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ARTICLE

Moodoo the Tracker: Spatial Classroom Analytics for Characterising Teachers' Pedagogical Approaches

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Abstract

Teachers' spatial behaviours in the classroom can strongly influence students' engagement, motivation and other behaviours that shape their learning. However, classroom teaching behaviour is ephemeral, and has largely remained opaque to computational analysis. Inspired by the notion of Spatial Pedagogy, this paper presents a system called 'Moodoo' that automatically tracks and models how teachers make use of the classroom space by analysing indoor positioning traces. We illustrate the potential of the system through an authentic study with seven teachers enacting three distinct learning designs with more than 200 undergraduate students in the context of science education. The system automatically extracts spatial metrics (e.g. teacher-student ratios, frequency of visits to students' personal spaces, presence in classroom spaces of interest, index of dispersion and entropy), mapping from the teachers' low-level positioning data to higher-order spatial constructs. We illustrate how these spatial metrics can be used to generate a deeper understanding of how the pedagogical commitments embedded in the learning design, and personal teaching strategies, are reflected in the ways teachers use the learning space to provide support to students.

Keywords Spatial modelling · Indoor localisation · Learning spaces · Teaching · Multimodal learning analytics

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An earlier, shorter version of this paper (Martinez-Maldonado et al., 2020a) is the foundation for this article, which has been significantly extended in light of feedback and insights from AIED 2020.

Moodoo is a fictional character (a skilled Aboriginal tracker) in the Australian film Rabbit-Proof Fence. Aboriginal trackers could find people and things by developing acute senses to notice seemingly minute details, such as the way a footprint has been made (Holíková, 2012).

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Introduction

Previous research has found that teachers' positioning in the classroom and proximity to students can strongly influence critical educationally relevant aspects such as students' engagement (Chin et al., 2017), motivation (Fernandes et al., 2011), disruptive behaviour (Gunter et al., 1995), and self-efficacy (Koh & Frick, 2009) (see review by O'Neill & Stephenson, 2014). This is why *teaching guides* (e.g. Arends, 2014; Jones et al., 2007; Scrivener, 2005) and professional support staff and peers (Britton & Anderson, 2010) often recommend or prescribe to teachers how to position themselves in specific locations of the classroom. These guides and feedback from peers are important for many teachers, particularly for those teaching assistants or tutors in higher-education (HE) who rarely receive formal pedagogical training and feedback on how to position themselves in the classroom (Ellis et al., 2016; Gerritsen et al., 2018). Unfortunately, these teaching guides typically do not refer to the evidence used to prescribe certain spatial behaviours.

Most research with a focus on understanding spatial dynamics of classroom teaching rely on observations or peer/self-assessments (Britton & Anderson, 2010). Yet, these strategies are hard to scale up (Fletcher, 2018) and frequently are susceptible to bias (Shortland, 2004). Questions thus remain regarding how to identify optimal positions where teachers should place themselves during a class, how particular learning spaces should be arranged to ensure maximum student engagement, and how teachers can gain insights into their own pedagogical approaches and spatial behaviours. Again, this is largely because of current limitations in methods to capture and analyse evidence about spatial dynamics of the classroom.

Despite the online learning revolution, physical classrooms remain pervasive across all educational levels (Asino & Pulay, 2019), but classroom activity has largely remained opaque to computational analysis (Martinez-Maldonado et al., 2018), with only a small number of artificial intelligence (AI) and analytics innovations targeting physical dynamics of teaching and learning (see reviews in Santos, 2016; Zawacki-Richter et al., 2019; Chua et al., 2019). For example, there is a growing interest in using novel sensing technologies to automatically analyse classroom activity traces to model behaviours such as students' engagement (Hutt et al., 2019) and mood (Morshed et al., 2019); teachers interactions (Bosch et al., 2018) and discourse (Jensen et al., 2020) during lectures and students' physical activity (Ahuja et al., 2019; Watanabe et al., 2018).

Tracking systems have emerged recently, enabling the automated capture of positioning and proximity traces from authentic classrooms. Different technologies have been used to this end, including wearable devices attached to students' shoes (Saquib et al., 2018), computer-vision systems (Ahuja et al., 2019), and indoor positioning trackers (Echeverria et al., 2018). Some systems even summarise the time a teacher has spent in close proximity to a student or group of students, to raise an alarm if a threshold is reached (e.g. An et al., 2018; Martinez-Maldonado, 2019b). However, very little work has been done in exploring what kinds of metrics researchers can generate from low-level *x–y* positioning data that could be useful to characterise classroom activity in ways that are meaningful to teachers.

This paper presents Moodoo, a system for modelling spatial teaching dynamics which has been implemented as an open-source library that contains spatial metrics of teaching behaviours. We build on the foundations of Spatial Analysis (Fischer, 2019) and Spatial Pedagogy (Lim et al., 2012), to explore and propose a set of metrics that can help in characterising teachers' spatial strategies in a classroom. We deployed the system in an authentic physics education study, in which seven teachers wore indoor positioning trackers while teaching in pairs (see Fig. 1), enacting three distinct learning designs. In total we analysed 18 classes and use the findings to map the x–y positional data to higher-order spatial constructs, and propose a composable library of algorithms that can be used to study instructional behaviour in different teaching scenarios. We illustrate how these spatial metrics can be used to generate a deeper understanding of Spatial Pedagogy in two ways: 1) by extracting and comparing spatial metrics across learning designs, each imbued with a particular pedagogical approach; and 2) by presenting and discussing spatial behaviours from teachers who displayed quite distinctive personal pedagogical approaches.

The rest of the paper is structured as follows. Section 2 presents the foundations of spatial pedagogy and spatial analysis in the classroom. Section 3 introduces the educational context and Sect. 4 describes how the positioning data were collected. Section 5 presents the modelling approach and the spatial metrics that the system can extract from indoor positioning data of the teacher. Section 6 describes the illustrative study presenting results of the analysis of 1) spatial metrics of teachers enacting the three different learning designs; and 2) an analysis of how three teachers displayed distinct spatial behaviours while enacting the same learning design, based on their personal ways to embrace the intended pedagogical approach. Section 6 presents a discussion of the implications of this system for teaching practice, the limitations of our study, the pervasiveness of this approach, and ethical implications of using sensing technologies in the classroom. The paper concludes with some final remarks in Sect. 7.

