Classroom Analytics: Telling Stories about Learning Spaces using Sensor Data

Roberto Martínez-Maldonado, Lixiang Yan, Joanne Deppeler, Michael Phillips and Dragan Gašević

Abstract The increasing use of interactive devices and networked technologies is blurring the boundaries of the physical classroom by enabling learners and teachers to connect with digital content, systems and people located elsewhere. An underexplored opportunity enabled by emerging sensors and classroom technologies is that multimodal data traces of physical classroom activity can be automatically captured and rendered visible with the purpose of supporting teaching and learning. Positioning and proximity sensor data can be used i) to generate a deeper understanding of embodied aspects of learning and spatial aspects of instruction, and ii) to provide evidence that enable assessment of effectiveness of the design of physical spaces in education. This chapter presents three data stories that illustrate potential emerging contributions of multimodal classroom analytics to enable new ways to study the teaching and learning processes that unfold in physical learning spaces. Through these stories, we illustrate how analytics for classroom *proxemics* can enable: i) the creation of interfaces that provide feedback to learners and educators about activity in the physical classroom; ii) new ways to assess pedagogical activity in learning spaces to inform space re-design or co-configuration; and iii) new approaches to speed up analysis cycles that currently depend on classroom observations.

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1 Introduction

The technologies that support ubiquitous computing (e.g., the Internet, microprocessors, mobile protocols and affordable portable computing devices) are now enabling hybrid learning experiences to be designed for both physical and online spaces (Singh & Thurman, 2019). On the one hand, the increasing use of interactive devices and improvements in networked technologies are blurring the boundaries of the physical learning space by allowing teachers and learners to connect with digital content, systems and people located elsewhere (Kohls, 2017; Cohen et al., 2020). On the other hand, learning experiences are no longer confined to unfold in a particular physical place (e.g., the classroom or the laboratory). Instead, on-site and synchronous/asynchronous online learning tasks are being combined and blended, to various extents, often with the purpose of redistributing the study activity in space and time (Ellis & Goodyear, 2016). Yet, an underexplored opportunity enabled by emerging sensors and computer vision technologies is that digital data traces of the spatial behaviours of teachers and learners can now be automatically captured and rendered visible for the purpose of supporting teaching and learning (Pishtari et al., 2020; Chua et al., 2019), and space re-design (Waber et al., 2014).

Understanding how spatial behaviours in the physical learning space can influence learning is critical. Previous research has found that teachers' positioning in the classroom and proximity to students can strongly shape aspects such as students' motivation (Fernandes et al., 2011), disruptive behaviour (Gunter et al., 1995), self-efficacy (Koh & Frick, 2009), and engagement (Chin et al., 2017). Moreover, social interactions of learners with their peers in the physical learning space are associated with enhanced levels of emotional well-being (Montague & Rinaldi, 2001) and increased learning performance (Gašević et al., 2013) and are essential for developing 21st-century skills (Bell, 2010).

Evidence about such spatial behaviours, and how the physical learning space is actually used, is fragmented across various research areas (Ellis & Goodyear, 2016; McArthur, 2015) and rarely reaches educational decision makers and the designers of those spaces. The term proxemics has often been used to refer to the study of the maintenance of specific zones in physical spaces that people perceive as meaningful according to their culture (Danesi, 2006). Although proxemics has provided a theoretical lens to study classroom activity, measuring social interactions in physical learning spaces is often difficult in practice, as it commonly relies on direct observations (Hurst et al., 2013) and interviews (Ryser et al., 2009), which are hard to scale up and are susceptible to bias. This all makes it hard for educators, indoor designers, furniture providers and other educational decision makers to make informed decisions regarding the design and re-design of physical learning spaces to maximise the opportunities to improve teaching and learning.

This chapter focuses on the timely opportunity to use emerging, inexpensive positioning technology to generate evidence about the activity of teachers and learners unfolding in **physical learning spaces that are becoming increasingly hybrid. The chapter discusses a facet of hybridity that is yet to be deeply explored: how can *digital* traces automatically captured from the physical learning space be used to**

make commonly ephemeral *face-to-face* teaching and learning practices available for automated computational analysis. We particularly discuss the potential of bringing learning analytics innovations into physical classroom spaces to inform pedagogical practice, space design, and design for learning. The term *Classroom Analytics* is used as a lens to connect proxemics, pedagogy, data and space design. We describe three short data stories that illustrate how analytics for classroom proxemics can enable: i) the creation of interfaces that provide **digital forms of feedback** to educators about activity in the physical classroom; ii) new ways to assess pedagogical activity in **hybrid** learning spaces that can be used to inform space re-design or co-configuration; and iii) new approaches to analyse learners' activity in **hybrid** learning spaces that cannot be easily accomplished through observations.

