Characterising Individual-Level Collaborative Learning Behaviours Using Ordered Network Analysis and Wearable Sensors

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Abstract. Wearable positioning sensors are enabling unprecedented opportunities to model students' procedural and social behaviours during collaborative learning tasks in physical learning spaces. Emerging work in this area has mainly focused on modelling *group-level* interactions from low-level *x-y* positioning data. Yet, little work has utilised such data to automatically identify *individual-level* differences among students working in co-located groups in terms of procedural and social aspects such as task prioritisation and collaboration dynamics, respec- tively. To address this gap, this study characterised key differences among 124 students' procedural and social behaviours according to their per- ceived stress, collaboration, and task satisfaction during a complex group task using wearable positioning sensors and ordered networked analysis. The results revealed that students who demonstrated more collaborative behaviours were associated with lower stress and higher collaboration satisfaction. Interestingly, students who worked individually on the primary and secondary learning tasks reported lower and higher task satisfaction, respectively. These findings can deepen our understanding of students' individual-level behaviours and experiences while learning in groups.

Keywords: Collaborative Learning · Learning Analytics · Educational Data Mining · Ordered Network Analysis · Stress · Satisfaction

1 Introduction and Related Work

Recent studies in the emerging area of multimodal learning analytics (MMLA) are promoting the use of sensing technologies to model students' activity in the physical places where collaborative learning occurs [3]. These sensor-based innovations have shown the potential to capture students' physical and physiological data traces with high granularity and automation, enabling new opportunities to explore students' perceived experiences (e.g., stress and satisfaction) of collaborative learning in authentic settings [18]. Understanding these experiences is critical for pinpointing the potential impact of the learning design on students' cognitive and affective processes and creating mechanisms to support reflection [16, 30]. In contrast, studying such physical and physiological aspects of collaborative learning using traditional data collection methods (e.g., survey, interview, and direct observation) can be labour-intensive and intrusive [14].

1.1 Wearable Sensors

Wearable positioning sensors have been increasingly used to model student behaviour that demonstrates knowledge or effective collaboration skill development (i.e., procedural and social behaviours, respectively) during co-located collaborative learning tasks [21, 30]. Hall's [11] seminal work on *proxemics theory* has been used as the theoretical foundation for modelling students' interactions with other individuals and different spaces of interest from their positioning trace data captured in maker spaces [2], the classroom [22], the library [21] and open learning spaces [29]. For example, a zone-based model consisting of multiple spaces of interest (e.g., patient bed site and medical trolley) was developed to model students' within-group movements from positioning traces [5]. Based on such a model, social and epistemic network analyses have been used to unpack students' interpersonal interaction and spatial transition during collaborative learning [7]. Teachers have demonstrated a profound interest in using such evidence to support reflective practices [30].

1.2 Collaborative Learning Behaviours

However, most of the aforementioned works have only focused on capturing *group-level* dynamics. Little work has explored whether wearable positioning sensors can also capture evidence about *individual-level* procedural and social behaviours in co-located collaborative learning, limiting the potential to support personalised feedback and individualised reflective practices. Additionally, while prior studies have investigated the behavioural differences between groups with different performance (evaluated by teachers) [28, 30, 33], more work needs to be done to understand the associations between individual students' procedural and social behaviours (e.g., task prioritisation and collaboration) and their perceived experiences (e.g., stress and satisfaction) in collaborative learning. Understanding these associations could reveal valuable insights about whether students have demonstrated behaviours in accordance with teachers' learning design intentions and whether students' subjective experiences of their behaviours are in line with the intended learning objectives. For example, collaboration has been perceived as a potential mitigation strategy that adult learners would adopt to reduce their personal stress level [13]. Likewise, working with others has also shown positive impacts on students' affective states and learning satisfaction [4]. Thus, it is essential to identify whether students have collaborated to resolve the learning tasks or merely to reduce their perceived stress and enhance their personal learning satisfaction. Such insights could help teachers to identify potential dissonance between their learning designs and students' perceived learning experience, contributing evidence to support post-hoc reflective practices.

