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Temporal networks in collaborative learning: A case study

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Abstract

Social Network Analysis (SNA) has enabled researchers to understand and optimize the key dimensions of collaborative learning. A majority of SNA research has so far used static networks, ie, aggregated networks that compile interactions without considering *when* certain activities or relationships occurred. Compressing a temporal process by discarding time, however, may result in reductionist oversimplifications. In this study, we demonstrate the potentials of *temporal networks* in the analysis of online peer collaboration. In particular, we study: (1) social interactions by analysing learners' collaborative behaviour, part of a case study in which they worked on academic writing tasks, and (2) cognitive interactions through the analysis of students' self-regulated learning tactics. The study included 123 students and 2550 interactions. By using temporal networks, we show how to analyse the longitudinal evolution of a collaborative network visually and quantitatively. Correlation coefficients with grades, when calculated with time-respecting temporal measures of centrality, were more correlated with learning outcomes than traditional centrality measures. Using temporal networks to analyse the co-temporal and longitudinal development, reach, and diffusion patterns of students' learning tactics has provided novel insights into the complex dynamics of learning, not commonly offered through static networks.

KEYWORDS

collaborative learning, CSCL, learning analytics, social network analysis, temporal networks, uptake

Practitioner notes

What is already known about this topic

- Representing students' interactions as networks helps researchers analyse the patterns of interactions, roles, and the relations between constructs.
- Network level measures help quantify the level of collaborative group interaction, cohesion, and reciprocity.
- Node level centrality measures have proven useful in predicting students' performance.
- The majority of Social Network Analysis research has so far used static networks.

What this paper adds

- The analysis of temporal networks offers a future potential opportunity to understand the longitudinal evolution of collaborative learning networks, both visually and quantitively.
- Temporal features of students' centralities are more correlated with good grades compared to traditional centrality measures.
- Temporal networks can help analyse the longitudinal unfolding, reach, and diffusion patterns of students' interactions.
- Reachability offers an opportunity to map students' sphere of influence as well as maps the uptake of cognitive content of the interactions.

Implications for practice

- Temporal network offers a future potential opportunity to optimize collaborative learning as well as offer timely support.
- Temporal network methods offer a future potential opportunity to understand students' influence in a network and reach of their interactions.
- Temporal network offers a future potential opportunity to understand the unfolding of interactions over the entire period of a course while not overlooking the time factor.

INTRODUCTION

The successful implementation of collaborative learning requires some essential elements to be realized; particularly, the development of its *social* and *cognitive* dimensions (Janssen & Bodemer, 2013; Soller et al., 2005). The *social* dimension represents the relational processes through which interactions, norms, and roles emerge. A robust *social* dimension serves as a backbone for building productive interpersonal relationships, successful knowledge co-construction, and a cohesive group, thus catalysing cognitive gains (Janssen & Bodemer, 2013; Kreijns et al., 2013). The *cognitive* dimension represents students' knowledge, skills, values and behaviours, such as self- and social regulation (Kreijns et al., 2013). To be able to optimize students' learning processes, and harness the key roles of these two dimensions, we firstly need to understand them adequately. In this, the use of Social Network Analysis (SNA) methods can enable such understanding. This, in turn, can help us to create a solid ground for optimizing students' learning and for further improving the settings in which it occurs. In terms of SNA, the *social* dimension can be captured by analysing and visualizing the social ties among actors, the network structure, and roles (Cela et al., 2014). The *cognitive* dimension can be captured by representing content analysis elements as networked components to study, for example, the interplay between students' self-regulation, knowledge co-construction, and epistemics (Dado & Bodemer, 2017). Such network representations have afforded investigators a wealth of visualization and statistical methods (Burt et al., 2013).

SNA tools have already proven to shed light on several aspects of collaborative learning, including interaction patterns, group dynamics and the learning environments in which they occur (Cela et al., 2014). A majority of SNA research in education, however, has so far used static networks, ie, aggregated networks that compile all interactions, with no regard for *when* certain activities or relationships occurred in the learning process (Dado & Bodemer, 2017; Peeters, 2019). Recent research has shown that compressing a temporal process by discarding time may be a reductionist oversimplification of reality (Holme & Saramäki, 2019). As Reimann (2009) posits: "the theoretical constructs and methods employed in research practice frequently neglect to make full use of information relating to time and order. This is especially problematic when collaboration and learning processes are studied in groups that work together over weeks, and months, as is often the case" (p. 239). Based on these findings, we deem it necessary to use temporal networks to study the dynamics of collaborative learning as a process that unfolds over time (Reimann, 2009) in order to better understand the ways in which such a process materializes and progresses.

In this study, we demonstrate the potentials of temporal networks in the analysis of computer-supported collaborative learning (CSCL) interactions. In particular, we examine: (1) social interactions through the analysis of peer collaboration, part of a case study in which students worked together on several academic writing tasks online, and (2) cognitive interactions through the analysis of students' self-regulated learning (SRL) tactics (annotated content of the interactions). We do so while accounting for temporal aspects, both the 'co-temporal' and 'longitudinal.' By 'co-temporal' we mean learners' interactions occurring in close proximity of one another (eg, within a session or a day). By 'longitudinal' we mean the full duration of a course or its segments.

As this paper aims to compare and contrast the analysis of temporal versus static networks, we believe that the contributions could be manifold. First, it demonstrates how to examine the temporal evolution of the relationships between learners in a CSCL environment, as well as how to use such information to analyse the learning process in collaborative groups. Second, it illustrates how different temporal profiles reflect the influence and sphere of the students' interactions, and how such patterns are associated with better academic achievement. Third, it provides visual and quantitative illustrations of the longitudinal development, reach, and diffusion patterns of SRL tactics; how students use such tactics in their learning process, and how these tactics spread or diffuse over time.

BACKGROUND

Recently, attention to the dynamics of learning has kindled the interest in methods that can be used to uncover the *time* dimension of the learning process, based on the examination of students' (log) data (Chen & Poquet, 2020; Csanadi et al., 2018; Vu et al., 2015). In their study on the use of log data for CSCL research, Wise and Schwarz (2017) assert that there is a wealth of data mining, natural language processing and multimodal analytics to support online and collocated CSCL. Methods include epistemic network analysis, process mining, sequence mining, and, more recently, temporal networks.

One of the methods that has been gaining ground in recent years is epistemic network analysis. It is a quantitative ethnographic technique for modelling the co-temporal structure of interactions or discourse. Epistemic network analysis has for example, been used to study interrelationships between coded elements of discourse or text to understand the patterns of associations of eg, knowledge, skills, and behaviour (Shaffer et al., 2016). It allows to study dynamic interactions between the networked elements using a 'moving window' to model the co-temporal unfolding of cognitive learning activities (Csanadi et al., 2018; Shaffer et al., 2016). While epistemic network analysis has proven useful in the understanding of many phenomena, it falls short when it comes to the *longitudinal* modelling of temporal interactions (eg, across the full duration of a course). Furthermore, epistemic network analysis does not allow for the calculation of temporal features such as temporal centralities, reachability, or concurrency.

Process mining is another method that has been used to study the temporal processes of learning (Pechenizkiy et al., 2009). Process mining models the transition between events in the form of a visual process model that has been used to study, for instance, students' approaches to assessment (Pechenizkiy et al., 2009), the use of different learning strategies (Ahmad Uzir et al., 2020) and SRL tactics (Peeters et al., 2020). The new models are visually intuitive, yet, subject to the chosen algorithm and individual choices made by the researcher (eg, the threshold of included events), which may result in a model that is overfitting (hardly generalizable) or underfitting (far from reality; van der Aalst, 2012). Similar to epistemic network analysis, process mining lacks the capacity to model the longitudinal unfolding of the learning process; nor does it present a method for calculating temporal centralities.

