Investigating Collaborative Problem Solving Temporal Dynamics Using Interactions Within a Digital Whiteboard

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Abstract: Collaborative Problem Solving, the resolution of complex problems with the collaboration of multiple people pooling their knowledge, skills and effort is postulated as an essential 21st century skills for the future workforce. Collaborative Problem Solving has been embraced in schools where both online and face-to-face collaboration are afforded through the proliferation of educational technology tools. Assessing the amount of collaboration that has taken place among the students has however been challenging. In this research, we seek to identify the collaboration patterns of our students by mining the temporal sequence of their actions logs captured within a digital whiteboard tool. With the use of Hidden Markov Model, we have uncovered three collaboration states of students (Low Activity, Solitary Contributor, Cognitive Collaboration) from the temporal sequences of their actions within the digital whiteboard. Contrary to common belief, the level of collaboration was also found to have no influence on the quality of the final artifact produced by a student team. Collaborative behaviour was also discovered to persist within the team which suggests opportunities for implementing interventions at an early phase of the learning activity for a longer-lasting team collaboration.

1 INTRODUCTION

The modern workspace is becoming increasingly global. Modern technology has afforded businesses to build global teams located in different parts of the world to work together and navigate the business towards continual growth. It is thus paramount that modern and future workers learn to collaborate in distributed and diverse settings for the attainment of common business goals. To stay ahead of their competition and achieve higher profitability, businesses realize the need to create new products and services or uncover new innovative ways of doing things. The discovery of new innovations however necessitates the transcending of disciplinary boundaries as well as the effective collaboration among experts from the different disciplines. Collaborative Problem Solving (CPS), a process where multiple people pool their knowledge, skills and efforts to solve complex problems is thus postulated as an essential skill not only in work but also in education (OECD, 2017). It has in fact been identified as an essential 21st century skill for the future workforce (Care et al., 2012; Graesser et al., 2018).

CPS is conceptualized as a complex skill encompassing critical thinking, problem solving, decision making and collaboration (Care et al., 2016). It has been embraced in many contexts including schools (James and Johnston, 1996; Hennessy and Murphy, 1999; Scoular and Care, 2020), online learning (Rosen et al., 2020) and military tasks (Swiecki et al., 2020). It entails individuals working together responsively to solve a problem. Assessing the amount of collaboration that has taken place is however a challenging endeavour (Hao et al., 2017). Within the educational context, students interact with and influence each other in CPS. From the teacher's perspective, it is essential to have a gauge of the level of collaboration taking place within a learning activity so that interventions to enhance collaboration can be implemented if necessary. Some studies (Rabbany et al., 2014) have since used interactions and participation of students in a collaborative setting as a measure of collaboration. In addition, the proliferation of educational digital tools in teaching and learning has also made it easier to capture and store students' interactions and actions performed within the tool itself. These interaction logs in turn offer a treasure trove

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for mining or uncovering the collaborative activities of students.

Educational technology tools are prevalent in the modern classroom and the use of some of these tools are further accelerated during the Covid-19 pandemic when many educational institutions had to transform from synchronous to asynchronous form of teaching. To ensure that the learning outcomes are not compromised when they pivot to online teaching, educators leveraged on tools such as Zoom for delivery of lessons and Learning Management System (LMS) for dissemination of teaching materials. Messaging platforms are also used to maintain communications with, foster collaboration and enhance engagement of their students. The compendium of educational technology tools helps in replicating to a certain extent, the learning experience and engagement of face-to-face teaching in an online environment.

Digital whiteboard is one such tool that affords both teachers and students to collaborate and complete tasks online without the need to meet face to face. Digital whiteboards are cloud-based and provides a virtual space for teams to brainstorm and organize ideas. A physical whiteboard or pen and paper have traditionally been used for groups of learners to work on collaborative tasks constrained to a collocated face-to-face setting though. In comparison, a digital whiteboard offers the possibility for multiple learners to work collaboratively and simultaneously in an asynchronous fashion. With digital whiteboards, learners are also not confined by the physical limits of a physical whiteboard or paper. With a digital whiteboard, the produced artifact and action traces of learners are also automatically captured and stored.

Emerging research has investigated collaborative behaviour in problem-solving tasks using the "coding and counting" method where the interaction logs are classified into category and various statistical measures are then computed (Andrews-Todd and Forsyth, 2020; Tausczik et al., 2014) for each category. The computed statistical measures are then compared for conclusions on the effects of the manipulated variables on group behaviour (Suthers, 2006). CPS is however an interactive and temporal process where the actions are produced as a series of inter-connected steps. By aggregating counts over a fixed period of time, the "coding and counting" technique loses the valuable temporal information embedded within the interactions (Kapur, 2011).