Fig. 1 Physics laboratory classroom taught by two teachers while wearing indoor positioning sensors contained in a badge (bottom-right)

Background and Related Work

Foundations of Spatial Pedagogy

Although fragmented across multiple areas (McArthur, 2015), research investigating the relationship between classroom spaces and teaching processes has a long history. In the nineteenth century, observational studies by Barnard (1854) informed the design of teacher-centric lecture classrooms to maximise surveillance of students. More recent works also used systematic observations to investigate how teachers' proximity to students influences aspects that can impact learning. For example, Rubin (1972) conducted a 6-week observational study in a local school which suggested the potential positive role of the close proximity between the teacher and the students in the development of attitudes towards learning and in their performance in written work. Kounin (1970)'s earlier classroom management studies in high school, and elementary schools also suggested the importance of the teachers' presence near students to address misbehaviours that could be distracting to others during classes. Gunter et al. (1995) used the term *proximity control* to refer to strategies use to control students' disruptive behaviours. In fact, a review by Shores et al. (1993) found that teacher movement in the classroom can contribute to addressing students disruptions by increasing the effectiveness of teachers' interaction with students as they come into close proximity to each other. In contrast, Giangreco et al. (1997) found that a prolonged educator proximity to students could negatively affect students' sense of ownership of their own work and self-efficacy in the context of special education. These works focused on trying to find correlations between student–teacher distances and some critical aspect that can influence learning. Yet, contemporary studies have started to focus on how to characterise teachers' pedagogical approaches based on their spatial behaviours.

Lim et al. (2012) coined the term *Spatial Pedagogy* (SP) to refer how certain spaces in the classroom can demonstrate different meanings depending on the positions and distances between teachers, students and classroom resources. Authors observed two teachers, during one class session each, using the same classroom to differentiate pedagogical strategies and created state diagrams to represent the spaces of the classroom in which the teacher was moving, frequency to which a space was visited, and transitions. Instead of trying to find correlations between teacher's proximity and student outcomes, an observer manually coded teachers' positions (one observation per second) to then visualise the directionality and frequency of static and dynamic movement with the purpose of comparing teaching approaches. Although this was a small scale study, the authors managed to observe that one of the teachers constructed a less formal relationship with the students by moving frequently and standing off-centre, while the other teacher constructed a formal and professional relationship delivering the lesson from a static cantered position. However, they also observed that the less formal relationship was compensated with a display of power and authority through language and gestures, suggesting that SP should be investigated further together with other semiotic resources (e.g., language, gestures, teaching materials) to examine the impact of directionality, positioning and the degree of random movements in the classroom on effective teaching and learning. Chin et al. (2017) conducted a similar but slightly larger study with four teachers, in which they demonstrated that the teacher's use of space is influenced by the type of instructional activities in class. The authors of these studies suggested the need for automated approaches that could help scale up their analysis, given the potential to support teachers' reflections and inform pedagogical improvement.

Although the literature described above suggests that teachers' classroom positioning can have some effect on aspects related to learning, most analyses have been based on self-report questionnaires, and observations made on some classes, visualised until recently mostly through manually produced diagrams (e.g. Lim et al., 2012). Automating the analysis of spatial classroom dynamics has the potential to enable new research in learning spaces that can extend the analysis of the use of space with other semiotic resources (e.g., language, gestures), allowing for an objective, accurate, and timely feedback to teachers. In the next section, we elaborate on current approaches that automatically study teachers' positioning.

Spatial Analysis and Positioning Technology in the Classroom

There has been a growing interest in exploring physical aspects of the classroom using automated analytics innovations (Chua et al., 2019). Currently, although the most effective mechanism to explore how students and instructors use space and interact in that space is for experts to observe classroom sessions, more researchers are investigating and developing methods for automatic detection of actions and movements inside the classrooms (Ahuja et al., 2019). For example, various researchers have used automated video analysis to model students' postures and gaze (Raca et al., 2015), as well as gestures (Ahuja et al., 2019), teacher's walking (Bosch et al., 2018), interactions between teachers and students (Ahuja et al., 2019; Watanabe et al., 2018). Yet, these innovations do not track the *x*–*y* positions of teachers in the whole classroom and are thus more practical for lecture-based settings or similar situations where the interest is not in deeply understanding the spatial behaviours of teachers. Chng et al. (2020) sensor-free solution can address this issue. Authors used various depth cameras to triangulate the positions of students and characterise the types of social interactions in a makerspace. Although promising, authors did not discuss to what extent their solution can enable uninterrupted indoor positioning tracking.

To address the occlusion issues that can emerge with computer-vision solutions (Saquib et al., 2018) and potential surveillance concerns related to the use of video cameras in classrooms (Derry et al., 2010), there has been an increased interest in using wearable sensing solutions (Griffiths et al., 2019), such as micro-location technology, i.e., beacons (Motohashi et al., 2017). Beacons transmit information only about their existence and do not use background monitoring to track other devices or people. Thus, beacon-enabled location-based approaches have been used in education to monitor attendance (Huang et al., 2019), or to enhance feedback given to students and instructors. For example, (Echeverria et al., 2018) used location sensors positioned in the classroom to investigate and improve teamwork strategies of nursing students in healthcare. The movement data was automatically analysed, while the results were visualized and presented to the teams as individualized feedback of the teamwork strategies, progress, and outcomes. Similarly, Riquelme et al. (2020) investigated how groups of students used and interacted with physical materials in indoor environments during collaborative learning activities, and identified three different roles students undertake during collaboration. Wake et al. (2019) used a beacon-enabled tool to collect data from firefighters during training to identify patterns and provide feedback on good and bad movements in fire situations. More recently, a pilot study was performed at the Hong Kong Polytechnic Institute to explore ways in which universities can enhance physical learning spaces, and eventually develop intelligent campuses (Griffiths et al., 2019).

Some work has attempted to close the feedback loop by displaying some positioning traces back to teachers. For example, ClassBeacons (An et al., 2018) summarise the amount of time a teacher has spent in close proximity to groups of students and displays it through a lamp located at each group's table. Similar work displayed the same information on a teacher's screen with alarms indicating potentially neglected students (Martinez-Maldonado, 2019b), or simple graphs (Saquib et al., 2018) and heatmaps (An et al., 2020) have been used to show what parts of the classroom teachers visited the most.

The above studies indicate that there is an emerging interest in using sensing technologies to analyse teachers' positioning traces. Yet, none of these works has addressed the need for creating spatial metrics (beyond counting the times a teacher comes close to certain students) from the large amounts of indoor positioning data, that may be relevant for teachers' professional development. Whilst we can learn from metrics used in broader areas such as Spatial Analysis (Fischer, 2019), these are commonly applied to outdoor data, in which the granularity of data is coarse and the particularities of the educational context are not considered. There is an identified dearth of indoor positioning analytics tools in non-educational contexts (Cheema, 2018; Marini, 2019; Nandakumar et al., 2013). This paper (besides its shorter version presented at AIED 2020, Martinez-Maldonado et al., 2020a) contributes to this body of research by documenting the implementation of automated spatial metrics that map from low-level *x–y* teacher's positioning data to higher-order spatial constructs.

