Mapping students' temporal pathways in a computational thinking escape room

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Abstract
This case study explored the applicability of sequence mining and process mining methods on qualitative video data of a group-based problem-solving situation. For the case study, audio and video data were collected from a pilot experience of an educational escape room, which was designed to practice the application of computational thinking (CT) skills. The escape room combined digital and physical affordances into CT puzzles and challenges. To examine processes and patterns of collaborative learning and problem-solving in the context of the CT escape room, video data from pre-service teachers' game activities were collected. A unique contribution of this case study is that it demonstrates how sequence and process mining methods can be applied to a type of qualitative content analysis often found in research on collaborative learning.

Keywords
Computer science education, educational escape rooms, teacher education, collaborative learning

1. Introduction

One popular definition of escape rooms is, "live-action team-based games in which players encounter challenges in order to complete a mission in a limited amount of time" [1]. Due to their collaborative nature, educators have studied escape rooms as an environment to practice teamwork-related skills such as collaboration, communication [2], [3], and leadership [4], [5]. Educational escape rooms have been explored in a wide range of disciplines to foster the development of domain-specific skills and knowledge [6]. In the context of computer science, escape games have been used, for example, for teaching computer networks and security [7], programming [8], [9], software modeling [10], educational robotics [11] as well as for computational thinking competences [12].

The growing interest behind educational escape rooms is fueled by their compatibility with modern methods of learning such as computer-supported collaborative learning [13], problem-based learning [14], and game-based learning [15]. According to theories of collaborative learning [7], the process of problem-solving is organized into cyclical and iterative actions, such as problem identification, questioning, analysis, and generating and evaluating solutions. Moreover, the success of collaborative learning strongly relies on the

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group's patterns of interaction [17], and it has been shown that variations in interactional processes lead to more or less productive collaboration [18]. Thus, the identification of the group's interaction patterns can facilitate an enhanced understanding of successful collaboration [19] as well as understanding of what is needed in terms of game design to support learners to become better collaborators and problem solvers.

Despite the increasing evidence of the benefits of educational escape rooms, there is a lack of exemplars on how to capture the complex process of learning and patterns of interaction that emerge in escape room settings. Research on educational escape games has largely focused on students' perceptions [1,13] and knowledge advancement [14], but many interactive processes at the foundation of collaborative learning remain to be underexplored in the context of educational escape rooms. However, in these activities, students' actions, choices, and interactions are intertwined with dynamic social and environmental conditions, which also calls for new methodological solutions for tracing socially and materially mediated patterns of interaction emerging in escape rooms.

This case study presents a pilot study of an educational escape room conducted in a teacher education course at the University of Eastern Finland. The educational escape room was designed to practice computational thinking (CT) skills through puzzles that incorporated CT challenges and combined digital and physical affordances. To examine processes and patterns of collaborative learning and problem-solving in the specific context of the CT escape room, we collected video data from pre-service teachers' game activities. The aim of this case study is to demonstrate a proof-of-concept how sequence and process mining methods can be applied to a type of qualitative content analysis often found in research on collaborative learning. The study uses sequence mining to extract insights from time-ordered temporal data [21], and process mining to extract insights from time-ordered event logs [22]. These two methods (process and sequence mining) are often combined [23], [24] to study the multifaceted nature of the temporality of students' activities. To our knowledge, escape room activities have not been analyzed using these methods before. In addition to a methodological proof-of-concept, the study also presents new insights into the process of collaborative learning and problem-solving in escape room settings.

