Teacher Tracking with Integrity: What Indoor Positioning Can Reveal About Instructional Proxemics

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Automatic tracking of activity and location in the classroom is becoming increasingly feasible and inexpensive. However, although there is a growing interest in creating classrooms embedded with tracking capabilities using computer vision and wearables, more work is still needed to understand teachers' perceived opportunities and concerns about using indoor positioning data to reflect on their practice. This paper presents results from a qualitative study, conducted across three authentic educational settings, investigating the potential of making positioning traces available to teachers. Positioning data from 28 classes taught by 10 university teachers was captured using sensors in three different collaborative classroom spaces in the disciplines of design, health and science. The contributions of this paper to ubiquitous computing are the documented reflections of teachers from different disciplines provoked by visual representations of their classroom positioning data and that of others. These reflections point to: i) the potential benefit of using these digital traces to support teaching; and ii) concerns to be considered in the design of meaningful analytics systems for instructional proxemics.

CCS Concepts: • **Applied computing** → **Education**; • **Human-centered computing** → *Ubiquitous and mobile computing systems and tools.*

Additional Key Words and Phrases: Learning analytics, indoor positioning, proxemics, location analytics

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1 INTRODUCTION

Accurate physical positioning of objects and people in indoor spaces has long been a key challenge in ubiquitous computing [1, 63]. Different technologies have been used to this end, for example, by triangulating WiFi [82], Bluetooth [65], infrared [49], visible light [40], audio [59], and radio [84] signals; or by using inertial sensors [44] or computer-vision [41]. Significant advancements have been made in improving the accuracy of such systems (see reviews in [64, 83]) and in creating context-aware applications in a range of areas such as blind navigation

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Fig. 1. Authentic classroom settings this paper focuses on: (C1) a typical collaborative classroom with moveable tables, (C2) a nursing simulated wardroom, and (C3) a physics laboratory.

support [31], augmented reality [38], retail [68] and emergency response [50]. Yet, there remain underexplored opportunities in making indoor positioning data and analytics available to key stakeholders to provide deep insights into how people use physical spaces, optimise activity workflows or help people reflect on their own behaviours [52, 60] (e.g. see emerging applications in healthcare [46, 66]).

In the educational sector, teaching guides (e.g. [6, 42, 72] and professional support staff or peers [12] often recommend or prescribe to teachers how to position themselves in specific locations of the classroom (termed *instructional proxemics* [20, 57]). These guides and feedback from peers are important for many teachers, particularly for those in higher-education (HE) who rarely receive pedagogical training (e.g. teaching assistants, tutors and academics) nor feedback on how to position themselves while delivering classes [26, 30]. Unfortunately, these guides commonly do not refer to the evidence used to prescribe such strategies. Moreover, feedback from other people can be susceptible to bias [73] and it is hard to scale up [29]. A growing number of analytics prototypes and products that show digital traces of students' *online* behaviour are being made available to educators [8, 9, 71]. However, in most institutions the majority of teaching is still face-to-face, yet there is little work on providing data-driven support for teachers to improve their practice in physical learning spaces [21, 54]. This gap unlocks opportunities to use indoor positioning data to derive effective teaching strategies for various learning situations.

Although *instructional proxemics* — the study of teachers' positioning in relation to the existing classroom layout and students' seating arrangement — is not new, most work has relied on self-reported and observational data from a small number of classes. For example, observational work has reported how mobility strategies in the classroom can strongly influence students' engagement [20], motivation [28], disruptive behaviour [33], and self-efficacy [45]. Findings however may not generalise across educational contexts [37] and teachers rarely can reflect on their positioning strategies using evidence [48].

