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Two tales of time: uncovering the significance of sequential patterns among contribution types in knowledge-building discourse

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ABSTRACT

As collaborative learning is actualized through evolving dialogues, temporality inevitably matters for the analysis of collaborative learning. This study attempts to uncover sequential patterns that distinguish "productive" threads of knowledge-building discourse. A database of Grade 1–6 knowledge-building discourse was first coded for the posts' *contribution types* and discussion threads' *productivity*. Two distinctive temporal analysis techniques – Lag-sequential Analysis (LsA) and Frequent Sequence Mining (FSM) – were subsequently applied to detecting sequential patterns among contribution types that distinguish productive threads. The findings of LsA indicated that threads that were characterized by mere opinion-giving did not achieve much progress, while threads having more transitions among questioning, obtaining information, working with information, and theorizing were more productive. FSM further uncovered from productive threads distinguishing frequent sequences involving sustained theorizing, integrated use of evidence, and problematization of proposed theories. Based on the significance of studying temporality in collaborative learning revealed in the study, we advocate for more analytics tapping into temporality of learning.

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Introduction

Effective collaborative learning is constituted through interactive, dynamic, and sustained dialogues over time. Vygotsky's (1978) observations and analyses of how learners appropriate knowledge and patterns of thinking through social interaction and communication in a meaningful social context attest to the importance of collaborative learning. In the current sociocultural and technological milieu where innovation determines economic progress, Scardamalia and Bereiter (2014) have further explicated that collaborative discourse for idea improvement is a common means for knowledge creation. Similarly, almost all other models of knowledge creation, including *expansive learning* (Engeström, 1987) and the *knowledge spiral* model (Nonaka & Takeuchi, 1995), rely on collaborative discourse. It is thus essential for education researchers to employ efficient means to study how learners collaborate for idea improvement.

To unpack the trajectory of collaborative learning, researchers have pointed out the need to examine the intricate interpersonal interactions that leads to group cognition (Stahl, 2006) and the

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interactions between ideas and the collective development of conceptual artefacts (Halatchliyski, Hecking, Goehnert, & Hoppe, 2014; Scardamalia & Bereiter, 2006). One conventional way to analyse interpersonal interactions in collaborative learning supported by computer-mediated communication is the use of quantifiable online behavioural measures. Examples of such measures include counts of notes posted, notes read, notes replied to, notes revised, written words, etc. A key strength of such measures is that they can easily be automated, leading to their wide implementation in learning management systems (e.g. Edmodo, Moodle, and Canvas). Going further, these counting measures could be combined with the social dimension of collaborative learning to further uncover social dynamics in groups. For example, a study applying Social Network Analysis found that when teachers in an online discussion environment formed a socially cohesive community, they were also contributing more and longer posts, implying more deliberate online engagement (Chai & Tan, 2009). Such analysis revealing group dynamics could provide instant feedback concerning online activities to learners and the instructor for reflection. Such analysis, however, does not take into account of the shared knowledge produced by groups, not to mention the dynamic and interactive process of inquiry that contributes to the advancement of such knowledge content. Efforts of using network analysis to consider quantifiable measures of different aspects of discourse have shown promise but are still emerging (Halatchliyski, Moskaliuk, Kimmerle, & Cress, 2014; Oshima, Oshima, & Matsuzawa, 2012).

As an alternative to quantified measures of online behaviours, content analysis has been broadly employed to understand collaborative learning activities, using data usually derived from records documented in a database. De Wever, Schellens, Valcke, and Van Keer (2006) have reviewed various useful content analysis schemes that allow researchers to unpack the criticality or progression of online discourse. With such analysis, it is particularly beneficial for assessing the outcome of group knowledge work at a given point of time. The issue, however, is that it is hard to make clear the effective discourse moves that lead to effective group work. Content analysis alone, without taking into account the temporality factor, is not likely to elucidate the effective discourse moves required for productive online inquiry and knowledge advancement. Therefore, its use and usefulness for understanding group collaborative and interactive process is also limited.

The significance of time and temporality for understanding collaborative learning has been recognized in earlier research. However, in contrast to a wide spectrum of other popular techniques, it was fairly recent when temporality was explicitly recognized as an important angle for analysing collaborative learning (Dyke, Kumar, Ai, & Rosé, 2012; Kapur, 2011; Mercer, 2008; Wise & Chiu, 2011). This phenomenon could be attributed to an empirical research gap, in that "thinking about the role of time in knowing and learning does not or only seldom figure in published research accounts" (Roth, 2006, p. 229). It could also be caused by a methodological challenge, as little guidance is available for gathering temporal data and studying temporality of collaborative learning (Littleton, 1998). To tackle this challenge, a workshop series have been organized at various conference venues including the Learning Analytics and Knowledge Conference (Chen, Wise, Knight, & Cheng, 2016; Knight, Wise, Chen, & Cheng, 2015). The present study attempts to contribute to this dialogue by showcasing the application of two temporal analytic techniques to the investigation of student dialogues in a widely used online learning environment.

Temporality of learning processes

Interaction necessarily unfolds in time and it has to be understood temporarily. This notion is reflected in extensive research of collaborative groups (Hmelo-Silver, 2003; Stahl, 2006). Perhaps it is because this notion is so much taken for granted, there is surprisingly very few studies where researchers investigate the temporal dimension of learning (Roth, 2006). In many empirical studies of collaborative learning, a quantitative method referred to as "coding and counting" is normally applied, which involves coding interaction data, counting occurrences of different types of interactions, and inspecting significant links between occurrences and interested learning outcomes

(Suthers, 2006). In some cases, this approach is combined with narrative accounts of group interactions attending to causal and temporal links among interactions. Undoubtedly, such analyses based on "coding and counting" are useful in uncovering patterns that contribute to the productivity of collaborative learning. However, applying such a "coding and counting" approach often leads to loss of temporal information related to interactions. As a result, measures produced by this approach tell us a certain proportion of interactional content that was coded in a particular category but nothing about the sequence of different categories (Kapur, 2011). As counting data are aggregated over time, the data get "flattened out" in the temporal dimension and information about temporal variation is abandoned.