2. Methodology

2.1. Context and description of the educational escape room

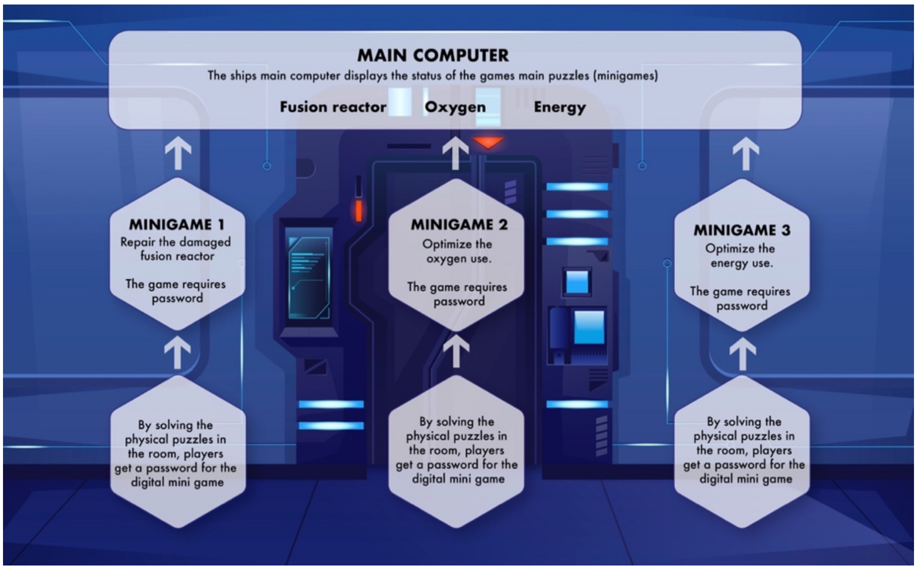

Figure 1: CT escape room design

The context of this study is an escape room game designed to practice computational thinking (CT) skills. The game design combined interdisciplinary expertise from University of Eastern Finland's School of Education, from the educational technology research group in the Faculty of Science and Forestry, and experts on computational thinking education in the School of Computing. The game was implemented in the university's Sm4rt LOC escape room laboratory that comprises escape rooms equipped with monitoring and sensor equipment, as well as a separate monitoring room (for more detailed description, see [25].

In the background story of the game, aimed for K-12 education, the ancestors of the players have sent 80,000 hibernated children to the heavily polluted Earth's orbit for the survival of humankind. After centuries have passed and pollution levels have dropped, the computer wakes up a group of children (the players). The players' task is to prepare the spaceship for their return to Earth by solving a number of critical technical problems. The game's puzzles consist of physical puzzles and digital mini-games running on Android tablets and a game server monitoring game progress (Fig. 1). All puzzles involve some CT-related tasks designed to practice, for example, the idea of step-wise, deterministic program execution and understanding of binary logic and bit flips, or to familiarize the participants with the shortest-route problem (Fig. 2). Kahila et al. [26] provides a more detailed description of an earlier version of the game design.

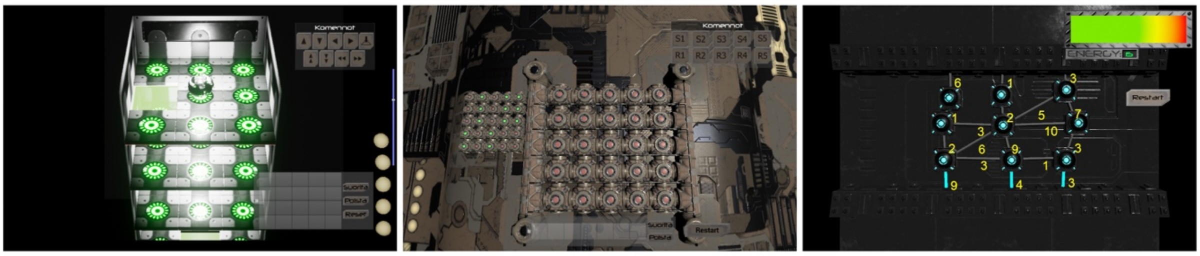

Figure 2: CT minigames (Kahila et al.,2020)

2.2. Participants

Twenty-four pre-service teachers (education students in a teacher training programme) participated in the case study in spring 2021. The students (N=24) were grouped into six teams, and they were given a short introduction to the game. While the escape room game was part of their studies, participation in research was voluntary. Before the game, the students were informed about the aims of this study, and all gave their informed consent to use the data collected. The analysis of the present case study focused on actions of one four-member team (two females, two males). This group was selected because the team was the quickest at solving the escape room puzzles, indicating successful collaboration.

2.3. Data collection

All six escape room game sessions were videotaped, and conversations recorded (Fig. 3). The groups spent between 35 and 57 minutes in the escape room, yielding 4 hours and 29 minutes of video data. In addition, the groups were interviewed after the game. In these group interviews, a number of questions were intended to capture students' game experiences as well as their experiences of teamwork. Video data and interview data were transcribed verbatim.

Figure 3: Example of video data collected from the game play.

2.4. Data analysis

2.4.1. Qualitative analysis

The data analysis began by watching the videotaped game and reading the audio transcripts from the game. This round of analysis showed that the group was engaged and their interaction was very embedded by nature. The students spent time observing, searching, and discussing environmental hints, and verbal utterances were short and content-specific. This required that transcribed verbal actions were interpreted with the help of video data that provided context for each utterance.