1.3 Ordered Behavioural Connections

Prior MMLA studies on collaborative learning behaviours have often used epistemic network analysis (ENA), a widely used network analysis technique for the modelling of learning phenomena [1, 23, 24, 26], to capture relationships between different behaviours. For example, ENA has been used to differentiate between low-performing and high-performing groups in clinical simulations based on the co-occurrence of their socio-spatial behaviours [30] and verbal communication behaviours [32] across different learning scenarios and phases. While ENA can uncover valuable insights regarding the structure of connections among different behaviours, it does not account for the order of these connections. Such orders may be important for understanding individual students' procedural and social behaviours as this directional information can significantly alter the meaning behind individuals' behaviours. For example, students moving from working individually on the primary task to working collaboratively on the secondary task could potentially signal distraction by others, whereas the opposite behaviour could potentially represent successful identification of the primary objective. Therefore, adopting a method that can capture ordered connections among different behaviours, such as ordered network analysis (ONA; further elaborated in Sect. 2.4), can potentially provide additional insights for unpacking individual students' procedural and social behaviours in co-located collaborative learning.

1.4 Research Questions and Contributions

We address the gaps in the literature identified above by characterising the differences in individual students' procedural and social behaviours based on their perceived experiences in collaborative learning using ONA and wearable positioning sensors. Specifically, we address the following research questions:

- **RQ1**) To what extent do students' procedural and social behaviours, modelled from positioning data, differ based on their perceived stress?
- **RQ2**) To what extent do students' procedural and social behaviours differ based on their perceived collaboration satisfaction?
- **RQ3**) To what extent do students' procedural and social behaviours differ based on their perceived task satisfaction?

The current study used wearable positioning sensors and a novel network analysis approach to characterise students' individual-level procedural and social behaviours during a co-located collaborative learning activity. The *x-y* positioning data of 124 students were collected from 31 healthcare simulations using wearable positioning sensors. These data were mapped into eight different procedural and social behaviours that were expected by teachers according to their learning design. Three ordered network analyses were conducted to identify key differences between students' individual-level behaviours according to their perceived stress, collaboration satisfaction, and task satisfaction. The findings from this study contribute empirical evidence to support the use of ordered network analysis and sensing technologies in capturing evidence about individual students' procedural and social behaviours in co-located collaborative learning. Such evidence could advance our understanding of students' behavioural strategies, provoke evidence-based student reflections, and empower the assessment of the learning designs' potential cognitive and affective impacts on students.

2 Methods

2.1 Study Context

The current study was conducted in a face-to-face clinical simulation unit. The simulations took place in a technologically-hybrid classroom equipped with authentic medical devices (e.g., oxygen masks) and high-fidelity patient manikins with measurable vital signals (e.g., controllable heart rates, pulses, and respiration rates). The patient manikins were voice-played and controlled by teaching staff from a control room that could directly observe the classroom through a one-way mirror. Each simulation consisted of a group of four students, with two taking on the role of the graduate nurses who entered the classroom at the beginning of the simulation. The other two ward nurses waited outside the classroom and could be called in by the graduate nurses for help. Students were often unaware of the multiple events that would unfold and were expected to demonstrate several critical behaviours, including familiarising themselves with the situations, evaluating the priority of different tasks, and distributing their attention among these tasks efficiently. The high complexity of the tasks also demands students to work collaboratively with other group members to achieve shared goals.

The *primary task* of the simulations involved students working collaboratively to resolve the medical emergency of a clinically deteriorating patient after being assigned several *secondary tasks* (e.g., completing a pre-operation check and an intravenous delivery). They also needed to deal with a patient relative (role-played by teaching staff) who impatiently demanded completing her husband's patient release process (the distraction task). The simulation was live-streamed in a debriefing room to students who were not currently participating as a part of the simulation unit. As this study focused on unpacking individuals' procedural and social behaviours during the simulations, we focused on analysing these behaviours when all four students were in the classroom.

2.2 Apparatus and Data Collection

The Pozyx Creator Kit [19] was used to capture participants' indoor positioning traces inside the simulation classroom. Each participant was assigned a wearable

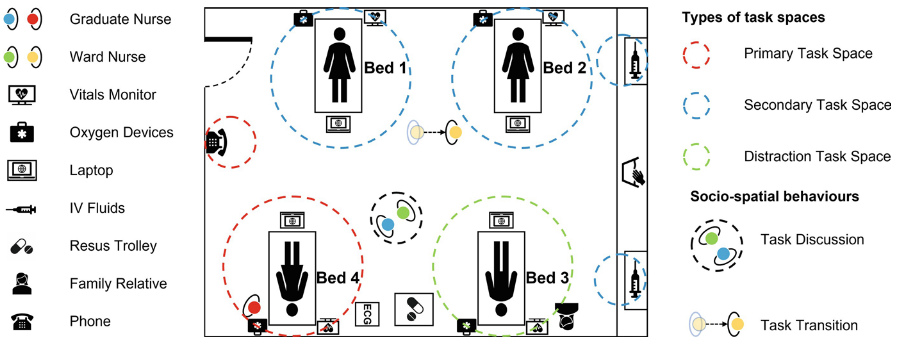

Fig. 1. Floor plan of the learning spaces divided into different task spaces.