A growing body of research is starting to attend to the temporal dimension of collaborative learning. For example, Wise and Chiu (2011) analysed temporal patterns of knowledge construction in online discussions. By applying Statistical Discourse Analysis, a technique that attends to the progressive nature of knowledge construction, they identified "pivotal posts" that initiate new segments of discussion of higher knowledge construction quality. In another study, researchers incorporated interactive sliding window visualizations to understand how interactions develop over time and provided means to detect temporal irregularities in collaborative learning (Dyke et al., 2012). More recently, visualization techniques and scientometric methodology were combined to develop a novel approach of tracing idea flows in an online learning community (Halatchliyski, Hecking et al., 2014). These prior studies highlighted potential fruitfulness of tapping into the temporal dimension of collaboration. As collaborative learning is a complex social phenomenon that unfolds over time and involves various "actors" (e.g. learners, ideas, and technology), the analysis of temporality deserves more attention in learning analytics research (Chen et al., 2016; Knight et al., 2015).

The present study

The central goal of the present study is to demonstrate the significance of investigating temporality by applying two distinct temporal analysis techniques in a specific research context. In this section, we introduce the research context, data sources, and applied analysis techniques.

Research context: ways of contributing to knowledge-building discourse

The need for analysing temporality could be well demonstrated in the research of Knowledge Building[1] (Scardamalia & Bereiter, 2006), a renowned constructivist pedagogy in the learning sciences (Lipponen, Hakkarainen, & Paavola, 2004). To help students see ideas as knowledge objects, the KnowledgeBuilding pedagogy puts ideas at the centre and engages students to take *collective cognitive responsibility* for improving them through communal discourse (Scardamalia, 2002). Such discourse in a knowledge-building community is normally supported by Knowledge Forum, an online space where students can contribute ideas, in the form of *notes*, to shared knowledge spaces known as *views* (Scardamalia, 2004). Figure 1 shows a sample *view* that contains several clusters of *notes*.

Previous research has extensively documented various epistemic moves important for knowledge-building discourse, including posing questions, drafting hypotheses, and designing experiments to test hypotheses (Scardamalia, 2002; Zhang, Scardamalia, Lamon, Messina, & Reeve, 2007). From a research perspective, an intriguing question is how the synergy of different discourse moves or different types of contributions could bring about productive discourse that effectively advances knowledge. To start tackling this question, researchers have developed an inventory of "Ways of Contributing to Explanation-seeking Discourse" by applying the grounded theory approach on multiple years of Knowledge Forum notes produced by Grade 1–6 students (Chuy et al., 2011; Resendes, Scardamalia, Bereiter, Chen, & Halewood, 2015). Table 1 presents this coding scheme, which includes 6 mutually exclusive contribution categories and 24 sub-categories. This scheme has been useful in guiding content analysis of students' online discourse and eliciting measures

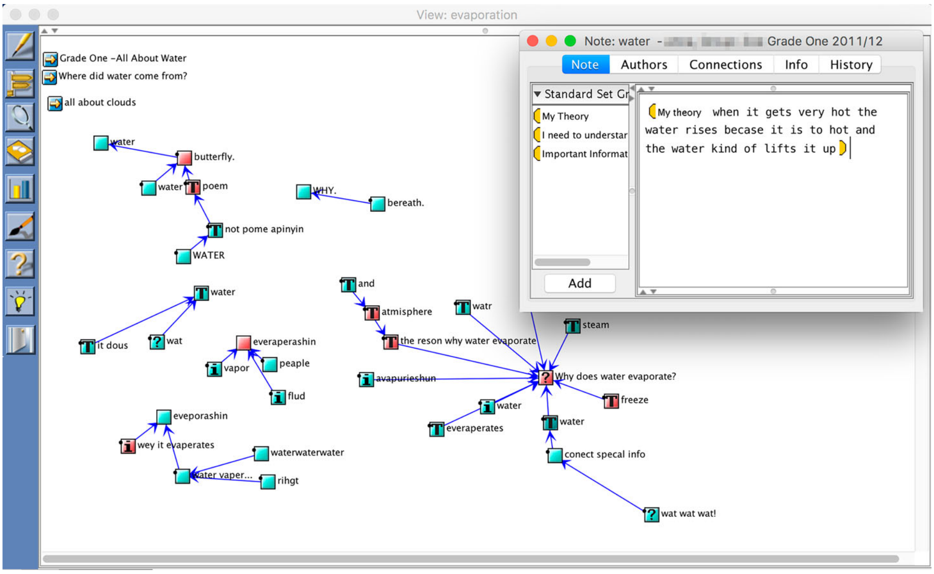

Figure 1. Knowledge Forum (v. 4.8), a collective, online community space that organizes student ideas, presented in the form of *notes* (blue squares), under different *views*. Blue arrows among notes denote *building-on* actions, a key mechanism to advance collective knowledge. Detailed information about Knowledge Forum's functionalities can be found in Scardamalia (2004).

potentially useful for diagnosing discourse (Resendes et al., 2015). However, previous research in this area has neglected the temporal relations among different types of contributions. Since knowledge-building discourse is a complex theory-building process that involves interactions among facts, theories, explanations, and the various types of actions to improve theories (Scardamalia & Bereiter, 2006), an important dimension for understanding the discourse remains missing when the temporal

Table 1. Coding schemes for knowledge-building discourse.

Main categories	Sub-categories
Questioning (Q)	1. Formulating an explanatory question
	2. Asking a design question
	3. Asking a factual question
Theorizing (T)	4. Proposing an explanation
	5. Supporting an explanation
	6. Improving an explanation
	7. Seeking an alternative explanation
Obtaining Information (OI)	8. Asking for information
	9. Designing experiment to test hypothesis
	10. Reporting experiment results
	11. Introducing facts from sources
	12. Introducing facts from experience
	13. Identifying design problems
	14. Improving design problems
Working with Information (WI)	15. Providing information to support a theory
	16. Providing information to discard a theory
	17. Weighing explanations
	18. Accounting for conflicting explanations
Syntheses and Analogies (SA)	19. Synthesizing available ideas
	20. Creating analogies
	21. Initiating rise-above
Supporting Discussion (SD)	22. Using diagrams to communicate ideas
	23. Giving an opinion
	24. Acting as a mediator

Note: Adapted from Chuy et al. (2011) and Resendes et al. (2015).

relations among different contribution types are taken out. The traditional "coding and counting" approach could reveal the contribute make-up of knowledge-building discourse at a particular moment, but falls short in addressing intricate interactions among different contribution types.