Table 1
Coding scheme

Primary actions	
Observing	Silent observation of the space, seeking hints
Asking	Asking questions, triggering interaction or further inquiry
Responding	Verbal responses that are clearly related to the previous utterance(s) and are rather short without particular new content
Analyzing	Analyzing ideas, problems, environmental hints, or other cues
Experimenting	Experimenting, testing or evaluating puzzle solution
Instructing	Giving instructions or helping other(s)
Regulating	Coordinating teamwork, e.g., by dividing tasks
Team composition	
All together	All team members are together and focusing on the same object
Divided	Team is divided in the escape room and working with different objects
Team members' verbal contributions	
Student 1	Contribution from team member
Student 2	Contribution from team member
Student 3	Contribution from team member
Student 4	Contribution from team member

The data were then analyzed using qualitative content analysis [27]. The unit of analysis was an utterance, i.e., one line of transcript. The analysis proceeded iteratively, where the coding began with a set of theory-driven codes derived from the literature on collaborative learning [16], [28], and the set of codes was complemented with data-driven codes that emerged from the video data analysis. The codes were mutually exclusive so that the utterance could represent only certain primary verbal actions, reflecting the problem-solving action at hand. A total of 441 utterances from the group were coded.

Sometimes the whole group worked together, but at times they also divided tasks and worked separately. Thus, in the analysis social setting and focus of attention were used to determine the social context of every utterance: who was speaking and whether that verbal contribution was part of whole group actions or not. Table 1 presents the coding scheme applied for analyzing students' learning actions in the escape room setting.

2.4.2. Quantitative analysis

The transcripts of gameplay data were cleaned, prepared, and analyzed using methods from learning analytics. The sequential and temporal aspects of students' actions were analyzed using sequence and process mining. **Sequence mining** is particularly useful for extracting insights from time-ordered data [21]. Therefore, it was well suited for analyzing the sequence of actions in the escape room. Sequence index plots were used to represent the sequence of each student's actions during gameplay. Index plots were used to represent each student's sequence of actions as stacked bars of color-coded blocks, where each block is a single action. The index plots were created using the TraMineR R package [21]. **Process mining** is useful for discovering, visualizing, and representing the process of students' learning. It has been frequently used with sequence mining to model students' time management strategies [23] or their learning process when faced with tasks like programming assignments [24] or academic writing tasks [29]. Two types of process mining were used: frequency-based process mining and stochastic process mining. In frequency-based process mining, nodes of a graph represent the fraction of times that an action was performed and edges represent the percentage of times the transition between two action occurred. In stochastic process mining, transitions represent the first order Markov (FOM) transition probability from an action to another. Frequency-based process mining was used to model the process of individual/group-based actions, while stochastic process mining was used to model the significant probabilities between actions where no distinction between individual and combined actions was made.

3. Results

The results of sequence mining offered valuable insights on students' order of actions in the escape room. The index plot (Fig. 4) represents the sequence of each of the four students' actions as a horizontal bar in which each colored block represents a separate action. The x-axis indicates the order in which each action was implemented by a given student during the escape room game. A longer sequence indicates that a student consecutively repeated the same action multiple times. Fig.4 shows that students 1 and 2 were very active during the whole game, especially when the group was working together. Student 1 also led the regulation of joint actions, for example, by dividing tasks. Moreover, students 1 and 2 played a very active role when the group was solving digital minigames, while students 3 and 4 were mostly observing the actions of the active two. The initial actions of students 1 and 2 were dominated by analysis, followed (in sequence) by asking and experimenting. Students 3 and

4 had an initial start with diverse actions, followed by experimenting. It is also notable that students 3 and 4 were more active when the group was solving physical (non-digital) puzzles. Moreover, while students 3 and 4 were less active in verbalizing their actions and oftentimes were mainly responding to the initiatives of others, they still participated in and engaged in joint actions.