Ultra-Wideband tag that transmitted signals at 60 Hz to five anchors, affixed to the side walls of the simulation classroom. Pozyx's proprietary engine automatically computed these signals into real-time x-y coordinates using wireless Two-Way Ranging algorithms. Positioning data was only available when participants were located inside the simulation classroom. Participants also completed a post-survey (Table 1) containing three single-item measures to capture their perceived task, collaboration satisfaction, and stress after the simulation, each with a seven-point bipolar Likert scale, ranging from *strongly disagree* (1) to *strongly agree* (7). The positioning and survey data of 208 students across 52 simulations were captured with their informed consent and under the ethical approval of [Anonymised] University (Project ID: [Anonymised]). This study focused on analysing the 124 students who participated in the same simulation scenario, where the learning design emphasised task prioritisation and collaboration as they were required to actively identify and attend to the primary task while handling the distraction and secondary tasks. Whereas the other 84 students participated in a different scenario that was less complicated and more straightforward.

Table 1. Items on students' perceived task (S1), collaboration (S2), and stress (S3).

Item	Details	*M*	*SD*
S1	I am satisfied with my task performance during the simulation	4.49	1.37
S2	I am satisfied with the collaboration performance of my group	5.67	1.20
S3	I felt high levels of stress during the simulation	5.97	1.15

2.3 Feature Extraction

A total of eight different procedural and social behaviours behavioural features were modelled from students' positioning traces to inform on their task prioritisation and collaboration (Table 2). The learning space was first divided into three different spaces of interest based on their related learning tasks and the inputs from the simulation unit coordinator, including primary, secondary, and distraction task spaces (Fig. 1). A student was registered as in a given task space if located within 1.5 m (large circles) or 1 m (small circles) from the centre of the task space (euclidean distance) for more than ten consecutive seconds to reduce the likelihood of misidentifying students' walking behaviours as working on the related tasks [10]. The students were registered as working collaboratively if two or more students were in the same task space. Together, these two conditions were used to model the first six procedural and social behaviours in Table 2. The remaining two procedural and social behaviours were modelled from positioning traces outside of the task spaces (circles) either by themselves (*task transition*) or within one-meter proximity of other students for more than ten consecutive seconds (*task_discussion*). These proximity thresholds were based on prior studies [17,33] and were validated by experienced teachers.

Table 2. Procedural and social behavioural features.

Label	Procedural and social behaviours
primary_ind	Students working individually on the primary tasks
primary _col	Students working collaboratively on the primary tasks
secondary_ind	Students working individually on the secondary tasks
secondary_col	Students working collaboratively on the secondary tasks
distraction_ind	Students working individually on the distracting tasks
distraction _col	Students working collaboratively on the distracting tasks
task_discussion	Students discussing with others outside of the task spaces
task_transition	Students transiting from one task space to another

2.4 Ordered Network Analysis

We used ONA to analyse the differences in individual students' procedural and social behaviours based on their perceived stress (RQ1), collaboration (RQ2), and task satisfaction (RQ3) of the simulation. ONA was chosen in this study because previous work has demonstrated its analytical and visual affordance in identifying key differences between individuals' learning behaviours [6,27].

We used the ONA R package to conduct the analysis [15]. The ONA algorithm follows similar computational procedures implemented in ENA with an additional set of functions to account for the order. As in ENA, we first binary coded each student's actions in the simulations using the eight procedural and social behaviours (Table 2) as codes, where 1 and 0 represented the presence or absence of a given behaviour, respectively. The connection and unit of analysis are within each individual student, so each activity only contains the behavioural codes of one student at a given time (within 10 s). With the coded data set, the ONA algorithm used a sliding window to accumulate code connections for each student, showing how their current behaviours were connected to the behaviours that occurred within the *recent temporal context* [25], defined as a specified number of lines preceding the current line in the data. In this study, we defined the recent temporal context as being six lines, each line plus the five previous lines. This decision was made because six lines in the data represent a sixty-second time interval in the simulation, as most behaviour engagement for a given line, was contained within a one-minute window. After the connection accumulation stage, each student's connection counts were represented as a high-dimensional vector, where the connection strength and connection direction between each pair of codes were recorded. The ONA algorithm then performed a dimensional reduction to project those high-dimensional vectors onto a two-dimensional metric space. Each group's average network was summarised as a mean point (represented as a square in network visualizations) in the space and each individual student's network was summarised as a point, or ONA point, (represented as dots in network visualizations). For the dimensional reduction in this study, we used a technique that optimises the differences between the mean of two groups called Means Rotation (MR) [1] – in this case, students in high and low perceived stress (RQ1), collaboration (RQ2), and task satisfaction (RQ3). We applied MR on each of the three groups to compare the high and low conditions within each group. The groups were created based on teachers' recommendations, where students with a rating of 1–4 and 5–7 were categorised into the low and high groups, respectively, for each item in Table 1. The resulting two-dimensional space highlighted the differences between groups (if any) by placing the means of the group as close as possible to the X-axis of the space (see [27] for details).

