads. It is worth noting that only statistically significant edges ($p < 0.05$) were included in Figure 2. Blue arrows represent positive (excitatory) relationships, whereas dotted arrows indicate negative (inhibitory) relationships.

The greater trajectory variability observed in peer-only threads is likely related to their higher participant counts (see Table 1) and the presence of peer-specific instructional behaviours (e.g., *feedback* and *peer interaction support*), which introduce additional interaction pathways not observed in instructor-only threads.

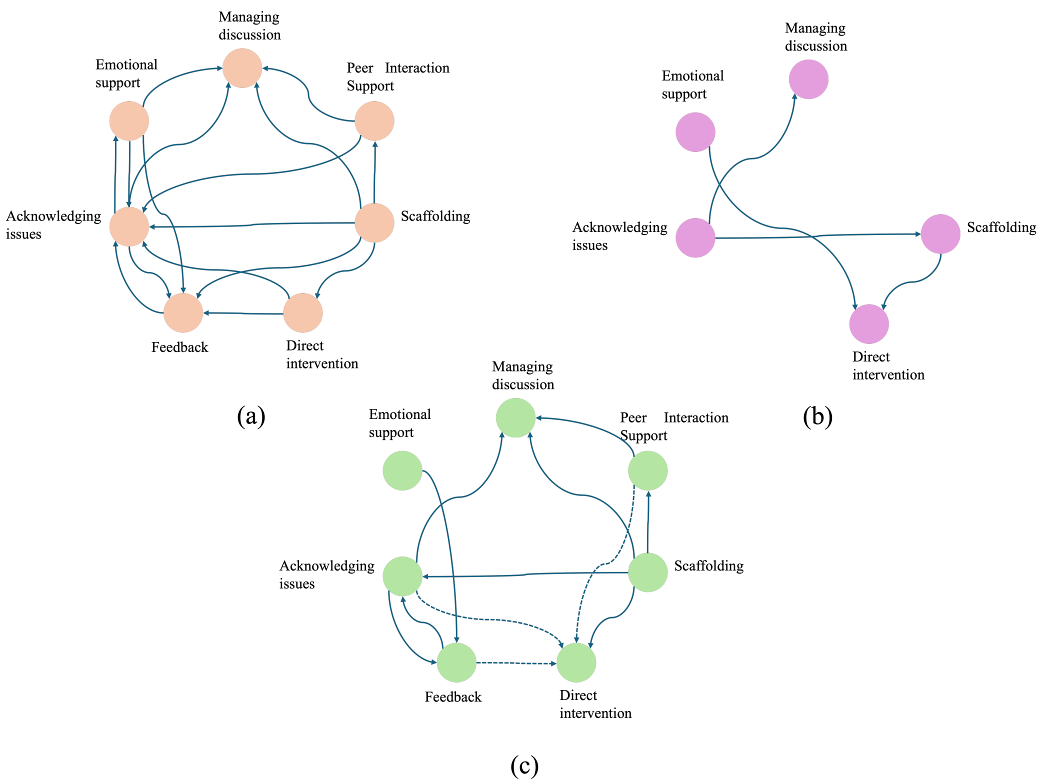

Figure 2. (a) The temporal network of instructional interactions for discussions by peers only. (b) The temporal network of instructional interactions for discussions by experts only. (c) The temporal network of instructional interactions for discussions involved both peers and experts. *Note*: All relationships are statistically significant ($p < 0.05$). Threshold: Only consider the ones with weights bigger than 0.1 for positive; no threshold is applied for negative.

In addition, although some edges were statistically significant, their corresponding weights were close to zero and were therefore not considered substantively meaningful. Thus, we report only edges with absolute weight values greater than 0.1. As a result, negative relationships were not present in two of the network visualizations. Because our focus was on interactions among different behavioural categories, self-loops were removed from the network figures. Table 7 reports the weight values associated with each edge in Figure 2.