2 Proxemics, data, spatial pedagogy and space design

The body of work focused on the study of how teachers and students use the classroom space can be referred to as *classroom proxemics* (Martinez-Maldonado, Schulte, et al., 2020). Foundational work on proxemics defined the cultural expectations of interpersonal distances (Hall, 1966), that is, the physical distance that individuals choose to maintain between themselves and others while interacting. By focusing on teachers, McArthur (2008) suggested the need for thoroughly investigating how the classroom design influences student and teacher perceptions of learning, spatial behaviours, interpersonal distances and practices in the physical learning environment. For example, some institutional architecture provides an optimal environment for teacher-centric practices. This is the case of lecture rooms, originally designed back in the 19th century (Barnard, 1854), that promote linear seat arrangements to maximise a teacher's monitoring and control, and students' attention directed towards the teacher. It is also the case of novel architectural approaches, such as open learning spaces (Reh et al., 2011) and flexible classrooms (Neill & Etheridge, 2008), which are challenging teacher-centric pedagogical practices by promoting flexibility, movement, integration, and student agency and choice.

The notion of proxemics has also provided a theoretical lens to investigate the impact of architectural design and the use of the space on classroom dynamics. Eberts & Lepper (1975) analysed how preschool children can be characterised by their spatial behaviours in the classroom and other school spaces. Jones & Aiello (1973) investigated variations in the interpretation of interpersonal distances according children's age and their cultural backgrounds in a primary school. Cardellino et al. (2017) studied the impact of interpersonal distances and the spatial configuration of the classroom on the number of students receiving high-quality visual attention from the teacher in the context of primary education. Similar studies have been conducted in the context of higher-education, for example, to investigate how teachers utilise the classroom space based on their individual characteristics or the learning tasks being enacted. In fact, this has been the focus of contemporary research, termed as Spatial Pedagogy (Lim et al., 2012) or Instructional Proxemics (McArthur, 2008; Chin et

al., 2017), seeking to understand the meanings of certain areas of the classroom according to the spatial positioning of teachers in relation to students, and digital or material resources.

In sum, the research described above shows the sustained interest in understanding how teachers' and students' positioning in physical learning spaces, across all educational levels (i.e., from K12 to university) can impact learning. However, most analysis approaches have been based on self-reported rubrics, and observations made on a small number of classes. This has limited the kind of studies that can be conducted to understand spatial behaviours in terms of scalability (i.e., only a limited number of classroom sessions can be observed) and precision of the distance measurements which are critical for analysing proxemics (i.e., interpersonal distances are commonly approximated by an observed or self-reported by students and teachers). In fact, McArthur (2015) explained that this is one of the reasons why empirical research investigating how the same learning design is enacted under similar conditions across various learning spaces is very limited. This motivates the need for automated tools that can support the collection of accurate positioning and proximity data that can facilitate the scalability of classroom proxemics studies.

3 Analytics for classroom proxemics

There has been a growing interest in using sensing technologies to automatically capture activity data in classrooms and other learning spaces. Conducting systematic classroom observations by trained experts is still the most comprehensive method to capture rich information to deeply understand classroom phenomena. Yet, in recent years, several researchers have demonstrated the potential of using automatically captured data to identify patterns that can be hard to see with the "naked eye". Automated video analysis has been one of common approaches to data capturing and analysis. Video-based solutions have been used to model fine grained physical behaviours such as students' posture, gaze (Raca et al., 2015), and gestures (Ahuja et al., 2019). Similarly, some teacher's behaviours, such as walking (Bosch et al., 2018) and interactions with students (Ahuja et al., 2019; Watanabe et al., 2018) in lecture-based classooms, have been automatically coded. Multiple synchronised cameras encircling the physical learning space have been used to identify approximate student locations and the types of social interactions and spatial behaviours of students in makerspaces (Chng et al., 2020) and secondary school contexts (Howard et al., 2018). However, these video-based technologies have not been used to provide precise positioning information that could be used to identify the exact positions of students and teachers in complex learning spaces (the only exception is the work by Chng et al. who used depth cameras to estimate interpersonal distances in a small makerspace). Moreover, at the moment, video-based solutions are still susceptible to occlusion and are therefore impractical to follow particular students over time.

For this reason, other researchers have been using alternative tracking technologies based on wearable micro-location technologies. Although teachers and learners

have to wear a small tracker or a mobile device, the precision of the positioning data that can be captured can be very accurate. For example, Wake et al. (2018) proposed the use of bluetooth-based beacon technology to collect data from firefighters during training sessions to identify patterns and provide feedback for improving their performance in future emergency situations. Riquelme et al. (2020) have used the same technology to track students' mobile phones in a library setting and investigated the emerging roles that students enacted while collaborating.