To answer our three research questions, we created three ONA subtracted plots. For each plot, a two-sample Mann-Whitney U test was conducted to test whether the differences in directed connections between the two conditions were statistically significant. We chose to use the Mann-Whitney U test because the Intraclass Correlation Coefficient (ICC) scores for the outcome variable (i.e., ONA points) are all below 0.3 across all three conditions (i.e., perceived stress groups, collaboration, task satisfaction), indicating that a substantial amount of the variance in students' ONA networks is due to variation between groups, rather than variation within groups. Therefore, the Mann-Whitney U test is a more appropriate choice to compare the two groups. In ONA subtracted plots, both the node size and the edge thickness were proportional to the frequency of behaviour occurrence. Between each pair of nodes, a chevron was placed on the edge side with relatively heavier weights. The coloured circle within each node represented directed connections made from one code to itself, also known as self-transition. The larger the coloured circle was, the more self-transition that code had made to itself. We used a blue-red colour coding scheme across all three subtracted plots, where blue represented the high-group and red represented the low-group.

3 Results

3.1 RQ1: Perceived Stress

The Mann-Whitney U test revealed significant differences in the directed connections of procedural and social behaviours between low-stress (N = 32, Mdn = −0.12, Q1 = −0.18, Q3 = 0.21) and high-stress students (N = 92, Mdn = 0.01, Q1 = −0.18, Q3 = 0.21) among the x-axis ($U = 1876$, $p = 0.02$, $r = 0.54$). As shown in Fig. 2, low-stress students were strongly characterised by their focus on collaboration despite the task priority. For example, they demonstrated high self-transition in *primary_col*, *distraction_col*, and *task_discussion*, which are all procedural and social behaviours related to collaboration but for different task types. We also observed more directed connections toward working collaboratively in low-stress students, as they were more likely to transit to *primary_col*, *secondary_col*, and *distraction_col* from working either collaboratively or individually on other tasks. On the other hand, high-stress students were strongly characterised by both frequent self-transitions and directed connections to *primary_ind* from other behaviours, suggesting that these students spent the majority of their time working individually on the primary task despite their prior procedural and social behaviours. Such findings were expected as students who were left alone working on the primary tasks could experience higher pressure when trying to resolve the medical emergence of the deteriorating patient, whereas having others to help with this stressful task or collaborating on other less stressful tasks could potentially mitigate their perceived stress.

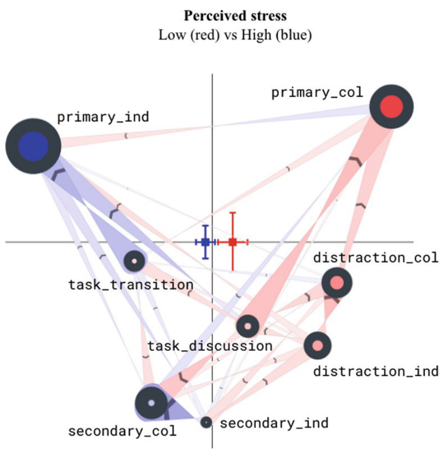

Fig. 2. The differences in directed connections between students with low (red) and high (blue) perceived stress (Color figure online)

3.2 RQ2: Collaboration Satisfaction

Although the Mann-Whitney U tests showed that the differences in the directed connections of procedural and social behaviours between low collaboration satisfaction (N = 20, Mdn = 0.11, Q1 = −0.06, Q3 = 0.29) and high collaboration satisfaction students (N = 104, Mdn = −0.04, Q1 = −0.24, Q3 = 0.15) were not significant on either axis ($p = 0.059$, $r = 0.21$ on the x-axis, $p = 0.082$, $r = 0.18$ on the y-axis), visually investigating the subtraction plot (Fig. 3) still revealed some insights.