In this study, we thus seek to identify the collaboration patterns of students by mining the temporal sequence of their actions logs captured within a digital whiteboard tool.

2 RELATED WORK

In the study by Perera et al. (2008), the authors tasked their students to work collaboratively to develop software solutions for clients. The entire software development process activities from ticket issuance and tracking, documentation to source code version control were tracked through an open-source professional software development tracking system. Clustering was first applied to identify patterns characterising the behaviour of groups and individual students. Sequential pattern mining techniques were next applied to reveal temporal patterns or sequence of events characterising the work of stronger versus weaker students and groups. The results also indicated the value of analysis on the resource and individual level rather than just the group level. The authors postulated that the results can be used to both educate the students on aspects of group work and as a form of formative feedback to the students to nudge them towards good collaborative practices.

The research by Martinez et al. (2011) was motivated by the goal of mining large amounts of data generated from learners' interactions with interactive tabletop. The authors captured the raw interaction logs from 6 groups of 3 students and compacted them into sequences of actions before clustering the sequences based on edit distance between the clusters. Their findings revealed that the high performing groups tended to discuss their thoughts and work in parallel with different objects while the low performing groups tended to work sequentially with objects.

More recently, Zhou et al. (2022) transcribed and coded zoom video recordings of college students solving exercises within an online physics game. They applied a temporal analysis technique, Multilevel Vector Autoregression (mlVAR) on transcribed video sequences of 10-seconds windows for the investigation of CPS processes. The models were applied separately on successful and unsuccessful CPS sequences. The findings revealed six temporal relationships common to both groups (successful and unsuccessful CPS sequences), six unique to only successful attempts and another eight unique to only unsuccessful attempts.

The above three studies applied and demonstrated the feasibility of temporal mining techniques for revealing differences in collaboration patterns between high and low performing groups in CPS. In the current study, we continue this line of research by utilizing action logs from students collaborating on a digital whiteboard. The first two studies discussed above compiled the raw interactions logs into frequent sequences of coded actions before the application of clustering techniques to cluster the sequences into groups for analysis of collaboration behaviour. The sequences of coded actions are however specific to a unique learning activity and would not be applicable to a different learning activity. To illustrate, the action sequences in the study by Martinez et al. (2011) comprises of frequently occurring actions such as moving, enlarging and shrinking of objects. The enlarging and shrinking of objects is however specific to a tabletop scenario where the objects are first displayed in a minimized form due to space constraint on the tabletop and may not recur in another learning scenario. Thus, in our study, we investigate into the use of more generalizable features that can apply to most CPS scenarios.

This leads to our research question: Can we identify collaboration patterns of students from their sequence of actions working on a digital whiteboard over a specified time-period in a CPS scenario using generic features?

3 METHODOLOGY

The participant of this research comprises of 30 year-one university students (by convenience sampling) from the faculty of computer science and information systems and the faculty of accountancy within our university. They were part of the 2 classes of 42 students and 34 students undertaking the course of data management taught by the author in 2 separate semesters of academic year 2022. The data management course spans a total duration of fifteen weeks and covers the fundamentals of relational database which includes data modelling, data design (Entity-Relationship diagram) and database implementation. This research has been reviewed and approved by the university's institutional review board and all 30 students have given written consent for their data to be used in this research.

3.1 Digital Whiteboard

The digital whiteboarding software – Miro (http://www.miro.com) was introduced to the students in week 2 of the course. In each lesson, the students were first introduced to the concepts to be covered in the class. Other than instructor elaboration on some demonstration exercises, in-class exercises were dispersed throughout the entire lesson. An active learning approach was undertaken where students worked on the in-class exercises on the digital whiteboard collaboratively in groups of three.

The digital whiteboarding software, Miro facilitates discussions and interactions among groups with a mix of remote and in class students. Miro offers collaboration features such as chat and zoom integration and more importantly synchronous interaction features where participants can see each other's annotations and drawings on a real time basis. For this study, we only store and analyse the historical action logs of the students within the digital whiteboard platform. Although chat and zoom integration were offered by the digital whiteboard, the voice recordings and chat history were not used for this study.

