Footprints at School: Modelling In-class Social Dynamics from Students' Physical Positioning Traces

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Schools are increasingly becoming into complex learning spaces where students interact with various physical and digital resources, educators, and peers. Although the field of learning analytics has advanced in analysing logs captured from digital tools, less progress has been made in understanding the social dynamics that unfold in physical learning spaces. Among the various rapidly emerging sensing technologies, position tracking may hold promises to reveal salient aspects of activities in physical learning spaces such as the formation of interpersonal ties among students. This paper explores how granular *x*-*y* physical positioning data can be analysed to model social interactions among students and teachers. We conducted an 8-week longitudinal study in which positioning traces of 98 students and six teachers were automatically captured every day in an open-plan public primary school. Positioning traces were analysed using social network analytics (SNA) to extract a set of metrics to characterise students' positioning behaviours and social ties at cohort and individual levels. Results illustrate how analysing positioning traces through the lens of SNA can enable the identification of certain pedagogical approaches that may be either promoting or discouraging in-class social interaction, and students who may be socially isolated.

CCS Concepts: • **Applied computing** → *Collaborative learning*; *Computer-assisted instruction*; *Learning management systems.*

Additional Key Words and Phrases: classroom analytics, social networks analysis, social ties, indoor positioning, proxemics

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1 INTRODUCTION

Although the current COVID-19 pandemic temporarily displaced physical classrooms with online environments, in the foreseeable future, physical/hybrid learning spaces will resume as the primary place of education in several sectors. This is rapidly becoming evident particularly for primary and secondary education [32], and for tasks that involve psychomotor [36] and experiential learning [27] (e.g., hands-on laboratory sessions). In fact, besides the benefits of certain classroom resources for particular learning tasks, the physicality of certain learning spaces provides irreplaceable opportunities for students to establish social presence, build community, and socially engage face-to-face with peers and teachers [46]. Engaging in productive social face-to-face interactions is essential for students to develop 21st-century skills [5] and contributes to students' mental well-being [24] and academic achievement [14].

Learning spaces are becoming increasingly complex and technologically hybrid [16]. Novel architectural approaches (such as open learning spaces [38] and flexible classrooms [48]) are challenging current pedagogical practices. As a result, new approaches are needed to generate a deeper understanding of the social dynamics of the learning space in light of these emerging pedagogies and architectural designs.

Learning analytics (LA) could play a key role in dealing with this increase in complexity of current and future learning spaces. Although the majority of LA innovations have focused on supporting teaching and learning using students' digital traces from online learning platforms (e.g., MOOCs and LMS) or personal computer logs, there has been an emerging interest in extracting learning analytics from physical learning spaces (see review in [10]). The growing maturity of sensing and tracking technologies are enabling unprecedented opportunities to explore educational constructs which were previously difficult to capture from co-located situations. Gaining insight into students' social interactions in the physical spaces where they learn could be beneficial for teachers to better orchestrate the learning tasks and resources; and for researchers and developers of learning spaces to identify the impact of architectural designs, classroom configurations, and new pedagogies.

Different approaches are emerging in the growing body of LA and educational data mining research to automatically model spatial aspects of teaching and learning. These approaches have utilised various forms of technologies and data sources, including WiFi data [35], computer vision algorithms [1, 6], thermal sensors [7], and wearable technologies [30, 42]. They have also focused on a range of learning spaces, such as small fabrication rooms [9], healthcare simulation rooms [12], the library [40], laboratories [30], regular classrooms [1, 42], and lecture rooms [6]. Out of these approaches, physical positioning tacking is one of the promising methods in providing *fine-grained* data for capturing in-class social interactions because of its high spatial-temporal precision [30]. Yet, little work has been conducted in exploring what kind of cohort-level metrics can be extracted from physical positioning traces to inform about the students' social interaction in group activities. Likewise, individual-level metrics that can reflect the formation of students' social ties over time are also lacking. Moreover, all these previous works have been limited to track the activity of a small number of students or teachers during short periods of time, and in confined spaces or under controlled conditions. No previous work has explored these longitudinal positioning data from a large sample of teachers and students interacting across multiple authentic learning spaces and its opportunities to model and find positioning insights to understand teaching and learning phenomena better.

This paper presents an exploratory study that shows how granular *x-y* physical positioning data can be analysed to model social interactions among students and their teachers across physical learning spaces in a school. We conducted an 8-week longitudinal study in which positioning traces of 98 students and six teachers were automatically captured every day in an open-plan public primary school. Positioning traces were analysed using social network analytics (SNA) to extract a set of metrics to characterise students' positioning behaviours and social ties at cohort and individual levels.

The contribution of this paper to the LA community is twofold: 1) we present the first longitudinal study that captured physical positions of a large sample of students and teachers (>100), with high spatial-temporal precision, while engaging in their regular activities across various learning spaces at their school; 2) we present a set of cohort-level and individual-level metrics that can be extracted from granular *x-y* positioning data as potential indicators of classroom social activity and the social ties individual students form with others.

2 BACKGROUND AND RELATED WORK

2.1 Social interactions in physical learning spaces

The various forms of social interactions and ties that can be formed among students and teachers are influential in students' learning process and can influence academic success [25]. Individually, research has shown that in-class social interactions are associated with students' emotional well-being and learning performance [14, 33]. When these social interactions are studied at a cohort-level, they can provide insights into constructs such as the extent to which a group is socially connected; participation levels of a classroom [19]; and the *homophily* of student interactions [35] (this is, the extent to which students build ties with peers who share similar attributes with them such as gender and prior attainment). These cohort-level constructs can also be influential to student satisfaction in collaborative learning [11]. Hence, finding ways to capture traces of in-class social interactions may help educational researchers and practitioners to better comprehend the social aspect of activities unfolding in physical learning spaces.