Several studies have focused on creating interfaces that can be used by teachers to interact with data collected through indoor-location technologies. For example, Echeverria et al. (2018) used ultra-wideband (UWB) radio sensors to investigate how nurses work in teams during high-stakes simulation-based learning tasks in the context of nursing education. The positioning and proximity data of students and their teacher were automatically analysed and the results were visualised and presented back to them to provoke reflection on spatial strategies. Saquib et al. (2018) developed a system called Sensei that relied on small positioning trackers embedded on student shoes and that was used to automatically track teacher and student spatial behaviours in Montessori primary schools. The positioning data was visualised and made available to teachers to augment their manual observations, design individualised tasks for each student, and identify potential interaction needs for particular students. An et al. (2018) also investigated ways in which positioning data could be shown back to teachers to gain awareness about classroom teaching behaviours such as how they distribute their time across the students. An et al. also summarised the amount of time a teacher has spent in close proximity to groups of students and displayed this information using lamps located at each group's table An et al. (2018) and heatmap visualisations An et al. (2020).

In sum, there is an emerging interest in using sensing technologies to study classroom proxemics. Indoor-positioning technologies are very rapidly becoming more accurate, inexpensive, and portable. The next section illustrates how some of these sensing technologies have been used to automatically capture salient aspects of teaching and learning activity in three authentic learning spaces.

4 Three illustrative data stories on classroom analytics

This section presents three data stories to illustrate the potential of analytics for classroom proxemics to support various aspects of teaching, learning and educational research. Each story presents the first-hand experiences that the authors of this chapter have developed for the purpose of enabling: i) the creation of interfaces that provide feedback to educators about activity in the physical classroom; ii) new ways to assess pedagogical activity in learning spaces to inform space re-design or re-configuration; and iii) new approaches to analyse activity in learning spaces that cannot be easily accomplished through direct observations.

4.1 Data Story 1: a teacher dashboard about spatial data

Educational context. This story unfolded in the context of an undergraduate course – Socially Responsive Design. The story focuses on three randomly chosen 3-hours tutorial classes (A, B and C) taught by the same educator in the same (8 x 10 meters) classroom, equipped with moveable tables, a projector and pinnable walls. Three very distinctive learning designs were enacted in each of these classes. Class A involved continuous small team design work. Class B was divided into two parts: i) group oral presentations in which each team, in turns, reported on their progress using the projector; and ii) team project meetings. Class C was also divided in two parts: i) poster presentations, in which each team, in turn, presented their design prototypes pinned to the walls and close to their table (2 hours); and ii) team project meetings (1 hour). Each team used the same table in each class. More details about and empirical results from the study in which this story unfolded have been reported in an expanded format elsewhere (Martinez-Maldonado, 2019).

Data and analytics. The *x-y* positions of the teacher were automatically tracked using the Pozyx.io UWB sensor system at 2Hz. The teacher wore a sensor by attaching it to her belt and additional sensors were located above each table, inside a casing, to automatically calculate the distance between the teacher and each team of students. Positioning data was presented to the teacher in two ways. A short debrief was conducted after classes in which the teacher was asked to reflect and comment on her spatial behaviours based on the visual representations of her data printed on paper. Additionally, a teacher's dashboard was made available during the classes through a personal computer located at the teacher's table (see Figure 1). The sensors on each team table and the one worn by the teacher were represented as hexagons and a blue circle, respectively. A heatmap (using a gradient from green to red) of the teacher's position was presented in the background of the dashboard, where a red colour represented areas in the classroom where the teacher remained for a longer time. Proximity data was used to estimate the time the teacher attended specific groups working at the tables (measured as whether the teacher was within a range of 2.5 meters (m) from the table sensor, considering the dimension of each table was 2x2m). The least attended tables that had not been attended in the last *t* minutes (*t* = 20 in our study) were highlighted in orange colour.

Data Story. Figure 2 presents three heatmap visual representations of the teacher spatial behaviours during classes A, B and C, which were presented to the teacher after the classes. For Class A the teacher mainly remained at the centre of the classroom (see Figure 2, left, point 1). This teacher explained that at the beginning of the class she was standing in the middle of the classroom giving instructions to all students. Based on the learning design followed in Class A, students were expected to work in teams without interacting with other teams. Thus, the teacher divided her time by visiting one team after the other. This is reflected by clusters of data points located in close proximity to each student table (see point 2).

In contrast, in Class B the teacher sat behind a table from the classroom which she set up as a desk, and listened to the student presentations from there during the first half of the class (see Figure 2, centre, point 3). Then, similar to class A, the
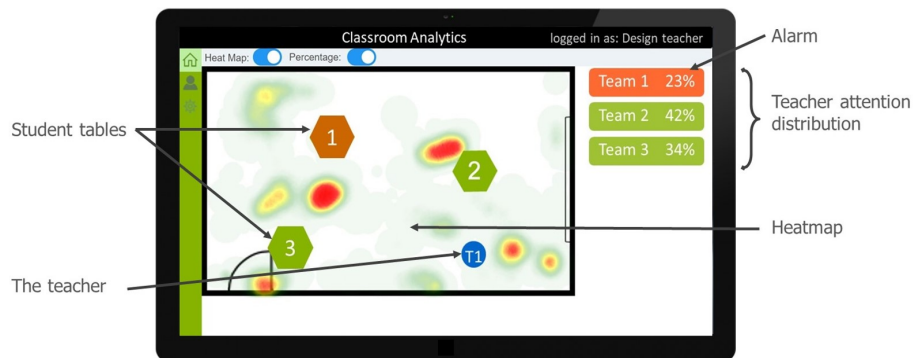
Fig. 1: Dashboard showing live the teacher's position (blue circle) in a (8x10 m) classroom and student tables (hexagons). Teacher-student attention time shown at the right (the least attended team is highlighted in orange.

teacher visited each team in the third hour of class B while students were having project meetings (see point 4).

