

# Uncovering socio-temporal dynamics in online discussions: An event-based approach

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Online discussions are widely adopted in higher education to promote student interaction. However, prior research on online discussions falls short to estimate the effect of multiple factors collectively shape student interaction in online discussion activities. In this study, we applied a dynamic network analysis approach named relational event modelling to a data set from an online course where students participated in weekly discussion activities. In the relational event models, we incorporated multiple factors including participant characteristics, network formation mechanisms and immediate participation shifts. Results indicated that the instructor was more likely to initiate interactions but less likely to receive responses. Popularity, activity and familiarity established in prior relational events positively affected future events. Immediate participation shifts such as local popularity, immediate reciprocation and activity bursts also played a positive role. The study highlights the importance of considering multiple factors when examining online discussions, demonstrates the utility of relational event modelling for analysing online interaction and contributes empirical insights into student interaction in online discussions.

### *Implications for practice or policy:*

- Supporting online discussions in college classrooms requires instructors to consider multiple actors including pedagogical designs, technological affordances, learner characteristics and social dynamics.
- Educators could go beyond simply counting student posts to paying attention to how students interact at a micro level.
- Educators and instructional designers could pay attention to socio-temporal dynamics in online discussions and evaluate whether emerging dynamics in a particular course are desirable and conducive to student learning.

*Keywords:* online learning, online discussions, network analysis, relational event modelling (REM), temporal analysis

## Introduction

Asynchronous online discussions are widely adopted to promote student interaction at all levels of education. Online discussions can enrich student learning, sustain participation and support under-served students, as shown by previous studies (Jo et al., 2017; Rakovic et al., 2020; Zheng & Warschauer, 2015). However, productive online discussions do not occur automatically. To effectively scaffold discussions through proper and well-timed interventions, one needs to understand the factors that propel discussion activities.

Unfortunately, explanatory models of online discussions remain rare. It is well understood that pedagogical designs and technological affordances would shape online learning discussions (Guzdial & Turns, 2000). Research also shows that other factors such as learner characteristics and social dynamics may influence online discussions (B. Chen & Huang, 2019; Vaquero & Cebrian, 2013). However, holistically

considering these factors – pedagogical, technological, social, temporal – when modelling online discussions to explain how they develop, remains a challenge.

This study responds to the research gap by tackling the following question: How do multiple factors – social, cognitive, temporal – collectively shape social interaction among peers in asynchronous online discussions? To this end, we seriously considered the temporal dimension of online discussion and conceptualised social interaction in online discussions as a complex, dynamic phenomenon that is shaped by these many factors in tandem. To properly capture temporal dynamics, we adopted a network analysis method named relational event modelling (REM), which is sensitive to both the timing and sequence of events, and applied it to a data set of online discussion activities. In the following sections, we elaborate on factors shaping social interaction in online discussions. We then introduce REM and report the findings. We conclude by discussing the study’s conceptual, methodological and practical implications.

## **Related work**

### **Factors shaping interaction in asynchronous online discussions**

Social participation and interaction in online discussions are shaped by diverse factors including pedagogical design, technological affordances, learner characteristics and social dynamics.

When it comes to pedagogical factors shaping online discussions, various elements of teacher decisions and behaviours can come into play, including discussion prompts, task structures, instructor feedback and instructor presence. In a teacher-centred class, the interactions would naturally centre on the teacher. In contrast, pedagogical models that emphasise student agency are conducive to patterns in which the teacher would be in the periphery within class communication (J. Zhang et al., 2009). Besides the activity structure, the task environment of a discussion activity also shapes how students respond to each other. An instructor could ask students to share news articles, critique course readings, provide peer feedback or construct shared knowledge, leading to different discussion behaviours and outcomes (Lee & Recker, 2021). In addition, the instructor’s participation in the discussion also matters as well as students’ perception of the instructor’s presence (Cho & Kim, 2013; Mullen & Tallent-Runnels, 2006).

Technological configurations of online discussion environments also impact learner activity in online discussions. Technology designs that direct user attention away from unread notes can hasten the death of discussion threads and throttle inactive threads from being reactivated (Hewitt, 2005). Specialised discussion environments such as Knowledge Forum may have encoded strong pedagogical viewpoints on social interaction (Scardamalia & Bereiter, 2008). In contrast, general discussion tools such as social network sites may offer technological features that serve educational purposes (Rachtham et al., 2012) while also potentially distracting student learning as social network sites prioritise personal profiles and social ties over subject matter-focused dialogues.

Interaction in online discussions is also shaped by learners’ knowledge, skills and dispositions. For example, learners’ individual motivation and goal orientation influence both the quantity and quality of their contributions (Cho & Kim, 2013). Some learners prefer lurking over posting, especially when English is not their first language (Shafie et al., 2016). Gender differences in online discussions have also been observed, with female students overall writing more messages than males but less so in mixed groups (Cho et al., 2022). These personal differences manifest in different levels of participation or post intensity, often measured by the count of forum posts.