The Learning Context

The authentic learning context providing the focus for this study was part of the regular classes of a first-year undergraduate unit at the University of Technology Sydney. This includes weekly 2½ hour laboratory classes (labs) in which students run experiments. A teacher and a teaching assistant co-teach each lab in the physical classroom (see Fig. 1). Each lab typically has 30–40 students working in 10–13 small teams of 2–3 students each. Eighteen labs were randomly chosen (1–18) for the study. All labs were conducted in the same (16.8 × 10 m) classroom equipped with workbenches, a lectern, a whiteboard, and multiple laboratory tools. Seven teachers (T1-T7) were involved in these classes. T1, the *unit coordinator*, designed the learning tasks and did not teach any class. T2 and T3 were the *main teachers* for 12 and 6 classes respectively, and T4-T7 supported T2 and T3 as *teaching assistants* in various combinations (please see Table 1).

We followed six cohorts of students (laboratory classes) for three weeks (eighteen labs in total). In each week, the classes exhibited one of three possible learning designs (LD1-3), reflecting a distinctive pedagogical approach. LD1 was a *prescribed lab*, in which all students had to do the same experiment following a step-by-step guide. For this learning design, students need to follow the guide and teachers to provide support when students get stuck in the experimentation process, or to ask reflective questions for students to think about the implications of the experiment. In contrast, LD2 was a *project-based lab*, in which students were asked to formulate a product-evaluation project, with each team testing a different appliance such as vacuum cleaners or pedestal fans. This learning design gives much more agency to students in setting up the task, while the teachers' role is to help students in dealing with the complexity of their projects. Finally, LD3 was a *theory-testing lab,* in which 4–5 experiments were set up by the teacher and students had to move round one experiment at a time, and predict the outcome of each without further guidance. For this learning design, teachers act as demonstrators of experiments and also clarify mathematical questions that students may

Table 1 Laboratory classes (labs) considered in this study

Learning design	Class session	Main teacher	Teaching assistant	# of students	Duration (hours)
LD1 Prescribed lab	1	T2	T4	36	2.20
	2	T2	T5	37	2.12
	3	T2	T6	39	2.00
	4	T2	T6	33	2.20
	5	T3	T7	38	2.18
	6	T3	T7	37	2.29
LD2 Project-based lab	7	T2	T4	34	2.15
	8	T2	T6	38	2.30
	9	T2	T6	35	2.30
	10	T2	T6	30	2.30
	11	T3	T7	36	2.30
	12	T3	T7	39	2.20
LD3 Theory-testing lab	13	T2	T5	30	2.25
	14	T2	T6	33	2.30
	15	T2	T6	34	2.30
	16	T2	T6	31	2.25
	17	T3	T7	32	2.26
	18	T3	T7	26	2.00

have while modelling the phenomena they are observing. This means LD1 was enacted in classes 1–6 in the first week of the term. LD2 was enacted in classes 7–12 in the second week with the same students from week 4. LD3 was enacted in classes 13–18 in the third week with the same students from the previous two weeks. For example, the same cohort of students attended classes 1, 7 and 13.

Apparatus

The *x* and *y* positions of the two teachers in each lab were automatically recorded through wearable *badges* (Fig. 1, right) based on the Pozyx ultra-wideband (UWB) system, at a 2 Hz average sampling rate (with an error rate of 10 cm). Eight *anchors* were temporarily affixed to the classroom walls to estimate the positions of the badges. UWB sensors do not require a straight line of sight and are not affected by signals of students' personal devices (Alarifi et al., 2016) (Fig. 2).

Given the large number of teams in each lab (10–12), the positions of students' experiments were captured by an observer using a tablet-based observation tool whenever there was a change in the position of teams. For LD1 and LD2, students mostly stayed at the benches where they installed their experiments. For LD3, students moved to each experiment setup, so these were recorded by the observer. These positions can also be automatically tracked by providing a tag to each team of students as we have done in a previous pilot study (Martinez-Maldonado, 2019b).

Moodoo: Indoor Positioning Metrics

This subsection presents the metrics defined for teachers' positioning, grounded in the notion of Spatial Pedagogy (Lim et al., 2012). The metrics have been implemented as a composable, open source library in Python (https://gitlab.erc.monash.edu.au/rmat0024/moodoo). Table 2 provides a summary of the metrics that are presented in this section.

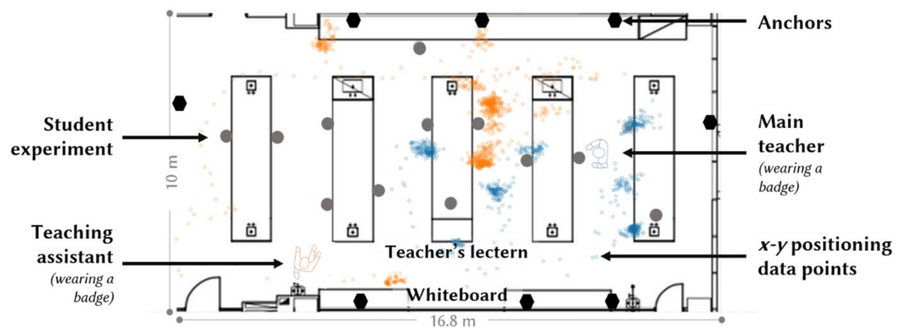


Fig. 2 Floor plan of the classroom in Fig. 1 with data points from two teachers (the main teacher in in blue and the teaching assistant in orange)

Table 2 Summary of spatial metrics for characterising classroom pedagogies

	METRICS	CALCULATION
Metrics related to teachers' stops Input parameters: *d* and *t*	Number of stops	The Centroid c(x,y) of a set of datapoints close to each other by a distance *d* (in millimetres) and time *t* (in seconds)
	Total stop time	The total time of a classroom activity during which a teacher remained without moving
	Time per stop	The average duration of teacher's stops
Metrics related to teachers' transitions	Number of transitions	The transition between two consecutive stops in relation to particular centroid
	Distance walked	The total distance a teacher walks during a classroom activity
	Speed	The average walking speed of the teacher
Metrics related to teacher-student interactions Input parameter: *iDis*	Total attention time	The total time a teacher spends near to students or groups of students by a distance *iDis* (in millimetres)
	Number of visits to student (groups)	The total number of visits a teacher does to each of the groups of students as part of the classroom activity
	Duration of each visit	The average duration of a teacher's visits to each of the groups of students as part of the classroom activity
	Number of visits per student (groups)	The average number of visits a teacher makes to each group of students during the classroom activity
	Index of dispersion	Distribution of teacher's attention calculated from the number of visits and the total time a teacher spends with each student or group
Metrics related to proximity to classroom resources Input parameter: *dObj*	Time at lectern	The total time a teacher spends near the lectern by a distance *dObj*
	Time at whiteboard	The total time a teacher spends near the whiteboard (or any other classroom resource) by a distance *dObj*
Metrics related to co-teaching Input parameters: *dTeacher* and *tTeacher*	Instances of co-teaching	The number of times when two teachers are within each other's inter-personal spaces (close to each other by a distance *dTeacher* measured in millimetres), for longer than a set period of time (*tTeacher*, measured in seconds)
Metrics related to focus of positional presence Input parameter: *m*	Spatial entropy	The proportion of data points in each cell of the grid (*m*-by-*m* grid, where *m* is measured in millimetres) creating a matrix of proportions, which is later vectorised and Shannon entropy calculated in bits

Metrics Related to Teachers' Stops

A teacher's *stop* is defined as a sequence of positioning data points that are a short distance apart in space and time. According to the notion of SP, this can denote a period in which the teacher is "*positioned to conduct formal teaching*" or stands "*alongside the* *students' desk or between rows*" of seats to interact with students (Lim et al., 2012, pp. 237).