The students were tasked with a group assignment to be submitted by week 8 (which involves designing an ER diagram for a provided scenario). The students were required to form groups of maximum 3 students to complete the assignment using Miro. The students who participated in this research conducted their discussion both synchronously and asynchronously as afforded by the online collaboration features of Miro. Only the action logs for the assignment (and not the in-class exercises) were stored and used for analysis. The students were briefed on the aims and details of the research and we only use the Miro canvases of students whom have given informed consent to participate in the study. This research was also submitted to and approved by our university's Institutional Review Board (IRB).

The board history feature in Miro stores a list of historical actions performed by the logged in user. The logged information includes the user who performed the action, the date and time of the action and details on the specific action performed e.g. add, edit and delete and the object acted on e.g. text, line, shape, sticky note e.t.c. Miro offers a Representational State Transfer (Fielding and Taylor, 2002) Application Programming Interface (REST API) interface for developers to extend on the current capabilities of Miro but unfortunately does not provide for the retrieval of board histories through REST API. Thus, we developed our own Python program to web scrap (Mitchell, 2018) the board histories of the 10 groups' canvases. The scrapped logs are stored as comma delimited files.

The raw logs contain details of the user actions such as the user's name, date and time of action and the action type i.e. add, edit or delete. We then aggregated the action details into sessions of 10 minutes in duration. From the action logs, a session with 10 minutes duration would have accumulated adequate number of actions with a higher possibility of other members of the team acting on the whiteboard canvas within the session and thus the decision on breaking into 10 minutes session. The action logs were not continuously in time dimension and there could be long breaks (up to a few days) between consecutive actions. Actions that had a prior long break were considered as a new session of actions. This also explains why duration of some sessions may not be exactly 10 minutes.

We next computed the number of pauses, number of unique users, number of actions and the length of duration for each session. These constitute the features that were passed into our machine learning model for prediction. To reiterate, these features were chosen as they are generic across different learning scenarios. We define pauses as breaks between consecutive actions that are more than a minute but less than 10 minutes in duration. Pauses between actions are posited as periods of cognitive processing in a number of research (O'Brien, 2006; Lacruz et al., 2012; Shrestha et al., 2022). We also consider pauses as a time period where students stop to think about either the past actions or the next action to take which would very probably lead on to better or 'more considered' future actions. The number of unique users within a session signifies the amount of collaboration taking place. We consider that a session which has a number of students acting on the same whiteboard canvas would likely be evident of collaboration and discussion taking place among the students. The number of actions is the total count of the add, edit and delete actions within a session while the duration length is the length of each session in seconds.

3.2 Hidden Markov Model (HMM)

Taking temporality into account is important in the modelling of collaboration behaviour among groups. Comparing 2 groups of students collaborating to work on a common problem, the trajectory of actions (performed by the students) across the time domain would likely differ for the 2 groups. The Hidden Markov Model (Rabiner, 1989) lends itself well in the modelling of the temporal sequences of actions for uncovering collaboration sequences.

HMMs consist of stochastic Markov chains based on a set of hidden states whose values cannot be directly observed with the relationship between a hidden state and the actual observations being modelled with a probability distribution. HMMs adhere to the Markov property which states that the state of a model at time t is only dependent on the state of the model at time t-1 and not on other prior states such that

$$P(S_j^{t+1}|S_i^t) = P(S_j^{t+1}|S_i^t, S_m^{t-1}...S_n^0) \tag{1}$$

A HMM is described by the tuple {S, O, A, B, π} where

N: Number of hidden states

S: $\{S_1, S_2, ..., S_n\}$

M: Number of observation symbols

O = $\{O_1, O_2, ..., O_m\}$

A = $\{a_{ij}\}$, where $a_{ij} = P(S_j^{t+1}, S_i^t); i, j = 1, ..., N$

B = $\{b_{ik}\}$, where $b_i(k)$=$P(O_k|S_i)$

The model parameters are valid probabilities that must satisfy the following constraints:

$$\sum_j^N a_{ij} = 1, \sum_k^M b_j(k) = 1 \tag{2}$$

The probability of being in state i at time t_0 is given by π = $\{\pi_i\}$, where π_i = $P(S_i^0)$

HMMs can be used in unsupervised learning and we adopted the unsupervised learning approach in this research. This allows for the discovery of hidden patterns without tedious human labelling as is done in many other studies (Boussemart et al., 2009; Li and Biswas, 2002; Trabelsi et al., 2013). In unsupervised learning, the model parameters $H = (A, B, \pi)$ are learned by maximizing $\sum_S \log(P(O^S|H)$, the sum of the posterior log-likelihoods of each training sequence O^S using a form of expectation-maximization (Dempster et al., 1977) called the Baum-Welch algorithm (Baum et al., 1972).