To bridge the gap of analysing temporality in discourse-centric learning such as knowledge building, the present study explores two temporal analytic techniques, Lag-sequential Analysis (LsA) and Frequent Sequence Mining (FSM), and contrasts their usefulness for analysing knowledge-building discourse. Data analyses in this study attempt to answer the following research question: What are the underlying temporal patterns that could distinguish productive knowledge-building dialogues – dialogues with apparent attempts to advance collective knowledge? To tackle the research question, we performed secondary analysis of knowledge-building discourse data that have already been coded in previous research (see Chuy et al., 2011; Resendes, 2013; Resendes et al., 2015).

Data sources

Secondary data analysed in this study consisted of one year of Knowledge Forum notes, collected from Grade 1 to 6 students who were learning science. These students were from a Knowledge-Building school in downtown Toronto. In this school, there was only one class in each grade (except for two blended-grade Grade 5/6 classes); each class had approximately 22 students with equivalent number of girls and boys. In this school, Knowledge Building is introduced to students from Junior Kindergarten and Knowledge Forum is used from Grade 1. Thus, all students and teachers involved in this study were comfortable with this pedagogy and its supporting technology. In a typical school year, science learning in each grade is organized around an overarching topic, such as "water" or "trees," which further expands to a few big ideas in that content area. Students bring in their authentic problems of understanding, build explanations together based on their real ideas, and make constructive use of authoritative sources when necessary to improve their ideas. To make their ideas public and open to be improved by the community, students write notes in Knowledge Forum, in addition to extensive face-to-face classroom dialogues (see Chen & Hong, 2016, for a detailed review).

In this study, a total of 1101 notes produced by six grades in one year were analysed. An overview of the grades, science units, and Knowledge Forum notes is provided in Table 2. Primary data analysis on this dataset was conducted in previous research concerning "Ways of contributing to knowledge-building discourse" and knowledge advancement in science learning (Chuy et al., 2011; Resendes, 2013; Resendes et al., 2015). This analysis included three aspects: (1) coding *types of contribution* in each note – based on content analysis using the aforementioned Ways of Contributing scheme (one note could contain multiple contribution codes or coded discourse units, and if so, codes are sorted in the order they appear); (2) identifying *inquiry threads* – through grouping sets of notes by shared principal problems (Zhang et al., 2007); and (3) determining the *productivity* level, *productive* or *improvable*, of each inquiry thread – based on whether there was any occurrence of the *Improving an Explanation* contribution in the Ways of Contributing scheme (see Table 1). Two raters coded types of contributions of all notes and achieved an overall inter-rater consistency of 95.52% (Grade 1, 99.27%; Grade 2, 98.65%; Grade 3, 82.5%; Grade 4, 99.57%; Grade 5/6, 97.63%). One rater identified all inquiry threads, with two examples, a productive thread and an improvable

Table 2. An overview of the dataset.

Grades	Units	No. of posts	No. of threads	Productive threads	Improvable threads
Grade 1	Water	298	12	9	3
Grade 2	Trees	117	6	4	2
Grade 3	Fungus	193	8	5	3
Grade 4	Rocks and Minerals	262	11	6	5
Grade 5/6	Astronomy	231	13	7	6

one, provided in Table 3. Previous reports of this dataset have mainly focused on "counting" measures of contribution types (see Resendes, 2013; Resendes et al., 2015).

Data analysis

To recognize temporality as an analytical angle for this dataset, we examined the transitional relations among contribution types in knowledge-building discourse by applying two distinctive temporal analysis techniques.

Lag-sequential Analysis

LsA is a statistical method developed to identify sequential contingencies or cross-dependencies in sequences of behaviours or events (Faraone & Dorfman, 1987; Sackett, 1979). As a simple and yet valuable method for summarizing interactions between behaviours or events, it has been found useful for studying interactions in many different contexts, including disruptive behaviours in classrooms (Gunter, Jack, Shores, Carrell, & Flowers, 1993), eye gaze patterns between clinicians and patients (Montague et al., 2011), and communication in business meetings (Lehmann-Willenbrock, Allen, & Kauffeld, 2013). Comparing to "counting" measures in content analysis, LsA as it is applied to the analysis of knowledge-building discourse takes transitional relationships between contribution types into account and may reveal temporal differences between productive and improvable inquiry threads.

To conduct LsA in this study, and to make LsA more accessible to other researchers as well, we implemented an R package named LagSeq[2] based on previous documentation (O'Connor, 1999; Sackett, Holm, Crowley, & Henkins, 1979). Using LagSeq, we incrementally computed a number of sequential measures, including: (1) *transitional frequencies* among all major contribution types – how often a particular transition occurred (e.g. *Questioning→Theorizing*) for a specified sequential interval; (2) *expected transitional frequency* – the expected number of times a transition would occur under the null hypothesis of independence or no relation between the codes; (3) *transitional probabilities* – a conditional probability indicating the likelihood of, for example, event B occurring,

Table 3. Examples of productive and improvable inquiry threads.