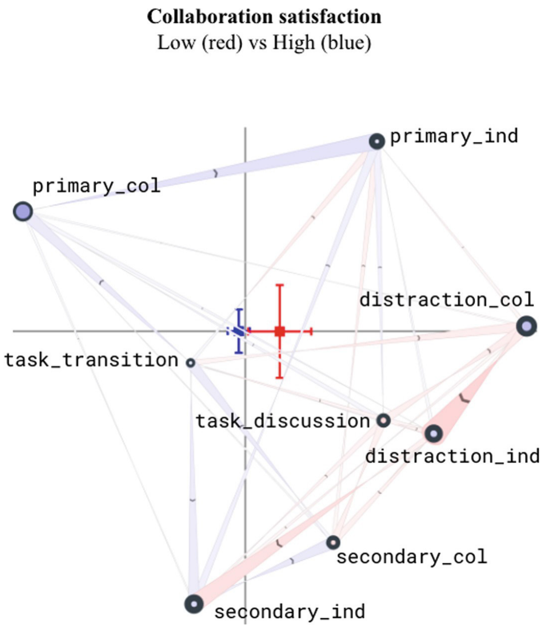

Fig. 3. The differences in directed connections between students with low (red) and high (blue) perceived collaboration satisfaction (Color figure online)

The high collaboration satisfaction students were characterised by their focus on working collaboratively on the primary (*primary col*) and distraction task (*distraction col*), and the directed connections that lead toward *primary col*, such as the triadic connections between *task transition*, *secondary ind*, and *sec- ondary col*. Whereas the two directed connections from *distraction col* to *distrac- tion ind* and from *distraction ind* to *secondary ind* characterised the procedural and social behaviours of low collaboration satisfaction students. These findings were expected as more collaboration was consistent with higher self-rated collaboration satisfaction, and more directed connections toward working individually on different tasks could lead to lower collaboration satisfaction.

3.3 RQ3: Task Satisfaction

We found significant differences in the directed connections of procedural and social behaviours between low task satisfaction (N = 57, Mdn = 0.11, Q1 = −0.27, Q3 = 0.57) and high task satisfaction students (N = 67, Mdn = −0.12, Q1 = −0.40, Q3 = 0.06) among the x-axis ($U = 1305$, $p = 0.002$, $r = 0.48$). As shown in Fig. 4, low task satisfaction students were strongly characterised by working individually on the primary task (*primary_ind*) and working collaboratively on the secondary tasks (*secondary_col*). The directed connections from *primary_ind* to *task_transition* and from *primary_col* to *primary_ind* further suggested that low task satisfaction students were stuck to the primary task by themselves, despite having other students come to help occasionally and transiting in and out of the primary task spaces. This finding is interesting as these students were prioritising the right task (primary task) but felt they did not perform well, task-wise. One potential explanation is that these students were unsatisfied with their task because they felt overwhelmed by the primary task as they were working on it mostly by themselves, whereas this task was designed for at least two students.

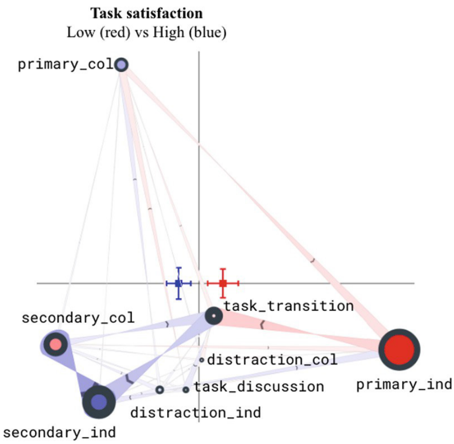

Fig. 4. The differences in directed connections between students with low (red) and high (blue) perceived task satisfaction (Color figure online)

On the other hand, high task satisfaction students were characterised by their focus on working individually on the secondary tasks (*secondary_ind*), the directed connections from *secondary_col* to *task_transition* and then to *secondary_ind*, and working collaboratively on the primary task (*primary_col*). The later finding (*primary_col*) was expected from students. The first two findings were unexpected, as these students were satisfied with their task despite prioritising the secondary task and working individually for an extensive duration. A potential explanation of such findings is that these students may not have deliberately focused on the secondary task but were assigned to these tasks during team discussion and responsibility delegation. Consequently, their high perceived task satisfaction could originate from completing the secondary tasks, which follow a more straightforward procedure than the primary tasks. Additionally, they may also have felt that they were less responsible for the primary task.