We model the observations as Gaussian distributions as the features are continuous valued. We also took the logarithms of both number of actions and duration length before passing them as features into the model. Models with a number of hidden states ranging from 2 to 6 were trained multiple times with different randomly assigned initial parameters in order to avoid convergence to a local optimum. The training was performed through the unsupervised Baum-Welch learning technique. We used the Bayesian Information Criterion (BIC) for determining the number of hidden states for the HMM. BIC allows for the comparison of models with different number of hidden states, trained on the same underlying data. BIC penalizes the likelihood of the model by a complexity factor proportional to the number of parameters P in the model and the number of training observations K.

$$BIC = -2\log(\mathcal{L}(H)) + P\log(K) \tag{3}$$

Table 1: BIC values for the various number of hidden states.

No. of hidden states	BIC
2	2075.14
3	1115.91
4	1089.71
5	365.75
6	291.65

From Table 1, although the BIC value for 6 hidden states is the lowest, we chose 3 hidden states model instead as the results are more interpretable.

4 RESULTS

The mean values of the features learned by the chosen 3 hidden states HMM is shown in Table 2.

State 1 is characterized by low number of pauses, one participating user with a low number of actions within a short duration and thus we labelled it as the "Low Activity" state.

State 2 is characterized by high number of pauses, one participating user with a moderate number of actions within a moderate duration and thus the label of "Solitary Contributor".

State 3 has high number of pauses, high number of participating unique users and high number of actions within a long duration of time. This suggests a session with multiple users performing actions on the canvas but with more pauses or more deliberated actions. We infer that the users may be discussing and acting after cognitive processing of the impact of their actions and thus the label "Cognitive collaboration".

Table 3 shows the probability of transiting from the source states in rows to the destination states in columns. From the table, a user who is in "Low Activity" state is likely to either stay in this state or transit to "Solitary Contributor". A user who is in the "Solitary Contributor" state is more likely to stay in the "Solitary Contributor" state and a user who is in the "Cognitive Contributor" state would likely remain in this state. Across the different groups of students, we then summed up the predicted hidden states across the sessions to gauge the difference in collaboration patterns across the groups. The proportion of states aggregated across all the sessions for the different groups of students is shown below. Only groups of students with more than 20 sessions are shown below as we wanted to compare between groups which were more active i.e. worked substantially more and longer on their whiteboard canvas. Teams 1, 3, 4, 5 and 8 were identified as the more 'active' groups and a comparison of the collaborative behaviour of the more 'active' groups is shown in Figure 1.

5 DISCUSSION

From the results, we have identified collaboration states of students from their sequence of actions working on a digital whiteboard. As manifestations of students' interaction patterns, these states provided insight into the collaboration behaviours of the students. Specifically, we have inferred from the trained HMM, the 3 states of collaboration – Low Activity, Solitary Contributor and Cognitive Collaboration. The "Low Activity" state denotes a session where students are not acting on the whiteboard canvas while the "Solitary Contributor" state denotes a session where a single student is working on the whiteboard canvas. The ideal session will be the "Cognitive Collaboration" state where multiple students are working on the whiteboard canvas and the actions are more deliberated as hinted by the occurrence of pauses within the session.

We further analysed the temporal evolution of students' collaboration patterns with the state transition matrix. The state transition matrix in Table 2 indicated that students in the "Solitary Contributor" session tend to remain so and this applies for the "Cognitive Contributor" state as well. We thus conclude from the state transition matrix that a team who is collaborative and encourages participation from their members tend to stay collaborative while a team possibly with a dominant member who makes the most contribution tend to continue demonstrating solitary or non-collaborative behaviour. This signifies that if we can implement interventions to encourage the students to collaborate at the initial stage of the project work, then the collaboration will likely persist.

As shown in Fig 1, teams 1, 3 and 8 had proportionately more sessions that were predicted as "SC" states while teams 4 and 5 had proportionately more sessions that were predicted as "CC". This suggests that teams 4 and 5 are more collaborative as compared to the other teams. The whiteboard canvas assignments of the teams were assessed by a different instructor and all 5 teams scored at least a B grade for their assignment. This indicates that the extend of collaboration within a team as predicted from their members' interaction actions on the whiteboard canvas seem to have no impact on their work quality. We surmise that this may possibly be attributed to the "SC" teams having cognitively capable member who did most of the work.