Sociological factors prominent in human society also play significant roles in online discussions. For example, students would be more likely to respond to someone with a “superior” status, such as being the course instructor or being “popular” in a class (Vaquero & Cebrian, 2013). Reciprocity, another common social behaviour, can also come into play as peers tend to reciprocate responses (Cheung et al., 2008). Peer pressure generated by active participants in online discussions can drive more students to

participate (X. Zhang, 2023). These social factors are not only related to the intensity of participation but can also be closely interrelated to the quality of contributions (Galikyan et al., 2021).

Taken together, social interaction in online discussions is collectively shaped by pedagogical, technological, learner and social factors. Of course, what is said within a discussion or how learners respond to each other as reflected within their discourse is also an important factor of how online discussions unfold. The cognitive content of discussion posts has been examined in prior studies to support its importance (G. Chen et al., 2020; Zingaro & Oztok, 2012). However, it can be argued that the content of the discussion is a function of pedagogical and technological affordances of the online discussion environment as well as individual characteristics that manifest through social factors during the process of interaction (B. Chen & Chen, 2023). In other words, what and how learners are talking about can be actually explained by these factors, and therefore, they can be of primary importance in explaining how online discussions unfold.

### Consideration of time in online discussions

It is of great importance to consider a temporal dimension in modelling online discussions as they are generated by the interplay of the factors discussed above. Although prior studies on online discussions have uncovered various factors contributing to online interactions, the temporal dimension often gets side-lined in these studies (Knight et al., 2017). Traditional research methods rely on the coding and counting of discussion activities (Jeong et al., 2014), by and large ignoring the pace, order and duration of learning events. In rare cases when temporal factors are considered, the analysis of time often lacks in granularity and includes only factors such as the learner's perception of time, the instructor's temporal expectations and high-level summative information about temporal participation patterns. For instance, B. Chen and Huang (2019) used temporal information about student participation to divide students into two categories (early-starters and late-arrivers) and found early-starters tend to occupy central positions in their interaction network. Such analysis extracts high-level temporal information for traditional methods (e.g., group comparisons) and falls short in uncovering granular temporal patterns in student interactions. To consider the temporal dimension of online discussions, researchers need to interrogate the conceptualisation of time and order and seek analytical methods that are both congruent with the conceptualisation and capable of uncovering the turn-by-turn unfolding of interactional events.

In this paper, we argue for modelling social interactions as discrete relational events that unfold over time with the occurrence of each event depending on various factors. A *relational event* can be defined as a "discrete event generated by a social actor and directed toward one or more targets" (Butts, 2008, p. 159). A *relational state* between two social actors (e.g., between two students in a course), in contrast, can be considered as a function of a series of relational events between these actors. Prior studies have often considered student interaction in online forums as network ties. However, a tie in a network in essence represents a relational state of "being replied to," such as Student A has replied to Student B five times while B has replied to A three times in a course. In this case, relational events such as replies are aggregated to depict a state. Although investigating social interaction as relational states allows researchers to discern interaction patterns, conceptual rigour could be hampered if the aggregation of relational events over time is done superficially. Indeed, every relational event, for example, Student A replying to a post created by Student B at  $t_1$ , arises from its unique context. This event is essentially different from another reply from A to B at  $t_2$ . Simply aggregating two events together to make a claim about a relational state between the students treats these events as equal, neglecting the unique contexts in which these events occur and different forces that may drive these events. As elaborated above, when one student decides whether to interact with another student, many factors might be at play, including the student's personal traits, the other student's post content, whether they are assigned to the same group and any earlier interactions between these two students. The accumulated relational events between students contribute to the formation and changes of their relational state, such as whether two students have developed a shared interest, which creates new conditions for future relational events. To understand how online discussions unfold, it is more conceptually sound to focus on the event level, treating a relational event as a distinct phenomenon that is bounded by its context and contributes to the dynamic and emergent process of social interaction in online discussions.

## The present study

The present study put these various perspectives together to model online learning discussions. Informed by prior work around the factors shaping online discussions such as pedagogy, technology, individual characteristics, social dynamics and the need to model them as relational events unfolding over time, we asked: Considering pedagogical and technological factors, in which ways do learner characteristics and social dynamics collectively shape social interaction in asynchronous online discussions in higher education context?

## Research context

### Participants

The study was situated in an undergraduate, online course at a large public university in the United States of America. The course covered topics related to technology and ethics and attracted undergraduate students from a wide range of disciplines. One section of this course ( $n = 20$ ) participated in this study.

The course design followed social constructivist perspectives of learning. The instructor used a tool named Yellowdig to support asynchronous online discussions among students. We elaborate on the technological and pedagogical conditions for online learning discussions in this course to properly explain the type of influence they could have over the unfolding discussions.

### The discussion tool

The discussion environment Yellowdig resembles social network sites like Reddit. As illustrated in Figure 1, a student can share posts – known as *pins* – that can be commented on or reacted to (e.g., like) by other students. Students could also mention each other in a post or comment.