Measuring social interactions in physical learning spaces is often difficult in practice. It is particularly challenging to conduct longitudinal analysis based on traditional data collection methods that are commonly used to analyse in-class activities such as surveys, interviews, and direct observations [23]. Survey studies are convenient for capturing the number of social interactions from a large sample of students but lack precision in terms of the duration and quality of social ties formed [8, 19]. They also depend on participants' memories of experience, which can be biased and incomplete [39]. Interviewing students can provide in-depth details about the quality of social interaction, but it is difficult to scale up [41] and still suffers from potentially incomplete memories of experience. Ethnographers often study in-class social interactions through direct observations. This method could capture the development and changes in students' social ties and spatial behaviours [20]. However, all these methods are intrusive, labour-intensive, susceptible to bias, and thus, impractical to implement in authentic learning spaces for longitudinal monitoring [26].

2.2 Foundations of proxemics

The notion of *proxemics* can provide the foundations for alternative data collection methods to automatically model social aspects of students' activity in physical learning spaces. Proxemics refers to the study of how physical space is used during social interactions and the interpersonal distances or proximity individuals maintain with each other in social encounters [21]. This term has evident relevance for the analysis of human behaviours in physical learning spaces [44]. For example, decades of studies in social psychology have shown that physical proximity is one of the best predictors of social relationships such as in friendship and acquaintances [4].

Proxemics has been operationalised to provide the basis for measuring the social interactions in the learning spaces using automated measuring approaches [28, 42]. Promising implementations are emerging in the LA community. For example, Chng et al., [9] classified instances of social interaction by detecting when two students were collocated within one-meter proximity of each other. Martinez-Maldonado et al., [31] also applied the one-meter proximity rule to estimate the time teachers spend with different groups of students in a physical classroom. As illustrated in these studies, a methodological application of proxemics could potentially capture in-class social interactions in a non-intrusive, real-time, and scalable manner [9, 28]. The next subsection provides a more detailed description of the current technological solutions for tracking spatial behaviours in learning spaces.

2.3 Indoor-sensing technologies and learning analytics

The collection and analysis of proximity data are becoming increasing viable as sensing and tracking technologies mature [10, 28]. For example, Nguyen et al. [35] used WiFi data to identify the collocation of students in a same room and generate a deeper understanding of the homophily of student interaction (i.e. students tending to interact with people who are like them) based on demographics and academic achievement. However, the spatial-temporal precision of WiFi data is coarse and can be very noisy. These data cannot reliably be used to understand student participation in in-class social activities, as well as 1-to-1 social interactions. Likewise, thermal sensor data are promising in detecting the physical presence of students in a classroom and provide insights about student attendance [7]. However, similar to WiFi data, the coarse granularity of the information these data provide can neither capture the types of social interactions nor provide insights into the dynamics of individual social interactions.

Classroom video recording has been used for capturing proximity data and generating insights about in-class social interactions. Bosch et al. [6] used automated video analysis to model teacher movements during a lecture. Ahuja et al. [1] expanded these sensing capabilities through EduSense, a computer vision system that automatically extracts the relative positions of teachers and students to the camera. This system has the potential of detecting social interactions through a x-y coordinate system. Such potential is demonstrated by Chng et al. [9] who translated motion and posture data into x-y positioning data, and then, classified in-class social interactions based on physical proximity. However, outside of lecture-style or small classrooms, video-based approaches are impractical because in multiple learning spaces student movements will cause visual occlusion and damper the precision and continuity of the proximity data [30].

In contrast, wearable positioning tracking devices provide a more robust and accurate way to capture fine-grained, continuous positioning data that can be used to model in-class social interactions. For example, ClassBeacons [3] deployed tracking devices to teachers and tables around a classroom to model the time teachers spent with each group of students. Similar work is shown in Moodoo [29], an automatic system that models teachers' positioning strategies in a classroom. The authors demonstrated that these tracking devices can be used to generate physical positioning analytics in various learning settings, including collaboration, simulation, and laboratory learning spaces [30]. Although these studies only tracked teachers, the data already generated valuable insights about classroom dynamics. For example, both ClassBeacons and Moodoo captured the social interactions between teachers and different *groups* of students, which can help teachers reflect on strategies to effectively use their time to attend students who need more attention.

Wearable tracking devices have also demonstrated potentials in generating insights about different types of student interactions [10]. Riquelme et al. [40] used beacons to track the movement and interaction patterns of students with other student groups and various objects within a library. Through clustering and pattern analysis, these positioning data provide insights about potential collaborative learning behaviours under experimental conditions. Similarly, Stehle et al. [45] illustrated the gender homophily of student interactions in an authentic primary school with large sample of students, however, only for two consecutive days. The only longitudinal study that is closer to ours, conducted under authentic conditions is Sensei [42]. This is a system that models teacher-student and peer social interactions using tiny wearable proximity sensors. This study demonstrated the potential of proximity tracking in early-childhood classrooms, by distributing trackers to each teacher and student. Sensei demonstrated the potential of physical positioning traces in augmenting teachers' manual observations and provided insights that would have otherwise been lost. The system captured the evolution of classroom social participation, the interactions among students, and between students and teachers. Although the study only involved 10 students and two teachers, it is already valuable in generating insights about the social dynamics of students in physical learning spaces for both practical and research purposes.

The studies mentioned above have been limited to providing either descriptive, cohort-level, or individual-level insights about a few students and teachers in a small and confined leaning space or many students but for a short period of time. None of these works examined both the social participation at a cohort level (e.g. of a class) and interactions between individuals. As far as we know, and from a recent systematic literature review [10], the work we present in this paper is the first in exploring both cohort-level and individual-level metrics from the physical positioning traces of over 100 students and teachers in an authentic primary school engaged in multiple learning activities and making use of various learning spaces for an extended period. Through this study, we explore the potential of physical positioning traces in generating fine-grained insights about the different aspects of the social dynamics in physical learning spaces.