Automatically tracking activity in the classroom is becoming increasingly feasible and inexpensive, with a growing number of classroom setups equipped with computer-vision systems (e.g., [2, 10, 39, 69]) and sensors embedded in the furniture, objects or wearables (e.g., [5, 53, 67, 70]) capable of tracking teachers' and students' movement and interactions. Recent studies explored the potential of interfaces that alert teachers which students have received little attention in the classroom [5, 53]. However, more work is required to understand teachers' perceived opportunities and concerns when using positioning data to reflect on their practice, which in turn, can serve to create analytics interfaces that might be pedagogically meaningful.

In response, this paper contributes to generating a deeper understanding about what indoor positioning data can reveal about instructional proxemics. We conducted a qualitative study to investigate the potential of making positioning traces available to HE teachers. Four studies were conducted in three authentic classrooms: a typical collaborative classroom with moveable tables (Figure 1, C1), a nursing simulated ward (C2) and a physics laboratory (C3). These were instrumented with an Ultra-Wideband (UWB) indoor positioning system to capture data from 10 teachers, teaching solo and in pairs. These were analysed, visualised and evaluated by teachers to reflect on their teaching strategies and those of others. The paper documents teachers' reflections provoked by basic visual representations of their positioning data, the envisaged usage of these data to support learning and teaching, and potential concerns to be considered in the design of classroom positioning systems.

2 BACKGROUND

The fundamentals of instructional proxemics and the current work in indoor positioning analytics (particularly applied to learning spaces), are two areas especially relevant to our study.

2.1 Proxemics and instruction

The term *proxemics* points at foundational work by Hall [35] who defined it as the study of how people use the physical space and interpersonal distance to mediate interaction according to the cultural context. This foundational work set the basis for creating systematic notation systems to study the use of space, both qualitatively and quantitatively [80]. The notion of proxemics has evident application in architecture and interior design [36] as well as to analyse behaviour in indoor and public spaces [23].

Proxemics is highly relevant in education because characteristics of the physical learning space can strongly shape pedagogical approaches deployed, and the interactions among teachers and students [13]. For example, proxemics has been applied in the design of flexible learning spaces [74] and to analyse behaviours associated with effective teaching [18]. However, research on proxemics in learning spaces is dispersed [56] partly because different terms have been used to refer to the same aim: studying how teachers and students use the classroom space. Moreover, most of the work conducted to date has been based on direct observations and video analysis [34, 78]. For example, Lim et al. [48] proposed, based on classroom observations, the term spatial pedagogy to explain the meaning of certain spaces in the classroom according to teachers' relative proximity to students, furniture and materials. Others have used the term *instructional proxemics* [20, 57] to focus on the impact of teachers' positioning on aspects such as engagement, attention and disruptive behaviour. Mcarthur [56] explained that instructional proxemics provides a conceptual lens that blends instructional communication and pedagogy with information and user experience design to generate understanding of activity in spaces of learning. Yet, some authors [48, 53, 57] have pointed out at the need for automated approaches to facilitate the collection of positioning and contextual evidence to more deeply investigate instructional proxemics and to apply research findings in practice to assist teachers.

The next section describes the current data-intensive approaches that could address the automated analyses of classroom positioning/location data. Although the term *positioning* is coordinate oriented (e.g. identifying x and y position in a room) and *localisation* is feature-oriented (e.g. identifying people in a map), in practice, both terms are commonly used interchangeably [85] and this is how they will be used in this paper too.

2.2 Indoor positioning technology in learning spaces

As argued above, a great extent of research in indoor positioning has focused on improving the accuracy of algorithms [64, 83] and providing location-based services, mainly to facilitate navigation (e.g., [31, 38, 50]) or tailored alerts (e.g. [68]). A less explored aspect is how to effectively analyse large amounts of data generated through sensors and computer-vision systems, to identify insights for end-users or decision makers [19, 52, 60].

Some examples in healthcare and sports settings demonstrated the potential of positioning analytics in decision making. For example, clinicians have identified workflow bottle-necks in emergency rooms using positioning data of healthcare staff captured manually [66] and automatically [25]. Similar data has helped in detecting risk of injury for residents of an aged care facility [46]. Analytics using wearables and computer vision have a longer history in sports science, including indoor and outdoor positioning systems to support mobile coaching, assessment of team strategies, and performing deep game analysis [47].