Figures 2(a) and (b) show that peer interactions exhibited more diverse instructional strategies than instructor interactions. Specifically, peer-only networks included two additional nodes (i.e., *peer interaction support* and *feedback*) that were not present in instructor-only networks. In addition, peer interactions demonstrated more complex interconnections among behavioural categories. The node that most frequently received positive influences from other nodes was *acknowledging issues*. Peers were more likely to engage in this behaviour following actions such as *direct intervention*, *emotional support*, *feedback*, and *scaffolding*. Furthermore, *feedback* and *managing discussions* were often observed following behaviours such as *acknowledging issues*, *emotional support*, and *scaffolding*. The strongest positive edge was observed from *scaffolding* to *direct intervention* (weight = 0.39), indicating that *direct intervention* most frequently followed *scaffolding*.

In contrast, the instructor-only network contained fewer nodes and exhibited less complex interaction patterns. In this network, *direct intervention* tended to follow both *emotional support* and *scaffolding*. Additionally, following *acknowledging issues*, *managing discussions* and *scaffolding* were more likely to occur.

Table 7. Weight values for network figures.

Source	Target	Weight
Peer only		
direct intervention	acknowledging issues	0.126
emotional support	acknowledging issues	0.127
feedback	acknowledging issues	0.196
peer interaction support	acknowledging issues	0.106
scaffolding	acknowledging issues	0.225
scaffolding	direct intervention	0.392
acknowledging issues	emotional support	0.111
acknowledging issues	feedback	0.198
direct intervention	feedback	0.110
emotional support	feedback	0.142
scaffolding	feedback	0.141
scaffolding	peer interaction support	0.151
acknowledging issues	managing discussions	0.131
emotional support	managing discussions	0.139
peer interaction support	managing discussions	0.191
scaffolding	managing discussions	0.148
Expert only		
emotional support	direct intervention	0.189
scaffolding	direct intervention	0.168
acknowledging issues	managing discussions	0.110
acknowledging issues	scaffolding	0.162
Both expert and peer		
feedback	direct intervention	-0.163
peer interaction support	direct intervention	-0.151
feedback	acknowledging issues	0.166
scaffolding	acknowledging issues	0.241
scaffolding	direct intervention	0.271
acknowledging issues	feedback	0.147
emotional support	feedback	0.123
scaffolding	peer interaction support	0.139
acknowledging issues	managing discussions	0.120
peer interaction support	managing discussions	0.124
scaffolding	managing discussions	0.135

To investigate interaction patterns in threads involving both peers and instructors, we analyzed the temporal dynamics of mixed-participant discussion threads. Figure 2(c) illustrates the network of temporal interactions among instructional strategies. In addition to positive relationships, several negative (inhibitory) relationships were observed. For instance, behaviours such as *acknowledging issues*, *feedback*, and *peer interaction support* were associated with a decreased likelihood of subsequent *direct intervention*. In contrast, *scaffolding* positively predicted not only *direct intervention* but also *acknowledging issues*, *managing discussions*, and *peer interaction support*. Furthermore, a reciprocal positive relationship was observed between *acknowledging issues* and *feedback*.

Across networks, several recurrent temporal trajectories were identified. In instructor-only threads, a "support-to-guidance" trajectory was prominent, in which *emotional support* and/or *acknowledging issues* tended to precede *scaffolding*, which in turn predicted subsequent *direct intervention*. In peer-only threads, an "acknowledgement-centred" trajectory emerged, characterized by multiple strategies (e.g., *direct intervention*, *emotional support*, *feedback*) converging on *acknowledging issues*, followed by transitions to *feedback* and *managing discussions*. In mixed-participant threads, "instructor moderation" was reflected in inhibitory relationships, where peer-specific behaviours (e.g., *feedback* and *peer interaction support*) reduced the likelihood of subsequent *direct intervention*.