Thus, a stop can be modelled from *x–y* teacher's data grouping data points based on a centroid C(*x,y*) point, distance *d* and time *t* parameters; where *d* is the maximum distance from the current data point to C, and *t* is the minimum time to group consecutive points (see Fig. 3). For example, for our illustrative study we chose $d = 1000$ mm, since this distance is considered within a teacher's personal space (Sousa et al., 2016); and $t = 10$ s to disregard very short stops. These parameters can be further calibrated according to the context and the tracking technology used. From the defined stop construct, other metrics can be calculated, such as the total or partial number of stops, average stopping time; or more complex metrics in relation to other sources of evidence, such as student locations and classroom resources (e.g. work-benches).

Metrics Related to Teachers' Transitions

Considering the conventional stages in the development of a class lecture and the nature of the required interaction, teachers organise themselves spatially by constructing four different types of space (i.e., authoritative, personal, supervisory, and interactional) in the classroom (Lim et al., 2012). For example, the teacher paces "*alongside the rows of students' desks as well as up and down the side of the classroom transforming these sites into supervisory spaces*" (Lim et al., 2012, pp. 238). Moreover, various studies reported that effective teachers move more, compared to "average" teachers (Seals & Kaufman, 1975), and that teachers are more effective when they move equally between the right and left sides of a classroom (Hesler, 1972). Another example considering kinesthetic patterns, showed that a teacher's slow and deliberate movement as 'invigilating' can be perceived as 'a patrol' and might have a negative impact on students' attitudes (Kress et al., 2005).

A teacher's *transition* is defined as a sequence of positioning data points that follow a trajectory between two stops. This includes all those positioning traces generated while, for example, the teacher moves from attending one group of students to another group. A linear quadratic estimation algorithm (Wang et al., 2015) (i.e. Kalman filtering) was applied as a pre-processing step in order to convert the *x–y* data points into smooth walking trajectories. Next, the teacher's walking trajectory is modelled as the transition between two consecutive stops in relation to their centroids (see Fig. 3, right). From teachers' transitions, other related metrics can also be calculated, such as the distance walked, speed and acceleration, and the transitions between specific groups of students or classroom areas.

Metrics Related to Teacher-Student Interactions

Lim et al. (2012) proposed that a space in the classroom becomes *interactional* when the teacher is in sufficiently close proximity to students to enable conversations or consultation. The close proximity between a teacher and students reduces

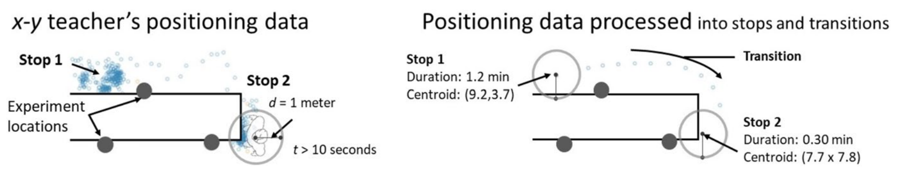


Fig. 3 Modelling from raw x–y positioning data (left) to teachers' stops and transitions (right)

the previous established hierarchical and interpersonal distance, and facilitates interaction. In a study by Hazari et al. (2015), the authors reported that when teachers position themselves with greater proximity to students (creating fewer traditional physical boundaries), students' engagement increased. In fact, how teachers physically position themselves is fundamentally focused on power. For example, a teacher can assert power and authority through spatial distance (i.e., positioning in the centre of a classroom or at the back of a classroom creating surveillance from a vantage point) or through language and gestural communication. This way teachers can create learning environments where students do not feel comfortable to speak up, engage, and respond.

Although the interactional space may be shaped by the learning task, furniture, preferences (Andersen, 2009), and cultural context (Hall et al., 1968; Martinec, 2001), a teacher standing within the interactional space of students (*iDis*) can be classified as a potential teacher-student interaction (a teacher *stop* in close proximity to one or more students). In our study, we accounted for the parameter $iDis = 1000$ mm as the maximum distance to define a teacher's stop as a teacher visiting that team. From this construct, other metrics can be calculated, such as teachers' total attention time per student/group, frequency and duration of teachers attending certain students, and sequencing of teacher-student interactions.

Additionally, an index of *dispersion* can be calculated to identify how evenly teachers' attention is distributed in terms of the number of visits and the total time spent with each student or group. In our illustrative study, we calculated the Gini index (Gastwirth, 1972), which is commonly used to model inequality or dispersion (with a single coefficient output ranging from 0 to 1, where 0 represents perfect equality of attention to each group).

Metrics Derived from Proximity to Classroom Resources of Interest

Teachers' proximity to certain resources in the classroom also gives meaning to x–y data. For example, teachers create an authoritative space when they conduct a formal briefing to students before they start a group activity, as well as a personal space when they spend time behind their desks to prepare for the next stage in the lecture (Lim et al., 2012). Positioning in the classroom according to the resources of interest thus takes on different meanings, and requires different usage of semiotic resources (e.g. gesture, language) for effective

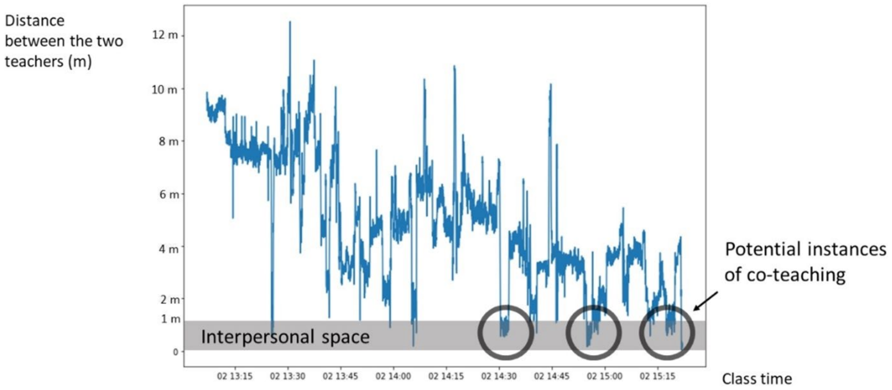


Fig. 4 Detecting potential instances of co-teaching. The time series show the distance between both teachers during a laboratory class (session 10). When the distance is below the parameter dTeacher = 1 m, and both teachers are stopped, a potential instance is detected

pedagogical discourse. In our study, the teacher's close proximity to the lectern or a whiteboard can be indicative of activities such as lecturing to the whole class or explaining formulas. These resources of interest are completely context dependent and can be selected by the teacher (as in our study), an educational decision maker or a researcher interested in assessing the use of the learning space. For this purpose, the parameter *dObj* delimits the proximity of resources of interests that are close to the teacher (calibrated to 1000 mm in the study). The resources of interest can be configured as an x–y coordinate in the floor-plan of the learning space.