6 CONCLUSION

We performed mining of students' raw interactions within a digital whiteboard using HMM in a CPS scenario. The students were collaborating in groups of 3 to work on an entity-relationship diagram design assignment. Our objective was to identify collaboration patterns of students from their sequence of actions working on a digital whiteboard over a specified time-period in a CPS scenario using generic features.

Table 2: Mean values of the features learned by 3 hidden states HMM.

Hidden State	No. of pauses	No. of unique users	No. of actions	Duration in secs	Description
1	0.96	1.00	2.62	1.00	Low Activity (LA)
2	3.29	1.01	8.59	227.80	Solitary Contributor (SC)
3	4.11	2.37	11.79	353.59	Cognitive Contributor (CC)

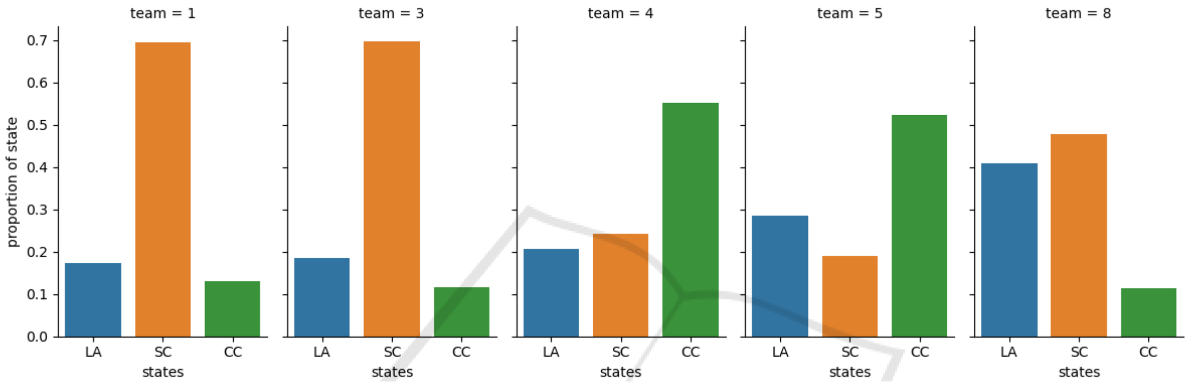

Figure 1: Comparison between collaborative behaviour of more ”active” groups.

Table 3: Transition probabilities between the various states.

Hidden State	LA	SC	CC
LA	0.38	**0.47**	0.15
SC	0.27	**0.58**	0.15
CC	0.17	0.27	**0.56**

From the raw interaction logs extracted from the digital whiteboard, we collated them into sessions with each session comprising of generic features such as number of pauses, number of unique users, number of actions and the length of duration. These were then passed into a HMM for unsupervised learning of the hidden states and the transition probabilities between the various states.

The results revealed 3 clusters of collaborative behaviours namely “Low Activity”, “Solitary Contributor” and “Cognitive Collaboration” and that early collaborative behaviour tend to persist. This suggests opportunities for implementing interventions at an early phase of the learning activity for a longer-lasting collaboration among the team members. Comparing the collaborative behaviour of “active” groups, we conclude that the extend of collaboration has no bearing on the quality of their final artifact though. For future work, we would like to investigate the generalizability of our work by extending it into a different CPS scenario using digital whiteboards.

REFERENCES

Andrews-Todd, J. and Forsyth, C. M. (2020). Exploring social and cognitive dimensions of collaborative problem solving in an open online simulation-based task. *Computers in human behavior*, 104:105759.

Baum, L. E. et al. (1972). An inequality and associated maximization technique in statistical estimation for probabilistic functions of markov processes. *Inequalities*, 3(1):1–8.

Boussemart, Y., Las Fargeas, J., Cummings, M. L., and Roy, N. (2009). Comparing learning techniques for hidden markov models of human supervisory control behavior. In *AIAA Infotech@ Aerospace Conference and AIAA Unmanned... Unlimited Conference*, page 1842.

Care, E., Griffin, P., and McGaw, B. (2012). *Assessment and teaching of 21st century skills*. Springer.

Care, E., Scoular, C., and Griffin, P. (2016). Assessment of collaborative problem solving in education environments. *Applied Measurement in Education*, 29(4):250–264.

Dempster, A. P., Laird, N. M., and Rubin, D. B. (1977). Maximum likelihood from incomplete data via the em algorithm. *Journal of the royal statistical society: series B (methodological)*, 39(1):1–22.