Finally, for class C, the learning design promoted students and the teacher to move around the classroom spaces. During the first 2 hours, all the students and the teacher would surround one table at a time, for students at that table to perform a poster presentation of their designs created before the class. For this reason, the teacher remained at different areas of the classroom that were not visited in the previous two classes (e.g., see the position close to the door in Figure 2, right, point 5) to listen to the students' presentations at each table, mainly facing to the wall where students pinned their designed materials.
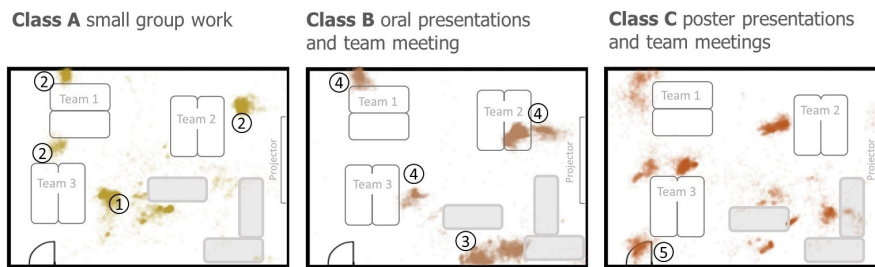

Fig. 2: Positioning data heatmaps from one teacher enacting the same learning design in the same learning space.

Implications for teaching and learning. In sum, this data story illustrates how the spatial behaviours of the teacher can reflect the kinds of learning activities unfolding

in the same physical learning space. This can have broader implications for learning spaces research. For example, although the three classes involved group work in different forms and to various extents, the role of the teacher and the ways she used the classroom space drastically changed according to the lesson plan. Scaling up the collection of teacher positioning data could enable researchers and designers of learning spaces to understand the meanings of the different areas of the classroom and understand how teachers appropriate the space in relation to tasks designed to support student activities and learning.

The most important lesson from this story is that feeding these positioning data back to the teacher in real-time (e.g., using the dashboard shown in Figure 1) or for post-hoc analysis (e.g., like the paper-based representations shown to teachers in this study) can provoke reflections about how spatial behaviours with the purpose of supporting professional development. Moreover, it would be possible to identify the data signature of effective teaching practices that could be used for training novice teachers.

4.2 Data Story 2: two instructional approaches in the same classroom

Educational context. The second story illustrates how positioning data can provoke reflection on different spatial behaviours and instructional approaches from two teachers enacting the same learning design in the same learning space. This story unfolded in the context of the undergraduate unit: Integrative Nursing in Practice. The study focused on six 3-hours simulation classes (1-6) for which the same learning design was repeated. Two nursing teachers (T1 and T2) individually taught three classes each (1-3 and 4-6, respectively). The team-based clinical simulation tasks in these classes were conducted in the same (13.5 x 7 metres) learning space that mimics a hospital ward equipped with 5-6 beds with a patient manikin in each. In these classes, between 23 and 25 nursing students were organised in five teams of 4-5 to look after a simulated patient each in a hypothetical scenario, while the teacher either enacted the role of the doctor or simply observed the practice of the various teams of pre-service nurses. The aim of the simulation task in this story was to help nurses learn how to react when a patient is having an allergic reaction to a medication. More details about and empirical results from the study in which this story unfolded have been reported in an expanded format elsewhere (Martinez-Maldonado, Mangaroska, et al., 2020).

Data and analytics. Similar to the previous story, the *x-y* positions of the teachers were automatically tracked using the UWB sensor system. In this case, also the positions of some students were tracked so the data capture was normalised to 1Hz. The sensor was put inside a belly-bag which was worn by the teacher and students during the class. A debrief was conducted after the classes in which teachers were asked to reflect and comment on their spatial behaviours and those of the students based on the visual representations of their positioning data printed on paper. This story focuses on the contrasting instructional behaviours of the teachers. These data

was presented to teachers as heatmaps of activity on the floorplan of the simulation classroom.

Data Story. Figure 3 presents four heatmap visual representations of the teacher spatial behaviours during classes taught by T1 (classes 1 and 2) and T2 (classes 3 and 4). These heatmaps illustrate two contrasting teaching strategies which they consistently followed for the three classes each taught. T1 stayed either at the teacher's desk (see Figure 3, both heatmaps at the left, point A) or circulating very closely to patients' beds where students were mostly working (see point B). T1 described that her teaching approach focused on coming into close proximity to one team at a time to review their skills and answer questions. T2 followed a completely different spatial approach for his teaching. He moved a chair to the middle of the classroom (see Figure 3, both heatmaps at the right, point C) and remained there while, sometimes, getting closer to the patient beds. Although T2 also moved around the patient beds, he was not as close to students compared to T1. T2 indicated that he prefers to position himself at a central space in the class (where he placed a chair) or between Beds 4 and 3 (see point D).