Metrics Related to Co-Teaching

Having more than one teacher in the classroom is a common practice (Friend et al., 2015), an example from our study being pairs of teachers co-teaching classes in different combinations. However, we note that co-teaching brings as many challenges as opportunities in higher education. On the positive side, it varies in content presentation, allows for individualise instruction, and more easily supports scaffold learning experiences (Graziano & Navarrete, 2012). On the negative side, many studies have reported mixed feelings among students about co-teaching (Dugan & Letterman, 2008; Vogler & Long, 2003; Waters & Burcroff, 2007). However, students also believe that because of different perspectives, co-teaching opens more opportunities for engagement between teachers and students (Graziano & Navarrete, 2012).

Modelling the instances when both teachers are within each other's inter-personal spaces (*dTeacher*), for longer than a set period of time (*tTeacher*), can assist teachers to reflect how often and where this occurs. Figure 4 illustrates how potential co-teaching incidents were automatically classified when the teachers' inter-personal distance fell within the threshold parameters. In our study, the parameter *dTeacher* was set to 1000 mm and *tTeacher* to 10 s, similar to the heuristic considered above (Martinec, 2001).

Metrics Related to Focus of Positional Presence (Spatial Entropy)

From findings in a qualitative study (Martinez-Maldonado et al., 2020d), teachers contrasted two extreme mobility behaviours: 1) a teacher walking around the classroom mostly supervising, without engaging much with students (unfocused positional presence), and 2) a teacher focusing most of his/her attention on a small number of students or remaining only in specific spaces of the classroom (focused presence). From the *x*–*y* positioning data, the spectrum between these two extreme behaviours can be modelled based on the notion of *spatial entropy* (Batty et al., 2014) which has been used to measure information density in spatial data (Altieri et al., 2018). To calculate the entropy, we create a *m*-by-*m* grid ($m = 1000$ mm in our illustrative study) from the two-dimensional *x*–*y* data. The proportion of data points in each cell of the grid is calculated, creating a matrix of proportions. This is then vectorised and Shannon entropy is calculated (resulting in a positive number in bits). The closer the number is to zero, the more focused teacher's positioning was to specific students or spaces in the classroom.

Illustrative Study: Analysis and Results

This section demonstrates the potential of the metrics related to the constructs presented above through exemplars of how positioning traces i) reflect the characteristics of the learning designs, and ii) can be used to characterise contrasting personal instructional behaviours.

Dataset, Pre-Processing and Analysis

A total of 835,033 data points were captured by the indoor positioning system used in the 18 classes. Each data point consisted of i) an identifier of the teacher, ii) a timestamp and iii) *x*–*y* coordinates of the classroom position of that teacher in millimetres (e.g., [teacher1, 18/02/2019 9:39:20.34, 5600, 8090]).

Three pre-processing steps were conducted before analysing the data using Moodoo.

1) *Sampling normalisation*: the positioning data was down-sampled to 1 Hz by calculating the average position of a teacher per second.
2) *Interpolation*: as sensors are susceptible to missing readings for a few seconds (Gløersen & Federolf, 2016), a linear interpolation was applied to fill gaps for cases in which there was not at least 1 data point per second. The resulting dataset contained 60 positioning data points per minute and per teacher.

3) *Segmentation*: each class was segmented into three phases according to a common macro-script for the three LDs defined by the unit coordinator. Phase 1 includes the main teacher of the class giving instructions from the lectern (average duration 13 ± 8 min, n = 18). Phase 2 corresponds to the period in which all students start working on the experiment(s) of the day in small teams (1.5 h ± 18 min). Phase 3 corresponds to the time when some teams complete their experiments and start leaving the class (33 ± 22 min). The analysis of this paper focuses on Phase 2, which enables comparison across the classes considered. The resulting dataset comprised a total of 290,228 data points.

The data analysis involves processing the *x–y* positioning data from teachers enacting each learning design (LD1-3) using Moodoo. We report Moodoo's metrics for each teacher by LD, and normalising the results according to the class with the shortest Phase 2 which lasted 1:07 h. We ran a Mann–Whitney U test to evaluate differences in the metrics among each pair of learning designs (i.e. LD1-LD2; LD1-LD3 and LD2-LD3). Therefore, the median and interquartile range (IQR) values are reported accordingly. All the metrics for one class can be obtained in less than 1.5–2 min using a regular personal computer. This way, Moodoo metrics can potentially be obtained during the class to provide real-time support or to be used immediately after the class to support reflection.

Results: Comparing Learning Designs

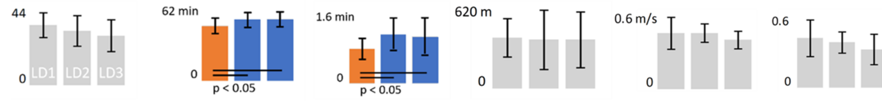
An overview of the resulting teachers' positioning metrics per learning design (LD) are presented in Tables 3 and 4, below. The median and IQR (Q3-Q1) values are presented by metric (columns/cols) and LD (rows). Bar charts are shown at the bottom of each table to facilitate comparison. Significant differences among pairs of LDs ($p < 0.05$) are emphasised in blue and orange (representing higher and lower values, respectively).

Overall, when teachers enacted LD1 they featured a higher number of stops (median 42 stops) than when enacting LD2 and LD3 (35 stops). This difference was not significant given the high variability of teachers' behaviours (see col 1, IQR values, in Table 3). Yet, stops were significantly longer for LD2 ($U = 35$, $p = 0.02$) and LD3 ($U = 37$, $p = 0.02$). For example, every time a teacher stopped while enacting LD2 s/he spent a median of 1.4 (IQR 1.6–1) minutes in that position before moving to the next space in the classroom. In contrast, most of the stops during LD1 were briefer (0.8, 1–0.7 min). This can be explained by the nature of students' task. In LD2 and LD3, students worked on more complex projects. In LD1, all students conducted the same experiment with teachers mostly providing corrective feedback, resulting in shorter pauses.