5. Discussion

This study reveals substantial differences in the frequencies, types, and temporal patterns of instructional behaviours enacted by instructors and peers in a large-scale online math discussion forum. Consistent with RQ1, peers exhibited higher posting frequencies and were significantly more likely to engage in behaviours such as acknowledging issues and providing feedback than were instructors. Importantly, these differences were examined using thread-level proportional measures rather than raw behaviour counts, which mitigates base-rate effects associated with unequal numbers of peer and instructor posts. As such, our findings reflect relative strategy use within discussion-based instructional interactions, rather than simple differences in activity volume. With respect to RQ2, we identified distinct temporal dynamics across instructor-only, peer-only, and mixed-participant discussion contexts. Specifically, instructor-only threads demonstrated more structured and linear behavioural trajectories, whereas peer-only threads exhibited more diverse and less predictable patterns. Notably, in mixed-participant contexts, instructor interventions following peer contributions were associated with a reduced likelihood of subsequent peer direct intervention behaviours. These findings characterize role enactment and interaction dynamics within asynchronous, forum-based learning environments. Below, we discuss these findings in light of existing literature and elaborate on their implications for instructional support design and methodological advancement within the learning analytics field.

5.1 Differentiated Instructional Strategies: Instructors versus Peers

Our findings underscore the contrasting strategies employed by instructors and peers, which can be understood as distinct behavioural trajectories that reflect different pedagogical intents and levels of expertise. Instructor contributions followed more structured, goal-oriented behaviour sequences, typically initiating interactions with emotional support or acknowledgement, followed by scaffolding moves such as questioning or elaboration prompts, and often concluding with direct instruction or discussion management. Within the studied platform, instructors occupy a designated instructional role and typically intervene selectively rather than responding to every post. This role configuration may partially account for the lower overall prevalence of instructor-coded behaviours observed in comparison to those of peers. These sequential patterns align well with existing models of online instructional facilitation, such as the Five-Stage Model (Salmon, 2012) and the Online Learning Interaction Model (Xie & Ke, 2011), and our findings extend these frameworks by showing how specific micro-level discourse behaviours unfold within each stage. In particular, the temporal trajectories we identified provide empirical evidence for the progression from social presence to cognitive engagement assumed in these models (e.g., Garrison et al., 2000; Salmon, 2012), but rarely quantified in prior work. We distinguish between variability attributable to interactional structure (e.g., participant volume and role distribution) and variability that reflects pedagogically meaningful shifts in instructional support (e.g., transitions from affective support to cognitive scaffolding and subsequent direct intervention).

In contrast, peer contributions appeared more fragmented and variable. While some peers exhibited patterns similar to instructor-like sequences, others demonstrated more oscillatory or affect-driven behaviours, often revolving around acknowledgement and positive feedback rather than conceptual scaffolding. Because peer-only, instructor-only, and mixed-participant contexts were analyzed within the same platform and under comparable interaction affordances, the observed differences are unlikely to be artifacts of the forum medium itself, but rather reflect differences in participant roles and interaction structures. This aligns with prior findings that peer contributors, particularly in unstructured or voluntary contexts, often prioritize social cohesion over deep cognitive support (King, 1999; De Smet et al., 2008). Our results further nuance these theories by highlighting how peers' behavioural oscillations challenge linear stage-based models of facilitation, suggesting that peer-driven interactions may require an adapted or expanded framework that accounts for fluid movement between affective and cognitive behaviours rather than a unidirectional progression (De Smet et al., 2008). From a learning analytics standpoint, these behaviour sequences highlight the need to model not only what behaviours occur, but how they co-occur and evolve over time to support or hinder learning processes.

Furthermore, the high frequency of issue acknowledgement by peers (almost seven times that of instructors) suggests a behavioural signature that may indicate either a collaborative disposition or uncertainty in content mastery. This pattern offers a theoretically meaningful extension to prior research by identifying acknowledgement-heavy sequences as a potential marker of novice instructional behaviour, consistent with distinctions between novice and expert instructional moves (Roscoe & Chi, 2007; Chi, 2009). These nuanced behavioural signals can be leveraged in real-time learning analytics dashboards to detect struggling participants and deliver just-in-time scaffolds. In sum, our comparative behavioural analysis provides a foundation for data-informed intervention design in online learning systems that incorporate both instructor and peer support structures, while also refining existing facilitation theories by demonstrating how expertise level shapes the temporal organization of instructional behaviours. These findings are most directly applicable to asynchronous, discussion-based learning environments with distributed instructional support, although the analytic approach may be transferable to other instructional contexts.