When the teachers examined each other's positioning heatmaps they could reflect on the pedagogical approaches each followed. T1 showed interest in the more supervisory approach followed by T2 and how T2 enacted the role of the doctor during the simulation. T1 also explained that she wondered if students adapted to the teaching approach of T2 and came to him to the central area of the classroom to ask for help.
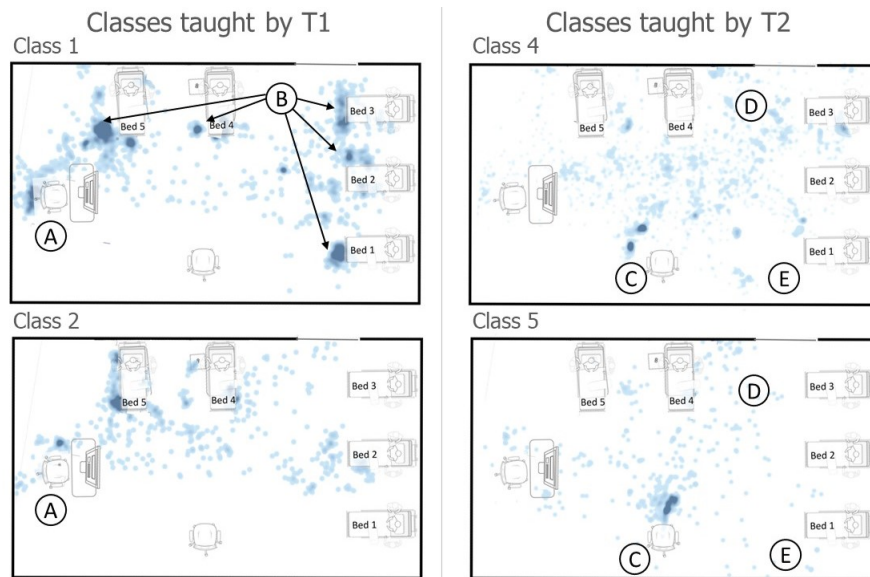

Fig. 3: Positioning data heatmaps from teachers conducting healthcare simulations in the same learning space. Classes taught by T1 (left) and T2 (right).

Both teachers also identified a problematic feature of the architectural design of the classroom. Next to bed 1 there was a column that left very little space for the teacher to go closer to the students working in that location (see point E). This suggests the potential to investigate if there truly exist generalised issues with the indoor design of the built environment of the learning space or if some of these issues are actually just reflecting teacher preferences. Similar to the teacher who was featured in Data Story 1, T1 also emphasised the potential of using positioning data for training new teaching assistants.

Implications for teaching and learning. Although the learning design is a critical factor that impacts the kind of observable spatial patterns that can emerge from the teachers' positioning data (as illustrated by Data Story 1), differences in teaching approaches can also break such 'expected' patterns. This emphasises the potential role of positioning data for assessing if the physical learning spaces are being used as intended and for identifying if the space is (at least temporarily) modified to fit the needs of a particular learning design or pedagogical approach. This is evidence that researchers and designers interested on the co-configuration of the learning space rarely have available.

4.3 Data Story 3: tracking student spatial behaviours at school

Educational context. The final data story shifted the focus from teachers' spatial behaviours to identify potential socially isolated students in physical learning spaces. This story involved 98 Year-6 students and six teachers (four full-time teachers, one aide, and one part-time teacher) in a primary school. The school building was designed as an open area with movable furniture that can be rearranged to adapt different types of pedagogies (as shown in Figure 4). This wall-less area was divided into different learning spaces. Among many school subjects, students' social interactions in Reading sessions were particularly interesting as students were explicitly instructed to study in groups. Although students were assigned to four different spaces in *Reading* based on their prior attainment, they can still move freely around the learning spaces and interact with whom they desired.

Data and analytics. The physical positioning traces of students and teachers were captured over eight school weeks. A total of 23 Reading sessions were recorded and the duration of these sessions were between half to one hour. Both teachers and students were assigned with a Quuppa QT1-1 positioning tag (worn as a wristband) that transmits their x-y coordinates. Teachers kept a register of the tags and distributed them to the students when a school day would begin and collected them back at the end of the school day. These physical positioning data were captured by 14 Quuppa Q17 locators that were installed around the learning spaces (see Figure 4). The locators captured positioning traces at 5Hz, and with an accuracy of 10cm.