In educational contexts, Sensei [70] and EduSense [2] are two recent classroom setups, enriched with ubiquitous technologies, that allow pervasive tracking of teachers and students. Sensei relies on tiny proximity sensors embedded into shoes or other materials to provide relative positions of people and objects in a classroom. This allowed creation of basic visualisations that can assist teachers to observe what parts of the classroom they visited more and which students they interacted with longer. EduSense is a computer vision system that detects proximity of students and the teacher to the camera as well as some kinesthetics behaviours, such as raising a hand, and facial features. While the technologies used in these studies provide relative proximity rather than continuous position tracking, the data captured can certainly serve to generate a deeper understanding of instructional proxemics. For example, authors of Sensei visualised the proximity of teachers to students in the classroom as heatmap visualisations, and authors of EduSense quantified the relative distance of teachers and students to the camera.

There has also been a growing interest in exploring physical aspects of the classroom using learning analytics techniques [21]. Some authors have used video feature analysis to identify students' posture during a lecture [69]; quantify the interactions between lecturers and students [79]; model teacher's behaviours such as walking or gesturing during a lecture [10]; and visualise walking trajectories in the classroom [39]. A key limitation of video-based approaches is that they depend on the position of static cameras which do not provide precise positioning data and they can be impractical for regular classroom use due to potential ethical issues related to unintended surveillance [70]. Wearable sensors have also been used to track teachers and students. For example, Prieto et al. [67] modelled teacher's tasks using wearable sensors (eye tracker, accelerometer, electroencephalogram device and a camera). Through the eye tracker, the system could estimate the relative position of the teacher to certain classroom spaces. Some work also explored the use of wearable sensors to track the exact positions of team members in healthcare [25] and firefighting [77] training scenarios.

Besides Sensei [70], two other recent works have offered teacher-facing positioning analytics. ClassBeacons [5] shows the amount of time a teacher has spent in close proximity to groups of students through a tangible device located at each group's table. Similar work [53] provided a tablet-based dashboard showing a floor map of the classroom with representations of the locations of groups of students, a heatmap of where the teacher has been most of the time, and alarms indicating potentially neglected students. Whilst the use of positioning data was positively appreciated by teachers in both studies, concerns also emerged in terms of disruption [5], usefulness of the visualised positioning data [70], and potential misinterpretation of the data if context is not considered [53]. This suggests the need to further investigate, from a human-centred perspective, the pedagogical implications of automatically collecting positioning data in the classroom, the ethically-aware design considerations to support teachers, and the potential critical role of other stakeholders.

2.3 Contribution to knowledge

In response to the challenges identified from the previous research findings presented in sections 2.1 and 2.2, the work presented in this paper addresses the gap between the need to capture better evidence to inform instructional proxemics (section 2.1) and the emerging work in ubiquitous computing (ubicomp) focused on creating interfaces that support teachers' awareness (section 2.2). The contributions of this paper to knowledge in ubicomp are the documented reflections of teachers from different disciplines (design, health and science) provoked by visual representations of their classroom positioning data and that of others. These reflections point to i) the potential benefit of using these digital traces to support teaching and teachers' reflective practices; and ii) concerns to be considered in the design of meaningful analytics systems for instructional proxemics.

3 TEACHING CONTEXTS

Three authentic *collaborative classrooms* are described. A collaborative classroom is a learning space and its associated pedagogical approach that emphasises group learning; enabling students working together in small groups or teams, plus one or more teachers providing tailored feedback [22]. This paper articulates results from four studies (S1-4) conducted in three authentic teaching contexts (C1-3 shown in Figure 1), all located at University of Technology Sydney.