In terms of distance walked and speed, there were no significant differences by learning design (cols 4 and 5). This means that the learning designs did not strongly shape the way the teachers walked in the classroom as a cohort, in this

Table 3 Positioning metrics related to teachers' stops and transitions – median (IQR)

	Stops	Total stop time (mins)	Time per stop (min)	Distance walked (m)	Speed (m/s)	Dispersion (gini index)
LD1	42 (4)	52.5 (9)	0.8 (0.3)	370 (162)	0.5 (0.2)	0.5 (0.3)
LD2	35 (2)	58.4 (7)	1.4 (0.6)	303 (117)	0.6 (0.1)	0.4 (0.2)
LD3	35 (18)	58.1 (12)	1.1 (0.5)	440 (441)	0.5 (0.2)	0.4 (0.3)



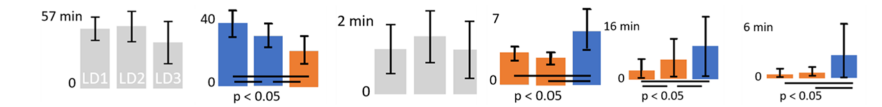
study. However, there were differences between teachers at a per case (exemplified below).

Table 4 shows more results for those cases in which teachers were in close proximity to students (cols 1–4) and classroom resources (5–6). There was a significant difference between the three LDs regarding the number of visits to students' experiments (LD1-LD2, U = 36, p = 0.02; LD2-L3, U = 33, p = 0.01; LD1-LD3, U = 13, p = 0.001). There was a larger number of visits for LD1, in comparison to LD2 (col 2), which contributes to describing a *supervisory* pedagogical approach (Batty et al., 2014) provoked by the prescribed learning task. However, the total attention time to experiments was very similar between LD1 and LD2 (column 1, 41.5 and 42.7 min, respectively). In contrast, for the *theory-testing lab* (LD3) teachers acted as demonstrators, dividing their attention (34, 44–24 min, col 1) visiting around 5 times each of the 4–5 experiments (col 4).

Regarding proximity to objects of interest, teachers significantly spent more time at the lectern and the whiteboard for LD3 compared to LD1 (U = 28, p = 0.01) and LD2 (U = 42, p = 0.04). This could be because in LD1 classes the task is prescribed, so teachers did not need to show additional information through the computer (lectern) or whiteboard. For LD2 and LD3, teachers commonly had to explain formulas using the whiteboard. Additionally, classes enacting LD3 occurred later in the semester after student partial results were published, with students often asking clarification questions regarding these LD3 classes. This explains the longer presence of teachers at the lectern.

Table 4 Metrics related to teacher-student interactions and proximity to objects in the classroom – median (IQR)

	Attention time (min)	Visits to experiments	Visit duration	Visits per experiment	Time at lectern	Time at whiteboard
LD1	41.5 (12)	37 (10)	0.9 (0.7)	3 (0.6)	0.6 (5.3)	0.3 (1)
LD2	42.7 (20)	29 (7)	1.3 (1)	2.5 (1)	3.5 (11.5)	1 (2)
LD3	34 (20)	23 (14)	0.9 (0.8)	5 (4)	7.3 (13)	2.9 (5.3)



Results: Comparing Personal Spatial Pedagogies

In the results from the comparison of learning designs presented above, neither the computed index of dispersion (Table 3, col 6), nor entropy, showed any significant difference between LDs. However, we now illustrate how the spatial metrics can be used to generate a deeper understanding of personal teaching strategies, specifically, how three teaching assistants displayed contrasting spatial behaviours, even when enacting the same learning design.

Table 5 presents selected metrics obtained from positioning data from 1) T6, a highly focused teaching assistant who spent much of his time attending 3–4 groups of students; T4, a more 'balanced' teaching assistant who distributed her time across all the groups of students; and T5, a teaching assistant who was mostly unfocused, walking constantly around the classroom without attending any specific group. All assistants had the same partner (main teacher T1). These behaviours were identified by the main teacher in a qualitative study presented elsewhere (Martinez-Maldonado et al., 2020d), and correspond to lab sessions 4, 2 and 1, respectively.

Figure 5 shows heatmaps corresponding to how these teaching assistants moved in the classroom space in Phase 2 of three LD2 classes. T6 focused on two benches of the classroom (Fig. 5, left), stopping almost half the number of times compared to the other two teachers (25 versus 40 and 46 stops, see Table 5, row i), and walked very little during the duration of the class compared to the other teachers (see Table 5, row ii). Evidently, the main teacher had to attend students sitting at the remaining desks. This was captured by the metric that counted the times both teachers got close to each other (3 versus 7 and 10 for the other two teachers, see Table 5, row iii) suggesting that for T6's class, both teachers split the class in halves, for each teacher to focus on one side of the classroom each.

In contrast, T4 and T5 circulated around other benches, with T5 constantly circulating (see Fig. 5, right), making the space between the work-benches his *supervisory* zone. T5 ended up walking for more than 1 km during the class (1208 m). The measure of spatial entropy captured this behaviour (Table 5, row iv). T6 featured the lowest entropy among the teachers in the dataset (2.9 bits). This signals that this

Table 5 Contrasting individual spatial pedagogical approaches. Selected Moodoo metrics for three teachers who displayed distinct spatial behaviours

Metrics	T6- Highly focused teacher	T4 – Balanced teacher	T5 – Un-focused teacher
i) Stops (#)	25	40	46
ii) Distance walked (m)	274	603	1208
iii) Instances of co-teaching (#)	3	7	10
iv) Spatial entropy (bits)	2.9	5.3	6.2
v) Dispersion (Gini index)	0.7	0.4	0.04
vi) Avg attention time per visit (min)	2	1.5	0.4
vii) Time spent near student experiments (%)	50%	84%	10%

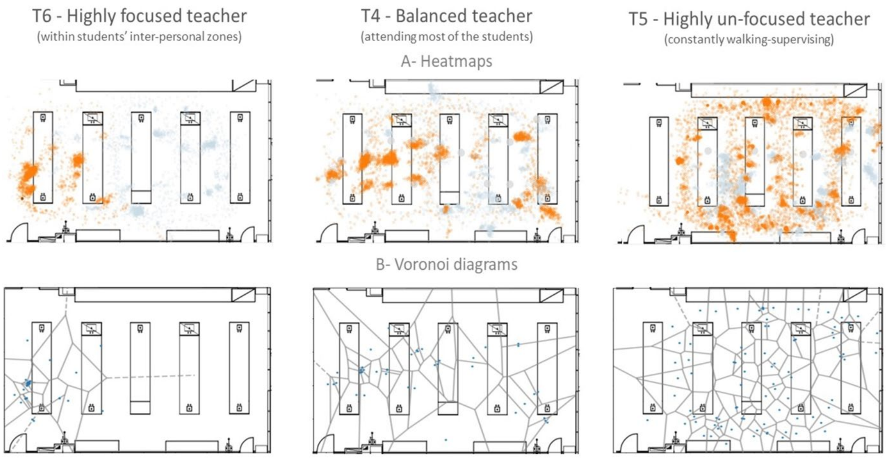


Fig. 5 Contrasting spatial pedagogical approaches. Left: a teacher focusing on certain students during a class. Centre: a balanced teacher who spread her time across various groups of students. Right: a second teacher mostly walking around the classroom, supervising

teacher mostly used a limited area within the classroom space. For T5, the spatial entropy was the second highest (6.2 bits), pointing at the more spread distribution of data points in the classroom space. T4 also featured a relatively high score (5.3 bits).