Finally, sequential analysis enables researchers to calculate the probability that one action follows another one, thus offering an understanding of the progression of learning (Jovanović et al., 2017; Matcha et al., 2020). The insights generated by sequential analysis allows researchers to effectively mine the typology of a (learning) process. However, it lacks the relational aspect that network methods offer. In this paper, we argue that temporal networks can complement the available methods (eg, epistemic network analysis and process mining) and offer tools for the study and understanding of *longitudinal, relational,* and *temporal* aspects of the learning process in CSCL settings. A full review of the temporal methods is beyond our article, and thus, interested users may refer to Lämsä et al. (2021)

Temporal networks

The study of temporal networks—often referred as time-varying networks—is a growing subfield of network science that is concerned with the study of time-ordered interactions (Holme, 2015; Holme & Saramäki, 2012, 2019). An increasing visualization and mathematical repertoire of tools have made temporal networks widely viewed to be fundamentally advantageous in modelling dynamic phenomena, including social interactions (Holme, 2015; Holme & Saramäki, 2012, 2019), allowing researchers to make fine-grained inferences about temporal networks' topology (ie, the emergence and dissolution of certain structures or interactions in a network), and flow (ie, the level and direction of connectivity between nodes, informing us on the transfer and exchange between them) (Holme & Saramäki, 2019; Nicosia et al., 2013). In the next section, we review the structural properties of temporal networks as well as previous research using temporal networks in education.

A temporal network is composed of nodes (actors or vertices) representing the interacting elements, and edges (relationships or interactions) with onset (start or activation) and offset (exit or deactivation) times for each edge (Holme & Saramäki, 2019; Nicosia et al., 2013). The network can be one of two types: (1) a contact sequence when the duration of the contact is negligible, eg, instant messages (Figure 1a) or (2) a time interval network, when the duration of the contact is of importance eg, social meetings (Figure 1c; Holme & Saramäki, 2019; Nicosia et al., 2013). The resolution of the network can be as high as the logging mechanism that has been used to record the data allows, which may be as precise as a fraction of a second. Yet, to make sense of the data, researchers often have to aggregate the edges by creating time intervals, mostly equally sized, which is commonly referred to as temporal granularity (Nicosia et al., 2013).

As a paradigm, temporal networks should not be simply summarized as a generalization of static networks (Holme, 2015; Holme & Saramäki, 2019), neither should they be confused with static networks that account for the chronological order of interactions. The differences between temporal and static networks are manifold. First, temporal networks are constrained by time, ie, paths between nodes have to follow a time-ordered sequence of contacts (time-respecting paths). In these network representations, when information is transmitted from A to B at time point T1 and from B to C at T2, this order cannot be reversed (Holme & Saramäki, 2019). Second, interactions are temporary, ie, edges form and dissolve, contrary to aggregate networks which depict edges as permanent connections (Holme & Saramäki, 2019). Third, interactions in temporal networks are non-transitive (Holme, 2015; Holme & Saramäki, 2019). In a static network (Figure 1b), one can, for example, reach from node A to C through B. However, this is impossible in the contact sequence temporal network (Figure 1a) since the edge A–B dissolves before B–C forms (Holme & Saramäki, 2019; Masuda et al., 2021).

Fourth, static networks tend to overestimate the true connectivity of a network which is likely to render an unrealistic picture of the examined process (Holme & Saramäki, 2019). The network may appear densely connected while it has periods in which most nodes are disconnected, depending on the point in time. Compare, for example, the network in Figure 1b with the time point 3 in Figure 1c. The static network looks well-connected while the temporal network at this point, shows limited connectivity.

Another type of network is the *ego* network, which is helpful for the mapping of the social capital of a node, contacts, and sphere of influence (Burt et al., 2013). A static ego network maps the reach of immediate contacts (a measure of eg, social capital, access to

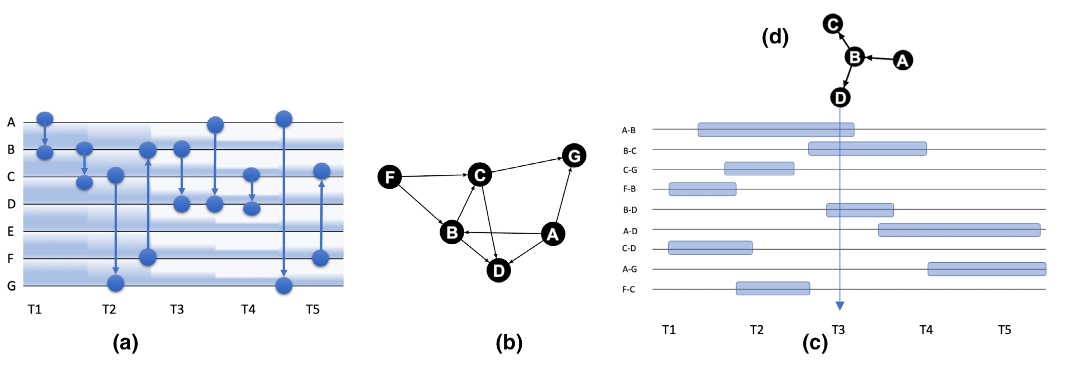

FIGURE 1 (a) A contact sequence temporal network where interactions are instant and have negligible duration and edges have negligible durations (eg, instant messages). (b) A static network representing the same A and C networks. (c) The time interval network shows interactions with various durations. (d) The network at T3 looks less connected compared to the network in (d)

immediate resources and diversity), which can be expressed mathematically as degree centrality. Closeness centrality maps the distance and reach to nodes in the network. However, both degree centrality and closeness assume that connections are persistent and, when formed, do not dissolve. This is not the case, however, and this assumption thus results in an overestimation of the connectivity and reachability of a node. This may be counterintuitive in the learning process where edges are essentially transient. Therefore, temporal reachability may be more appropriate to estimate the true reach and influence of a node as it requires concurrency and time order as essential conditions.

How relevant are temporal networks to CSCL?

CSCL involves groups of collaborators who work together on individual or shared tasks over varied periods of times. As learners post, reply or reciprocate each other's interactions, they leave chronologically ordered fined-grained, time-stamped data that chronicles the collaborative process in detail (Reimann, 2009). Wise and Schwarz (2017) have argued that analysing collaborative processes in CSCL often involves treating interaction and collaboration as idiosyncratic or unique processes, comprised of a number of interaction units that come to have meaning in an ever-evolving mediated context. In order to develop a unified approach to analyse these processes, multimodal analytics, including aspects of time and space, are considered to enable researchers to better and faster understand the dynamics within CSCL in this regard and distinguish key events as they unfold.

Suthers and Desiato (2012 refer to the process of building on each other's interactions as 'uptake'. In this context, replies to posts are temporally contingent. The understanding of such temporal processes is of paramount importance to analyse how students co-construct knowledge by taking up each other's ideas and build threads that are contingent on others.

Suthers and Desiato (2012) have further proven that uptake networks, in combination with network measures such as 'proximity prestige', can help distinguish where the most engaged discussions in CSCL contexts are taking place. This information could help educators know when and where activity occurs, as well as monitor engaged and disengaged actors. Uptake networks, which consider contingencies between different events in which a participant's action builds on, or takes over, some aspects of events that came before it, also take into account these temporal and spatial dimensions (Suthers, 2015; Suthers & Desiato, 2012). In order to visualize the levels of uptake in CSCL, one can aggregate these contingencies and divide them into sessions. Suthers (2015) suggests that 'uptake that crosses partitions can be used to identify influences across space and time, and uptake within partitions can be analysed to study the interactional structure of a session' (p. 371), highlighting the importance of temporal dimensions in the study of CSCL.