3.1 Design education context

The teaching situation in the *design* context (C1) was part of regular classes of a third-year undergraduate unit that immerses students in a problem-based experience through weekly 3-hour classes of 15-20 students organised in small teams of 4-5. Study 1 (S1) was a pilot study focused on **four randomly chosen classes** (A, B, C and D) conducted in weeks 3, 4, 5 and 6 of the second semester, 2018, **taught by the same female teacher (T1)**, who was also the coordinator of the unit (thus, the most experienced teacher for this unit). The classes were conducted with the same students (15 students organised in three teams of 5) in the same (8 x 10 meters) classroom. The room is equipped with moveable tables, a projector and pinnable walls. Students arranged the tables in a similar way at the beginning of each class, forming three large tables. Each class exhibited a very distinctive instructional design. Classes A and B involved 3 hours of continuous *design work*. Class C was equally divided into two parts: i) *group oral presentations* in which each team, in turns, used the projector to report on their progress; and ii) team meetings. Class D was also divided in two parts: i) *poster presentations*, in which all the class would move to each table in turns for teams to present prototypes (2 hours); and ii) team meetings (1 hour).

3.2 Health education context

The teaching situation in the *health* context (C2) was part of regular classes of a third-year undergraduate unit that includes various team-based clinical simulations conducted in classrooms equipped with a patient manikin in each of the 5-6 beds. Students are commonly organised in teams of 4-5 to look after a simulated patient each in a hypothetical scenario, while a teacher enacts the role of a doctor when required, but otherwise observes the practice of the various teams of nurses. Study 2 (S2) was also a pilot-study focused on one simulation conducted in **six regular classes** (1-6), in the first semester, 2019. **Two highly experienced nursing teachers (T2 and T3, one female and one male, respectively)** individually taught three classes each. Different to S1, each class was attended by different students (from 26 to 30 nursing students in each organised in **six teams of 4-5)** in the same (13.5 x 7 metres) simulated hospital ward. The aim of the simulation was to help nurses learn how to react when a patient is having an allergic reaction to a medication. Students were intended to perform specific actions such as: assessing the patients' vital signs at specific moments, administering intravenous (IV) antibiotics and timely ceasing of the antibiotic after the patient reacts with chest tightness.

3.3 Science education context

The teaching situation in the *science* context (C3) was part of regular laboratory classes of a first-year undergraduate unit that includes various weekly 2½ hour classes aimed at providing students with a space for them to run experiments; advised by a teacher and a teaching assistant, both *co-teaching* in the classroom. Each class typically has between 30 and 40 students working in **10-13 small teams of 2-3**. Two larger studies (S3 and S4) were conducted in this context. S3 focused on **twelve classes** (1-12) and S4 on **six classes** randomly chosen

(13-18), conducted in weeks 4, 5 and 6 of semester 1, 2018 and 2019 respectively. **Seven teachers (T4-T10, T7 the only female)** were involved in these classes. T4, the coordinator of the unit, designed the learning tasks and did not teach any class. T5 and T6 were the main teachers for 12 and 6 classes respectively, and the other four teachers (T7-T10) were teaching assistants. All classes were conducted in the same (16.8 x 10 metres) classroom equipped with work-benches, a teacher's desk, and multiple laboratory tools and devices.

Each class exhibited one of three possible instructional designs (ID1-3). ID1 was a *prescribed lab*, in which all students had to do the same experiment following a step-by-step guide. ID2 was a *project-based lab*, in which students were asked to formulate a product testing project, with each team working with a different product, such as vacuum cleaners or pedestal fans. Finally, ID3 was a *theory-testing lab*, in which 4-5 experiments were set up by the teacher and students had to move to one experiment at a time and predict the outcome of each without further guidance. The classes were conducted with the same students in the same classroom for each of the observed weeks. This means instructional design ID1 was enacted in classes 1-4 and 13-14 in week 4. ID2 was enacted in classes 5-8 and 15-16 in week 5 with the same students of the week 4, respectively. Finally, ID3 was enacted in classes 9-12 and 17-18 in week 6.