4 Discussion

This study characterised the differences in individual students' procedural and social behaviours based on their perceived stress, collaboration, and task satisfaction in co-located collaborative learning using wearable positioning sensors and ordered network analysis. For the first research question (RQ1), we identified that students who prioritised and worked on the primary task alone were associated with higher post-simulation stress than those who focused on collaborating with others despite task prioritises. This finding resonates with prior literature on the potential effects of collaboration as a mitigation strategy for reducing students' personal stress levels [13]. While this strategy could benefit collaborative learning tasks with a clear goal, the current finding further illustrated that it could potentially distract students from the primary task in learning contexts requiring them to identify and prioritise different tasks.

Similar findings were also uncovered in the second research question (RQ2), where students' perceived collaboration satisfaction was characterised by their social behaviours (collaboration) but unrelated to their procedural behaviours (prioritisation). Both these findings (RQ1&2) suggest that, in complex collaborative learning settings with multiple tasks and uncertain goals, merely capturing evidence of students' social behaviours might be insufficient to support student reflection. Additional evidence on students' procedural behaviours is also needed for a holistic view of their learning behaviours. Consequently, educational technologies and learning analytics tools that aim to support student reflections in collaborative learning need to have context-sensitivity instead of relying on a fixed set of features and measurements [8].

For the third research question (RQ3), we found that low task satisfaction students focused on the primary task alone. In contrast, students with high perceived task satisfaction were characterised by collaborating on the primary task (as expected) but even more by working individually on the secondary tasks. While such findings were unexpected based on the learning design, where students who focused on the primary task were expected to have higher task satisfaction as they were prioritising the right task, these findings resonate with prior literature on the socio-emotional connections between belonging and satisfaction [4]. For example, students who worked individually on the primary task may have felt unsupported by other group members, leading to lower task satisfaction. The high task satisfaction in students who worked individually on the secondary tasks resonates with prior findings on the positive association between self-efficacy and student satisfaction [20]. As the secondary tasks were more straightforward than the primary task, where students already knew the required actions, they could potentially have higher self-efficacy and more success in completing these simpler tasks, resulting in higher task satisfaction. These findings revealed some unexpected associations between the learning designs and students' collaborative learning behaviours and experiences, which teachers may need to address during post-hoc reflections to ensure that students have a clear understanding of the learning tasks and objectives.

Implications and Ethical Considerations. The findings have several impli- cations for future quantitative ethnography and learning analytics research. Specifically, combining quantitative ethnography approaches (e.g., ENA and ONA) with novel data streams (e.g., physical and physiological data) could potentially reveal valuable insights regarding the temporal dynamics of individuals' learning behaviours. As our findings show, wearable positioning sensors combined with ordered network analysis can capture and unpack students' procedural and social behaviours in physical classrooms. Such sensor-based approaches could potentially empower future studies that aim to gain deeper insights into the cognitive process behind students' collaborative learning strategies [9], for example, uncover behavioural features for distinguishing between productive and unproductive collaboration. This potential could fuel the development of educational technologies that aim to automate the process of systematic observation in physical classrooms. Such technologies could potentially reduce teachers' workloads, generate behavioural evidence to support reflective practices, and make formative assessments in physical classrooms more sustainable [31]. As we only used wearable positioning sensors, future studies can combine other wearable sensors to capture multimodal behaviour traces (e.g., physiological and verbal behaviours [12]), providing further opportunities to unpack and triangulate students' cognitive and affective process during collaborative learning [3]. Additionally, sensor-based approaches could contribute to the advancement in learning space and design research as individualised evidence regarding students' interaction with the physical environments can be captured with minimum intrusion and automatically, potentially benefiting further longitudinal research. However, such data-driven approaches could also elicit potential ethical and privacy concerns, such as data misuse and unintended surveillance. Educational stakeholders must be aware that even simple x-y positioning data can contain critical information (e.g., learning behaviours) besides spatial coordinates when analysed with contextual information. Future studies must consider these ethical implications before deploying sensor-based systems in physical classrooms [31].

Limitations and Future Directions. The current approach has limitations as we characterised students' procedural and social behaviours based on their proximity to the different task spaces instead of whether they have demonstrated such behaviours. Although this approach is valid in our study as the task spaces were purposely designed for the corresponding tasks, future studies conducted outside of such confined learning contexts (e.g., in open learning spaces [29]) should validate if students are engaged in certain behaviours based on proximity, especially when multiple tasks can unfold in a same physical location. Finally, providing a qualitative interpretation of the raw data is difficult in the context of a static paper, given that the data is dynamic and position-based. In future work, we will explore representations that afford these kinds of descriptions.