Previous research in temporal networks

In addition to studies that have addressed the temporal aspects of learning (Section 'Temporal networks') and studies that have covered the temporal aspects of uptake and contingencies in CSCL (Section 'Previous research in temporal networks'), the use of temporal networks has started to gain momentum. However, such studies have so far been scarce. Vu and colleagues (2015) used Relational Event Modelling (REM) to study the social and temporal structure of learner interactions in a massive open online course environment. Their findings stress the mutual dependency between interactions in discussion forums on the one hand, and the measured academic success on the other, as well as between interactions in discussion forums and predicting future success. Similarly, Chen and Poquet

(2020) have applied REM to capture aspects of temporal participation and social dynamic factors such as preferential attachment and reciprocity. They have been able to capture the bursty nature of interactions and the role of familiarity as a motivator to form ties. Saqr and Nouri (2020) used temporal network methods to visualize and quantify student interactions in a collaborative learning course setting. Their results revealed the bursty pattern of interactions as well as the value of temporal centrality measures in the early prediction of students' performance.

All in all, given the paucity of research that has used temporal networks, this study aims to contribute to the literature by studying the potentials of temporal networks –compared to static networks—in a collaborative learning context by exploring temporal network analysis on three levels: graph-level (which is related to the collaborative group), node-level (which is related to the individual collaborators) as well as visualization (which explores the visualizations of both levels: group and individual). First, we investigate the use of temporal graph-level measures to analyse the evolution of collaborative group networks (RQ1); second, we investigate the value of temporal node-level measures as correlates of performance and reach (RQ2); third, we investigate the value of temporal network visualizations as possible tools for visualizing the collaborators and the collaborative process (RQ3). In answering every research question, we compare the resulting insights with static network analysis whenever relevant. The research questions of this study are as follows:

RQ1: How can temporal networks help analyse the longitudinal evolution of collaborative learning networks?
RQ2: To what extent do temporal features of students' interactions correlate with performance (represented as grades) compared to traditional centrality measures calculated with static networks?
RQ3: How can temporal networks help analyse the co-temporal and longitudinal unfolding, reach, and diffusion patterns of students' self-regulated learning tactics?

METHODS

Context

In this study, we aim to demonstrate the potentials of temporal networks in the analysis of CSCL interactions. The dataset used in this study originated from a case study in which first-year foreign language majors of English ($n = 123$) at the University of Antwerp (Belgium) used Facebook as a collaborative space for peer review in an academic writing course. It was a blended course, with 12 face-to-face contact hours, an online self-access module on academic literacy, and a peer review space on Facebook. Learners were required to write three 300-word essays over the course of three months. They could brainstorm in class and were reminded regularly that they could consult with their peers on Facebook about their writing or about the challenges they faced at any given time. There were no teachers present in the online group.

Data and theoretical lens

In order to analyse the data and make inferences about the CSCL patterns that can be distinguished, the log data was coded using the principles of digital conversation analysis to distinguish recurring learning activities for academic writing. The examination of these learning activities focused on the students' self-regulated learning (SRL) tactics, which refer to the specific, applied ways in which an SRL strategy (eg, goal setting or reflecting) is being used to meet a goal in a certain situation (Oxford, 2016). Learners engaged in *planning*, as they discussed how to proceed in writing and learning, *organization*, as they discussed goals, objectives and requirements of the tasks, and *identity construction*, as they shared personal stories, expectations and experiences about their academic trajectory (Peeters et al., 2020). These tactics are part of the strategic *forethought* phase (Oxford, 2016). Next, learners spent time on *text composition*, discussing textual features and structure of the writing tasks, *argumentation*, or discussing thesis statements and argumentation for the writing tasks, *resource management*, where they shared and evaluated resources and user-generated content, *bonding*, where they talked about hobbies, free time and leisure, and *acknowledgement*, where they expressed positive emotions and gratitude. These tactics are part of strategic *performance* in learning. Finally, learners *reflected* on the purpose of the tasks and the course and *evaluated* their performance by discussing and applying feedback from peers and educators. These tactics are part of *reflection* and *evaluation* in the SRL process. Further details on the theoretical lens and coding process are detailed in Peeters et al. (2020) as well as in the Appendix Table S3

Analysis

The analysis methods implemented in this study are charted in Figure 2. To answer the first and second research questions, a temporal post-reply temporal network was constructed according to Saqr and Nouri (2020) and Vu et al. (2015). Another static post-reply network was constructed using the same data to compare the results generated by both networks. The graph and node-level measures are reported as a time series (TS) of 49 time points (the active days of the course): a time point for every single day. We calculated the dynamic

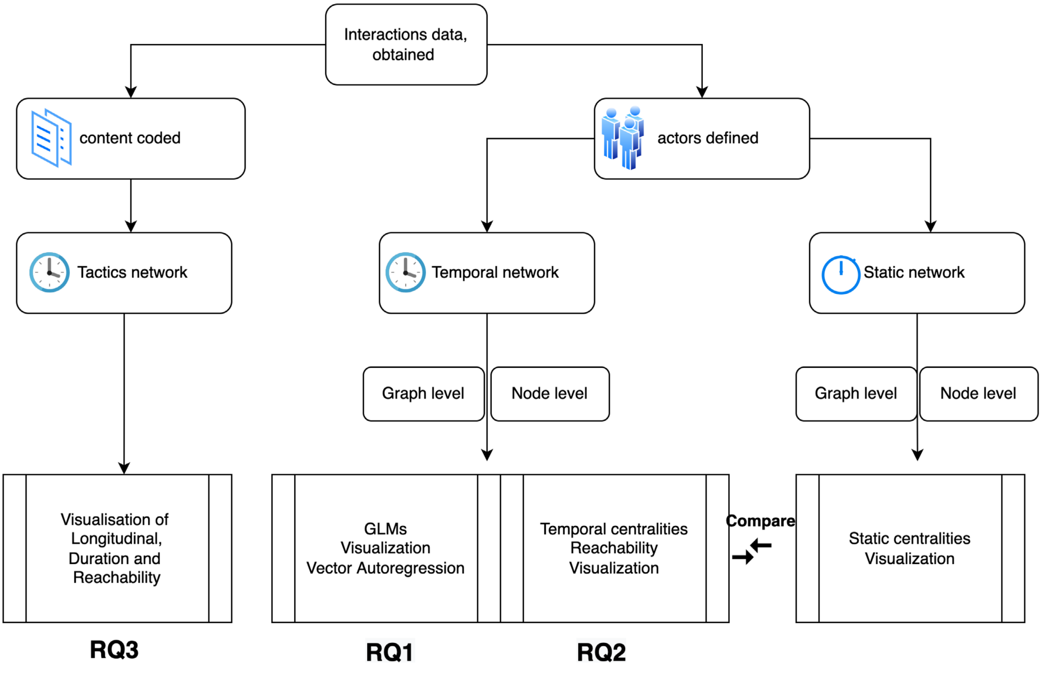

FIGURE 2 A flowchart of methods implemented in the study

Graph Level (GL) measures which reflect the level of interactivity, embeddedness, distribution of participation among students, type and quality of ties, and mixing patterns of high and low achievers using the Tsna R Package (Bender-deMoll & Morris, 2016). *Dynamic GL measures calculated* at each time point: (1) dynamic density (ie, the sum of edges divided by the maximum possible edges) as an indication of the activity and distribution of interactions among the whole group, (2) dynamic mutuality (ie, the number of reciprocated edges) as an indication of the strong relations, valued mutuality and balance, (3) dynamic simmelian ties (reciprocal strong edges where both nodes have mutual and strong connection to a third node forming a triad) to reflect frequency of tightly and strongly connected and cohesive subgroups of students, (4) high and low achievers' mixing pattern, ie, the probability of high achievers (top 50%) collaborating with low achievers (bottom 50%) to reflect the mixing pattern of students, (5) dynamic degree centralization (ie, the distribution of degree centrality among participants) that measures the distribution/dominance of centrality during the interaction process, and (6) dynamic Eigenvector centralization to reflect the distribution of Eigenvector centrality and measure the strength of connectedness of a student network. The GL measures were also calculated for the static network and compared to a null model of 1000 matching networks of the same number of nodes and interactions. For a detailed definition and calculation methods, please see Bender-deMoll and Morris (2016), and Freeman (1978).