The Voronoi diagrams presented in Fig. 5 (bottom) serve to visualise how teachers used the space. In these diagrams, each teacher's stop is represented by each coloured dot on the floor plan. Each polygon contains exactly one teacher's stop and every point in the polygon's edges is closer to its teacher's stop than to any other. This way, the Voronoi diagram of T6, who stopped at several places in the classroom, formed a web-like diagram, which lead to a higher score for the metric spatial entropy. The Voronoi diagrams for T4 and T6 contain points closer to where students had set their experiments (closer to the benches).

The index of dispersion (Table 5, v), calculated in relation to students' experiments, helps to characterise the contrasting behaviours with a resulting coefficient very close to 1 for T6 (0.7—highly unequal distribution of teacher's attention) compared to T5 (0.04 – more even distribution of attention). The more 'balanced' teacher also had a more balanced index of dispersion (0.4), suggesting that, although she distributed her time more equally (Gini index closer to 0), she may have spent more of her time on groups of students that needed more help.

In terms of teacher-student attention time, T6 and T4 spent 2 and 1.5 min in average each time they stopped near a group of students (Table 5, row vi), with T5 just making very short visits (shorter than 30 s), confirming his behaviour mostly focused on monitoring students without engaging. Finally, the more balanced teacher spent most of her time close to students' experiments (84% in Table 5, row vii), followed by T6, who spent at least 50% of his time close to students. In contrast, T5 stopped only 10% of the time near the students.

In sum, we propose that the metrics extracted from the indoor positioning data of the three teaching assistants examined here enable the formal quantification of differentiated behaviours that prior research has shown can promote learning. Once made visible, they can be reflected upon, and potentially improved to optimise teacher-student time, the use of the space and teaching resources. The next section further discusses the implications of the spatial metrics to characterise classroom pedagogies embedded in the learning design, and appropriated individually by teachers.

Discussion

In this section we summarise the key findings, share our critical reflections, consider the broader literature, and note the limitations of this work.

Implications for Teaching Research, Learning Design and Professional Development

Our work holds several *implications* for research and practice. In terms of research, the automated generation of metrics can potentially contribute to accelerating the study of activity in physical learning spaces. For example, the evidence needed to establish stronger relationships between teachers' proximity and students' behaviours, learning outcomes and self-efficacy could be effectively collected if compared to the observational studies which have been limited to examine these in a limited set of classes (e.g. Burda & Brooks, 1996; Giangreco et al., 1997; Gunter et al., 1995; Shores et al., 1993). Similarly, the automated capture and processing of positioning data can potentially streamline the analysis of spatial pedagogy which has been conducted by manually recording teachers' positions on a spreadsheet (e.g. Lim et al., 2012; Chin et al., 2017). Automating the analysis of classroom dynamics, and combining the metrics defined in this study with metrics from gesture data, language and dialog data, and learning design information, can enable new research in spatial pedagogy to objectively and accurately explore and construct a multimodal classroom experience. Moreover, it would be possible to model positioning traces from more than one teacher, as illustrated in our study, in order to understand the dynamics of co-teaching in the classroom such as relationships of power, coordination and effective space usage.

Yet, one key implication of this work is that curated representations of the metrics can enable teachers to reflect on the proportion of different types of learning activities comprising a teaching session, which can then lead to *changes in the learning design* as needed. The proposed metrics helped to characterise three learning designs using quantifiable observations of classroom positioning data. Consequently, we argue that such metrics can bring to the attention of teachers and learning designers certain characteristics that are expected in learning activities – for instance, increased teacher-student time ratio for a hands-on experiment design versus a lecture delivery. This is especially important in the training of new teachers, who have yet to establish their teaching practices and align it with the different types of learning activities defined in the learning design. Decisions to intervene and make changes are not automated by algorithms deliberately, as this involves another layer of human interpretation and understanding that suits the learning context in hand. Rather, these metrics would act as tools to aid teachers to make informed decisions (Gerritsen et al., 2018), contributing to the expansion of teachers' classroom capabilities, as envisaged in Luckin's work (2018) regarding AI in education.

While we note that the teachers would require some form of training to best utilise spatial pedagogy, we also identify the potential for teachers and other stakeholders to identify best teaching practices for professional development, as illustrated in our example of contrasting the different pedagogical approaches of two teachers. Finally, the data provided by positioning sensors, along with the metrics proposed in this paper, can contribute to the assessment of specific learning spaces, which is an identified gap in learning spaces research (Higgins et al., 2005).

As we will discuss in the next section, this list is not exhaustive and certain metrics might vary across contexts. Thus, our present implementation provides one set of metrics as a starting point towards investigating other dimensions of data to generate learning design-aware classroom positioning metrics. For more specific details about the implementation process or the calculation of additional derived metrics, please refer to our code library (https://gitlab.erc.monash.edu.au/rmat0024/moodoo).

Limitations and Future Work

In terms of the *limitations* of our illustrative study, we note that the parameters might need tuning to work with other types of learning spaces and learning designs. Although for this study we used the heuristic of 1 m to represent co-presence in each individual's interactional spaces (i.e., the distance from which a person can interact with other people or certain objects), the thresholds set for defining certain metrics might vary across contexts. For this reason, other classroom spaces that make use of the metrics need to test them for the right fit in their learning contexts. This points at the opportunity to generate learning design-aware classroom positioning metrics, that can guide instructional behaviour in ways productive for learning. Moreover, the analysis of significance of the metrics was not intended to support strong claims about which pedagogical approach is better, given the size of the dataset and the authentic conditions of the study which introduced several confounding variables. Controlled experimental studies are not recommended as they can hardly replicate emergent and often unexpected classroom situations that occur in authentic classes (Dillenbourg et al., 2011).

For future work, we envision three potential strands of research. A first strand could focus on the analysis of a larger dataset with the aim of mining the positioning data to identify patterns that could be used to differentiate instructional behaviours in the same learning space (similar to our study) or across different learning spaces (with the purpose of investigating the impact of the spatial design on instructional behaviours). To this end, the proposed Moodoo library is not tied to a specific underlying technology to capture positioning data. Both sensor and sensor-less (e.g., computer-vision based) technologies could be used to capture teaching positions at scale.