Table 1 presents an overview of the educational contexts this paper focuses on.

Table 1. Overview of educational contexts, instructional designs, teachers and students of the studies

Teaching context	Study	Instructional designs	Classes	Students per class	Teachers and roles
C1 Design education	S1	i) Small-team design work ii) Oral presentations iii) Poster presentations	4	15 students (3 teams of 5 students)	T1 – subject coordinator and experienced class teacher
C2 Healthcare education	S2	i) Nursing simulation: allergic reaction	6	26-30 students (6 teams of 4-5 students)	T2 and T3 – both subject coordinators and experienced class teachers
C3 Science education	S3 S4	ID1) Prescribed lab ID2) Project-based lab ID3) Theory-testing lab	12 6	30-40 students (10-13 teams of 2-3 students)	T4 – subject coordinator only T5 – main teacher in S3 and S4 T6 – main teacher in S4T7 (S4), T8, T9 and T10 (S3) – teaching assistants (tutors)

3.4 Apparatus and data collection

Classrooms shown in Figure 1 were instrumented with a Pozyx.io ultra-wideband (UWB) system for automatically tracking the (x and y) positions of teachers wearing a custom-made badge (e.g. Figure 2). A total of five, seven and eight 'anchors' (⬡ in Figure 3) were installed on the walls of classrooms C1, C2 and C3, respectively. These configurations reflected the different room sizes and ensured that every point inside the classroom was inside the anchor's bounding box. UWB sensors are suitable for tracking activity in classrooms in which multiple devices are commonly used by students because, unlike technologies such as infra-red, Bluetooth and ultrasound, do not require a straight line of sight and are not affected by other digital devices in the room [3].

Fig. 2. UWB indoor positioning badge worn by teachers.

The positions of each badge are obtained through a process called *multilateration*. Distances are first estimated based on the measurement of the time of arrival of radio signals (between 3.5 and 6.5 GHz) sent back-and-forth between each badge and the anchors. Once the badge has ranged with at least three anchors, it can geometrically compute its position, and this is sent to a central computer located in the classroom. This keeps a record of the streams of positioning data sent by the badge(s) being tracked in the classroom. The cost of UWB equipment is low, making it affordable and portable. The system provides an error rate of 10 cm, recording x and y positions at 2Hz average sampling rate.

The locations of the spaces in which each team of students commonly interacted (e.g. team tables, beds and experimental setups) were recorded. These served as proxies of students' positions. The positions of student tables in C1 were recorded by placing sensors on each table. For C2, sensors were located at the patients' beds to record their positions as beds were not moving. For C3, given the high number of teams, a software console paired with the tracking system was used by an observer to register where the experiments were located by students on the classroom floor plan (see Figure 3, right).

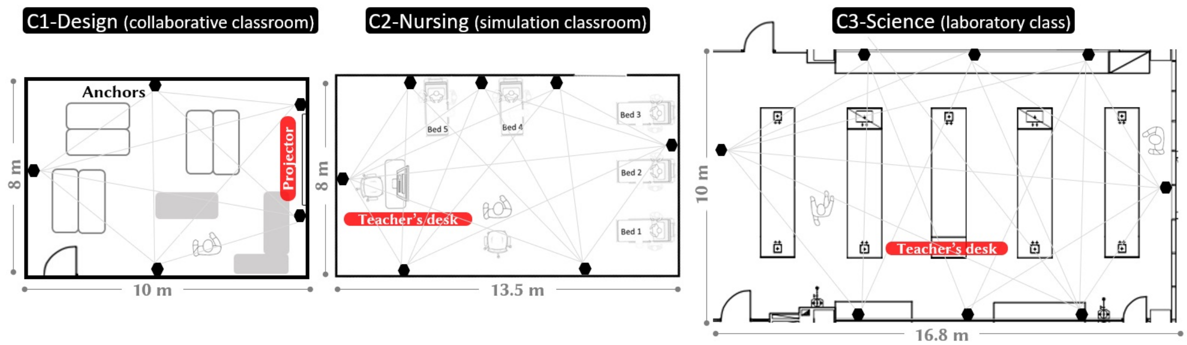

Fig. 3. Floor plans of the three classrooms instrumented with the indoor positioning tracking system.