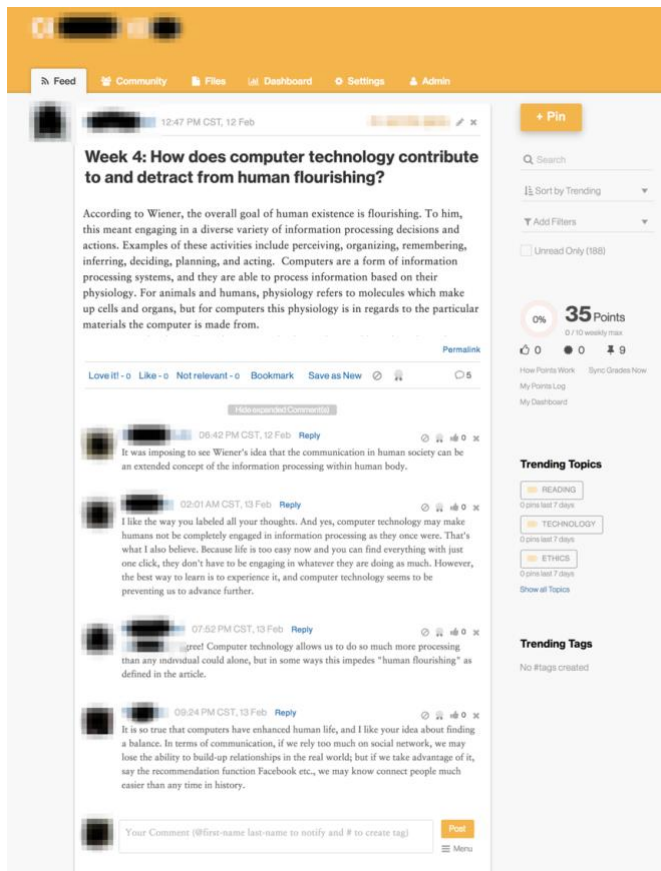


Figure 1. The interface of Yellowdig. This figure shows one pin created by one student that attracted four comments.

Similar to many social network websites, a class on Yellowdig has a news feed featuring posts by its members. This news feed can be sorted in different ways, and the default sorting algorithm places the most recent discussion activities on the top. When a pin receives a new comment or reaction, it will be placed on top of the news feed. However, Yellowdig is different from social network sites in that its user profile features are less emphasised. Rather than following or making friends with each other, students visit Yellowdig to participate in content-based discussions similar to those in online discussion forums. Overall, Yellowdig combines technological features of both discussion forms and social network sites to promote content-based discussions and social interaction among students.

#### *Discussion activity design*

Online discussion on Yellowdig was an integral part of this online class. Students participated weekly on Yellowdig to discuss readings and share ideas. Each week, they were asked to either make a post in response to a prompt or post a commentary on a news article related to the course topic. They were required to minimally contribute one post and comment on two posts each week. A labour-based grading practice was adopted. Students received points when they demonstrated enough effort to participate by posting substantive content (e.g., minimally 100 words in a post) and engaging with their peers.

#### **Data sources**

We were granted approval from the Institutional Review Board to analyse system logs from these classes. The scope of approval was limited to timestamped event logs; therefore, the post content had to be excluded from the analysis.

Interaction data from Yellowdig, including 274 posts, 514 comments, 36 mentions and 74 reactions, were the primary data source. Course materials, including the syllabus and weekly announcements, were gathered to inform the interpretation of results.

#### **Research hypotheses**

Drawing on the research literature (see the Related work section) and considering the research context, we narrowed down to a list of research hypotheses about participant characteristics and social dynamics. Our analysis was limited to system logs that did not include students' discussion content, which limited the scope of our hypotheses. The hypotheses were formulated in the order of how patterns may form in a social setting: sometimes it is an individual-level characteristic that shapes if someone replies or receives replies (the first set of hypothesis), sometimes it is the dynamics between a pair of people or an emergent triad (the second set of hypothesis), and sometimes it is a micro-level activity between the types of behaviours that usually follow each other such as responding to a set of comments from multiple peers (the third set of hypothesis). In each of these sets of hypotheses, we added either individual characteristics or social dynamics that may be influencing the emergence of online learning discussions, as per our proposed conceptualisation of social interaction in online discussions.

Our first set of hypotheses explains patterns of sending and receiving replies by considering individual characteristics and individual social status of discussion participants. Regarding participant characteristics, the literature shows that the timing of participation matters. Students' posts written earlier in the week tend to receive more replies (Zingaro & Oztok, 2012), and students who join online discussions earlier are more likely to occupy central positions in their interaction networks (B. Chen & Huang, 2019). Being time-consistent, meaning not participating in online discussions close to the deadline but spreading out effort across a week, is likely to be associated with social interaction. Also, sometimes being the instructor may or may not attract student interaction (Zingaro & Oztok, 2012). Therefore, we proposed the following hypotheses about participant characteristics that explain if online discussion participants with a particular characteristic are more likely to reply to others or receive replies:

- H1a: Learners with consistent temporal patterns of participation are more likely to reply to others.