	Productive thread: How does water vapour go back to water?		*Improvable thread: Why do we need water?*
Q	*I wonder*: How does water, when it turns into water vapour, go back into water?	Q	*I wonder*: who was the first person to drink water.
T	*New information*: because the sun is so hot that it melts the water vapour back into water …	SD	*My theory*: the first person to live.
OI	*New information*: when it rains the water falls out of the clouds.	Q	*I wonder*: why does water make us live?
T	<u>*My theory*: it evaporates into clouds again and makes rain.</u>	Q	*I wonder*: why people need water.
OI	*New information*: because water is water vapour.	T	*My theory*: Yes, we can survive with chemicals like us.
T	*My theory*: Maybe the cloud has something to make the water liquid again.	OI	*My theory*: you could see tiny germs in water.
WI	*New information*: Because when you put your hand over water vapour it blocks and turns back into water …	Q	*I wonder*: why is our body half made of water?
T	<u>*My theory*: it won't if you don't block it but if you do then it will turn back into water. It's a gas and if you block it with your finger or hand then it will turn back into water because you are stopping it from going up in the clouds and when it falls back down then it has to chill again.</u>	OI	*New information*: because we drink a lot …

Notes: This table presents two example threads and its Ways of Contributing codes. The productive thread is on the left, and the improvable one is on the right. In each thread, Ways of Contributing codes are presented in a column to the left of student notes, listed in chronological order. In student notes, italic text (e.g. *I wonder*) was introduced by students using the Knowledge Forum scaffolds (see Figure 1); underlined text denotes content coded as *Improving an Explanation*, which is indicative of productive discourse. In the productive thread, the students still demonstrate gaps in understanding but are definitely advancing their ideas in relation to the initial question. In contrast, theory development is not sustained in the improvable thread, which contains lots of questioning but no take up beyond students' initial ideas.

given that event A occurred, or the probability of B, given A; (4) *adjusted residuals* – *z* scores representing the statistical significance of particular transitions; and (5) *Yule's Q* – standardized measure ranging from −1 to +1 denoting strength of association. These measures are of increasing complexity and explanatory power, with latter measures building upon earlier ones (see O'Connor, 1999). *Yule's Q* was finally adopted to represent the strength of transitional association because it controls for base numbers of contributions and is descriptively useful (with a range from −1 to +1 and zero indicating no association). In addition, the sequential interval, namely *lag* in LsA, could be set to different values; for example, we can use *lag* = 1 to investigate direct transitions and *lag* = 2 to study indirect transitions with one event occurring in between (for example, capturing A→B in a sequence A→C→B).

Frequent Sequence Mining

FSM (Zaki, 2001), sometimes referred to as Sequential Pattern Mining, is a sub-domain of Frequent Pattern Mining (Han, Cheng, Xin, & Yan, 2007). Similar to LsA, FSM can be used to discover sequential patterns among events. Different from LsA, FSM detects frequent sequences of events that occur more often than a minimal frequency level in a dataset (e.g. 10% of all cases). It has been applied in education, for example, to the study of online collaborative learning in programming courses (Perera, Kay, Koprinska, Yacef, & Zaïane, 2009). To answer the research question in the knowledge-building research context, we used FSM to compare frequent sequences in productive versus improvable inquiry threads, so as to uncover additional insights about knowledge-building dialogues.

To conduct FSM, an R package *arulesSequence* was applied on the coded dataset. This package implements a SPADE algorithm, one of the most popular algorithms for discovering sequential patterns (Zaki, 2001). After data pre-processing, this algorithm was respectively run on two subsets of inquiry threads – productive and improvable threads. To illustrate the process of FSM, an example dataset is shown in Table 4. To comply with the *arulesSequences* package's terminology, each inquiry thread in Table 4 is treated as a *sequence*, that is, S1, S2, S3, S4; a coded contribution type within a thread is an event (or an item). The main task of FSM is to identify subsequences that occur frequently (above a customized threshold) in all present sequences. For example, in these four sequences in Table 4, the sequence <Q,OI> is a subsequence of S1, S2, and S3 and its *support*, defined as the frequency of appearance, is 0.75 (i.e. 3 out of 4 sequences), and the sequence <Q,T> is a subsequence of S1 and S4 so its *support* is 0.5. If the *support* threshold is set to 0.4, they will be both identified as frequent sequences in this dataset. There are additional parameters for FSM, including the maximum length of sequences (*maxlen*) and the maximum of gap between events in a sequence (*maxgap*), and further documentation can be found in Zaki (2001) and the webpage of *arulessequence*.[3] In this study comparing frequent sequences of events (or codes) in two different types of threads, R code with algorithm parameters for FSM are presented below:

```
library(arulesSequences)
# read baskets
bskt <- read_baskets(file, info=c("sequenceID","eventID","SIZE"))
# mine frequent sequences
fs <- cspade(bskt, parameter = list(support = 0.1, maxlen = 4, maxgap = 2), control = list(verbose = TRUE,
bfstype=TRUE))
```

Table 4. An example sequence dataset for FSM.

Sequence Id	Sequence
S1	<Q,T,T,OI,WI>
S2	<Q,OI,WI>
S3	<Q,OI,OI,WI>
S4	<Q,SD,SD,T>

Results

Were productive and improvable threads different in basic contribution measures?

The first comparisons between productive and improvable inquiry threads were made on a set of basic Ways of Contributing measures. This analysis was interested in finding out whether productive inquiry threads have different a make-up of contribution types compared with improvable threads. Basic counting measures used here included: (1) number of discourse units (each unit is defined by an individual Ways of Contributing code rather than a Knowledge Forum note), (2) number of discourse units after merging adjacent units of a same contribution type, (3) occurrences of each main contribution category, and (4) percentage of each main contribution category. Table 5 shows descriptive statistics of these basic contribution measures. To compare differences of productive and improvable inquiry threads, *t*-tests were conducted on these measures. Results found none of these descriptive measures different between two types of threads at the.05 significance level. Although previous studies found numbers of *Theorizing* and *Working with Information* contributions predicting individual knowledge advancement (Chuy et al., 2011), these "counting" measures fall short in predicting productivity of knowledge-building dialogues at the group level.

Uncovering sequential patterns: transitions among contribution types

Analysis of the basic measures did not identify any significant difference between productive and improvable threads. So what has made them different? If occurrences of contribution types were not proper indicators, was it because of the interplay among different contribution types? Were some contribution types following each other more often in productive threads? Without analysing temporality of knowledge-building discourse, an important piece of the story remains missing.