A second strand could focus on the development of additional features for the library, such as the implementation of a suite of visual representations to support teachers' sense-making of their instructional behaviours. For example, cumulative heatmaps of teacher's positioning (similar to Fig. 5) could be automatically generated, facilitating the visualisation of spaces that were not visited, which has been suggested to affect students' learning experience (Martinez-Maldonado, 2019b). Similarly, a histogram of metrics related to the proximity to classroom resources and teacher-student interactions could highlight areas of the classroom or students receiving less attention. Dandelion diagrams (An et al., 2020) that embed orientations in addition to positions, and layering other modalities of data, such as speech content (Ghahfarokhi et al., 2020), could also be tested with stakeholders in the future for richer insights. Yet, these visualisations will surely make additional challenges more evident, particularly related to the data literacy that teachers may need to make sense of positioning information.

Lastly, a third strand could investigate the applicability of these metrics for *in-class* or *after-class* instructional support. For instance, these metrics and visualisations could potentially be used as *in-class* instructional aids by giving early alerts of teacher's behaviour in relation to an expected learning design. An adaptive system could suggest that some students, groups or workbenches have not been visited yet. These alerts could be shown in a carefully designed dashboard for a tablet (Martinez-Maldonado, 2019a), in novel devices such as mixed-reality glasses (Holstein et al., 2018) or ambient displays (An et al., 2018). We also see potential value in after-class reports derived from these metrics and visualisations. These could provide timely opportunities for teachers, as well as learning designers, to reflect on classroom practices (Lockyer et al., 2013).

Pervasiveness in Tracking Teachers' Spatial Behaviours

Our current work adds to growing knowledge in the study of teachers' positioning and spatial behaviours in the classroom. Referred to as classroom proxemics or instructional proxemics, these can expand educational research and teacher professional development for improved teaching and learning outcomes. While early studies using manual data collection methods found the impact of teacher positions on student learning and engagement (Chin et al., 2017; Mcarthur, 2008), they also had limitations in their ability to scale and potential bias. New automated methods using sensors and location tracking devices to automate data collection (as demonstrated in the current study) can help overcome these issues, widening the opportunity for more extensive studies in the area.

Furthermore, there are noted challenges in the meaningful interpretation of constructs from positional data for the purpose of providing actionable insights to teachers (Martinez-Maldonado et al., 2020b). Moreover, there are operational challenges in terms of data collection and analysis when working with sensors and complex multimodal data (Blikstein & Worsley, 2018; Di Mitri et al., 2018). By devising a set of higher order metrics for modelling x–y positional data, implemented in the open source release of code to calculate those metrics, the current work is a positive step in the direction of widespread adoption of such advanced technologies to advance classroom research and teacher professional development. The growing availability of relatively cheap sensors and tracking devices will accelerate the adoption of such technologies, and their embedding into the physical infrastructure to assist non-obtrusive use. As more data and scenarios emerge from across different learning contexts, we may be able to achieve standardised metrics and gain generalisable insights to improve learning designs and learning space designs.

Ethical Concerns and Practical Challenges

The technical potential for pervasive activity tracking quite rightly raises important ethical questions. The kinds of location data collected by position tracking sensors in the current work do not contain fine-grained identifiable personal data such as collected using video-based approaches and wearables such as microphones, cameras and mobile eye-trackers, which might raise stronger privacy concerns due to intended surveillance (Derry et al., 2010; Martinez-Maldonado et al., 2020c; Prieto et al., 2018). In this research, data collection was conducted with the informed consent of all participants with awareness of what data is being collected and for what purposes, but we are mindful that “smart infrastructure” fades into the background when it is part of everyday life.

There are other ethical concerns and practical challenges that need consideration when working with positional traces from teachers and learners in real classrooms. The first comes with the interpretation of data and insights gleaned from the analysis of such data. While automation can remove humans from the interpretational loop, our use cases seek to maintain human agency, whereby teachers must play a major role in the interpretation and judgement of multimodal data (Worsley et al., 2016). That in turn brings its own risks: interpretations can be biased and can favour certain types of evidence, or be shaped by certain learning designs. There is the potential risk of over-interpreting inconclusive patterns in small data sets. We therefore envisage an important role for training to enable interpretation of automated metrics with integrity. Moreover, there may be an intention of using the metrics to summatively assess teachers’ performance. However, our previous qualitative studies found that is not desired by teachers and it may be concerning to try to judge their performance based only on positioning traces (Martinez-Maldonado et al., 2020c; Martinez-Maldonado et al., 2020d).

In sum, interpretation still requires deep contextual knowledge and an understanding of the use of space with other semiotic resources (e.g. language, gesture and teaching materials).

Spatial activity traces are only one part of the overall classroom scenario and do not provide a complete picture. As with many computational tools, they are best regarded as “another voice round the table” as professionals make sense of information and make decisions — a new kind of voice, which needs to be weighed with other sources of evidence when making judgements about complex human qualities.

To use Weick (1995) language, these kinds of metrics and visualisations are "sense-making support systems" to help stakeholders construct plausible narratives, not shortcuts to reach automated judgements. Hence, in an educational or training context, we frame these as tools for formative feedback, not summative assessment. This should always be considered in similar applications even if there are economic incentives for full automation.

Our own previous qualitative work has noted teacher concerns in sharing data with other stakeholders (e.g. administrators) to avoid unintended consequences, such as the use of data to assess performance, and misunderstanding of different teaching needs and individualistic styles (Martinez-Maldonado et al., 2020d). Hence, we posit that the comparison of data from different teachers should only be intended for their own feedback and professional development.

Conclusion

In conclusion, this paper presented a set of conceptual mappings from x–y positional data of teachers to higher-order spatial constructs (namely: teacher's stops, transitions, teacher-student interactions, proximity to objects of interest, instances of co-teaching and entropy of teachers' movement), informed by the concept of Spatial Pedagogy (2012). The resulting metrics, implemented in open source code, offer researchers new tools to study classroom activity in novel ways, developing our understanding of teacher-student proximity and physical behaviours at various learning settings. Further maturation of the tools opens the possibility for more evidence-based teacher professional development, bearing in mind our cautions regarding the need for training with such tools, and the risks around unethical use of such data. Our illustrative study showed how these spatial metrics can be used to generate a deeper understanding of i) how the pedagogical commitments embedded in the learning design can influence spatial aspects of teachers' behaviours, and 2) how personal pedagogical approaches are reflected in the ways teachers use the learning space to provide support to students. Future research should certainly further test the applicability of the metrics in other learning settings (i.e. in multi-class open spaces or lecture halls) and, expand the library with metrics that can better model how teachers and students use classroom space, as well as interact and move in such classrooms.

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