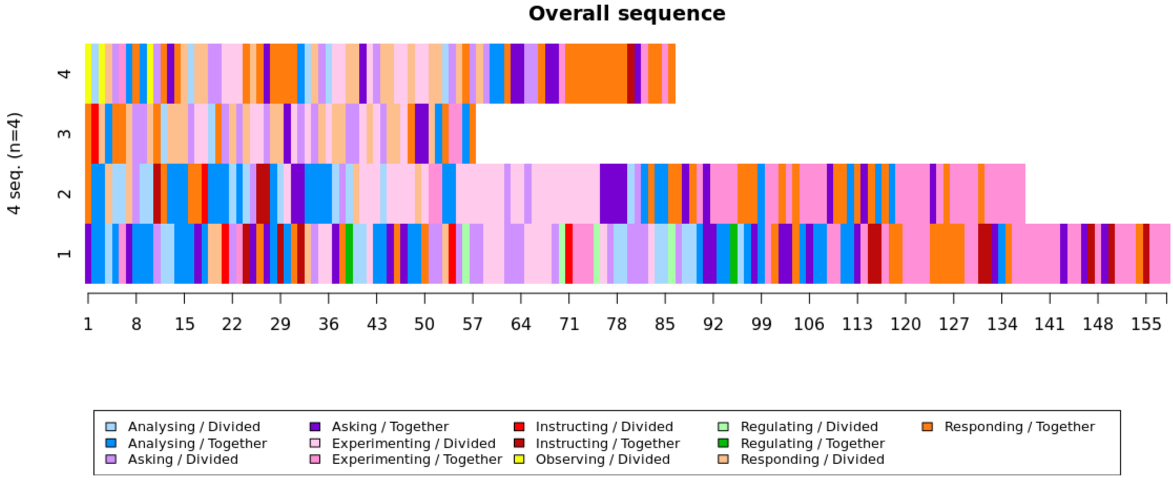

Figure 4: A sequence index plot representing the sequence of student actions, each colored block represents a single action: lighter colors represent actions that students performed divided, whereas darker colors represent actions that they performed together

Fig. 5 illustrates the process map of the CT escape room actions (Fig. 5), extracted by process mining. Group activities were valued in the group: The most frequent actions in the escape room were experimenting and responding in a group (15.7% of total actions each). Asking questions was, unsurprisingly, most of the time followed by responding (36.6% of following actions), and less often by analyzing (21.9%). Responding was also followed by analyzing (33.8%), and analyzing was followed by responding in comparable frequency (31%).

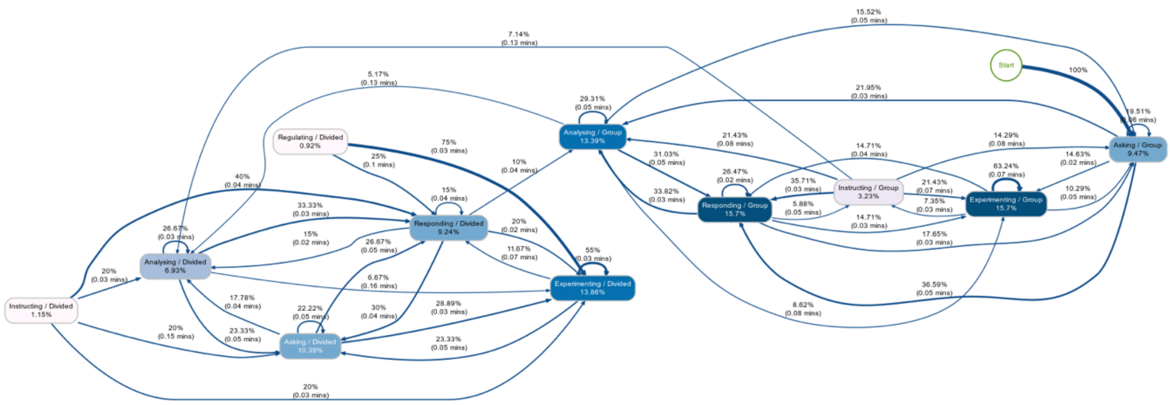

Figure 5: Process map of the analyzed group's actions in the escape room

Students performed most of the actions as a group, as can be noted from the higher frequency of actions in the rightmost part of the process map. Divided actions (carried out individually or in pairs) were less frequent and were dominated by experimenting (13.9% of all actions), asking (10.4%), and responding (9.2%). There were few transitions between actions performed as a group and actions performed divided and vice versa. Analyzing as a group was occasionally followed by splitting and analyzing while divided (5.2%), and so was instructing as a group (7.1%). On the contrary, responding while divided was the only divided action that was followed by students reuniting as a group to analyze together (10% of the time).