3 EDUCATIONAL CONTEXT AND METHODS

3.1 The Learning Space and Context

The study took place in an Australian primary school. The building is an open area with movable furniture to allow teachers and students to tailor the space according to their needs. Although there are no walls, the site has been divided into different learning spaces (see Figure 1, left and right). Six regular school subjects (namely Maths, Reading, Spelling, English, Writing, and Inquire) are taught within the building area. Other subjects, such as Physical Education and Sports were excluded as they occur outside of the tracking area. The pedagogical approach of the subjects Reading, Inquire, and English commonly involved instructed group-based activities. For the other four subjects, students could choose to study in their preferred format (individually or in groups). Students were organised by their teachers into four different groups for all subjects. In Reading and Maths, this allocation was based on students' *prior attainment* in their previous term, where Group 1 represented students who had attained the highest level in Reading or Math and Group 4 was for students with the lowest. For other subjects the groups were formed randomly. In all subjects, one teacher was assigned to each group but students could interact with students from other groups at anytime during a session.

The study received ethics approval by Monash University and the Department of Education and Training of the State of Victoria in Australia. Parents provided written consent for their children's participation. A total of 98 Year-6 students participated in the study and were assigned a wristband tag (see details in the next subsection). The six educators (four full-time teachers, one aide, and one part-time teacher) involved in the delivery of the subjects also participated in the study and each wore a card tag.

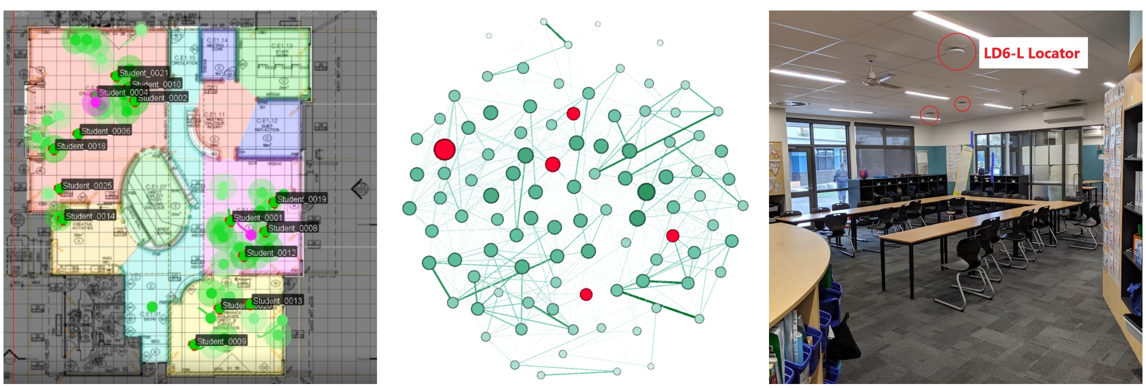


Fig. 1. Left - The learning spaces and illustration of the tracking system where the green/purple dots represent students/teachers, and the green/purple lines represent student/teacher movement. Middle - Example of a full social network of students in the reading lesson on 22/07/2019, from 10:00am to 11:00am (the red/green nodes represent teachers/students). Nodes with higher degree centrality are bigger in size and darker in color. Edges with higher weights (interaction time between two nodes) are thicker and darker. Right - One of the learning spaces in the tracked learning environment (LD6-L locators installed on the ceiling).

3.2 Apparatus and Data Collection

A total of 14 Quuppa LD6-L locators were placed at various locations of the spaces to record students' and teachers' x-y indoor positions (Figure 1, right). Each participant was assigned with a BLE (Bluetooth Low Energy) tag, a Tatwah

Mango BLE-WB200 wristband for students and a Jeewey JW-C1809C card tag for the teachers, that uses Bluetooth 5.0 or later technology (details of the devices are available at [37]). Teachers in the study kept a register of the wristbands and distributed them to students at the beginning of every school day and collected them back at the end of the day. In situations where students lost their wristband, teachers replaced the lost wristband with a new one and updated the register of that student. Positioning data were collected every day for eight weeks from July 22 to September 13, 2019.

Each locator sampled positions at a 5Hz rate using the Angle-of-Arrive method to determining locations, with a latency of 20ms and an accuracy of 200mm. The student position was only recorded if they were located within the tracking area (shown in Figure 1, left). Each data point consisted of the timestamp, the tracking identifier, and *x*-*y* coordinates with reference to the learning environment's floor-plan in meters (e.g., 22/07/2019 9:38:24.000, Student0001, 5.3775, 17.645). A total of approximately 172.63 million data points were collected. Positioning data points were then averaged to one data point per second for each tracker for normalisation purposes. Data corresponding to the six subjects were selected for analysis based on the school timetable. Data captured during breaks and subjects delivered outside the tracking area (e.g. Sports) were not considered. After screening out the days for empty data (sessions that occurred outside of the tracking spaces) and days with unusually low attendance (less than 50% attendance), a total of 35 maths, 23 reading, 14 inquiry, 14 spelling, 8 writing, and 7 English sessions were considered in the following sections for analysis. The duration of these sessions varied between 30 minutes to one hour.

3.3 Research questions

To identify the kind of insights that can be extracted from physical positioning traces, we proposed two exploratory **R**esearch **Q**uestions (RQs). These questions serve the purpose of guiding the exploration of the longitudinal positioning dataset, and identifying the potential value of physical positioning data to address higher-level educational questions:

(1) *RQ1. To what extent can differences in students' social interaction across school subjects be extracted from digital traces of spatial behaviours in the learning environment?* The purpose of this question is to explore social interaction at a *cohort-level* by i) identifying how the pedagogical approaches favoured by each subject resulted in the emergency of social interactions; ii) examining variations and the temporality of social interactions across school subject; and iii) identifying homophilic social interactions based on students' gender (across subjects) and level of attainment (in Maths and Reading).

(2) *RQ2. To what extent is it possible to characterise the social interactions of individual students based on the digital traces of their spatial behaviours?* This question aims at exploring social interactions at an *individual-level* by i) clustering students based on how long they interacted with peers over time, ii) examining changes in the composition of strong and weak ties across different clusters; and iii) investigating potential cases of students becoming socially isolated.