- H1b: Learners with consistent temporal patterns of participation are more likely to receive replies from others.
- H1c: The instructor is more likely to reply to others.
- H1d: The instructor is more likely to receive replies.

Our second set of hypotheses pertains to social mechanisms in the interaction process itself. First, factors associated with familiarity established in prior relational events are predictive of future events. There are different types of familiarity in the context of online discussion including popularity, persistence, reciprocity and triadic closure. Participants of online discussion also tend to reciprocate each other (Cheung et al., 2008), meaning that prior replies are likely to be reciprocated. Finally, because the discussion environment Yellowdig resembles the features of social network sites that aim to facilitate peer interaction in discussion threads, it is reasonable to hypothesise that when two students interact with a common peer within or across discussion threads, they are likely to interact with each other by forming a triadic closure (Bianconi et al., 2014). Based on these ideas, we proposed the following hypotheses pertinent to different types of familiarity formed in prior relational events – to model social dynamics at the level of dyads and triads.

- H2a: The number of a learner's prior interactions affects future incoming ties.
- H2b: Past interactions from A to B are to be reciprocated by new interactions from B to A.
- H2c: Past interactions from A to B are to be repeated, leading to new interactions from A to B.
- H2d: Two learners sharing an outbound discussion partner (i.e., a peer being replied to by both learners) also tend to interact with each other.

The third set of hypotheses pertains to the micro patterns of activity that may always happen together. Besides factors related to familiarity reflected in prior events, the literature suggests that the patterns of such local, turn-by-turn dynamics could also contribute to global interaction patterns. Recognising the importance of the details of interaction and sequential constraints in group conversations, Gibson (2005) proposed a number of *participation shifts* patterns. His inventory of participation shifts includes *turn claiming*, *turn receiving*, *turn usurping* and *turn continuing* (see also Butts & Marcum, 2017). Prior work in contexts such as email communication has demonstrated that these micro-level social dynamics patterns have explanatory power as they are building-blocks of socio-cognitive phenomena such as transactive discussion in learning settings where reasoning and uptakes of prior reasoning statements are essential for meaningful collaboration (Gweon et al., 2013). Technologically, we recognised Yellowdig's unique features and their potential impact on participation shifts. In particular, because Yellowdig places the more recent discussion activities (either the newest post or the post with the newest reply) on the top of the news feed, a reply from Student A to Student B may not only trigger a response from Student B ( $AB \rightarrow BA$ ) but also a third student, X, who happens to be viewing the news feed ( $AB \rightarrow XB$ ). Meanwhile, given Yellowdig is an asynchronous discussion environment which students may visit at any time, it could be possible that Student B would first respond to another peer, Y, before responding to Student A ( $AB \rightarrow BY$ ). Each student may interact with peers in a batch during each Yellowdig session ( $AB \rightarrow AY$ ). Based on the literature and technological features of Yellowdig used in the study, the following hypotheses about immediate, turn-by-turn effects were proposed:

- H3a: When B receives a message from A, B tends to immediately respond to A ( $AB \rightarrow BA$ ).
- H3b: When B receives a message from A, B tends to receive another message next from a peer other than A ( $AB \rightarrow XB$ ).
- H3c: When B receives a message from A, B would immediately participate but not necessarily respond to A ( $AB \rightarrow BY$ ).
- H3d: A student tend to interact with their peers in a batch, replying to multiple peers at a time ( $AB \rightarrow AY$ ).

To sum up, the three sets of research hypotheses were generated based on the proposed framework of factors shaped online discussions, with the consideration of temporal dynamics and constraints imposed on the patterns of discussion from the study's unique pedagogical and technology context.

## REM

To test these research hypotheses, the REM approach (Butts, 2008) was applied to the data set.

As a method of social network analysis, REM provides a systematic approach to model the emergence of network structures based on the collective influence of historical relational events, actor characteristics, and contextual factors (Butts, 2008). The purpose of REM is to “understand how past interactions affect the emergence of future interactions” (Quintane et al., 2013, p. 533). For instance, an event of Student  $s$  replying to Student  $r$  at a time point,  $t_1$ , is a relational event,  $a_1$ , and Student  $r$  responding to  $s$  at a later moment,  $t_2$ , is a subsequent event,  $a_2$ , which could be influenced by  $a_1$ . REM derives a set of statistics based on historical relational events (such as the count of prior  $s \rightarrow r$  events) and combines them with actor attributes (such as gender) and contextual factors (such as group affiliation and friendship) to predict the next relational event. Mathematically, a relational event model could be expressed as follows (Butts & Marcum, 2017, p. 55):

$$\lambda_{aA_t\theta} = \begin{cases} \exp(\theta^T u(s(a), r(a), c(a), X_a, A_t)) & \text{if } a \in (A_t) \\ 0 & \text{otherwise} \end{cases}$$

where  $\lambda$  represents the hazard of potential event  $a$  at time  $t$  given history  $A_t$ ; whereas  $\vartheta$  is a vector of real-valued parameters; and  $u$  is a vector of REM statistics about the event  $a$  initiated by its sender  $s(a)$  to its receiver  $r(a)$  at time  $\tau(a)$ . For example, reciprocity as a statistic measures the odds of Student  $i$  replying to  $j$  provided that  $i$  has previously responded to  $j$ . If reciprocity is of interest in a study, a statistic of reciprocity will be incorporated in the  $u$  vector of the relational event model, together with other variables, including potential covariates,  $X_a$ . Statistics such as reciprocity capture both social and temporal information in relational events and provide rich measures to describe social interactions (Leenders et al., 2016). More detailed explanation of REM is beyond the scope of this paper and can be found elsewhere (Butts & Marcum, 2017; Leenders et al., 2016).