Lag-sequential Analysis

To tackle this problem, LsA measures were computed with sequential *lag* set as 1 – that is, focusing on immediate transitions. As the initial step of LsA, Figure 2 visualizes basic transitional frequencies in two types of discourse threads. Preliminary visual analysis comparing these two visualizations indicates that productive threads had richer transitions involving *Working with Information* and *Synthesis and Analogies*. No statistical comparison was made at this point before controlling for base numbers of contributions in each category.

To statistically compare transitional differences between two types of inquiry threads, two-sided independent-sample *t*-tests were conducted on *Yule's Q* scores, at the significant level of .05 (see Table 6). Results indicated productive threads had significantly higher number of transitions from *Working with Information* to *Theorizing* than improvable threads ($t(48) = 2.10$, $p = .04$, Cohen's $d = .58$), and marginally more transitions from *Theorizing* to *Questioning* ($t(42) = 1.79$, $p = .08$, Cohen's $d = .51$). It could be inferred that in productive threads students worked more constructively with resources and engaged in deeper questioning, as they incorporated information into theorizing

Table 5. Descriptive statistics of basic contribution measures in two types of inquiry threads.

Measures	Productive	Improvable
Number of units	20.90 (9.15)	23.84 (12.44)
Number of units (merged)	14.23 (7.58)	15.74 (9.68)
Questioning	4.77 (3.33)	5.53 (3.47)
Theorizing	9.19 (5.49)	11.89 (6.34)
Obtaining Information	2.42 (1.50)	1.89 (2.08)
Working with Information	1.32 (2.06)	0.84 (1.64)
Synthesizing and Analogies	0.42 (0.92)	0.58 (1.02)
Supporting Discussion	2.77 (3.04)	3.11 (2.66)

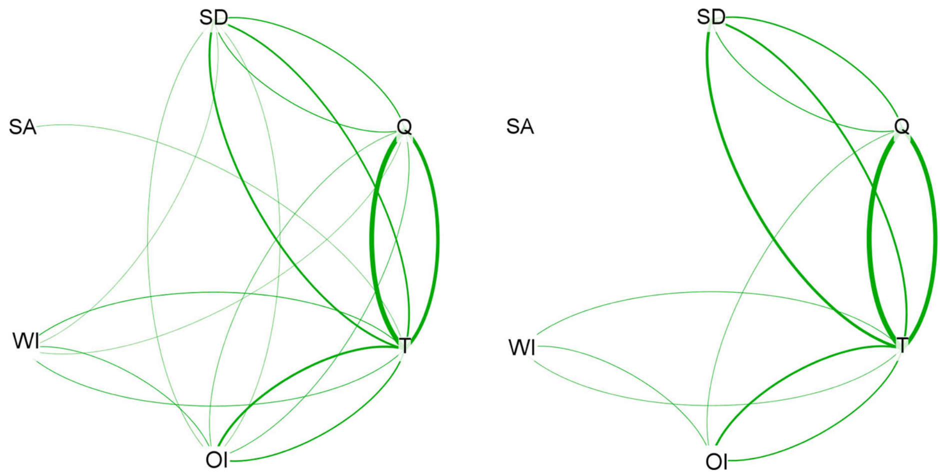

Figure 2. Transitional frequencies in two types of discourse threads. Left – productive threads; right – improvable threads. Each node of the graphs represents one contribution type main category (e.g. T denotes *Theorizing*). The directional links between two nodes should be interpreted clockwise; for example, both diagrams present transitions from WI (*Working with Information*) to OI (*Obtaining Information*) but not the other way around.

and questioned proposed theories more often. Meanwhile, productive threads had less transitions from *Theorizing* to *Supporting Discussion* ($t(44) = -2.23$, $p = .03$, Cohen's $d = .64$), as well as marginally less *Supporting Discussion* to *Questioning* ($t(40) = -1.83$, $p = .08$, Cohen's $d = .53$). Detailed analysis found most supporting discussion contributions fell into the *Providing an Opinion* sub-category. It appeared responding to theorizing and questioning by merely giving opinions was not sufficient for advancing knowledge.

To expand the analysis from direct to indirect transitions, we run LsA again with the sequential *lag* set as 2 (i.e. investigating the transition between two events which had another event that happened in between) (see Table 6). Results indicated productive threads had more indirect bidirectional transitions between *Questioning* and *Obtaining Information* ($t(45) = 1.88$, $p = .08$, Cohen's $d = .53$ and $t(40) = 1.99$, $p = .05$, Cohen's $d = .28$), as well as between *Theorizing* and *Obtaining Information* ($t(46) = 1.91$, $p = .06$, Cohen's $d = .53$ and $t(42) = 1.83$, $p = .07$, Cohen's $d = .53$). Therefore, the integration of *Obtaining information* with *Questioning* and *Theorizing* is also contributing to idea improvement. At the same time, similar to the analysis of immediate transitions, significantly less indirect transitions from *Questioning* to *Supporting Discussion* ($t(34) = -2.00$, $p = .05$, Cohen's $d = .60$) and from *Supporting Discussion* to *Theorizing* ($t(35) = -2.06$, $p = .05$, Cohen's $d = .60$) were identified in productive threads.

Table 6. Direct transitional patterns in two types of discourse threads.

	Upcoming move					
Current move	1	2	3	4	5	6
1. Questioning			+ + (*)			− − (†)
2. Theorizing	+ (†)		+ + (†)			− (*)
3. Obtaining information	+ + (*)					
4. Working with information		+ (*)				
5. Syntheses and analogies						
6. Supporting discussion	− (†)	− − (*)				

Notes: "+" denotes more frequent transitions in the productive dialogues, and "−" means vice versa. One occurrence of either + or − means direct transitions (i.e. $lag = 1$), and two occurrences means $lag = 2$.
$^{\dagger}p < .10$, $^{*}p < .05$.

Frequent Sequence Mining

Different from LsA, FSM focused on identifying frequent sequences in each type of threads. Our analysis was then to inspect whether there were sequences frequent for one type of threads but not for the other.