Fielding, R. T. and Taylor, R. N. (2002). Principled design of the modern web architecture. *ACM Transactions on Internet Technology (TOIT)*, 2(2):115–150.

Graesser, A. C., Fiore, S. M., Greiff, S., Andrews-Todd, J., Foltz, P. W., and Hesse, F. W. (2018). Advancing the science of collaborative problem solving. *psychological science in the public interest*, 19(2):59–92.

Hao, J., Liu, L., von Davier, A. A., and Kyllonen, P. C. (2017). Initial steps towards a standardized assessment for collaborative problem solving (cps): Practical challenges and strategies. *Innovative assessment of collaboration*, pages 135–156.

Hennessy, S. and Murphy, P. (1999). The potential for collaborative problem solving in design and technology. *International journal of technology and design education*, 9:1–36.

James, R. and Johnston, C. (1996). An evaluation of the effectivess of collaborative problem-solving for learning economics. Technical report, The University of Melbourne.

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*, 6:39–56.

Lacruz, I., Shreve, G. M., and Angelone, E. (2012). Average pause ratio as an indicator of cognitive effort in post-editing: A case study. In *Workshop on Post-Editing Technology and Practice*.

Li, C. and Biswas, G. (2002). Applying the hidden markov model methodology for unsupervised learning of temporal data. *International Journal of Knowledge Based Intelligent Engineering Systems*, 6(3):152–160.

Martinez, R., Yacef, K., Kay, J., Al-Qaraghuli, A., and Kharrufa, A. (2011). Analysing frequent sequential patterns of collaborative learning activity around an interactive tabletop. In *Educational Data Mining 2011*, pages 111–120. CEUR-WS.

Mitchell, R. (2018). *Web scraping with Python: Collecting more data from the modern web*. " O'Reilly Media, Inc.".

O'Brien, S. (2006). Pauses as indicators of cognitive effort in post-editing machine translation output. *Across languages and cultures*, 7(1):1–21.

OECD (2017). Pisa 2015 collaborative problem solving framework.

Perera, D., Kay, J., Koprinska, I., Yacef, K., and Zaïane, O. R. (2008). Clustering and sequential pattern mining of online collaborative learning data. *IEEE Transactions on knowledge and Data Engineering*, 21(6):759–772.

Rabbany, R., Elatia, S., Takaffoli, M., and Zaïane, O. R. (2014). Collaborative learning of students in online discussion forums: A social network analysis perspective. *Educational data mining: Applications and trends*, pages 441–466.

Rabiner, L. R. (1989). A tutorial on hidden markov models and selected applications in speech recognition. *Proceedings of the IEEE*, 77(2):257–286.

Rosen, Y., Wolf, I., and Stoeffler, K. (2020). Fostering collaborative problem solving skills in science: The animalia project. *Computers in Human Behavior*, 104:105922.

Scoular, C. and Care, E. (2020). Monitoring patterns of social and cognitive student behaviors in online collaborative problem solving assessments. *Computers in Human Behavior*, 104:105874.

Shrestha, R., Leinonen, J., Zavgorodniaia, A., Hellas, A., and Edwards, J. (2022). Pausing while programming: insights from keystroke analysis. In *Proceedings of the ACM/IEEE 44th International Conference on Software Engineering: Software Engineering Education and Training*, pages 187–198.

Suthers, D. D. (2006). Technology affordances for intersubjective meaning making: A research agenda for cscl. *International Journal of Computer-supported collaborative learning*, 1:315–337.

Swiecki, Z., Ruis, A. R., Farrell, C., and Shaffer, D. W. (2020). Assessing individual contributions to collaborative problem solving: a network analysis approach. *Computers in Human Behavior*, 104:105876.

Tausczik, Y. R., Kittur, A., and Kraut, R. E. (2014). Collaborative problem solving: A study of mathoverflow. In *Proceedings of the 17th ACM conference on Computer supported cooperative work & social computing*, pages 355–367.

Trabelsi, D., Mohammed, S., Chamroukhi, F., Oukhellou, L., and Amirat, Y. (2013). An unsupervised approach for automatic activity recognition based on hidden markov model regression. *IEEE Transactions on automation science and engineering*, 10(3):829–835.

Zhou, G., Moulder, R. G., Sun, C., and D'Mello, S. K. (2022). Investigating temporal dynamics underlying successful collaborative problem solving behaviors with multilevel vector autoregression. *International Educational Data Mining Society*.