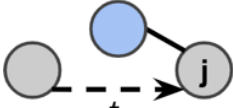
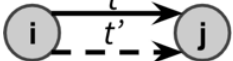
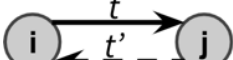
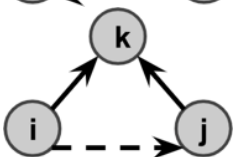
To test our hypotheses, we computed measures related to participant characteristics and sequential structural signatures reflected in their interaction logs (see Table 1). The relevant R package was used to calculate these measures and estimate model parameters. Below we explicate these measures derived for REM.

### *Actor or participant characteristics*

In terms of actor or participant characteristics, two variables were included to allow the testing of Hypotheses H1a–H1d:

- *Being the instructor.* This variable characterised whether a participant was the instructor of a course.
- *Profiles of the timing of participation.* Given the importance of timing in online discussions (see the Consideration of time in online discussions section), we derived profiles of participants’ timing behaviours. To characterise the timing of student participation, we used finite mixture models (Deb & Trivedi, 2013) to cluster learners in each course based on the distribution of a student’s logged activities per weekday, similar to the approach adopted in Park et al. (2018). Hence, students with similar activity on the same days of the week in a course would be clustered. For network modelling purposes, learners were grouped based on their cluster membership, which indicated the timing of their participation.

Table 1  
Independent variables in the relational event models

Effects	Visualisation	Description
<b>Actor attributes:</b>		
Time-consistent		Being time-consistent (or not)
Role		Instructor (vs. student)
<b>Past relational events:</b>		
<i>Nodal:</i>		
Total degree (NTDegRec)		Well-connected students to receive more interactions
<i>Dyadic:</i>		
Reciprocity (RRecSnd)		Past interactions to be reciprocated
Persistence (RSndSnd)		Past interactions to happen again
<i>Triadic:</i>		
Outbounding shared partner (OSPSnd)		Shared outbounding partner leads to direct interactions
<b>Immediate effects:</b>		
<i>Participation shifts:</i>		
AB → BA		Immediate reciprocation
AB → XB		Popularity, persistence of target
AB → BY		Pay-it-forward or hand-off
AB → AY		Activity bursts, persistence of source

Here we provide additional details about the finite mixture models used to identify timing profiles of learners. System logs used in the clustering included a rich set of behavioural indicators including creating or revising a post, reading a post, creating or revising a comment, reacting to a post or comment (liking or loving), and removing a post. Learners were then grouped based on the number of logs in Yellowdig they had each day of the week. The flexmix and mixtools R packages were used for the analysis. During finite mixture modelling, learners with consistent levels of activity on the same days were classified as belonging to the same latent group. In this course, a cluster of learners with significantly higher number of logs in general and on certain weekdays (Thursdays) than the rest of the class was labelled as time-consistent participants. These learner profiles – time-consistent and other learners – characterised the learners’ temporal participation patterns and were incorporated in the models.

*Social dynamics*

Measures of social dynamics on Yellowdig, as reflected by the sequential structural signatures, were calculated using the relevent R package. First, the following measures reflecting different types of familiarity in prior relational events were computed to examine H2a–H2d.

- *Total degree* provides information about the impact of a participant’s past events (as sender or receiver) on the probability of that same participant to be replied in the future. A positive coefficient indicates an actor’s higher prior relational events predicts a higher propensity for this actor to be involved in the next event.
- *Social persistence*, also called *inertia*, captures the tendency for an actor, *i*, to reply to another actor, *j*, if *i* has previously replied to *j*. This variable captures how much a relational event reoccurs. A positive coefficient indicates the occurrence of a relational event increases the propensity for this event to happen again.
- *Reciprocity* describes the tendency of an actor, *j*, to reciprocate *i* if *i* commented on *j*’s posts before.



- *Outbounding shared partner* is a triadic effect that indicates the tendency for two actors,  $i$  and  $j$ , with a shared outbounding partner,  $k$ , to interact with each other. In the context of Yellowdig discussions, this effect could be understood as when two students comment on a post made by a peer, they have a tendency to interact with each other as well.