5 Conclusion

This study illustrates the potential of combining wearable positioning sensors and ordered network analysis in characterising students' individual-level procedural and social behaviours based on their experiences during collaborative learning in physical classrooms. The findings emphasised the potential value of quantitative ethnography approaches and wearable sensors in supporting systematic observation and investigating the potential impacts of the learning designs on students' learning experiences.

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Conflict of Interest. The authors have declared no conflicts of interest.

Ethics Statement. Ethics approval was obtained from Monash University (Project ID: 28026).

Data Availability Statement. The data that support the findings of this study are available from the corresponding author upon reasonable request. The data are not publicly available due to privacy or ethical restrictions.

References

1. Bowman, D., et al.: The mathematical foundations of epistemic network analysis. In: Ruis, A.R., Lee, S.B. (eds.) ICQE 2021. CCIS, vol. 1312, pp. 91–105. Springer, Cham (2021). https://doi.org/10.1007/978-3-030-67788-6 7
2. Chng, E., Seyam, M.R., Yao, W., Schneider, B.: Using motion sensors to under- stand collaborative interactions in digital fabrication labs. In: Bittencourt, I.I., Cukurova, M., Muldner, K., Luckin, R., Mill´an, E. (eds.) AIED 2020. LNCS (LNAI), vol. 12163, pp. 118–128. Springer, Cham (2020). https://doi.org/10.1007/978-3-030-52237-7 10
3. Cukurova, M., Giannakos, M., Martinez-Maldonado, R.: The promise and challenges of multimodal learning analytics. BJET **51**(5), 1441–1449 (2020)
4. Delahunty, J., Verenikina, I., Jones, P.: Socio-emotional connections: identity, belonging and learning in online interactions. A literature review. Technol. Pedag. Educ. **23**(2), 243–265 (2014)
5. Echeverria, V., Martinez-Maldonado, R., Power, T., Hayes, C., Shum, S.B.: Where is the nurse? Towards automatically visualising meaningful team movement in healthcare education. In: Penstein Ros´e, C., et al. (eds.) AIED 2018. LNCS (LNAI), vol. 10948, pp. 74–78. Springer, Cham (2018). https://doi.org/10.1007/978-3-319-93846-2 14
6. Fan, Y., et al.: Dissecting learning tactics in MOOC using ordered network analysis. J. Comput. Assist. Learn. **39**, 154–166 (2022)
7. Fernandez-Nieto, G.M., Martinez-Maldonado, R., Kitto, K., Shum, S.B.: Modelling spatial behaviours in clinical team simulations using epistemic network analysis: methodology and teacher evaluation. In: LAK 2021, pp. 386–396 (2021)