To identify potential socially isolated students, students' social interactions were modelled from their physical positioning traces. Meaningful social interactions were identified if two individuals were collocated within one-meter proximity for more
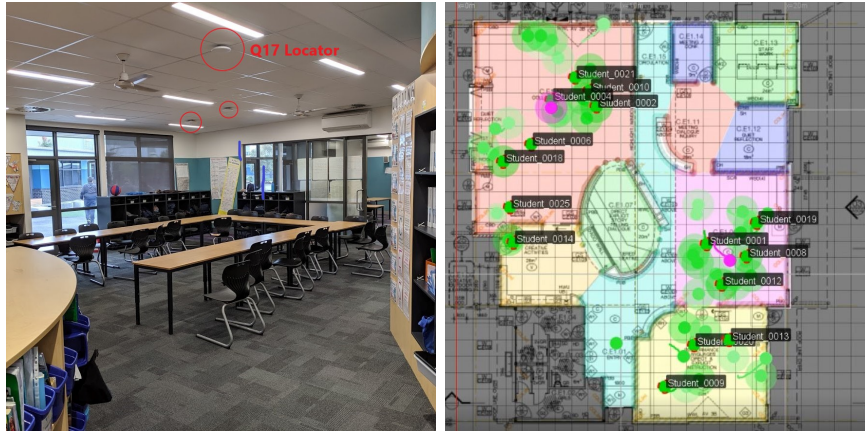
Fig. 4: A part of the learning spaces in the school building with the Quuppa Q17 locators installed on the ceiling (left). The learning spaces and illustration of the tracking system where the green/purple dots represent students/teachers, and the green/purple lines represent student/teacher movement (right).

than 10 seconds. For each Reading session, social network analysis was applied to extract the weighted degree centrality of each student, which was the total amount of time a student had interacted with others. K-mean clustering analysis was performed to group students based on the patterns of change in their weighted degree centrality. The 23 reading sessions that happened during the eight weeks were segmented into four quadrants (Q1 – Q4), each containing six/five consecutive sessions over a fortnight. Students' average weighted degree centrality was calculated for each quadrant, resulting in four features for the clustering analysis. Finally, in-depth analysis was performed to pinpoint critical times and potential reasons for students' decline in social interaction.

Data Story. Four clusters of students were identified based on the changes in their social interactions over time (see Figure 5). The social interaction of students in Cluster 1 remained constant throughout our study, whereas, students in Cluster 2 and 3 demonstrated increasing patterns in their social interaction with different initial values. Students in Cluster 4 were particularly interesting as they were the only students whose social interaction significantly decreased over time. This decline is potentially associated with the changes in the composition of their social ties with other students. This observation directed the investigation towards the dynamics in students' social ties, especially for the students in Cluster 4.

Of the students in Cluster 4, the case of Student 98 is presented here to illustrate a suspicious case of a student becoming socially isolated. This student fully attended the Reading sessions but had the lowest average social interaction. Initially, Student 98's social interaction was around the class average but suddenly dropped on the 14th of August 2019 (see the left of Figure 6). Afterwards, the student's social interaction remained considerably lower than the class average. In-depth analysis of
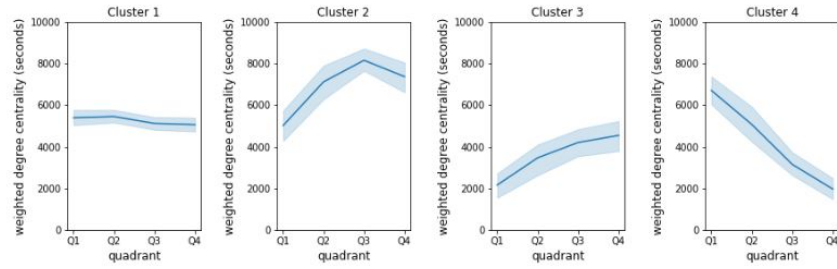
Fig. 5: Four clusters of students' temporality of social interactions in reading sessions (top).

the changes in Student 98's social ties revealed a substantial reduction from six to two ties when the sudden drop happened. In particular, the student had the strongest tie with Student 86 before the decline but this social tie cessation to exist afterwards. Whereas, a novel strong tie was formed with Student 49, whom Student 98 had never interacted with before (see the right of Figure 6). These insights might signal that potential social conflict may have occurred between Student 98 and Student 86, which may have resulted in a ceased friendship, and thus, the decline in her social interaction as Student 98 attempted to form new social ties. If this low level of social interaction prolonged in Student 98, it would be necessary for teachers to investigate and identify ways to support this student.
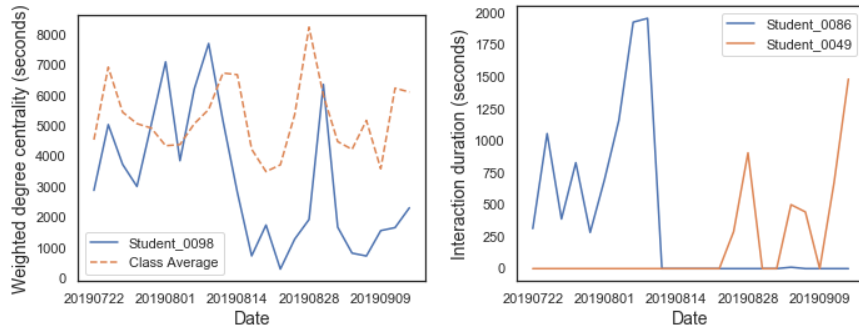

Fig. 6: Changes in the social interactions of Student 98 and the class average in reading sessions over the eight weeks (left). Changes in the amount of time (y-axis; seconds) Student 98 interacted with Student 86 (blue line) and Student 49 (orange line) over the eight weeks (right).