Statistics of turn-by-turn social dynamics, also referred to as “immediate effects” in REM (Butts, 2008), were also calculated for the testing of H3a–H3d. In particular, the following participation shifts (Gibson, 2005) were specified as part of REM:

- $AB \rightarrow BA$  indicates a tendency for an interaction from A to B to be immediately reciprocated.
- $AB \rightarrow XB$  indicates a local level popularity, meaning that when B receives a reply from A, B tends to receive another message next from a peer other than A.
- $AB \rightarrow BY$  indicates a case where the target of the second event is another actor Y other than A who initiated the first event.
- $AB \rightarrow AY$  captures the tendency of an actor A to initiate a series of events in a batch.

#### *Model fitting and selection*

For this course, we trained a series of relational event models using these variables following a forward selection strategy so that we evaluate the influence of each set of variables on relational events and how these variables were collectively shaping the emergence of relational events. Following Butts (2008), the models were evaluated based on the Akaike information criterion (AIC) and Bayesian information criterion (BIC) scores that are widely used to evaluate how well a model fits the data it was trained on.

## Findings

### Descriptive analysis of the interaction networks

Table 2 reports descriptive statistics of discussion activities in the class. On average, each participant authored 13.7 posts and 25.7 comments and connected with 16.3 class members. Based on descriptive statistics of the network structure, the class was densely connected and lowly centralised, with its nodes reachable to each other (see Table 2). Figure 2 presents a network visualisation of social interaction in the class. In this visualisation, the instructor and time-consistent students are colour coded. As shown in the figure, eight learners were identified as being time-consistent and the other 12 learners were not.

Table 2  
*Descriptive measures of the interaction network (undirected)*

Variable	Value
Total posts	274
Total comments	514
Mean degree	16.28
Network density	0.81
Diameter	3
Mean distance	1.18
Degree centralisation	0.18

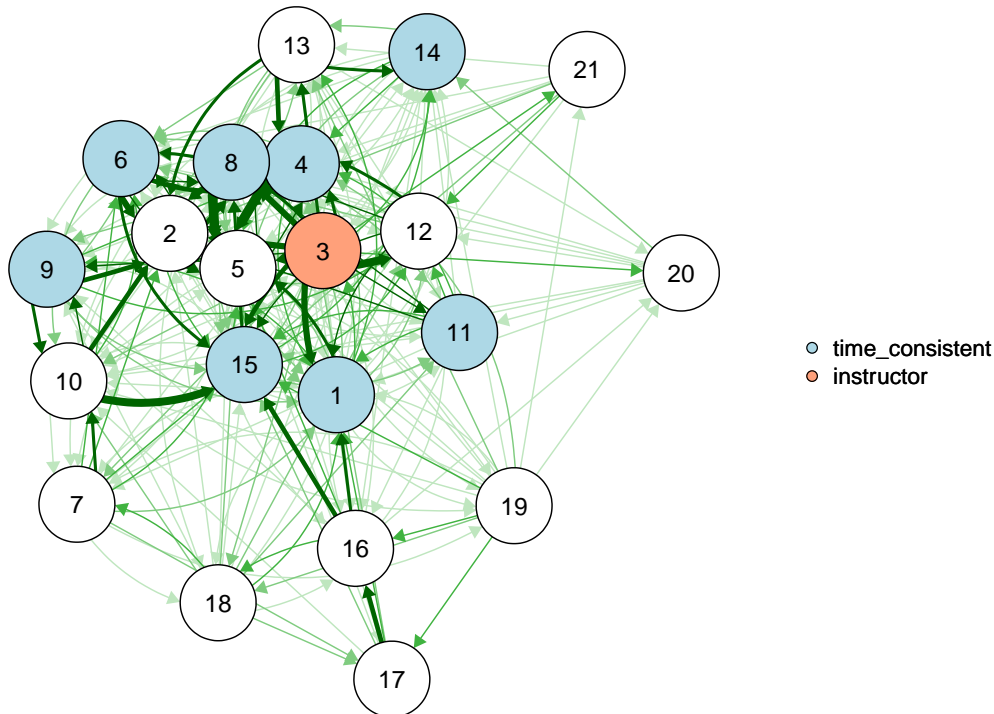


Figure 2. Network visualisation of social interaction in the course. Each node represents one participant, indexed by the number, with time-consistent students coloured in blue and the instructor coloured in orange. Each edge is directed, with its density representing the count of its occurrences throughout the whole semester.

### Results of REM

To examine the ways in which participant attributes and social dynamics collectively shape social interaction in the study, we trained a series of relational event models for the class.

#### *Goodness of fit*

The relational event models were fitted in a step-wise manner, with new factors gradually added to the model to test all the hypotheses (Butts & Marcum, 2017). Overall, the AIC and BIC scores decreased when variables were added to the null model showing improvement of the models. Based on the AIC and BIC scores, the full model provided the best fit. Below we report results of hypothesis testing based on the full model (see Table 3).