8. Gašević, D., Dawson, S., Rogers, T., Gasevic, D.: Learning analytics should not promote one size fits all: the effects of instructional conditions in predicting academic success. Internet High. Educ. **28**, 68–84 (2016)
9. Giannakos, M., Cukurova, M., Papavlasopoulou, S.: Sensor-based analytics in education: lessons learned from research in multimodal learning analytics. In: Giannakos, M., Spikol, D., Di Mitri, D., Sharma, K., Ochoa, X., Hammad, R. (eds.) The Multimodal Learning Analytics Handbook, pp. 329–358. Springer, Cham (2022). https://doi.org/10.1007/978-3-031-08076-0_13
10. Greenberg, S., Boring, S., Vermeulen, J., Dostal, J.: Dark patterns in proxemic interactions: a critical perspective. In: DIS 2014, pp. 523–532 (2014)
11. Hall, E.T.: The Hidden Dimension, vol. 609. Doubleday, Garden City (1966)
12. Järvelä, S., Dindar, M., Sobocinski, M., Nguyen, A.: Multimodal research for studying collaborative learning in higher education. In: Handbook of Digital Higher Education, pp. 199–210. Edward Elgar Publishing (2022)
13. Kinkead, K.J., Miller, H., Hammett, R.: Adult perceptions of in-class collaborative problem solving as mitigation for statistics anxiety. J. Contin. High. Educ. **64**(2), 101–111 (2016)
14. Luciano, M.M., Mathieu, J.E., Park, S., Tannenbaum, S.I.: A fitting approach to construct and measurement alignment: the role of big data in advancing dynamic theories. Organ. Res. Methods **21**(3), 592–632 (2018)
15. Marquart, C., Tan, Y., Cai, Z., Shaffer, D.W.: Ordered network analysis (2022). https://epistemic-analytics.gitlab.io/qe-packages/ona/cran/
16. Martinez-Maldonado, R., Echeverria, V., Fernandez Nieto, G., Buckingham Shum, S.: From data to insights: a layered storytelling approach for multimodal learning analytics. In: CHI, pp. 1–15 (2020)
17. Martinez-Maldonado, R., Echeverria, V., Schulte, J., Shibani, A., Mangaroska, K., Buckingham Shum, S.: Moodoo: indoor positioning analytics for characterising classroom teaching. In: Bittencourt, I.I., Cukurova, M., Muldner, K., Luckin, R., Millán, E. (eds.) AIED 2020. LNCS (LNAI), vol. 12163, pp. 360–373. Springer, Cham (2020). https://doi.org/10.1007/978-3-030-52237-7_29
18. Martínez-Maldonado, R., Yan, L., Deppeler, J., Phillips, M., Gašević, D.: Classroom analytics: telling stories about learning spaces using sensor data. In: Gil, E., Mor, Y., Dimitriadis, Y., Köppe, C. (eds.) Hybrid Learning Spaces. Understanding Teaching-Learning Practice, pp. 185–203. Springer, Cham (2022). https://doi.org/10.1007/978-3-030-88520-5_11
19. Pozyx: Unleash the power of real-time location solutions (2022). https://www.pozyx.io/. Accessed 21 Nov 2022
20. Prifti, R.: Self-efficacy and student satisfaction in the context of blended learning courses. Open Learn. **37**(2), 111–125 (2022)
21. Riquelme, F., et al.: Where are you? Exploring micro-location in indoor learning environments. IEEE Access **8**, 125776–125785 (2020)
22. Saquib, N., Bose, A., George, D., Kamvar, S.: Sensei: sensing educational interaction. PACM IMWUT **1**(4), 1–27 (2018)
23. Shaffer, D.W., Collier, W., Ruis, A.R.: A tutorial on epistemic network analysis: analyzing the structure of connections in cognitive, social, and interaction data. J. Learn. Anal. **3**(3), 9–45 (2016)
24. Shaffer, D.W., et al.: Epistemic network analysis: a prototype for 21st-century assessment of learning. IJLM **1**(2), 33–53 (2009)
25. Siebert-Evenstone, A.L., Irgens, G.A., Collier, W., Swiecki, Z., Ruis, A.R., Shaffer, D.W.: In search of conversational grain size: modeling semantic structure using moving stanza windows. J. Learn. Anal. **4**(3), 123–139 (2017)

26. Swiecki, Z., et al.: Assessment in the age of artificial intelligence. Comput. Educ.: Artif. Intell. (2022). In press
27. Tan, Y., Ruis, A.R., Marquart, C., Cai, Z., Knowles, M.A., Shaffer, D.W.: Ordered network analysis. In: Dam¸sa, C., Barany, A. (eds.) Advances in Quantitative Ethnography. Communications in Computer and Information Science, vol. 1785, pp. 101–116. Springer, Cham (2022). https://doi.org/10.1007/978-3-031-31726-2 8
28. Vrzakova, H., Amon, M.J., Stewart, A., Duran, N.D., D'Mello, S.K.: Focused or stuck together: multimodal patterns reveal triads' performance in collaborative problem solving. In: Proceedings of the Tenth International Conference on Learning Analytics & Knowledge, pp. 295–304 (2020)
29. Yan, L., et al.: Footprints at school: modelling in-class social dynamics from students' physical positioning traces. In: LAK 2021, pp. 43–54 (2021)
30. Yan, L., et al.: The role of indoor positioning analytics in assessment of simulation-based learning. Br. Educ. Res. J. (2022). In press
31. Yan, L., Zhao, L., Gasevic, D., Martinez-Maldonado, R.: Scalability, sustainability, and ethicality of multimodal learning analytics. In: LAK 2022, pp. 13–23. Association for Computing Machinery, New York (2022)
32. Zhao, L., et al.: METS: multimodal learning analytics of embodied teamwork learning. In: 13th International Learning Analytics and Knowledge Conference (2023). In press. https://doi.org/10.1145/3576050.3576076
33. Zhao, L., et al.: Modelling co-located team communication from voice detection and positioning data in healthcare simulation. In: LAK 2022, pp. 370–380 (2022)