4 METHOD

This section presents the research questions and methodology that served to address the gap identified in Section 2 and the analysis approach of the qualitative study.

4.1 Research questions

The qualitative study deployed across the three contexts employed a retrospective reflection technique [19] to investigate the opportunities and concerns of indoor positioning tracking to support teachers. The studies were all conducted using LATEP [55]. This is a protocol for understanding how non-data experts envisage the use of learning analytics systems using data-driven interviews. LATEP articulates three interconnected principles which have been applied to the design of physical spaces enriched with ubicomp technologies [7, 24, 61]: *visibility, awareness* and *accountability* [27]. *Visibility* is foundational as it entails the capability of clearly seeing relevant information about activity. *Awareness*, which rises from visibility, is the human ability of knowing what information has been shared and how people can use this information to change behaviour. *Accountability* refers to a series of norms and customs that can become mechanisms to regulate social behaviour as a result of making information visible, thus making people accountable for their own actions to one another.

Based on this rationale, our studies investigated the following three questions:

(1) **Is there any *added value* of making instructional positioning data visible to teachers?** (If so, what is the added value?) This question points to the foundational principle of systems aimed at enhancing

the visibility of activity which can be hard for a teacher to see, particularly in collaborative classrooms in which multiple teams of students work on their tasks in parallel.

(2) **What are the anticipated *uses* of these data for teachers and their visual representations to support teaching?** This question is directly related with the principle of awareness: once positioning data is made visible, what are the envisaged uses by teachers to support teaching and learning.

(3) **What is the potential impact of sharing instructional positioning data with other stakeholders on teachers' *accountability?*** This question explores the potential privacy and ethical considerations related to data sharing and making evidence, that is not commonly available, open to scrutiny.

4.2 Protocol

The **LATEP protocol** was used to structure a set of *data-driven interviews* with teachers from the three settings. After the classes were delivered and positioning data was collected, the protocol was operationalised in the form of 45-60 minutes semi-structured interviews as follows:

(1) Teachers were first asked to describe the instructional designs and the usual classroom dynamics of their classes; and comment on what they expected to see in the positioning data.

(2) A think-aloud protocol was followed to document how teachers explored the positioning data. Data were presented to teachers as (printed/digital) indoor maps containing positioning data of the classes relevant to them, including those taught by other teachers (for C2 and C3). This is one of the simplest ways to represent positioning data: registering the spatial data to a common coordinate system [32]. A similar visualisations approach was followed for representing data from Sensei [70] and the tablet-based classroom alerting system [53] reported above. On request, the same data was made available to teachers for each class divided into quartiles (see examples for Class C in context C1 in Figure 4). The maps were generated by normalising the positioning data to 1Hz to make them comparable. The maps were printed or presented digitally using a visual impairment aware colour palette.