These peer-driven oscillations between affective moves (e.g., acknowledging issues, emotional support) and cognitive moves (e.g., scaffolding, direct intervention) can also be interpreted through the lens of socially shared regulation of learning, in which regulation is distributed across participants and emerges through interaction. From this perspective, acknowledgement-and feedback-heavy sequences may reflect attempts to negotiate understanding and coordinate next steps, rather than a single participant executing a linear instructional plan.

5.2 Implications for Supporting Novice Participants

The behavioural patterns identified in this study offer actionable insights for improving peer support practices and instructional guidance in online discussion forums, particularly through learning analytics–enabled interventions. Existing research highlights the fact that, without structured guidance, peer contributors may offer only superficial or misdirected support (Keer, 2004; K. Topping et al., 2017). Our results affirm this concern and suggest opportunities for scaffolding novice participants by drawing on instructional behaviour patterns observed in instructor contributions.

One implication is the potential to design data-driven training modules informed by instructor behavioural sequences. By leveraging behavioural analytics to extract high-quality interaction trajectories, such as emotional support followed by cognitive scaffolding, educators can create annotated exemplars, walkthroughs, or simulations that expose novice participants to effective discourse moves. Such analytics-informed artifacts have been shown to support deeper learning in both teacher preparation and online peer mentoring contexts (Roscoe & Chi, 2007; Chi, 2009).

In addition to structured training, in-situ and social learning mechanisms offer promising complementary strategies. Our findings indicate that instructors often intervene in peer-led discussions, implicitly modelling effective instructional practices. These moments can be reframed as embedded learning opportunities. Learning analytics systems could be designed to surface these interactions to peer participants as reflective prompts or interactive dashboards (e.g., "Here's how an instructor followed up on a similar issue"), thus enabling scaffolded reflection-in-action. Prior research has shown that observational learning and situated feedback in authentic contexts are critical components in skill development (Cheng & Ku, 2009). Embedding these mechanisms into forum infrastructure represents a scalable path forward for enhancing peer support capacity.

5.3 Methodological Contributions to Learning Analytics

This study contributes methodologically to the learning analytics literature by demonstrating how scalable discourse analysis can be combined with temporal modelling to investigate complex social learning behaviours. Prior studies of peer support and instructional interaction have largely relied on manual coding schemes applied to small datasets and summarized using descriptive statistics (De Smet et al., 2008; Berghmans et al., 2013). In contrast, we employed transformer-based models (e.g., BERT, RoBERTa, XLNet) for automated behavioural coding across a corpus of over 100,000 discussion posts, enabling fine-grained and scalable annotation of instructional behaviours with high reliability. This reflects a broader methodological shift in learning analytics toward integrating NLP techniques for behavioural modelling at scale.

More critically, we extended analysis beyond static behavioural frequencies by applying VAR to model the temporal interdependencies among instructional behaviours. This approach allowed us to map behavioural trajectories and detect how specific discourse moves (e.g., feedback or questioning) tend to lead to or suppress others over time. Temporal network visualizations further enabled interpretability of these sequential relationships across different interaction contexts. Such multimodal integration (combining content-based, temporal, and structural analytics) demonstrates the methodological potential of learning analytics to uncover latent patterns in large-scale educational interaction data (F. Yang & Stefaniak, 2023; Moreau-Pernet et al., 2024; Wu et al., 2024).

6. Conclusion

This study conceptualizes instructional interactions in online discussion forums as a dynamic process comprising temporally interacting instructional behaviours. Using a combination of automated discourse coding, multilevel VAR, and network-based visualization, we examined how instructional behaviours unfold and interact over time in peer-only, instructor-only, and mixed-participant discussion threads within a large-scale online mathematics forum.