At the beginning of the process, the group divided and observed the environment. The transition to asking questions emerged when student 1 presented a question derived from observation of the environment. This question also attracted the attention of others and the group joined together:

Student 1: I was just thinking that if the time is running here that should we first stop this self-destruction? (Asking)
Student 2: Yeah, maybe (Responding)
Student 1: Here is a key. It was found next to it (Analyzing)
Student 3: Yeah (Responding)
Student 1: and it seems that it goes there (Analyzing)

Joint analysis of the problem-situation at hand led to exploration around physical puzzles and at this point, the group was again divided as students 1 and 4 were solving their own puzzle while students 2 and 3 were exploring another object. The following extract depicts how analyzing in a group was followed by analyzing the environmental hints individually. First, student 1 proposes that the group needs a new key to solve that particular physical puzzle and then, other members went to look for more hints. At this point, analysis of the environmental hints continued individually, and students talked about different material artefacts that they had discovered, such as plush toys, a UV-light and a box filled with more artefacts. However, when student 1 found a crucial hint under the table, a letter, the group joined again, and they began to analyze that letter together.

Student 1: Transmitter, so we need a new key to this transmitter (Analyzing)
Student 2: No, it does go like that (Analyzing)
Student 1: This is probably crucial (Analyzing)
[the group is divided]
Student 2: I don't know if these plush toys are some kind of bluffing (Analyzing)
Student 1: They can be bluffing (Analyzing)
Student 4: Yeah (Responding)
Student 4: It's so dark here that you can't see anything here (Analyzing)
Student 2: we have an flashlight (Analyzing)
Student 4: Here is some box filled with stuff...is this important? (Asking)
Student 1: What do we have here? (Asking)
Student 4: Oops (Analyzing)
Student 4: UV -light (Analyzing)
Student 1: Some letter to loved ones (Analyzing)
Student 2: We have UV -light (Analyzing)
Student 4: Yeah (Responding)
[Student 1 starts reading aloud the letter he found, and the group joins again]
Student 1: "Hi, this is a common greeting from our parents to you, the last representatives of mankind, with a heavy mind we are writing to you this farewell, this farewell message, because we will never see you again. But if you read this you have awakened and so there is hope...."

After the physical puzzles were solved, the group proceeded to digital minigames and, at this point, the team came together again. The following extract depicts how actions of experimentation around CT mini puzzles were mostly driven by the loop of contributions of students 1 and 2, although students 3 and 4 were also focused on the same object of action:

Student 2: That is, like that, like that, like that, then it is there, then like that, like that, like that, like that, like that, like that, like that, now, wait, to move just once, move once (Experimenting)
Student 1: Yes I will look how, let's take that pattern up (Experimenting)
Student 2: So, no, this top does not move, so the lowest move now (Experimenting)
Student 1: Yeah and now this moves (Experimenting)
Student 2: So, there is that whole (Experimenting)
Student 1: Yes (Responding)
Student 2: Okay, then just like that, like that, then, like that, like that, like that and like that, like that, like that (Experimenting)

While the frequency-based process map shows the ratios and frequencies of actions and their transitions, the FOM process map (Fig. 6) shows the statistically significant probable transitions (first order transition probabilities; t.p.). Asking was a common first order transition from all other actions, especially from observing (t.p. = 0.33), which highlights the central importance of inquiry in the process of playing in the escape room. Similarly, analyzing and responding were common transitions from most of the other actions. However, analyzing was only followed by experimenting (t.p. = 0.11), asking (t.p. = 0.14) or responding (t.p. = 0.24), and often led to further analyzing (t.p. = 0.44). Similarly, experimenting was only followed by asking (t.p. = 0.16) or responding (t.p. = 0.16), and often led to further experimenting (t.p. = 0.58).