Single-event sequence. Table 7 presents results of comparing frequent single-event sequences, that is, single Ways of Contributing codes, between two types of threads. Comparison of single-event sequences did not find any substantial difference. These results to some extent triangulated with the findings with basic descriptive analysis that two types of threads did not significantly differ in percentages of contribution types.

Multi-event sequence. We went further to compare sequences with multiple events, that is, frequent sequences involving multiple Ways of Contributing codes. This analysis would be more revealing in that it considers contingencies among different contribution types. Here, we improved the *support* parameter to 20%, which means that only frequent sequences appearing for 20% or more in either type of threads were considered. Results are presented in Table 8. Generally speaking, in improvable threads, students more frequently responded to *Obtaining Information* or *Theorizing* with *Supporting Discussion*, which was mostly about *Giving an Opinion* on a contribution. In productive threads, students had: (a) more sustained *Theorizing*, represented by several frequent sequences involving multiple {T}s; (b) more integrated use of evidence/information, represented by several frequent transitions between {T}, {OI}, and {WI}, such as <{T},{T},{OI},{T}>, <{OI},{T},{T}>, and <{T},{T},{T},{WI}>; and (c) more frequent attempts to problematize proposed theories, represented by <Q> occurring after <T>, as well as to propose explanations to solve problems, shown by transitions from <Q> to <T>. Despite analytical differences between FSM and LsA, these results were consistent with what was found using LsA: Effective dialogues require students to work more constructively with resources, engage in increasingly deepened questioning and theorizing, and problematize proposed explanations.

Discussion and conclusions

The present study argues for the importance of examining temporality in collaborative learning. Using a rich Knowledge Forum dataset, it attempts to investigate temporal patterns that can predict productivity of knowledge-building discourse. To avoid conventional quantitative approaches that merely rely on behavioural measures and to go beyond the "coding and counting" approach applied in many learning sciences studies, this study applies LsA and FSM to study transitional relations among different ways of contributing in productive and improvable dialogues. The findings indicate that while traditional counting measures fall short in distinguishing two types of dialogues, a few sequential patterns were identified. Based on findings from LsA, productive threads of inquiry involved significantly more transitions among *Questioning*, *Theorizing*, *Obtaining Information*, and *Working with Information*, while improvable inquiry threads showed more transitions involving *Giving an Opinion*. Therefore, responding to questioning and theorizing by merely giving opinions is not sufficient to achieve knowledge progress in knowledge building. These findings are consistent with existing literature in recognizing the importance of "constructive use of authoritative sources" as

Table 7. Comparing single-event frequent sequences.

Sequence	Productive	Improvable	Difference
<{SD}>	0.81	0.74	0.07
<{WI}>	0.48	0.42	0.06
<{SA}>	0.26	0.37	−0.11

Note: SD, supporting discussion; WI, working with information; SA, synthesis and analogies.

Table 8. Comparing multi-event frequent sequences.

Sequence	Productive	Improvable	Difference
<{T},{T},{T},{T}>	0.84	0.42	0.42
<{S},{T},{T},{T}>	0.52	0.21	0.31
<{Q},{Q},{T},{T}>	0.64	0.37	0.28
<{T},{S},{Q}>	0.48	0.21	0.27
<{Q},{T},{T},{T}>	0.90	0.63	0.27
<{T},{T},{OI},{T}>	0.42	0.16	0.26
<{S},{T},{T}>	0.61	0.37	0.24
<{OI},{T}>	0.71	0.47	0.24
<{T},{T},{T},{S}>	0.55	0.32	0.23
<{T},{S},{T},{T}>	0.39	0.16	0.23
<{T},{Q},{S},{T}>	0.39	0.16	0.23
<{OI},{OI}>	0.39	0.16	0.23
<{OI},{T},{T}>	0.64	0.42	0.22
<{Q},{Q},{T}>	0.64	0.42	0.22
<{T},{T},{T},{WI}>	0.32	0.11	0.22
<{T},{T},{WI}>	0.42	0.21	0.21
<{S},{Q},{T},{T}>	0.42	0.21	0.21
<{Q},{S},{T},{T}>	0.42	0.21	0.21
<{T},{S},{Q},{T}>	0.42	0.21	0.21
<{Q},{Q}>	0.68	0.47	0.20
<{OI},{S},{S}>	0.10	0.32	−0.22
<{T},{S},{S},{S}>	0.10	0.32	−0.22

an important component of productive knowledge building (Scardamalia, 2002; Zhang et al., 2007). The bidirectional linkages between *Obtaining Information* and *Theorizing* or *Questioning* also highlight the progressive characteristic involving deepening inquiry as an important feature of effective discourse (Scardamalia & Bereiter, 2006). The implication of this finding for facilitating knowledge building in the classroom may be the need for the teachers to explicitly guide students to engage in searching for appropriate authoritative sources of information; and subsequently use the information constructively to further refine their emerging theories. In other words, facilitating diverse discourse moves in addressing the need for theory building is necessary. FSM added further insights to LsA by considering longer spans of frequent sequences. Results further identified distinguishing patterns of productive threads including sustained *Theorizing*, integrated use of evidence represented in sequences of events, and more frequent attempts to problematize proposed theories. These features could be associated with the knowledge-creation mode of discourse, which is associated with explanation building, constructive use of information, and deepening inquiry (van Aalst, 2009; Zhang et al., 2007).

In this experimentation, LsA and FSM presented to be two different and yet complementary approaches towards temporal analysis. First, their underlying algorithms are different. While LsA relies on more basic matrix computation, the SPADE algorithm supporting FSM was essentially a process of searching and counting frequent sequences. FSM is to some extent more flexible in picking up sequential patterns because its tolerance with multiple event gaps, whereas LsA (at least the version we implemented) could only configure lag to a specific value (e.g. 1, 2) at a time. Second, because of such algorithmic differences, the nature of findings from two techniques was also quite different. LsA could conduct statistical significance tests on pair-wise comparisons between two cases, whereas FSM produces "interestingness" measures such as *support* which can be compared among multiple groups (Tan, Kumar, & Srivastava, 2004). This is the first study, as far as we know, that combines two unique temporal analysis techniques in one study of educational discourse.