Across analyses, we found that instructors and peers differed not only in the frequency of specific behaviours but, more importantly, in the temporal organization of those behaviours. Instructor-only threads were characterized by relatively structured and sequential trajectories, typically progressing from affective support and acknowledgement toward cognitive scaffolding and direct intervention. In contrast, peer-only threads exhibited more diverse and less linear trajectories, with frequent oscillations among acknowledgement, feedback, and other support strategies. In mixed-participant contexts, instructor interventions systematically altered subsequent peer behaviour, including reducing peers' likelihood of direct intervention and reorienting interactions toward social support and information exchange.

Beyond documenting behavioural differences, this work demonstrates the value of temporal dynamics analysis for advancing pedagogical and learning analytics research. Rather than treating instructional behaviours as isolated events, our approach reveals how instructional support is enacted as a process, with specific behaviours shaping what follows. These findings extend existing facilitation and scaffolding frameworks by empirically operationalizing their assumed temporal progressions in authentic, large-scale online interactions. From a learning analytics perspective, the identified trajectories provide a foundation for sequence-aware analytics that move beyond post-level classification toward process-oriented understanding of instructional interactions.

Methodologically, this study illustrates how transformer-based text classification can be responsibly integrated with temporal modelling to support scalable analysis of interaction processes, while maintaining transparency about classification limitations. By shifting the analytic focus from perfect labelling to robust pattern detection across thousands of threads, the study offers a rigorous and replicable approach for examining instructional dynamics in large online learning environments.

6.1 Limitations

Despite its contributions, this study has several limitations. First, the data were drawn from a specific online learning platform serving students primarily from a limited set of U.S. states. As such, the observed instructional behaviours and temporal patterns may not generalize to other educational contexts, subject domains, or cultural settings.

Second, the analysis focused on observable discourse behaviours rather than underlying cognitive or motivational processes. While this aligns with established approaches in discourse and learning analytics research, it limits our ability to make claims about learners' internal states or the instructional quality of individual behavioural moves. In addition, the multilevel VAR model assumes that behaviours at a given phase are primarily influenced by immediately preceding behaviours. Longer-range dependencies may exist and warrant more complex temporal modelling in future work.

Third, although automated text classification enabled scalable coding, classification accuracy varied across instructional behaviour categories, particularly for low-frequency categories. Importantly, the temporal analysis relied on aggregated transition patterns across thousands of threads rather than on the correctness of individual classifications. As a result, moderate classification noise is unlikely to systematically bias the estimated temporal relationships. Nevertheless, this limitation constrains fine-grained interpretation of rare behaviours.

Finally, this study examined the temporal organization of instructional behaviours without directly linking behavioural trajectories to learning outcomes. Consequently, we do not claim that particular sequences are inherently more effective for learning. Instead, our findings characterize interactional dynamics that are pedagogically meaningful in their own right and provide a foundation for subsequent outcome-oriented investigations.

6.2 Future Work

Future research could extend this work in several directions. One important avenue is to integrate temporal behavioural trajectories with direct indicators of instructional quality or learning outcomes, such as student performance measures or expert ratings, to examine how different instructional processes relate to effectiveness. Such integration would enable stronger pedagogical claims while preserving a process-oriented analytic perspective. Another promising direction is to improve the modelling of low-frequency instructional behaviours through expanded manual annotation, semi-supervised learning, or human-in-the-loop refinement. These approaches could enhance classification reliability without shifting the primary focus of analysis toward classifier optimization.

From a learning analytics perspective, future work could operationalize the identified temporal trajectories within learning analytics dashboards. For example, sequence-aware indicators could be developed to detect deviations from productive interaction patterns, support transition-sensitive prompts, or visualize instructional processes as they unfold over time. More broadly, applying adaptive temporal segmentation or behaviour-specific temporal representations may further improve the sensitivity of temporal models to heterogeneous instructional dynamics across different learning contexts.

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