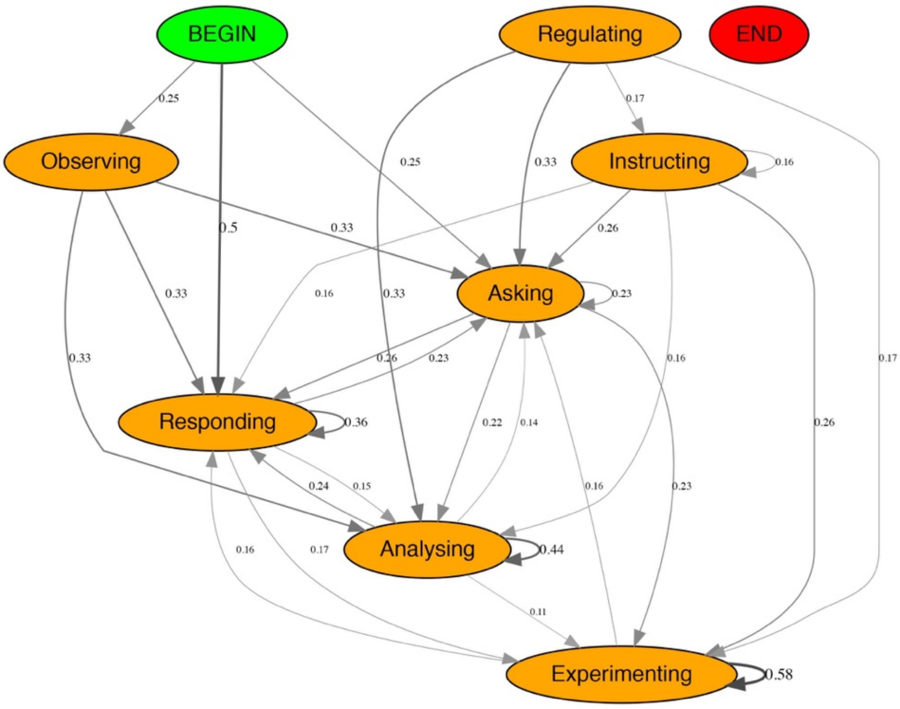

Figure 6: FOM of the process map of the escape room

4. Discussion and conclusion

While considerable attention has been given to studying and improving collaborative learning, the mechanisms of social interaction and patterns of action are still not fully understood [19]. Many processes at the foundation of collaborative learning are invisible, non-linear and temporal by nature, and thus, very challenging to capture and understand with traditional methods and instrumentation [30]. While advances in computational methods, such as in learning analytics, have provided new tools for researchers to examine students' activities, relations, and social interaction in unprecedented scale and detail [31], capturing face-to-face interactions in dynamic conditions, such as in escape rooms, calls for novel methodological solutions.

The current study contributes to the earlier studies on collaborative learning by demonstrating how sequence and process mining methods can be applied to a type of qualitative content analysis often found in educational research. The results from process mining and sequence mining indicated that successful gameplay in CT escape room setting engaged students to many activities that characterize the principles of collaborative learning and problem-solving [13], [14], [16]. The analysis of the evolving gameplay process revealed significant transition-related key activities of problem solving, including observing, questioning, analyzing, and experimenting. During the activities, the team regulated their activities as well as supported the participation of other team members, for example, by giving instructions and actively responding to the initiatives and questions of others.

Analyzing students' actions and conversations recorded during the escape room allowed us to closely follow the learning process and to make sense, at a high level of detail, of each situation that students faced while playing. But qualitative analysis alone does not enable one to extract general conclusions of the learning process. By combining qualitative analysis with process and sequence mining, we were able to "zoom out" of particular moments in the escape room and offer an overview of the gameplay dynamics as a whole. Learning analytics methods enable monitoring, tracking, and following the progression of gameplay, as well as using summarizing visualizations that can enable instructors to see the whole learning process in a single view. In particular, the sequence mining index plot provides a view of sequential patterns of gameplay and of the evolution of the actions implemented by each student throughout the game. Frequency-based process mining provides a view of the frequency of actions, the balance between divided vs. group work, as well as the transitions among them. Lastly, probabilistic process mining (FOM) provides a view of which transitions are most probably significant from "random". Recent research in the learning analytics domain points to the importance of combining process mining algorithms (i.e., FOM, and frequency based) to obtain a holistic picture of the analyzed process [32].

Qualitative results suggested that the CT escape room provided a unique environment to explore some basic CT concepts through the exercise of teamwork-related skills [19,28]. The results further confirmed that approaching computing skills through educational escape room can positively impact student engagement [8], also in the case of pre-service teachers. We hope that if pre-service teachers have positive experiences on learning CT through collaborative activities, those positive experiences may encourage them to develop their skills further and to teach CT in innovative manner in their future profession. Yet, it is worth pointing out that although this study provided evidence that educational escape room can support collaborative learning and problem solving, it has not assessed how pre-service teachers CT skills developed during the joint activities. Therefore, an interesting future line of research would be to study how and in what ways understanding of domain knowledge develops during the collaborative learning situated in the context of escape rooms.

While the limitation of the present study is that it analyzed only one successful group, it demonstrated the potential of learning analytics methods in studying learners' activities and interactions in an escape room context. In the future, a complete analysis of all teams can deepen our insights on the diversity of processes and patterns of collaborative learning and problem solving in escape room settings. Although further methodological development and collection of data across different target groups are needed, researchers aiming to trace temporal and sequential aspects of collaborative learning could find guidance in the methods demonstrated in this study.

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References

[1] S. Nicholson, "Peeking Behind the Locked Door: A Survey of Escape Room Facilities," *White Paper*, pp. 1–35, 2015.