Table 3  
Coefficient estimates in REM

	Coefficient	Standard error	p value
Sending time-consistent	0.10	0.13	.425
Receiving time-consistent	0.20	0.12	.085
Sending instructor	0.85	0.19	< .001***
Receiving instructor	-2.05	0.38	< .001***
Degree (NTDegRec)	12.33	1.45	< .001***
Reciprocity (RRecSnd)	0.53	0.16	< .001***
Persistence (RSndSnd)	1.30	0.15	< .001***
Closure (OSPSnd)	-0.01	0.01	.200
Reciprocation (AB-BA)	1.30	0.48	.007**
Pay-it-forward (AB-BY)	-0.61	0.38	.114
Activity bursts (AB-AY)	1.25	0.14	< .001***
Popularity (AB-XB)	2.96	0.09	< .001***

Note. \*\*\* $p < .001$ ; \*\* $p < .01$ ; \* $p < .05$

#### Participant attributes

First, we hypothesised that peer interaction in the setting could be predicted by participant attributes. Based on REM, we found the first two hypotheses could not be supported, meaning that time-consistent students did not show higher propensity of initiating interactions with their peers (H1a) or receiving replies from peers (H1b), suggesting that the timing profile of participant was not a significant factor for the occurrence of student interactions in the discussion environment.

We also hypothesised that the instructor role would positively impact social interaction. As revealed by the relational event models, being the instructor was associated with higher odds of initiating interactions in four classes (H1c). However, the instructor was significantly less likely to be responded by students (H1d). These findings suggested the instructor in the course was actively interacting with students but did not necessarily have stronger propensity of attracting student replies. Such dynamics reflected Yellowdig's strength in fostering peer-to-peer rather than student-instructor interactions.

#### Social dynamics

In terms of statistics related to prior relational events, total degree was confirmed to be a significantly positive predictor with the largest coefficient in the model (H2a). This indicated that students with more connections at a time point had higher propensity to involve in new interactions. Reciprocity was also found to be a positive contributor to peer interaction in the class (H2b), even though the coefficient was small. This means prior replies from one student to another was predictive of future replies in the opposite direction. This finding is consistent with prior work that reports reciprocity as a definitive mechanism of network formation in online environment. Social persistence or inertia was found positive and significant as well (H2c), indicating prior replies from one student to another had positive propensity to reoccur. This suggested that social dynamics in the discussion environment had a memory of interactions across the dyads that moved from serendipitous encounters to familiarity and eventually relational ties. Triadic closure, in particular the outbounding shared partner mechanism, was not a significant factor in the class (H2d). This finding revealed that two students were not more likely to interact with each other if they had previously replied to another peer, suggesting that there was not much of group formation processes based on triadic closure mechanism in the Yellowdig environment.

Finally, in terms of the turn-by-turn participation shifts, four hypotheses were tested. The pay-it-forward pattern (AB  $\rightarrow$  BY) was non-significant (H3c), while the other three factors were significantly positive predictors, including local popularity (AB  $\rightarrow$  XB) (H3b), immediate reciprocation (AB  $\rightarrow$  BA) (H3a), and activity bursts (AB  $\rightarrow$  AY) (H3d). These results suggested at the local turn-by-turn level, a student replied by a peer has high propensity to respond to the peer (immediate reciprocation) and be immediately replied by another peer (local popularity). Students also tended to send replies to multiple peers in a batch (activity burst), indicating a dominant feature of posting behaviour in this context was that learners

tended to respond to several learners at a time when they logged into the environment. These findings together point to a localised nature of online communication that occurs within that time when learners logged online and within the space of what is visible to them and still available to contribute.

## **General discussion**

In this study, we conceptualised online discussions in education as a dynamic phenomenon influenced by various forces and sophisticated interactions among them and posit that the research of online discussions needs to consider the temporal unfolding of discussion activities. Based on this understanding, we argue it would be more conceptually rigorous to investigate student interaction in these discussion activities as relational events. This event-based approach differs from the traditional state-based approach which makes claims about interpersonal relational states based on temporal aggregates of relational events between actors. The event-based approach advanced in this paper recognises the probable impact of prior events on later ones, whereas state-based approach fails to account for these nuanced patterns enacted by diverse factors. We suggest that understanding online learning discussions is more appropriate through an event-level examination that considers each relational event and the context where it occurs. To demonstrate this approach, we applied REM to a data set of student online discussions and tested three sets of hypotheses grounded in the literature and the research context.

The first set of hypotheses were related to participant characteristics and their average affect to make contributions or receive them. Results did not find time-consistent participants (i.e., those who logged into the system on the same weekdays across several days) more likely to send and receive replies. This finding contradicts earlier studies that recognised different timing of learner participation and its connection with discussion performance (B. Chen & Huang, 2019; Riel et al., 2018). We tested whether the instructor attracted or extended more replies and found them more likely to send replies but actually less likely to be replied. The instructor was actively participating but was less likely than the students to be replied to. This finding agrees with that reported in Zingaro and Oztok (2012). It is worth further research to find out whether the social feature of Yellowdig played a role in this study since Yellowdig centres attention on student posts, whereas traditional threaded discussion forums are often structurally centred on instructor prompts.