This study builds on previous research that highlights the importance of temporality. It contributes to learning analytics literature by introducing knowledge-building perspectives, and also to knowledge building and collaborative learning research by uncovering temporal patterns worth further investigation. By developing an open-source R program, it also makes LsA more accessible for researchers. For future directions, we will explore possibilities of developing embedded Knowledge-Building analytic tools to boost identified favourable discourse behaviours. Given manual content analysis applied in this study appears non-feasible for developing large-scale, real-time assessment tools, substantial efforts are needed to automate the process of coding by applying recent computational linguistics techniques (Rosé et al., 2008). It seems attainable to deploy natural language processing to detect the discourse moves as depicted in Table 1, if researchers could identify the discourse features. Since previous studies have showed efficacy of fairly simple tools in facilitating meta-discourse and boosting students' competencies (Resendes et al., 2015), future work of Knowledge-Building analytics based on the present study shows great promise in promoting collaborative learning. As more and more students are engaged in online courses for lifelong learning in distance education contexts, learning analytic that allows educators to efficiently debug discourse patterns for early intervention is invaluable. Even more exiting to us is the design of learning analytics that uncover patterns of important epistemic value and empower choice-making of learners themselves (Chen & Zhang, 2016).

Notes

1. Because the term "knowledge building" is used broadly, often without explicit definition, we use lower case with the generic term and capitalize Knowledge Building when referring to the approach originally developed by Scardamalia and Bereiter (2006).
2. The LagSeq R package for LsA can be found at: https://github.com/meefen/LagSeq
3. The *arulesSequences* R package: https://cran.r-project.org/web/packages/arulesSequences/

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References

van Aalst, J. (2009). Distinguishing knowledge-sharing, knowledge-construction, and knowledge-creation discourses. *International Journal of Computer-Supported Collaborative Learning*, *4*(3), 259–287. doi:10.1007/s11412-009-9069-5

Chai, C. S., & Tan, S. C. (2009). Professional development of teachers for computer-supported collaborative learning: A knowledge-building approach. *Teachers College Record*, *111*(5), 1296–1327.

Chen, B., & Hong, H.-Y. (2016). Schools as knowledge-building organizations: Thirty years of design research. *Educational Psychologist*, *51*(2), 266–288. doi:10.1080/00461520.2016.1175306

Chen, B., Wise, A. F., Knight, S., & Cheng, B. H. (2016). Putting temporal analytics into practice: The 5th international workshop on temporality in learning data. In *Proceedings of the sixth international conference on learning analytics and knowledge – LAK "16* (pp. 488–489). New York, NY: ACM Press. doi:10.1145/2883851.2883865

Chen, B., & Zhang, J. (2016). Analytics for knowledge creation: Towards epistemic agency and design-mode thinking. *Journal of Learning Analytics*, *3*(2), 139–163. doi:10.18608/jla.2016.32.7

Chuy, M., Resendes, M., Tarchi, C., Chen, B., Scardamalia, M., & Bereiter, C. (2011). Ways of contributing to an explanation-seeking dialogue in science and history. *QWERTY - Interdisciplinary Journal of Technology, Culture and Education*, *6*(2), 242–260.

De Wever, B., Schellens, T., Valcke, M., & Van Keer, H. (2006). Content analysis schemes to analyze transcripts of online asynchronous discussion groups: A review. *Computers & Education*, *46*(1), 6–28.

Dyke, G., Kumar, R., Ai, H., & Rosé, C. (2012). Challenging assumptions: Using sliding window visualizations to reveal time-based irregularities in CSCL processes. In J. van Aalst, K. Thompson, M. J. Jacobson, & P. Reimann (Eds.), *The future of learning: Proceedings of the 10th international conference of the learning sciences (ICLS 2012) - volume 1, full papers* (pp. 363–370). Sydney: ISLS.

Engeström, Y. (1987). *Learning by expanding: An activity-theoretical approach to developmental research*. Helsinki: Orienta-Kosultit Oy.

Faraone, S. V., & Dorfman, D. D. (1987). Lag sequential analysis: Robust statistical methods. *Psychological Bulletin*, *101*(2), 312–323. doi:10.1037//0033-2909.101.2.312

Gunter, P. L., Jack, S. L., Shores, R. E., Carrell, D. E., & Flowers, J. (1993). Lag sequential analysis as a tool for functional analysis of student disruptive behavior in classrooms. *Journal of Emotional and Behavioral Disorders*, *1*(3), 138–148. doi:10.1177/106342669300100301

Halatchliyski, I., Hecking, T., Goehnert, T., & Hoppe, H. U. (2014). Analyzing the path of ideas and activity of contributors in an open learning community. *Journal of Learning Analytics*, *1*(2), 72–93.

Halatchliyski, I., Moskaliuk, J., Kimmerle, J., & Cress, U. (2014). Explaining authors' contribution to pivotal artifacts during mass collaboration in the Wikipedia's knowledge base. *International Journal of Computer-Supported Collaborative Learning*, *9*(1), 97–115. doi:10.1007/s11412-013-9182-3

Han, J., Cheng, H., Xin, D., & Yan, X. (2007). Frequent pattern mining: Current status and future directions. *Data Mining and Knowledge Discovery*, *15*(1), 55–86. doi:10.1007/s10618-006-0059-1

Hmelo-Silver, C. E. (2003). Analyzing collaborative knowledge construction. *Computers & Education*, *41*(4), 397–420. doi:10.1016/j.compedu.2003.07.001

Kapur, M. (2011). Temporality matters: Advancing a method for analyzing problem-solving processes in a computer-supported collaborative environment. *International Journal of Computer-Supported Collaborative Learning*, *6*(1), 39–56. doi:10.1007/s11412-011-9109-9

Knight, S., Wise, A. F., Chen, B., & Cheng, B. H. (2015). It's about time: 4th international workshop on temporal analyses of learning data. In *Proceedings of the fifth international conference on learning analytics and knowledge - LAK "15* (pp. 388–389). New York, NY: ACM. doi:10.1145/2723576.2723638

Lehmann-Willenbrock, N., Allen, J. A., & Kauffeld, S. (2013). A sequential analysis of procedural meeting communication: How teams facilitate their meetings. *Journal of Applied Communication Research*, *41*(4), 365–388. doi:10.1080/00909882.2013.844847

Lipponen, L., Hakkarainen, K., & Paavola, S. (2004). Practices and orientations of CSCL. In J. W. Strijbos, P. A. Kirschner, & R. L. Martens (Eds.), *What we know about CSCL and implementing it in higher education* (pp. 34–50). Dordrecht: Kluwer Academic.