3.4 Modelling from Positioning Data to Interactions and Social Ties

The modelling from raw x-y positioning data to social interactions and potential social ties was performed in four steps:

1) *Interpolation.* Positioning tracking often suffers from missing values due to occlusion or detachment of trackers [15]. Therefore, linear interpolation was used to fill in any missing values between two valid data points, and with a limit of 60 consecutive missing values [29]. For a meaningful attendance, students' positioning must not be missing for more than ten minutes; otherwise, they are excluded from the analysis for that session since it most likely meant that the student did not come to session and their tracker was put away or they were outside of the tracking area during the period, and therefore not attending the session.

2) *Inter-personal distances.* Euclidean distances between each positioning tag were calculated at a one-second frequency to extract interpersonal distances among all teachers and students present in the learning environment. This involved calculating distances for all the paired combinations of students' and teachers' positions every second.

3) *Proximity threshold.* Hall's seminal work [21] proposed four different proximity categories: intimate (0 – 0.46 m), personal (0.46 – 1.22 m), social (1.22 – 2.10 m), and public (2.10 m and above). A recent study showed that, although these exact distances vary across cultures, most interpersonal interactions with acquaintances (or as in this study, a classmate or a teacher) tend to occur within 1.5m [44]. In particular, personal distance is the preferred distance where the majority of intensive and delicate interpersonal transactions occurs. However, no clear proximity rules have been established for school children sharing the same learning space. Therefore, based on the findings by Sorokowska et al. [44], and the proximity values used in previous educational studies [9, 31], the current study adjusted the personal (0.46 – 1.00 m) and social distances (1.00 – 2.10 m), respectively.

4) *Identifying potential interaction.* Thus, a student was classified as potentially interacting with another student or a teacher when two conditions were met. First, the two trackers were within personal distance or a one-meter proximity from each other and, second, the interaction lasted for more than ten consecutive seconds. This ten-second rule was implemented to differentiate student interactions from instances of unintended collocation, for example, while two students were passing by each other or a teacher is walking around supervising students [18].

3.5 Cohort-level metrics – RQ1

SNA was used to explore the dynamics of student interactions as network metrics have previously proven effective in quantifying social interaction in other educational contexts [19, 35]. Social interaction data were used to construct social networks for each sessions (e.g. see illustrative example in Figure 1, middle) related to each school subject to extract cohort-level metrics. A social network derived from the physical positioning data modelled, as detailed in the previous subsection, is undirected as the direction of the potential social interaction remains unknown from positioning data [9, 42]. Within the social network, a *node* represents a student or a teacher who can be connected to other individuals. If a social interaction occurred between two nodes, an *edge* is drawn to connect them. We defined the *weights* of these edges as the duration of the social interaction between two nodes.

From these social networks, which are hard to visually analyse because they are numerous and contain several nodes (as shown in Figure 1, middle), we extracted cohort-level metrics about the social dynamics of particular sessions. The rationale for considering these cohort-level metrics is the following:

Dyadic interaction. This social network metric has been used to model the extent of interaction between pairs of students in a cohort by calculating the number of edges in a network [19]. Sessions with more edges would suggest that students interacted with more peers or teachers for that session. Dyadic interactions have been found to correlate with students' academic performance, especially in linguistic and language subjects [47, 49].

Triadic interaction. The number of complete triads in a network would capture the triadic interactions within a subject. Complete triads exist when three nodes are interconnected with each other. The number of triadic interactions could potentially relate to students' preference for group learning in a subject [19].

Group cohesion. We also extracted the network density of each session as a measure of the cohesion of the cohort of students in the learning spaces. The network density measures the connectivity of the network, which is calculated as the proportion of connections present in a network over all possible connections. In a network with high density, students are more connected with each other and are likely to participate in group learning [8].

Homophily. The homophily of student social interaction refers to the extent to which students interact with others who share similar attributes with them. Prior work has revealed trends in terms of gender and academic performance homophily in student interactions [35, 45]. This feature of social interaction is captured by the assortativity coefficient, which measures the correlation between attributes of adjacent nodes [34]. We calculated assortativity coefficients based on gender, for all six subjects; and level of attainment, for the two subjects in which teachers used this to group students (Maths and Reading). These values ranged from -1 to 1, where a value of 1 (higher assortativity) indicates a tendency of social interaction occurring between individuals who share similar attributes; and -1 (lower assortativity) indicates more social interaction between individuals with different attributes. A score of zero would indicate no correlation between the occurrence of social interaction and individuals' attributes.

To explore the first research question, the median and interquartile range (IQR) values of these metrics were reported. For each of the first three metrics, we performed 15 Mann-Whitney U tests to compare the differences in metric distribution across subjects. A total of 45 comparisons were made. Due to multiple comparisons, we adjusted the significance threshold (alpha) using the Bonferroni correction method with the initial alpha value equal to 0.05. From these comparisons, we presented the similarity and differences between subjects based on the number of dyadic interaction, triadic interaction, and network density, respectively. We also present resulting gender assortativity coefficients for each subject and the attainment assortativity coefficients for Reading and Maths.

3.6 Individual-level metrics – RQ2

Individually, we were interested in exploring the development of students' social ties over time. This can be valuable to educational practitioners and researchers because it can enable the identification of students who are becoming less socially active in the physical learning environment. This can put students potentially at the risk of experiencing social issues or impaired academic performance [33]. The rationale for these individual-level metrics is the following:

3.6.1 Clustering student social interaction. Instead of presenting the descriptive data of each teacher or student, we clustered student social behaviours into different categories based on the development of their weighted degree centrality over time. The weighted degree of centrality corresponds to the total time a student has interacted with all other students or teachers in the learning spaces. To achieve this, we first extracted the weighted degree centrality for each student, and then performed cluster analysis on these centrality data. Data for the Reading sessions were chosen for the analysis because this subject involved group activities as part of instruction, and thus, provided context for interpreting the results as collaboration was expected to happen.