To study both the temporal evolution of GL *variables* what opportunities may exist to optimize the network, we represented GL measures as a psychological network, in which the nodes are variables and the relationships among them are represented as an estimated Vector Autoregression (VAR) model that is commonly plotted as a graph (graphical VAR). The graphical VAR model captures if a variable (a GL measure in our case) predicts another one in the next time window, ie, what is happening next as a result of what is happening now (lag-1) after controlling for all other variables. Details of the estimation and method are detailed in Epskamp et al. (2018).

To answer the second research question, we calculated the *dynamic node-level centrality measures* according to Saqr and Nouri (2020) at each time point: (1) dynamic outdegree centrality as the frequency of posts by a student to reflect a student's participation and contribution to the collaborative process; (2) dynamic indegree centrality, ie, the number of received replies, which reflects the uptake of a student's contributions; (3) flow betweenness, ie, the times a student has bridged or mediated interactions between others (dynamic flow betweenness considers all paths that involve the node and thus gives a better idea about actor interactivity), and (4) dynamic Eigenvector centrality as the sum of the students' centralities and the centrality of his/her connections, giving a better idea about the ego network and its strength. The static node level centralities were also calculated for each student for comparison. In addition, the diffusion centrality—the probability that a node spreads a property to neighbours, added to the probabilities of neighbours transmitting it further—to study the diffusion of students' tactics, detailed definitions, and computation methods are available in Freeman (1978), Liao et al. (2017), and Nicosia et al. (2013).

The temporal features of the dynamic centralities were calculated using R package tsfeatures (Hyndman et al., 2019) to investigate whether the pace of interactions is better correlated with performance. The following features were calculated: TS *mode* (mode of the TS using histograms with a seven-day (week) bin), *crossing points* (frequency of crossing the median) denoting a period of activity, *flat spots* (the maximum run length within the TS intervals) usually periods of inactivity, and the *entropy* of the time series according to the periods of regular contribution to the forum. To reveal the temporal reach and range of influence of nodes, we calculated the *reachability* as the number of reachable nodes using time-respecting forward paths. We also plotted the forward temporal path (the reachable sequence of nodes) to map the range of influence of a node and how this type of visualization can help us understand the reach and influence compared to the commonly used ego networks. We also plotted the hierarchal and transmissibility path plots to demonstrate the earliest uptake path using the R package NDTV (Bender-deMoll, 2018). The correlation coefficient was calculated using Spearman's Rank-Order Correlation.

To answer the third research question, a temporal network was created for the coded interactions. We demonstrated the longitudinal interactions between the examined tactics using a proximity timeline. A proximity timeline uses an innovative combination of layouts to visualize a relational process *longitudinally*. The algorithm slices the temporal network at each time point (creating 49 networks) and implements multidimensional scaling to cluster together related nodes according to their geodesic distance on a vertical timeline. A spline is then drawn connecting nodes along their position. This results in a timeline where closely related nodes are rendered close together through the plot. To reveal the reach and diffusion of each coded tactic, a hierarchal path was plotted as well as the transmissibility graph. The visualizations were implemented using the R package NDTV (Bender-deMoll, 2018). The performance measure was the total of the grades of the tasks submitted by the students.

RESULTS

To answer the first research question, we first calculated the GL measures of the static network and compared it to the plotted dynamic GL measures to show how the dynamic GL measures offer a more fine-grained and nuanced view of the properties of the network. This view, consequently, offers more insights into the interactions, the divisions of work, and the quality of formed ties. We later present how each of the dynamic GL measures influences each other and how to use these insights to optimize the learning process in CSCL. *The static GL measures network* shows that the network had 123 nodes, 2550 edges with a degree of 41.48. The density was 0.15 and the reciprocity was 0.12 (slightly below what was expected at random (the average value of the random model 0.17, $p < 0.001$)). The degree centralization was 0.6, which was significantly higher than what is expected at random (0.07, $p < 0.001$). The static GL measures point to a moderately active group with below-average reciprocity and high centralization denoting the possible presence of hubs in which students tend to communicate frequently.

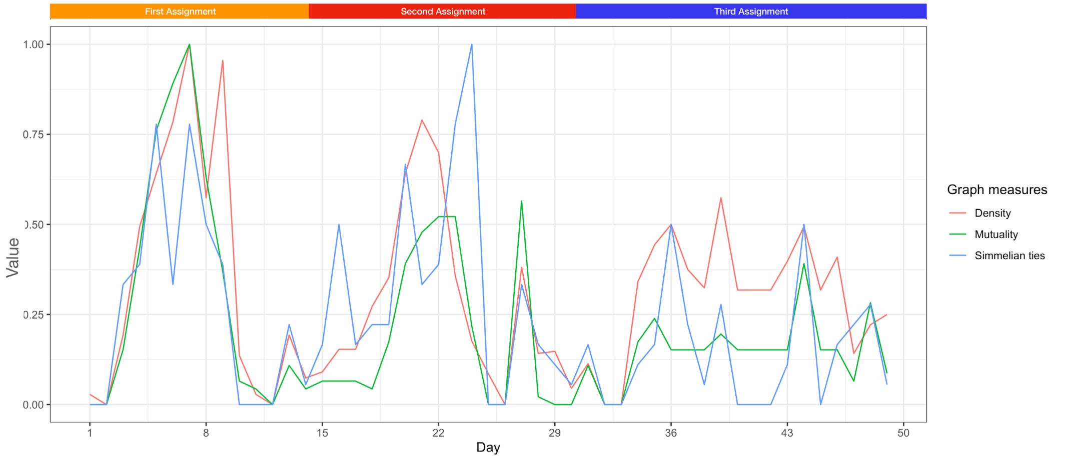

FIGURE 3 The dynamic GL measures and their evolution over time. The measures were normalized (range 0) to allow comparison

The dynamic network GL measures allow continuous fine-grained monitoring of the graph. The dynamic GL measures plot (Figure 3) shows a bursty pattern of the density, mutuality, and simmelian ties where the activity was more intense during the days the students had to work on their assignments, and low in-between, with smaller bursts of activity. The timeline of the density and mutuality measures were similar during the first assignment period. However, the simmelian ties tend to lag, which may be due to the time it takes to establish strong ties, form common interests, and have intense discussions. The simmelian ties started to peek after two weeks and stayed high until the fifth week. The mixing of high and low achievers (Figure 4) shows that simmelian ties peaked at the beginning of the course but soon (around the second assignment), the high achievers were more likely to interact with high achievers. Both plots of dynamic GL measures in which high and low achievers are mixed (Figures 3 and 4) exhibit a bursty pattern, with an intense period of activity at the beginning of the assignment and a slower pace in between assignments. These graphs also show more selective mixing of students over time, as well as the formation of strong ties.

The optimization of the network requires the relational as well as the temporal relationship between the variables to be analysed. We selected graphical VAR models resulting in a directed network as shown in Figure 5, where a blue arrow indicates that the source variable predicts the target variable after controlling for all other variables. The graphical VAR model shows that the formation of mutual ties predicts: (1) the formation of future mutual ties, (2) the formation of simmelian ties, (3) the mixing of high and low achievers, as well as (4) a denser network. Thus, an intervention that aims at optimizing collaboration in the network would best aim at increasing mutual interactions as a key to foster favourable collaboration patterns. Furthermore, the mixing of achievers predicts mutuality and simmelian ties. Interestingly, degree centralization predicts future Eigenvector centralization which in turn predicts future mixing. A possible explanation is that hubs may stimulate responses from all groups and stimulate future productive interactions. The values of correlations are detailed in Table S1.