Implications for teaching and learning. This data story illustrates the potential of physical positioning traces in helping teachers to identifying socially isolated students. The non-intrusive and automatic features of positioning tracking can allow

teachers or support staff to monitor in students who may become socially isolated and reflect on ways to support them. Although teachers can potentially notice if certain students may become isolated, it would be very challenging to observe behaviours of individual students longitudinally. The positioning technology can also enable teachers to monitor the social dynamics of students in many complex educational situations. For example, the social integration of a new student who joins a classroom after all other students already have become familiar with each other, and students' social well-being after school transitions. These scenarios would be difficult for teachers to comprehend with traditional survey and observation methods. Whereas, the utilisation of insights from physical positioning traces would augment their manual observation and equip them with the tools to deal with the increased complexity in the learning spaces.

5 Discussion

The three data stories presented above illustrated potential emerging contributions of multimodal classroom analytics to enable new ways to study the teaching and learning processes that unfold in physical learning spaces. There are various under-explored opportunities that can be enabled by indoor-positioning technologies. In this section, we discuss the potential benefits, challenges and caveats of using these sensing technologies in hybrid learning spaces.

Capturing physical aspects of the learning activity. Moving beyond the analysis of data logged by personal computers (i.e., click-streams and keystrokes), using emerging technologies to sense other aspects of learning activity can potentially contribute to generating a deeper understanding of the *materiality* of learning (Sørensen, 2009). That is, the physical aspects of 'traditional' intellectual tasks intended to occur in physical learning spaces (Goodyear & Carvalho, 2014). **This chapter emphasises the potential opportunity of extracting and analysing data from the physical learning space to generate a deeper understanding of *face-to-face* teaching and learning practices. This aspect of hybridity (i.e., making traces of activity unfolding in the physical world digitally available), can potentially serve to inform pedagogical practice, space design, and design for learning.** For instance, Riquelme et al. (2020) and Saquib et al. (2018) used positioning sensors in learning spaces (namely a library and a classroom, respectively) to understand how learners interact face-to-face with each other while using a combination of digital and material learning tools **(hybrid learning activities)**. These authors inspected how spatial behaviours can also provide cues about interaction among students and teachers during learning tasks that have been designed to focus on cognitive and social aspects of collaborative learning. Evidently, less conventional learning tasks that explicitly require the development of motor skills and spatial abilities, such as simulation based learning in healthcare (Echeverria et al., 2018) and fire emergency response (Wake et al., 2018), can directly benefit from analytics that automatically detect salient spatial behaviours for the purpose of reflection and improvement.

Multimodal evidence for advancing spatial pedagogy. As illustrated in the first two stories, another potential area of application of the classroom analytics is to support teacher training, professional development **and pedagogical practice**. In their work on spatial pedagogy, Lim et al. (2012) identified the temporal meanings that certain areas of the learning space can take according to the intended learning design and the particular instructional activities occurring in such spaces (e.g., providing direct instruction to all students in a class, talking with some students, using gestures to explain abstract concepts and using classroom resources such as the whiteboard or digital presentation tools). **Since activity happening in hybrid learning spaces is, by definition, complex, ill-structured and unpredictable (Cook et al., 2020), its analysis requires embracing the complexity of the multimodal interaction among people and physical/digital resources available in the environment.** In our empirical work (Martinez-Maldonado, Schulte, et al., 2020), while teachers showed appreciation of the potential of capturing traces of spatial behaviours to support their teaching practice, they also mentioned that more sources of evidence were needed to completely understand what was happening in the areas where they were physically positioned. Was the teacher talking to students or just observing? Was the teacher speaking loud to the whole class or to a couple of students who came to ask a question? Was it a class just after an exam so students were coming to the teacher to ask questions about their exam results? Not only does this call for a multimodal stance in which more data can be captured (e.g., audio and gestures) to give meaning to the positioning data, but also for the need of contextual information about the class to aid interpretation (e.g., did it happen at the beginning of the day or after/before a critical deadline?).