Clustering analysis was performed to group students based on the patterns of change in their weighted degree centrality across the 8 weeks. First, we segmented the 23 reading sessions that happened during the eight weeks into four quadrants (Q1 – Q4), each containing six consecutive sessions over a fortnight, except the fourth quadrant with only five sessions. For example, Q1 includes sessions 1–6, and Q2 includes sessions 7–13, and so on. This segmentation enabled capturing how students' social interaction developed over the eight weeks while facilitating interpretation, as it will be demonstrated in the next section [29]. Second, we calculated each students' average weighted degree centrality for each quadrant, resulting in four features for the clustering analysis. Third, we conducted K-means cluster analysis for the students based on their average weighted degree centrality in each of the four quadrants. Lastly, we identified the optimum number of student clusters by plotting the proportion of explained variance against the number of clusters and choosing the number for which changes in the explained variance were small (i.e. using the elbow method).

3.6.2 Ego network and changes in social ties. In addition to characterising students' social interaction into different clusters, we are also interested in personalised insights from individual spatial behaviours of each student, especially those who demonstrated a decline in the duration and number of potential social interactions. These insights could assist teachers and researchers for them to further investigate potential reasons behind students' behaviours. To this end, individual students' ego networks were explored. The ego network of an individual (the ego) contains all other individuals (alters) who are directly connected to the ego, as well as the linkages between the alters. These connections can point at the potential emergence of *social ties* because the current study occurred over 8-weeks, and thus, the ego and alters are likely to form social ties with each other.

The direct relationships between the ego and the alters are particularly interesting as these directly connected individuals could provide valuable insights for unpacking the development of students' social ties over time. For example, the strength of social ties can be classified into strong or weak, where strong ties represent frequent interactions with close friends and weak ties represent infrequent interactions with acquaintances or strangers [17].

To investigate this, we differentiated the strength of students' social ties based on the duration of social interaction. For each session, interactions shorter than five minutes were classified as weak ties, and those longer than five minutes were classified as strong ties. This threshold was chosen as a heuristic that enabled the discrimination of casual, short physical contacts from long co-presence in the same physical area. The changes in the composition of strong and weak ties were assessed for students in each cluster. We also presented a case of a single student within the decline group to illustrate the potential personalised insights that can be extracted to identify potential cases of growing social isolation.

4 RESULTS

4.1 Cohort-level insights – RQ1

4.1.1 Differences across school subjects. The sample distribution of network density, the number of edges, and complete triads for each subject are shown in Figure 2. Substantial differences with large effect sizes between the social interaction in four subjects were observed. The edges were significantly more numerous in Reading and English than in Maths ($U = 52$, $p < 0.001$, $r = 0.87$; $U = 33$, $p = 0.001$, $r = 0.73$) and Spelling ($U = 23$, $p < 0.001$, $r = 0.86$; $U = 11$, $p = 0.003$, $r = 0.78$). Complete triads were also significantly more numerous in Reading and English than Maths ($U = 52$, $p < 0.001$, $r = 0.87$; $U = 31$, $p = 0.001$, $r = 0.75$) and Spelling ($U = 4$, $p < 0.001$, $r = 0.98$; $U = 10$, $p = 0.002$, $r = 0.80$). Similarly, the network densities were significantly higher in Reading and English than Maths ($U = 38$, $p < 0.001$, $r = 0.91$; $U = 36$, $p = 0.002$, $r = 0.71$) and Spelling ($U = 19$, $p < 0.001$, $r = 0.88$; $U = 14$, $p = 0.005$, $r = 0.71$).

The finding related to the more numerous edges in Reading and English sessions can be indicative of more students being closely collocated with another students or the teacher. Yet, the presence of more triads would further suggest that these collocations were manifested in the form of triadic interactions or larger small groups working together. The higher network density would also indicate that students tended to congregate more cohesively while in Reading and English compared to Maths and Spelling. These differences can potentially be explained by the characteristics of the pedagogical approaches that distinguish each subject. For example, both English and Reading sessions in this school contained more instructed group-based activities, whereas no such activities were explicitly instructed in Maths and Spelling. In contrast, students were encouraged to work independently in Maths and Spelling as these subjects involved more independent problem-solving tasks.

4.1.2 Patterns within subjects. Within each subject, there was a wide-spread distribution in the number of edges, complete triads, and network density across sessions over the eight weeks. In this section, we closely analyse these variations for Reading and Maths as the difference in pedagogical approaches for these was explicit (favouring group and individual tasks, respectively). As shown in Figure 3 (left), in Reading, the metrics seem to follow an oscillation

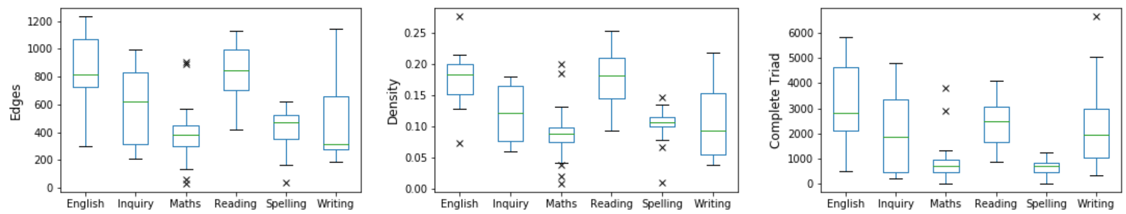


Fig. 2. Boxplots showing the number of edges (left), density (middle), and complete triad (right) in each subjects. The *y-axis* represents the corresponding values. The *x-axis* represents the six school subjects, and the cross represents outliers.

pattern with a frequency of three sessions per oscillation (two consecutive sessions with high values, followed by one lesson with low value). Interestingly, the majority of the local troughs and peaks in potential social interactions occurred on Mondays and Thursdays, respectively. Thus, this oscillation pattern could potentially reflect the instructional design within a subject with group tasks regularly scheduled later in the week. For example, Reading sessions on Mondays involved primarily individual activities, such as writing a book review or reflection, and sessions on Thursday involved discussions. Whereas, no such pattern was observed in Maths, suggesting a less structured pedagogy in terms of group activities but also confirming the lower levels of social interactions. Instead, the pedagogy for Maths seems to be more event-based; for example, the global peak around the 30th of August, 2019, could potentially reflect a more group-orientated pedagogy was implemented on that day.