To answer the second research question, temporal centrality measures were computed in the form of a time series with a temporal granularity of a single day to explore their temporal features using time series methods. Such temporal features have been shown in other learning contexts to contribute to our understanding of students' activities and improve predictive models (Jovanović et al., 2019). As Table 1 shows, the temporal features of centrality

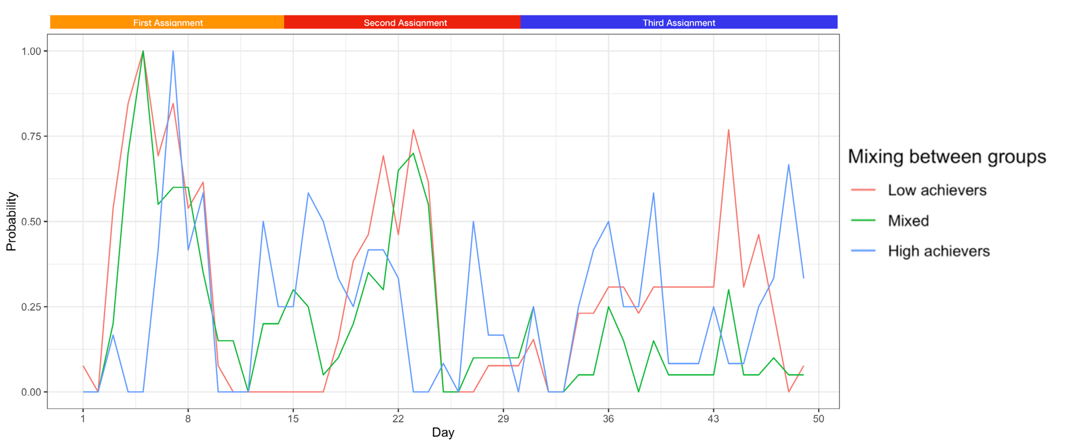

FIGURE 4 The dynamic plot of the mixing of high and low achievers. The measures were normalized (range 0 to 1) to allow comparison

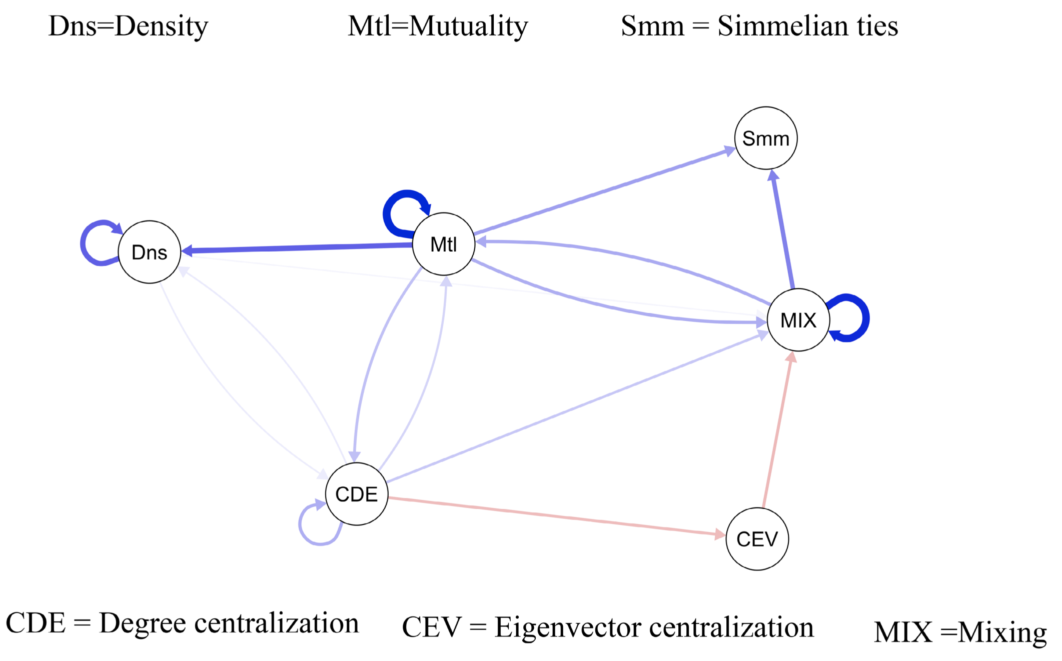

FIGURE 5 The dynamic graph level measures and how they predicts each other in the future

measures show higher and statistically significant correlation coefficients compared to the values of the corresponding static centralities. The correlation coefficient of the entropy of dynamic outdegree centrality was ($r = 0.44$, $p < 0.01$), compared to ($r = 0.23$, $p = 0.03$) for the static outdegree centrality. Similarly, crossing points also showed relatively higher correlation coefficients with grades ($r = 0.38$, $p < 0.01$), flat spots showed marked negative correlation coefficients ($r = -0.4$, $p < 0.01$). While the correlation coefficient of grades and the total aggregate of outdegree centrality was low and statistically insignificant ($r = 0.15$, $p = 0.10$). The comparison (using r-to-z transformation) between static outdegree centrality and the temporal features thereof was statically significant for all the three temporal features (crossing points, entropy, and flat spots), indicating significantly higher values for the temporal features, as can be seen in Table 1.

Similarly, the correlations coefficients between grades and the temporal features of indegree centrality were higher than the static centrality and statistically significant. For crossing points, the correlation was ($r = 0.31$, $p < 0.01$), entropy ($r = 0.24$, $p = 0.03$), and flat spots ($r = -0.25$, $p = 0.03$)) compared to their static centrality indegree centrality ($r = 0.20$, $p = 0.07$) and the total aggregate indegree centrality which was lower and statistically insignificant ($r = 0.11$, $p = 0.24$). For the flow centrality, the temporal features show similar patterns: higher correlation coefficients in the temporal features compared to the static centrality or its aggregate values. The crossing points of flow centrality was ($r = 0.26$, $p < 0.01$), entropy was ($r = 0.22$, $p = 0.10$) compared to the static flow centrality ($r = 0.21$, $p = 0.07$) and the aggregate total ($r = 0.14$, $p = 0.22$). Again, the same pattern was evident in Eigen centrality. The correlation coefficients with grades and crossing points ($r = 0.24$, $p = 0.02$) and entropy ($r = 0.22$, $p = 0.02$) were higher than the static Eigen centrality ($r = 0.22$, $p < 0.03$) or its aggregate total ($r = 0.06$, $p = 0.048$). Mode (most frequent value) showed lower or similar correlation coefficients (compared to static counterparts). Only in Eigen centrality the mode was the highest correlated parameter with grades ($r = .36$, $p < 0.01$). However, for indegree,

TABLE 1 Correlation between the temporal features of four centrality measures and grades and comparison of correlation to static centrality measures

			Confidence interval			Compared to static c	
Centrality	**Parameter**	***r***	**Low**	**High**	***p***	***Z***	***p***
Outdegree	Static	0.23	0.06	0.39	0.03		
	Total	0.15	−0.03	0.32	0.10	1.46	0.92
	Mode	0.22	0.05	0.39	0.03	0.15	0.56
	Crossing points	0.38	0.21	0.52	<0.01	−1.8	0.03
	Entropy	0.44	0.28	0.57	<0.01	−2.6	<0.01
	Flat spots	−0.40	−0.54	−0.24	<0.01	4.7	<0.01
Indegree	Static	0.20	0.03	0.37	0.07		
	Total	0.11	−0.07	0.28	0.24	0.18	0.96
	Mode	0.19	0.02	0.36	0.07	0.37	0.64
	Crossing points	0.31	0.14	0.46	0.00	−1.34	0.09
	Entropy	0.24	0.06	0.40	0.03	−0.41	0.34
	Flat spots	−0.25	−0.41	−0.07	0.03	3.0	<0.01
Flow	Static	0.21	0.03	0.37	0.10		
	Total	0.14	−0.03	0.31	0.22	0.87	0.8
	Mode	0.21	0.03	0.37	0.10	0.01	0.5
	Crossing points	0.26	0.09	0.42	0.03	−0.62	0.27
	Entropy	0.22	0.04	0.38	0.10	−0.1	0.46
	Flat spots	−0.12	−0.29	0.06	0.22	2.4	<0.01
Eigen	Static	0.22	0.05	0.38	0.03		
	Total	0.06	−0.11	0.24	0.48	1.75	0.96
	Mode	0.36	0.19	0.50	<0.01	−1.44	0.07
	Crossing points	0.24	0.07	0.40	0.02	−0.31	0.38
	Entropy	0.26	0.08	0.41	0.02	−0.54	0.29
	Flat spots	−0.32	−0.47	−0.15	<0.01	3.7	<0.01

flow and Eigen centralities, the differences between the temporal features and the centrality thereof were only significant in flat spots, see Table 1 for details.