The second set of hypotheses were generally about different types of familiarity reflected in previous relational events, modelled at the level of a dyad and a triad to account for various types of social dynamics that describe these two different social structures. Results identified total degree (i.e., popularity), reciprocity and social persistence as three significant contributors to the occurrence of relational events. That is, more active students were more likely to receive replies; more replies from one student to another predicted future replies between these two students in both directions. However, the triadic closure hypothesis was rejected, suggesting having a shared interaction partner did not lead to two students interacting with each other. The finding on popularity agrees with earlier studies, such as Vaquero and Cebrian (2013), that popular participants are more likely to receive replies. Social persistence found in earlier studies (B. Chen & Huang, 2019) was also significant in the study. The positive role played by reciprocity also agrees with earlier findings that participants of online discussion tend to reciprocate each other (Cheung et al., 2008). However, triadic closure found important in other contexts (Bianconi et al., 2014) was not a significant factor in this study.

Finally, the third set of hypothesis examined micro-level patterns of behaviour such as turn-by-turn participation shifts. We found participation shifts to explain online discussion patterns. Immediate reciprocation, local popularity and activity bursts were positive predictors of relational events. These local patterns were rarely examined in prior studies, even in studies of online discussions that applied REM (e.g., Vu et al., 2015). A learner who just replied to a peer had a high propensity to be replied to by another peer. The local popularity could be attributed to the technological design of Yellowdig that promotes the most recent discussion activity to the top of the news feed. Also, learners tended to respond to multiple peers at a time, that is, having activity bursts, in the discussion environment. The strong presence of

activity bursts is understandable given the discussion was asynchronous, so students were rarely present at the same time in the discussion environment.

This study's contribution to the literature is two-fold. First, we surveyed multiple sets of factors influencing social interaction in asynchronous online discussions. These factors include student characteristics, pedagogical practices, technological features and social dynamics. Building on the literature, this study recognises the nuances of online discussions and calls for methods that can cope with the complex dynamics. Second, by applying REM, this study contributes fresh empirical findings about socio-temporal dynamics in online discussions. Departing from prior work, REM allowed us to model the effects of these factors simultaneously (Butts, 2008; Butts & Marcum, 2017). This event-based approach enabled us to drill down to the event level and examine how specific temporal and social factors facilitate or hinder the occurrence of relational events. While earlier studies based on other methods have examined some of these factors, it is important to point out that REM allowed us to examine how these factors synergistically contributed to network formation in this study.

Empirical findings from this study have practical implications. First and foremost, sophisticated socio-temporal dynamics uncovered in this study suggest fresh angles to scaffold student participation and interaction in online discussions. Although prior work has documented various ways to scaffold online discussions, such as adopting questioning and participation roles strategies (K.-Z. Chen & Yeh, 2021; Wang, 2005; Wise et al., 2012; Zhu et al., 2023), this study suggests it might be fruitful to also help learners attend to not only posts at the top of the feed (Hewitt, 2005). Insights revealed by REM suggest various ways to facilitate peer interaction. Instructors and instructional designers who aspire to promote student interaction could consider those network effects as potential levers when designing discussion activities. For example, given the significance of familiarity for the occurrence of interactional events, instructors could support students to interact with less familiar classmates to boost familiarity in the class as a whole; similarly, as students were found to binge-post in this study, future iterations of the course could engage students to join the online conversation multiple times during a week to enhance the frequency and quality of their online encounters. Second, technology developers also need to carefully consider how a particular design decision may shape the nature of online discussions (Guzdial & Turns, 2000). In this case, Yellowdig has social features that decentralise discussions (to be less focused on the instructor) while also giving rise to local popularity by placing the posts with most recent replies on the top. We suggest that developers of educational technologies consider such implications when designing software features and pay close attention to educational meanings of these features. Finally, given the rise of learning analytics, analytic tools could be developed to provide information for the instructor and learners to take actions on information derived from system log data. Findings from this study suggest new ways to expand on current analytics that mostly describe relational states by incorporating a suite of sequential structure signatures that describe deeper socio-temporal dynamics.

Despite these contributions and implications, it is important to point out a few limitations with the present study. First, data available for analysis in the study were limited to behavioural logs in the discussion environment. As a result, we were unable to incorporate features of discussion content in the relational event models. Also, even though the main goal of this paper was to demonstrate potential of analysing relational events in online discussions, the interpretation of some findings would be complemented by qualitative interviews with students and/or student self-reports about their discussion practice.

Further work is needed to address these limitations. Future studies could incorporate other factors mentioned in the literature review but not examined in the study. For example, one direction could be to incorporate natural language processing techniques to capture features of the discussion content, so that the relational event models can be further enhanced. Another direction could be to create clear mapping between design patterns of online discussions and the REM statistics so that an instructor could purposefully adopt relevant statistics to evaluate discussion activities. Overall, this paper makes a strong case for examining online discussions as relational events and encourages future research and design to consider learner interactions as relational events that unfold over time in context.

## Author contributions

**Author 1:** Conceptualisation, Investigation, Formal analysis, Methodology, Writing – original draft, Writing – review and editing; **Author 2:** Data curation, Investigation, Formal analysis, Methodology, Writing – review and editing.

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