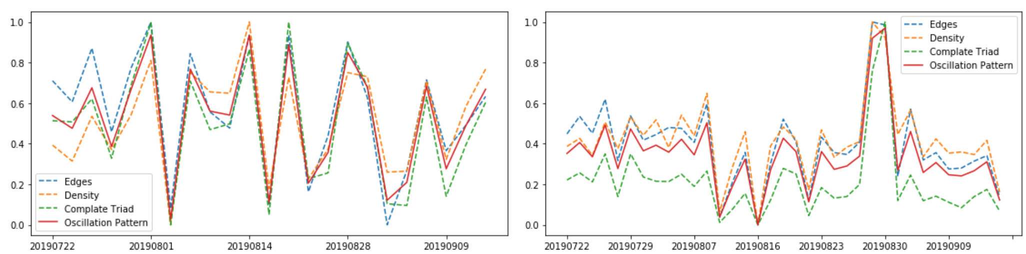


Fig. 3. Changes in edges, density, and complete triads over time in Reading (left) and Maths (right), where the *x-axis* represents the date, and the *y-axis* represents the normalised value ranging between 0 and 1. Colours and line types represent different metrics.

4.1.3 Homophily of student interaction. The homophily of student interaction based on gender and prior attainment are shown in Figure 4. In terms of student gender, the positive assortativity coefficients for English, Inquiry, Maths, Reading, and Spelling suggest a small-to-moderate tendency of same-gender social interactions occurring in these subjects. Whereas, for Writing, there was random mixing of social interaction between male and female students. On the other hand, the assortativity coefficients based on prior attainment in Reading and Maths are distributed around a value of zero. This is a surprising finding because it suggests that the social interactions in these two subjects were not related to prior attainment even though students were assigned to groups based on this attribute (and thus, values closer to 1 were expected). A potential explanation is that the open nature of the learning spaces allows students to move around freely during sessions and initiate a greater variety of social interactions with whom they desire, despite the teachers' ability-based grouping strategy.

4.2 Individual-level insights – RQ2

4.2.1 Clusters of social interaction patterns. A total of 90 students were included in the clustering analysis for the Reading sessions, after removing students who were entirely absent for any one of the quadrants. We identified four

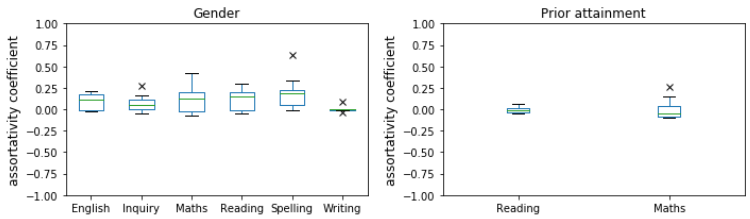
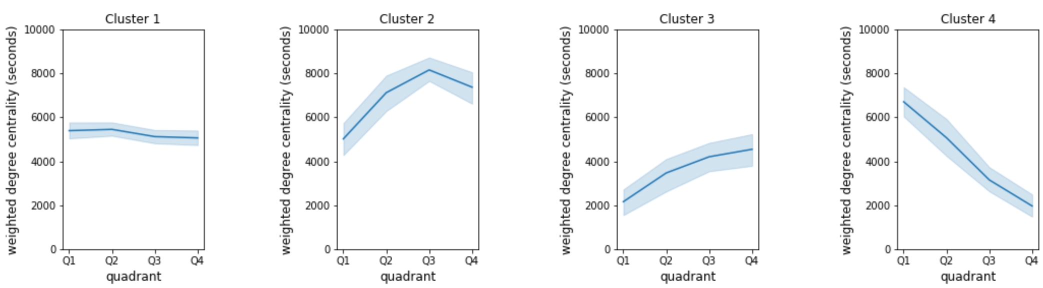


Fig. 4. Homophily of student interaction based on student gender in all six subject (left) and prior attainment in Reading and Maths (right). The *x-axis* represents the subjects, and the *y-axis* represents the assortativity coefficient ranging between -1 and 1.

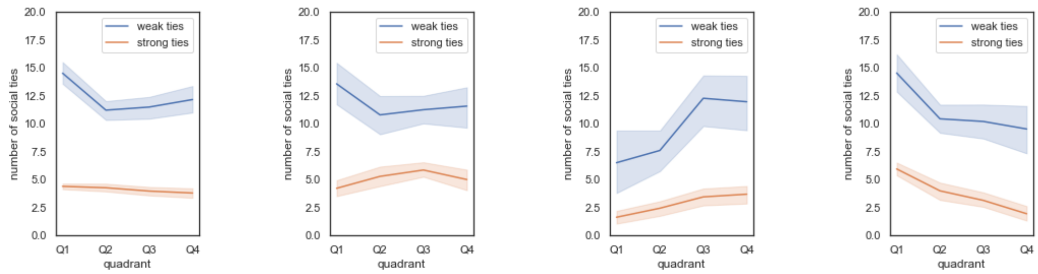
different clusters. Figure 5 shows the extents of detected social interaction of students in each cluster across the temporal quadrants (Q1-4). Forty-nine students were categorised into Cluster 1 (Figure 5a) labelled as 'consistent' students. These students maintained a consistently high level of social interaction over the eight weeks. Cluster 2 contained 17 students labelled as 'advance' students, whose social interaction was initially around the same as the consistent students but advanced to higher levels of social interactions over time (see peak in Q3 in Figure 5b). Twelve students belonged to Cluster 3 labelled as students who 'improved'. These students showed low-levels of social interaction in Q1 but may have gradually become more social over time (Figure 5c). Cluster 4 also contained 12 students, who were labelled as 'decline'. These students were the only group whose social interaction declined over time. Students were initially the highest in the duration of social interaction but dropped to the lowest by the end of week 8 (see drop from Q1 to Q4 in Figure 5d). This later cluster could be further inspected by teachers to investigate potential cases of social decline. We provide a further analysis of these clusters and individual cases below.