In summary, the temporal features—in our case—were more correlated with performance than the actual values of static centralities, or their aggregated values (total, mode) for outdegree centrality and were statistically significant for the flat spot feature of the indegree, flow and Eigen centralities.

The reachability maps show the reachable set of nodes or, in other words, the range of diffusion and transmissibility of, for instance, ideas, knowledge and information. A person is expected to have higher reachability when her/his ideas are more likely to be picked up by others and used to build a case or argument (Suthers & Desiato, 2012). To demonstrate how mapping reachability offers more information compared to the traditional ego networks, we visualized and compared two nodes with equal ego networks (11 nodes) in Figure 6. We then compared it to the reachability graph and the transmissibility graph. Figure 6a,b shows that both nodes have the same ego size according to statics representation. However, the reachability map shows a completely different story. Figure 6c shows that node 21—one of the two students in this example–can reach 20 nodes (16% of all nodes), while Node

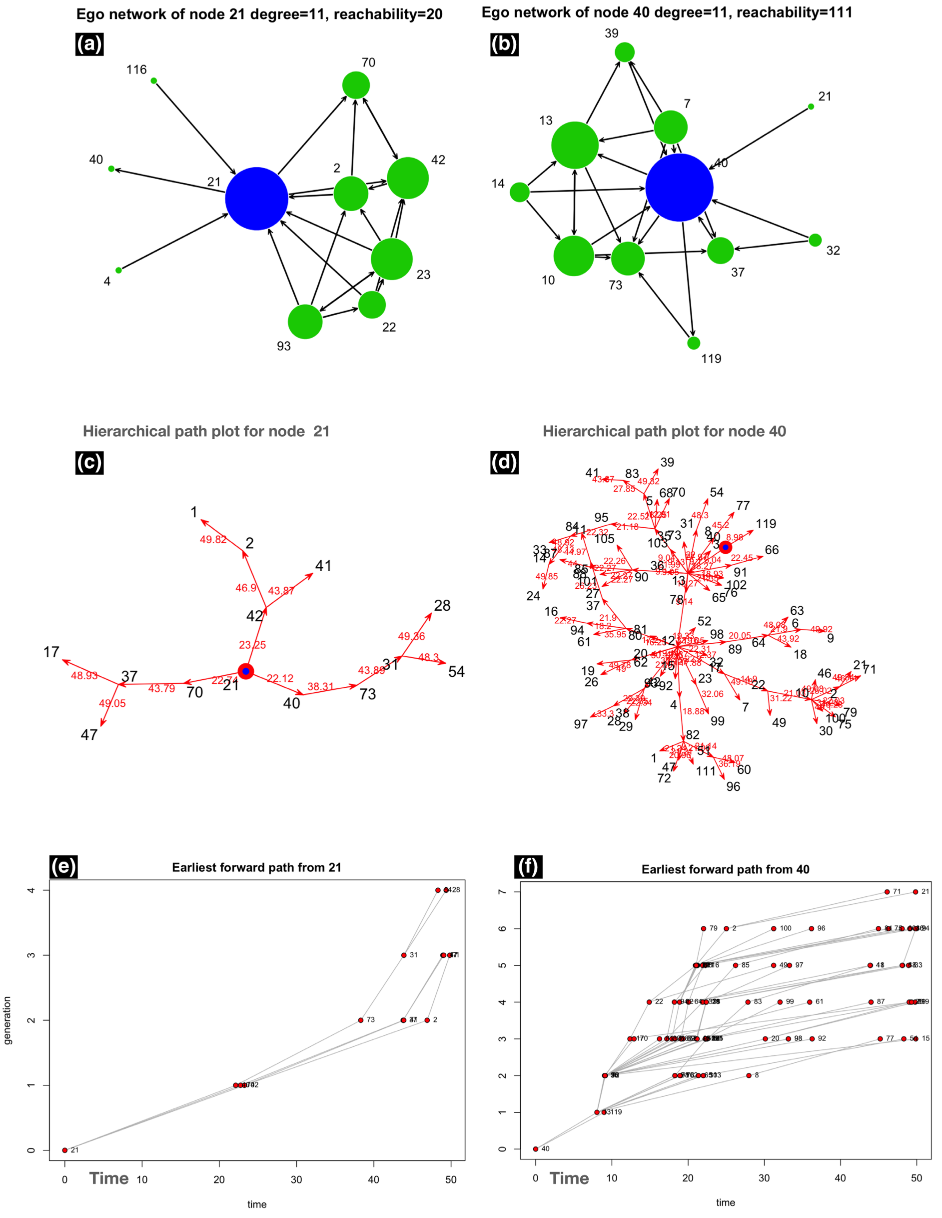

FIGURE 6 (a) and (b) (top) Two ego networks of nodes 21 and 40 with equal sizes. C and D (middle) the path visualization of the reachable nodes, (e) and (f) (bottom) transmissibility graph showing the forward transmission/diffusion of each node

40—another student– in Figure 6c can reach 111 nodes, which is 90% of the nodes. Thus, node 40 can communicate or get information from a bigger group. Figure 6d,e present the forward transmissibility graph, showing the path of probable transmission or diffusion. Again, Node 40 can reach larger contacts at different timepoints. It is obvious from the three graphs that reachability graphs offer a more nuanced view of how information may spread using concurrency and time respecting paths.

The possible practical value of measuring reachability was evaluated through (1) correlation measures with students' grades to see if reachability can be a possible indicator of success; (2) centrality measures to understand the structural factors that define the reachability and uptake of student contributions; and (3) coded SRL tactics to investigate which factors define the range and uptake of students' contributions. The results indicate that the correlation between the temporal reachability of a node and grades was $r = 0.33$, $p > 0.001$, which was higher than the static centrality measures of participation, and slightly higher than Eigenvector centrality, emphasizing the value of reachability as a possibly better indicator for students' success. Regarding the structural position of a node, reachability was strongly correlated with diffusion centrality, emphasizing the value of reachability as a measure for uptake. Regarding the coded SRL tactics, students who used the *identity construction*, *evaluating*, and *argumentation* tactics were more likely to have more reach as students are more likely—in our context—to take up such contributions and build on them. Detailed correlations can be found in Table S2.

To answer the third research question, using temporal networks to understand the forward pathways and reach of students' SRL tactics over time can contribute to our understanding of the way knowledge is constructed, how the collaboration between peers is managed, and how the learning process unfolds over time. The proximity timeline (Figure 7) was created by slicing the temporal network into separate networks for each day and using multidimensional scaling to place the closely linked nodes together along a horizontal line. This enabled us to trace the trajectory and the relationship between one tactic and all other tactics at any point in time (co-temporal), when a tactic is linked to (or close to) other tactics and when and for how long it swerves. In doing so, the visualization shows the co-temporal relationships (at each time point) as well as longitudinal progression of these relationships between the used tactics.