Littleton, K. (1998). Productivity through interaction: An overview. In K. Littleton & P. Light (Eds.), *Learning with computers* (pp. 179–194). New York, NY: Routledge.

Mercer, N. (2008). The seeds of time: Why classroom dialogue needs a temporal analysis. *Journal of the Learning Sciences*, *17*(1), 33–59. doi:10.1080/10508400701793182

Montague, E., Xu, J., Chen, P.-Y., Asan, O., Barrett, B. P., & Chewning, B. (2011). Modeling eye gaze patterns in clinician-patient interaction with lag sequential analysis. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *53*(5), 502–516. doi:10.1177/0018720811405986

Nonaka, I., & Takeuchi, H. (1995). *The knowledge-creating company: How Japanese companies create the dynamics of innovation*. New York, NY: Oxford University Press.

O'Connor, B. P. (1999). Simple and flexible SAS and SPSS programs for analyzing lag-sequential categorical data. *Behavior Research Methods, Instruments, & Computers*, *31*(4), 718–726. doi:10.3758/BF03200753

Oshima, J., Oshima, R., & Matsuzawa, Y. (2012). Knowledge building discourse explorer: A social network analysis application for knowledge building discourse. *Educational Technology Research and Development*, *60*(5), 903–921. doi:10.1007/s11423-012-9265-2

Perera, D., Kay, J., Koprinska, I., Yacef, K., & Zaïane, O. R. (2009). Clustering and sequential pattern mining of online collaborative learning data. *Knowledge and Data Engineering, IEEE Transactions on*, *21*(6), 759–772.

Resendes, M. (2013). *Enhancing knowledge building discourse in early primary education: Effects of formative feedback* (PhD thesis). University of Toronto.
Resendes, M., Scardamalia, M., Bereiter, C., Chen, B., & Halewood, C. (2015). Group-level formative feedback and metadiscourse. *International Journal of Computer-Supported Collaborative Learning*, *10*(3), 309–336. doi:10.1007/s11412-015-9219-x
Rosé, C., Wang, Y.-C., Cui, Y., Arguello, J., Stegmann, K., Weinberger, A., & Fischer, F. (2008). Analyzing collaborative learning processes automatically: Exploiting the advances of computational linguistics in computer-supported collaborative learning. *International Journal of Computer-Supported Collaborative Learning*, *3*(3), 237–271. doi:10.1007/s11412-007-9034-0
Roth, W.-M. (2006). *Learning science: A singular plural perspective*. Rotterdam: Sense Publishers.
Sackett, G. P. (1979). The lag sequential analysis of contingency and cyclicity in behavioral interaction research. In J. D. Osofsky (Ed.), *Handbook of infant development* (1st ed., pp. 623–649). New York: Wiley.
Sackett, G. P., Holm, R., Crowley, C., & Henkins, A. (1979). A FORTRAN program for lag sequential analysis of contingency and cyclicity in behavioral interaction data. *Behavior Research Methods & Instrumentation*, *11*(3), 366–378. doi:10.3758/BF03205679
Scardamalia, M. (2002). Collective cognitive responsibility for the advancement of knowledge. In B. Smith (Ed.), *Liberal education in a knowledge society* (pp. 67–98). Chicago, IL: Open Court.
Scardamalia, M. (2004). CSILE/knowledge forum. In A. Kovalchick & K. Dawson (Eds.), *Education and technology: An encyclopedia* (pp. 183–192). Santa Barbara, CA: ABC-CLIO.
Scardamalia, M., & Bereiter, C. (2006). Knowledge building: Theory, pedagogy, and technology. In R. K. Sawyer (Ed.), *The Cambridge handbook of the learning sciences* (pp. 97–115). New York, NY: Cambridge University Press.
Scardamalia, M., & Bereiter, C. (2014). Knowledge building and knowledge creation: Theory, pedagogy and technology. In K. Sawyer (Ed.), *Cambridge handbook of the learning sciences* (2nd ed., pp. 397–417). New York, NY: Cambridge University Press.
Stahl, G. (2006). *Group cognition*. Cambridge: The MIT Press.
Suthers, D. D. (2006). Technology affordances for intersubjective meaning making: A research agenda for CSCL. *International Journal of Computer-Supported Collaborative Learning*, *1*(3), 315–337. doi:10.1007/s11412-006-9660-y
Tan, P.-N., Kumar, V., & Srivastava, J. (2004). Selecting the right objective measure for association analysis. *Information Systems*, *29*(4), 293–313. doi:10.1016/S0306-4379(03)00072-3
Vygotsky, L. S. (1978). *Mind in society: The development of higher psychological processes*. Cambridge, MA: Harvard University Press.
Wise, A. F., & Chiu, M. M. (2011). Analyzing temporal patterns of knowledge construction in a role-based online discussion. *International Journal of Computer-Supported Collaborative Learning*, *6*(3), 445–470. doi:10.1007/s11412-011-9120-1
Zaki, M. J. (2001). SPADE: An efficient algorithm for mining frequent sequences. *Machine Learning*, *42*(1–2), 31–60. doi:10.1023/A:1007652502315
Zhang, J., Scardamalia, M., Lamon, M., Messina, R., & Reeve, R. (2007). Socio-cognitive dynamics of knowledge building in the work of 9- and 10-year-olds. *Educational Technology Research and Development*, *55*(2), 117–145. doi:10.1007/s11423-006-9019-0