(a) consistent (b) advance (c) improve (d) decline

Fig. 5. The patterns of change in social interaction for the four clusters of students in reading sessions. The y-axis represents weighted degree centrality, and the x-axis represents four quadrants. The blue lines represent the mean duration of social interaction in a cluster and the shaded areas represent the 95% CI.

4.2.2 Changes in strong and weak ties. As shown in Figure 6, the composition of strong and weak ties varied between students in each cluster. For *consistent* students, the number of strong ties remained around 3.5–4 ties over time, whereas, the number of weak ties was reduced. The *advance* students also showed a decrease in weak ties and an increase in strong ties are similar to the patterns of change in their weighted degree centrality. The students in the cluster *improve* demonstrated growth in both strong and weak ties, which is in line with their upward movement in social interaction. On the other hand, the *decline* students showed substantial drops in both strong and weak ties. From these observations, it is clear that the temporality of strong ties shared identical patterns with students' weighted degree centrality (Figure 5), whereas, changes in weak ties have large variance and contains more inconsistency. Thus, the changes in students' strong ties, instead of weak ties, might contain additional insights about the temporality of their social interactions.



(a) consistent (b) advance (c) improve (d) decline

Fig. 6. Changes in the composition of strong and weak ties for students in the four clusters. The y-axis represents the number of social ties, and the x-axis represents four quadrants each contains the average of 6 sessions, except Q4 which contains the average of 5 sessions. The blue/orange lines represent weak/strong ties and the shaded areas represent the 95% CI.

4.2.3 Potential social isolation: the case of Student 98. In addition to breaking down the composition of strong and weak ties, we can also investigate suspicious cases of students becoming socially isolated. In this subsection we illustrate the case of Student 98, in cluster 4, who had the lowest average social interaction although she attended all the reading sessions. A critical window was identified in Figure 7 (left), where Student 98's social interaction suddenly dropped after the 14th of August 2019 and remained considerably lower than the class average, except for a local peak. Unfortunately, this local peak only lasted for one day. On this day, Student 98 was interacting with a different set of students. This substantial change could potentially signal that Student 98 had encountered peer-related issues and withdrawn from group activities, which was problematic as the Reading sessions were group-oriented. Thus, to better understand the descent, we investigated the variation in social ties before (22/07/2019 – 14/08/2019) and after the descent (19/08/2019 – 12/09/2019), excluding the day of the local peak (29/08/2019). Each period contained 11 reading sessions.

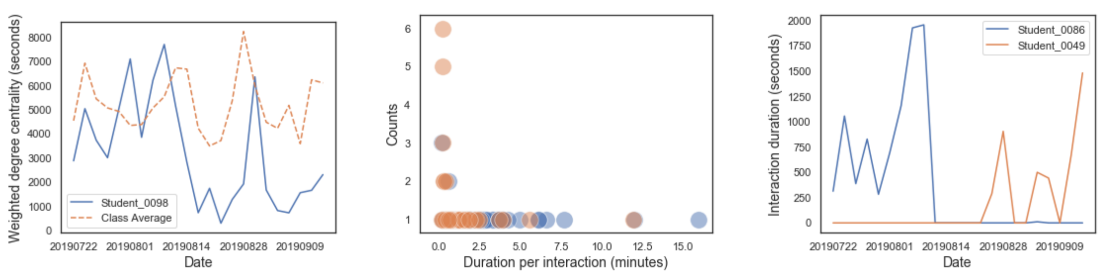


Fig. 7. Left - Changes in the weighted degree centrality for Student 98 and the class average in reading sessions over the eight week. Middle - Weighted degree distribution of Student 98's ego networks, where blue and orange dots represent social ties before and after the descent, respectively. Right - Change in the amount of time (*y-axis*; seconds) Student 98 interacted with Student 86 (blue line) and Student 49 (orange line) over the eight weeks.

Before the descent, Student 98 had six strong ties and 74 weak ties; however, afterwards, these numbers dropped to two strong ties and 54 weak ties (Figure 7, middle). All the prior strong ties either became weak ties or disappeared. This change is particularly visible when contrasting the strongest tie before and after. Student 98 had the strongest tie with Student 86 but this tie disappeared after the descent, and a novel strong tie with Student 49 was formed. It is clear that the interaction between Student 98 and Student 86 suddenly had ended on the 8th of August, 2019, and did not reemerge afterwards (Figure 7, right). The only exception was the 11 seconds on the 4th of September 2019 and this was more likely to be an instance of unintended collocation, instead of meaningful interaction. Whereas, Student

98 had never interacted with Student 49 until after the ceased interaction with Student 86. A possible explanation for this abnormal event is that potential problems may have occurred between Student 98 and Student 89. These results signalled the necessity for teachers to investigate, especially if the low level of social interaction persisted in Student 98. Consequently, Student 86 and Student 49 would be the valuable individuals for teachers to contact when trying to understand the social issues surrounding Student 98 (see Section 5.2 for the discussion about ethical implications).

5 DISCUSSION

5.1 Discussion against research questions

Here, we illustrated the different types of metrics about students' in-class social interaction that can be extracted from their physical positioning traces at both cohort and individual levels. These metrics could potentially augment teacher's ability to comprehend in-class social dynamics from multiple aspects and open up potential research opportunities.