In Figure 7, the tactic *text composition* (related to the tasks of the course), *argumentation* and *identity construction* remain intertwined and tightly linked all the way across the visualized course segment (which represents a period of two weeks, as an example). The visualization also shows that *planning* is only linked to other tactics at the beginning of the CSCL process, and later dissociates. *Resource management* is only linked to other tactics at the end of the first week and at the end of the second week. On the 10th day of the course, and close to the first assignment deadline, all tactics are dissociated. We also see the bursty nature of the interactions among tactics: they are tightly linked around the middle point (except for *planning* and *resource management*) and disperse more by the end of the second week.

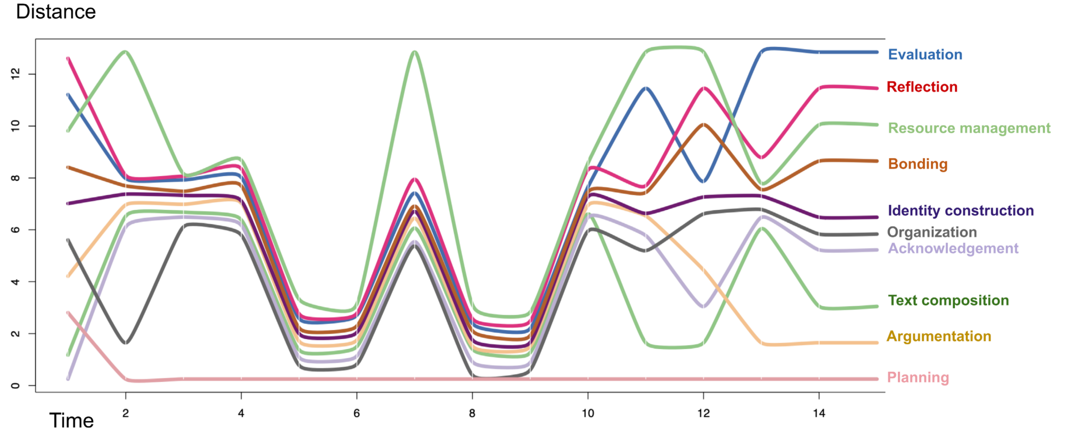

FIGURE 7 Shows the longitudinal and temporal relationship among the coded SRL tactics. Closely related nodes have shorter geodesic distance at the given time point

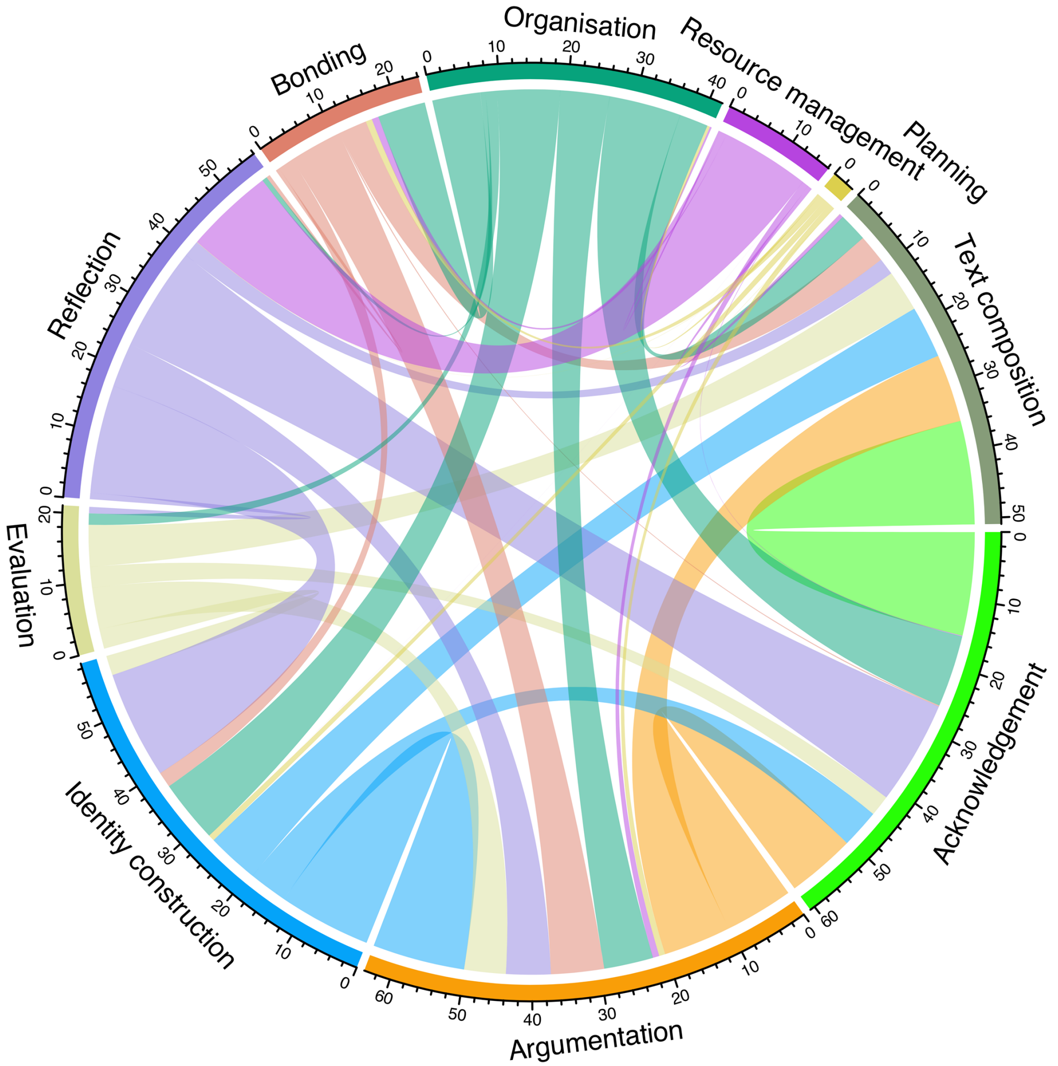

FIGURE 8 A chord network graph showing nodes as arcs and the edge thickness is corresponding to the duration of concurrency of the activated tactics

The visualization of concurrency (the time the tactics were simultaneously activated) in Figure 8 may help us understand another aspect of temporality, ie, duration of concurrency. In Figure 8, node size corresponds to the total duration of the activity that node represents; the edges show the total time these codes have been concurrent. This time-based visualization of duration and concurrency demonstrates another aspect of temporality (ie, *how long*). *Argumentation* has been found to be the most discussed tactic, followed by *text composition* (both tactics which are strongly task-related). We also uncovered a strong link between the *argumentation, acknowledgment, reflection*, and *identity construction* tactics, with marked thick edges, indicating a long duration of concurrency.

Another useful visualization of concurrency is the hierarchical path plot (Figure 9a) which shows the directed pathway of a tactic that respects time and requires concurrency between tactics (ie, the map of reachability of a tactic). It plots the temporal contingency of