Space design assessment and co-configuration. **Goodyear (2020) explained that creators of new spaces for hybrid learning are innovating and going beyond current design models. Other potential uses of the positioning data and analytics can thus include: supporting the assessment of these emerging space designs; providing evidence about how educators and students use and co-configure the hybrid learning spaces; and, eventually, playing a role in the creation of new design models for hybrid learning.** This potential was illustrated in the second story. One of the teachers explained that there were limitations in the current classroom configuration due to two factors: there was a column obstructing the access to students working around one of the hospital beds, and the beds were too close so there was no room for the teacher to come close to those students from those sides. Regarding the first issue, positioning data could help understand how teachers and students actually use the space and resources of the classroom in relation to how they were envisaged to be used. In Data Story 2, although it would be really hard to change a structural column of the building to enable easy access to one part of the classroom, this information could still be useful for the interior designer or the architect of the learning space to asses the current design *in-use* and optimise the designs of future learning spaces. Designers of learning spaces rarely receive feedback on how the spaces they built are actually used in practice. Regarding the second issue, Goodyear (2020) suggests that learning space design is complex, and its consequences are often unpredictable, partly because teachers and students play an

active role in appropriating and adapting the tools and spaces that have been designed for them. This way, positioning data could play a role in facilitating reflection on how the space can better support current practices. For example, if data from various classroom sessions confirm that the space obstructs the easy access of the teacher and puts in disadvantage to some students sitting in certain locations, the space could be re-configured permanently to minimise the issue.

Giving meaning to sensor data. The learning analytics community has mostly focused on the analysis of data logged by personal computers, often in the form of clicks-streams and keystrokes. However, even though 'clicks' are commonly associated to some discrete action (e.g., clicking on a button or dragging an icon), the community still faces the challenge of how to meaningfully model such clicks to higher-order educational constructs (Buckingham Shum & Crick, 2016). For the case of sensor data, it can be even more challenging to give meaning to the captured data which can be associated to unintentional actions or behaviours unrelated to the learning task. **This is particularly challenging for positioning data captured from hybrid learning spaces since the whole learning space can be considered as the *interface*. The wide range of digital resources used by teachers and students can attribute different meanings to the same physical space.** For example, in Data Story 1, the presence of the teacher in certain areas of the classroom had a strong meaning according to the learning design. Such meanings can change from class to class, during the same class or from one teacher to another (as illustrated in Data Story 2). **Moreover, the presence of digital technology (e.g., teacher's computer or equipment used by students) can strongly shape the kinds of interaction that may occur**. It can therefore be difficult to give meaning to positioning data and, without enough contextual information, there is a clear risk of misinterpretation. This has been highlighted by teachers who inspected their own data in various scenarios and who were concerned of potential biased interpretations of their data if shown to other people without contextual information (Martinez-Maldonado, Mangaroska, et al., 2020).

Human-centred design of interfaces. The three stories showcased how positioning data can be useful to provoke reflection. But much more work still is needed to design user interfaces for classroom analytics that can be used by teachers, designers, educational decision makers or students. For example, the third story presented the analysis of a student that may have potentially been isolated in the school. Timely communicating this insight to teachers could have contributed to the formulation of strategies to support this student if the student was indeed facing social challenges. **In some cases, students can also benefit from curated representations of their own positioning data. For example, in work conducted in parallel to Data Story 2, sensors were worn by nursing students for them to later reflect on their positioning and teamwork strategies (Fernandez Nieto et al., 2021). These positioning traces hold promise in supporting students and educators to reflect on potential errors made and in finding ways to optimise the use of space in emergency scenarios. Future work can focus on finding other ways in which students can benefit from positioning analytics in more regular learning situa-**

tions. Yet, a critical question remains: how can interfaces for classroom analytics be designed with integrity?

Particular ethical considerations. Potential ethical issues can emerge if the positioning or similar positioning data is simply shared with others without a clear purpose or contextual information. These can include misinterpreting the data, making unjustified judgements about performance or using the data for punitive purposes. To create effective interfaces using classroom data, we propose to apply human-centred design approaches to give an active voice to teachers, learners, and other educational stakeholders in shaping the design of interfaces they will end up using. This is work that the authors of this chapter are currently contributing to by conducting data-driven interviews with various stakeholders to understand their actual needs and preferences regarding how their data can be used and shared for the purpose of helping others (Martinez-Maldonado, Mangaroska, et al., 2020; Martinez-Maldonado, Schulte, et al., 2020; Martinez-Maldonado, Elliott, et al., 2020). **Moreover, future work in this area should consider the analysis of the trade-offs in using wearable and video-based technologies in the classroom, and the particular ethical issues that can emerge in tracking more than clicks and keystrokes (i.e., student actions that may not be related to the learnign task at hand).**

6 Concluding remarks

This chapter has presented three data stories that illustrate potential educational uses of classroom analytics, with a particular focus on spatial behaviours of teachers and learners in physical learning spaces. Indoor-positioning technologies are rapidly evolving, enabling novel ways to study how learning activity actually unfolds in learning spaces. We discussed potential ways in which classroom analytics can complement current methodologies, based on direct observations and ethnographic analysis, in learning spaces research. But we also illustrated how classroom analytics can enable to contribute to the automated capture of evidence that can provoke reflection on spatial behaviours according to the learning design (Data Story 1), productively compare the instructional approaches of different teachers (Data Story 2), or to detect students who may be facing social challenges in school and that may require closer attention (Data Story 3).

7 Acknowledgements

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