Cohort-level metrics can provide the opportunity for teachers to assess and compare their pedagogical approaches or learning designs. This could be particularly valuable for teachers in primary and middle schools, who are responsible for designing different instructional activities for many school subjects. Such tasks are already mentally exhausting, and assessing students' reactions to in-class activities across various subjects is almost impossible to accomplish manually [42]. Thus, if the cohort-level metrics are made available to teachers, they can use these insights to assess to what extent their teaching strategies promote social interactions and adjust their instructional designs accordingly. For example, if teachers in our targeted school decide to include more group activities in Maths, they could use cohort-level metrics to assess whether this inclusion had lead to more student social interactions in the learning spaces. A substantial increase in dyadic interaction, triadic interaction, and network density (like the global peak in Figure 3, right) after implementation could imply that the group activities might be considered effective in encouraging more student interactions.

Likewise, educational researchers may also benefit from cohort-level metrics to investigate the effectiveness of different pedagogies in the physical classroom. For example, the long debate of homogeneous versus heterogeneous grouping and their effects on student achievement can be investigated by combining insights about the homophily of student interaction with academic performance data [43]. This combination would reduce the recall errors and observer bias that are problematic in traditional survey and observational studies [39].

Individual-level metrics can empower teachers with personalised insights about each student. These insights can help teachers to identify students who might need additional help [9]. Within these students, the non-intrusive and automatic positioning tracking system would also allow the on-going monitoring of student social interactions. Thus, teachers may be able to identify sudden changes and perform timely investigation and intervention. Moreover, having access to information about individual students' ego network could better direct teachers in understanding the problems a student is experiencing. For example, the strong ties in an ego network are students who teachers or support staff can approach for more in-depth information about the situation of a troubled student. Similarly, the individual metrics can also be used for teachers to monitor how new students are integrated into the class after their move (e.g., a new student joins a class after all other students already know each other). Nevertheless, these proposed possibilities in educational practise require further, preferably, qualitative studies with teachers, to validate their feasibility.

Individual-level metrics can also enable educational researchers to include additional measures into their studies. For example, instead of measuring social interaction based on students' self-reports, researchers can now quantify student social interaction with the precise duration based on positioning traces. This new information would open up the possibility of exploring classroom social dynamics with greater precision and depth. In particular, the comparison between student social behaviours in newly formed classes and classes that are already established can be made possible through analysis patterns of change in students' individual-level metrics. These kinds of questions are important, especially during school transition (e.g. from primary to secondary school) when maladaptation is likely to occur [2].

5.2 Limitations and future work

Applying these cohort and individual level insights in practice comes with a major limitation. Notably, proximity-based identification is at most an estimation of the actual amount of social interaction in the learning spaces. This identification method is often criticised for falsely identifying nonreciprocal and unintended relationships from close proximity as meaningful relationships, especially in situations where most individuals are strangers [18]. In the current study, this limitation is less of an issue since students were in the same learning spaces for an extended period, and thus, were more likely to know each other. However, in newly formed classes, students' social dynamics can be quite different in comparison to the dynamics after several weeks or months when students have become familiar with each other. Thus, future work can focus on identifying social interaction in newly formed classes through qualitative validation studies to assess the extent and types of social interactions that can be accurately captured by physical positioning traces.

Ethical implications involve the dilemma between the potential risk of making decisions based on incomplete data and the increased risk of unintended surveillance from multiple data sources. Insights from position tracking data alone are insufficient to make factual and confident claims. Instead, these positioning data and associated metrics could provide guidance for teachers and educational stakeholders to investigate potential issues such as students becoming increasingly isolated, learning designs that do not promote interaction, teachers unintentionally approaching just a reduced number of students or new students struggling in forming social ties. In any case, more contextual information is needed to interpret these data. For example, the suddenly ended relationship between Student 98 and Student 86 could be the result of teachers reassigning students into different groups. In that case, the descent in Student 98's social interaction would reflect changes in teaching strategies, instead of social issues. In practical applications, teachers' observation can provide more contextual knowledge when interpreting the insights.

For potential research purpose, it is necessary to incorporate other sources of data with physical positioning traces. Perhaps, combining it with eye-tracking, motion sensor, other forms of visual and audio data, or ethnographic field notes. This multimodal learning analytics approach could increase the validity of the insights generated from physical data and help to triangulate students' actual social behaviours while maintaining the advantage of automation [28]. With multimodal data, future work could also try to aim at distinguishing constructive from destructive interactions by modelling students' emotions through facial, body language, and physiological data. However, with this approach, the potential ethical and privacy issues of unintended surveillance arise, since the de-identification of students become much difficult to achieve with multiple data sources [42]. Thus, future studies need to address the potential ethical implications of embedding more data sources while trying to enrich the level of insights and accuracy that can be made on students' in-class social interactions.

Categorising students and labelling them as socially isolated could establish grounds for discrimination and lower both students' self-esteem and teachers' expectations [22]. Therefore, training teachers to handle and use the insights confidentially and ethically is also essential. Especially, ensuring that teachers are adopting the principles from inclusive pedagogy for all students [13]. Besides, neither teachers should be using these insights to assess students' learning performance, nor school management should use it to evaluate teachers' performance.

6 CONCLUSION

The increase in the complexity of the physical learning spaces will likely continue as more novel technologies, and architectural approaches become available. Meanwhile, technology-empowered tools should be made available for teachers to deal with this increased complexity and assist the reflection on pedagogy. We demonstrated the potential of using students' physical positioning data from wearable tracking sensors to generate insights about students' in-class social dynamics on both individual and cohort levels. These insights have potential implications in assisting teachers in reflecting on their pedagogical design and identifying suspicious cases of students becoming socially isolated. Educational researchers can also use these insights to conduct in-depth investigations on classroom social dynamics and compare the effectiveness of different pedagogies. Our work contributes to the growing literature on physical and multimodal learning analytics, which are both marching toward the goal of empowering teachers with insights about teaching and learning phenomena in physical spaces. For future research, we will continue exploring how to model positioning data to understand key social aspects of the physical learning spaces, with more variety of data sources (e.g. body rotation data and systematic observations) and sample populations (e.g. higher education settings).

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