[2] R. Pan, H. Lo, and C. Neustaedter, "Collaboration, awareness, and communication in real-life escape rooms," in *DIS 2017 - Proceedings of the 2017 ACM Conference on Designing Interactive Systems*, 2017, pp. 1353–1364. doi: 10.1145/3064663.3064767.

[3] H. Warmelink *et al.*, "AMELIO: Evaluating the team-building potential of a mixed reality escape room game," in *Extended Abstracts Publication of the Annual Symposium on Computer-Human Interaction in Play (CHI PLAY '17)*, 2017, pp. 111–123. doi: 10.1145/3130859.3131436.

[4] C. M. Baker, G. Crabtree, and K. Anderson, "Student pharmacist perceptions of learning after strengths-based leadership skills lab and escape room in pharmacy practice skills laboratory," *Currents in Pharmacy Teaching and Learning*, vol. 12, no. 6, pp. 724–727, 2020, doi: 10.1016/j.cptl.2020.01.021.

[5] C. Wu, H. Wagenschutz, and J. Hein, "Promoting leadership and teamwork development through Escape Rooms," *Medical Education*, vol. 52, no. 5, pp. 561–562, 2018, doi: 10.1111/medu.13557.

[6] A. Veldkamp, L. van de Grint, M. C. P. J. Knippels, and W. R. van Joolingen, "Escape education: A systematic review on escape rooms in education," *Educational Research Review*, vol. 31, 2020, doi: 10.1016/j.edurev.2020.100364.

[7] C. Borrego, C. Fernández, I. Blanes, and S. Robles, "Room escape at class: Escape games activities to facilitate the motivation and learning in computer science," *Journal of Technology and Science Education*, vol. 7, no. 2, pp. 162–171, 2017, doi: 10.3926/jotse.247.

[8] S. Lopez-Pernas, A. Gordillo, E. Barra, and J. Quemada, "Examining the Use of an Educational Escape Room for Teaching Programming in a Higher Education Setting," *IEEE Access*, vol. 7, pp. 31723–31737, 2019, doi: 10.1109/ACCESS.2019.2902976.

[9] S. Lopez-Pernas, A. Gordillo, E. Barra, and J. Quemada, "Analyzing Learning Effectiveness and Students' Perceptions of an Educational Escape Room in a Programming Course in Higher Education," *IEEE Access*, vol. 7, pp. 184221–184234, 2019, doi: 10.1109/ACCESS.2019.2960312.

[10] A. Gordillo, D. Lopez-Fernandez, S. Lopez-Pernas, and J. Quemada, "Evaluating an Educational Escape Room Conducted Remotely for Teaching Software Engineering," *IEEE Access*, vol. 8, pp. 225032–225051, 2020, doi: 10.1109/ACCESS.2020.3044380.

[11] G. Christian *et al.*, "Exploring Escape Games as a Teaching Tool in Educational Robotic," in *Educational Robotics in the Context of the Maker Movement*, M. Moro, D. Alimisis, and L. Locchi, Eds. Cham: Springer International Publishing, pp. 95–106.

[12] D. Menon, M. Romero, and T. Viéville, "Computational thinking development and assessment through tabletop escape games," *International Journal of Serious Games*, vol. 6, no. 4, pp. 3–18, 2019, doi: 10.17083/ijsg.v6i4.319.

[13] P. Dillenbourg, S. Järvelä, and F. Fischer, "The Evolution of Research on Computer-Supported Collaborative Learning," in *Technology-Enhanced Learning: Principles and Products*, N. Balacheff, S. Ludvigsen, T. de de Jong, A. Lazonder, and S. Barnes, Eds. Netherlands: Springer, 2009, pp. 3–19.

[14] D. H. Jonassen and W. Hung, "All Problems are Not Equal: Implications for Problem-Based Learning," *Interdisciplinary Journal of Problem-Based Learning*, vol. 2, no. 2, 2008, doi: 10.7771/1541-5015.1080.

[15] D. W. Shaffer, K. R. Squire, R. Halverson, and J. P. Gee, "Video games and the future of learning," *Phi Delta Kappan*, vol. 87, no. 2, pp. 105–111, 2005.