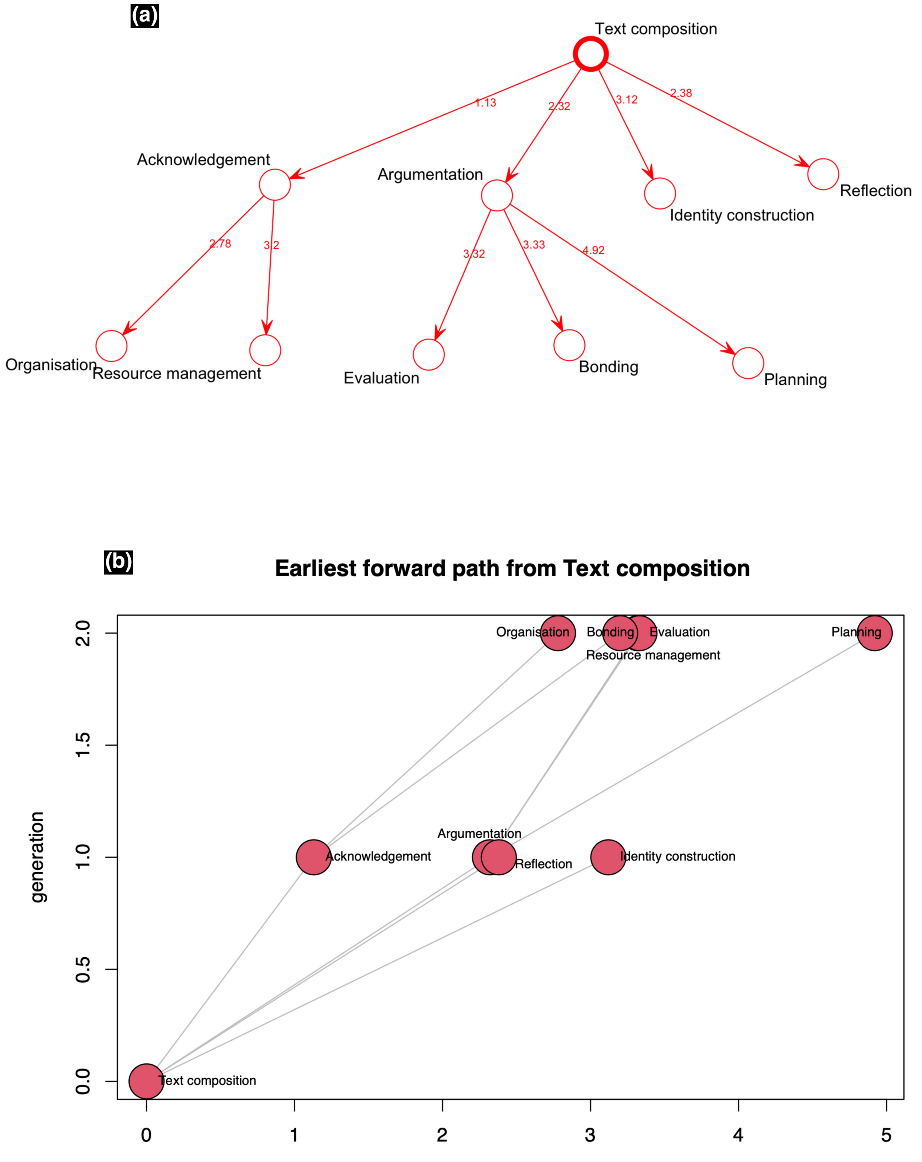

FIGURE 9 (a) A hierarchical path plot showing the earliest interactions between the *text composition* tactic and the tactic that followed. (b) A transmissibility graph showing the forward flow and earliest interactions with the *text composition* tactic

SRL tactics, ie, which tactic is contingent upon the other. It maps such a pathway, as well as calculates the time it takes to receive a response. The plotted path for *text composition*, for example, shows that discussing formal aspects of academic writing is often followed by discussing *argumentation*, which, in turn, is followed by evaluation, bonding, or planning tactics. Another possible path for *text composition* features *acknowledgment*, albeit with a short latency. The transmissibility graph (Figure 9b) shows the transmission process of these tactics and how they disseminate forward, with *planning* at the fifth time point (ie, the fifth day). This timeline shows that, after having written their essays and having discussed their argumentation, students can start planning their next steps, all over the course of one work week.

DISCUSSION

Interactions between peers, educators and other stakeholders in CSCL settings are relational, temporal, and longitudinal (Reimann, 2009). However, such aspects are barely studied and rarely combined. Nevertheless, the use of multimodal analytics, including time and space dimensions, have been found to enable researchers to better understand the CSCL process while it gives educators the opportunity to make timely decisions in their daily practice (Knight et al., 2017). We have seen that previous frequency approaches completely disregard time aspects, process mining approach poorly represents the relational aspects of CSCL, and ENA approach tends to solely focus on co-temporal relationships. This study aimed to apply temporal network modelling to reveal the importance of the time dimension in the learning process. This includes the emergence, pathways, reach, uptake, and relationships of learners and the content of their interactions, and how such social processes unfold over time. Our results have uncovered several interesting findings about the network configuration, the collaborating group, the actors, and the content of the discussions in our case study. Using temporal networks to study the GL measures helped the analysis of the *continuous* and *longitudinal* graph properties and enabled us to distinguish *when* key changes happened and *for how long* students were active and engaged within the collaborative group. Our work builds on the insights of Lee and Tan (2017), Suthers (2015), as well as Suthers and Desiato (2012) who have demonstrated the value of tracing knowledge uptake through networks. We extend such work through temporal networks in CSCL. To the best of our knowledge, our study is the first one to implement temporal networks to trace the reachability of students' influence and their contributions, the transmissibility pathway of contributions, as well as longitudinal reach.

Such fine-grained analysis may allow researchers to analyse how group interactions evolve and how learners adapt to changes in the collaborative process, for example, when a teacher would start contributing, or when a collaborator would withdraw. The use of Graphical VAR contributed to our understanding of how GL properties influenced each other. Our analysis has shown the role of mutual ties in promoting more mutuality, strong ties, and mixing of high and low achievers, offering possible future opportunities to optimize the collaboration process. For example, teachers could offer a collaborative script that helps students enhance argumentation and reciprocity (Janssen & Bodemer, 2013).

Regarding the second and third research questions, the temporal features of the centrality measures have shown promising results by being more correlated with grades, especially the entropy of the outdegree measures (representing the posting process). Such results corroborate the findings in other learning settings (Jovanović et al., 2019), and in temporal networks (Saqr & Nouri, 2020). Additionally, the reachability has shown slightly higher correlation coefficients than static centrality measures. More importantly, the visualization of the reachable sets of nodes as well as forward transmissions may be of interest to educators who wish to analyse students' interactions, their reach, and how ideas spread or diffuse in a CSCL setting. Interactions are more likely to spread when they are discussed, when they stimulate further discussion, or when they are used as a basis for co-constructing knowledge (Saqr & López-Pernas, 2021). These findings extend the work on the uptake of ideas in social networks (Suthers & Desiato, 2012). Our results provide a possible opportunity of tracing the uptake process (reachability and traversal pathways) as well as the collective role of the student in the uptake process while accounting for temporal pathways. Such measures may allow for the creation of better reflective visual dashboards that are used to monitor students or the contents of their interactions. We are unaware of previous studies that have studied reachability in this regard; however, interest in the concept of diffusion is starting to gain momentum in the learning analytics community (Saqr & López-Pernas, 2021).

This study has some limitations. Being a case study in a limited context restrains the generalizability of results. Nevertheless, we emphasize the methodological relevance of our contribution to a wide range of CSCL settings. Facebook posts and their reply structure are similar to the mainstream features of most popular learning management systems, and therefore, the methods used in this study should be applicable with little or no modification.

Future research

Future research may extend our work by studying different contexts and use probabilistic network methods to infer generative factors behind the formation and dissolution of ties. We also suggest investigating the value of using in-time interventions based on continuous temporal network monitoring. One can also expand on the temporal measures used in this study. Diffusion, concurrency, and influence maximization are uncharted territories in the field of learning in general. The patterns of temporality are barely studied in CSCL: research is needed to understand the implications of bursts in interactive processes. Furthermore, little is known about how to aggregate the temporal features of interactions. Future research could, therefore, explore different time series aggregations. Time series networks are an intuitive and novel way to represent temporal patterns and are yet unexplored in learning settings. Lastly, VAR models may offer a valuable tool for studying the complex interactions among variables, which can help predict the next steps in collaborative networks that are yet to be harnessed.

CONFLICT OF INTEREST

The authors have no conflicts of interests to declare.

ETHICS STATEMENT

Participant consent, data storage and analysis have been approved and executed following the rules taken up in the Guidelines for Ethical Review, published by the Ethics Committee for the Social Sciences and Humanities at the University of Antwerp (Belgium).

DATA AVAILABILITY STATEMENT

The data is not available as it concerns students' interactions, Facebook IDs and grades and is protected by privacy agreement.

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