[16] A. Csanadi, B. Eagan, I. Kollar, D. W. Shaffer, and F. Fischer, "When coding-and-counting is not enough: using epistemic network analysis (ENA) to analyze verbal data in CSCL research.," *International Journal of Computer-Supported Collaborative Learning*, vol. 13, no. 4, pp. 419–438, 2018, [Online]. Available: http://proxy.libraries.smu.edu/login?url=http://search.ebscohost.com/login.aspx?dire

ct=true&db=eue&AN=133377729&site=ehost-live&scope=site%0A10.1007/s11412-018-9292-z
[17] G. Stahl and F. Hesse, "Social practices of computer-supported collaborative learning," *International Journal of Computer-Supported Collaborative Learning*, vol. 1, no. 4, pp. 409–412, 2006, doi: 10.1007/s11412-006-9004-y.
[18] B. Barron, "When smart groups fail," *Journal of the Learning Sciences*, vol. 12, no. 3, pp. 307–359, 2003, doi: 10.1207/S15327809JLS1203_1.
[19] N. Miyake and P. A. Kirschner, "The social and interactive dimensions of collaborative learning," in *The Cambridge Handbook of the Learning Sciences, Second Edition*, R. K. Sawyer, Ed. New York: Cambridge University Press, 2014, pp. 418–438. doi: 10.1017/CBO9781139519526.026.
[20] V. Adams, S. Burger, K. Crawford, and R. Setter, "Can You Escape? Creating an Escape Room to Facilitate Active Learning," *Journal for Nurses in Professional Development*, vol. 34, no. 2, pp. E1–E5, 2018, doi: 10.1097/NND.0000000000000433.
[21] A. Gabadinho, G. Ritschard, N. S. Müller, and M. Studer, "Analyzing and Visualizing State Sequences in R with TraMineR," *Journal of Statistical Software*, vol. 40, no. 4, pp. 1–37, 2011.
[22] C. Romero and S. Ventura, "Educational data science in massive open online courses," *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, vol. 7, no. 1, 2017, doi: 10.1002/widm.1187.
[23] N. A. A. Uzir, D. Gaševic, J. Jovanovic, W. Matcha, L. A. Lim, and A. Fudge, "Analytics of time management and learning strategies for effective online learning in blended environments," in *Proceedings of the Tenth International Conference on Learning Analytics & Knowledge*, 2020, pp. 392–401. doi: 10.1145/3375462.3375493.
[24] S. López-pernas, M. Saqr, and O. Viberg, "Putting it all together: Combining learning analytics methods and data sources to understand students' approaches to learning programming," *Sustainability*, vol. 13, no. 9, 2021, doi: 10.3390/su13094825.
[25] V. Tahvanainen, S. Nenonen, and T. Harjula, "Implementation of Digital and Physical Learning Environment to 21st Century Skills - Case Escape Room in the University of Eastern Finland," in *Research Papers: The 20th EuroFM Research Symposium*, 2021, pp. 112–121.
[26] J. Kahila *et al.*, "Escape Room Game for CT Learning Activities in the Primary School," in *Koli Calling '20: Proceedings of the 20th Koli Calling International Conference on Computing Education Research*, 2020, pp. 1–5. doi: 10.1145/3428029.3428063.
[27] M. T. H. Chi, "Quantifying Qualitative Analyses of Verbal Data: A Practical Guide," *Journal of the Learning Sciences*, vol. 6, no. 3, pp. 271–315, 1997, doi: 10.1207/s15327809jls0603_1.
[28] S. Hennessy and P. Murphy, "The Potential for Collaborative Problem Solving in Design and Technology," *International Journal of Technology and Design Education*, vol. 9, no. 1, pp. 1–36, 1999, doi: 10.1023/A:1008855526312.
[29] W. Peeters, M. Saqr, and O. Viberg, "Applying learning analytics to map students' self-regulated learning tactics in an academic writing course," in *Proceedings of the 28th International Conference on Computers in Education*, 2020, vol. 1, pp. 245–254.
[30] S. Järvelä, H. Järvenoja, and J. Malmberg, "Capturing the dynamic and cyclical nature of regulation: Methodological Progress in understanding socially shared regulation in learning," *International Journal of Computer-Supported Collaborative Learning*, vol. 14, no. 4, 2019, doi: 10.1007/s11412-019-09313-2.
[31] M. Berland, R. S. Baker, and P. Blikstein, "Educational data mining and learning analytics: Applications to constructionist research," *Technology, Knowledge and Learning*, vol. 19, no. 1–2, pp. 205–220, 2014, doi: 10.1007/s10758-014-9223-7.

[32] J. Saint, Y. Fan, S. Singh, D. Gasevic, and A. Pardo, "Using process mining to analyse self-regulated learning: A systematic analysis of four algorithms," in *LAK21: 11th International Learning Analytics and Knowledge Conference*, 2021, pp. 333–343. doi: 10.1145/3448139.3448171.