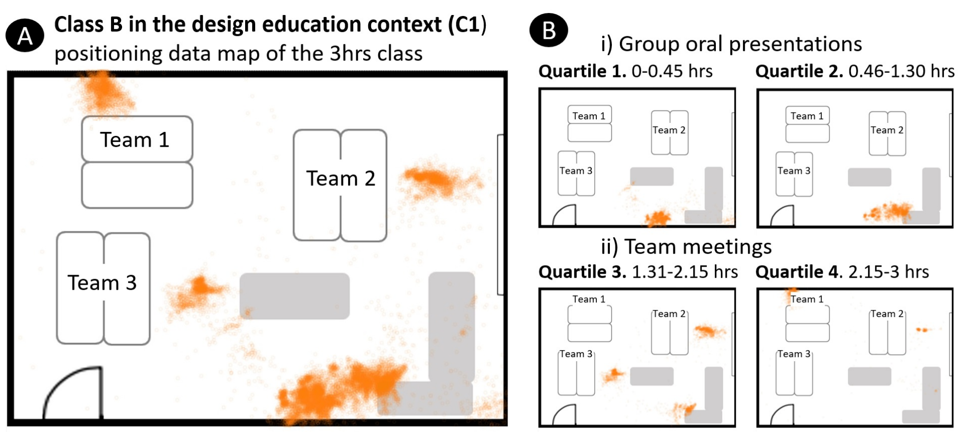

Fig. 4. Example set of visual representations of positioning data for each class presented to teachers, including: A) a positioning data map of the whole class duration and B) the data equally divided into quartiles.

(3) A post-hoc semi-structured interview was conducted to identify potential uses of the data. This included questions suggested in the LATEP protocol, and that match our main research questions, as follows:

- **Visibility**. *Key question*: what is being made visible through positioning data? *Secondary questions*: how do you think these data could be interpreted? What aspects of teaching these data allows you to identify?
- **Awareness**. *Key question*: what would you do with these data? *Secondary questions*: what do you think would be useful for the teacher: to have during or after the class?
- **Accountability**. *Key question*: what are the implications of showing these data to others? *Secondary questions*: who do you think should look at these data? should the data be given to: teachers themselves, other teachers, academic units, or students? do you think these data can be used to assess the performance of the teachers? what additional sources of data or metrics should be considered?

Interviews were video-recorded and transcribed for analysis.

4.3 Analysis

Following best practices of qualitative research [58], and given the direct alignment between the study protocol and the research questions, statements of interest from the think-aloud and post-hoc sessions were jointly identified by two researchers. These were thematically coded [11] by one researcher, and a sample of 15% of the transcribed statements by a second researcher, independently in two steps. First, a *deductive step* involved coding teachers' reflections according to the pre-set themes of the study protocol: a) visibility, b) awareness, and c) accountability. Secondly, an *inductive step* involved identifying emerging sub-themes. Resulting coded statements were examined by authors to reach agreement on similarity of vocabulary used in the second step. there was a substantial agreement between both researchers (Cohen's kappa k = 0.807 and k = 0.724 for the deductive and inductive steps, respectively). Next, researchers had several discussions to select instances that effectively illustrate opportunities and concerns of making traces of instructional proxemics visible, which are reported in the next section.

5 RESULTS

This section examines evidence from studies S1-4, organised by themes that correspond to the three RQs and emerging sub-themes.

5.1 Visibility: the added value of positioning data for teachers

Overall, teachers generally appreciated the potential value of making traces of their classroom movement behaviours visible, which are commonly ephemeral. For example, a teacher assistant in context C3 (i.e. science education) reacted as follows: *"It's amazing, like looking at your footprints all over the classroom, it's quite interesting"* (T7). A more experienced teacher stated the following *"It is the first time I've seen this kind of thing. It is really good because you see the real situation. I see the things I didn't see during my time in the class. Definitely, I think it is helpful"* (T5). However, the interest of the study is on identifying the added value of making their positioning data visible, beyond a general appreciation of the technological novelty. Five sub-themes emerged regarding visibility, namely, i) interpretation of the data based on the instructional design; ii) identification of differentiated instruction strategies; iii) identification of particularities of the classes that affect proxemics; and identification of iv) territoriality and v) temporality aspects of positioning strategies.

5.1.1 Positioning data and the instructional design. All teachers interpreted their positioning data based on the particularities of the instructional design. Some teachers (T1, T4-6) stated that this is the major factor that explains positioning changes from one class to another, with other factors, such as individual characteristics of the teachers, students and the learning space being also important, but secondary. For example, T1 mentioned that *"if a tool is built based on these [positioning data], there is the need for tuning the tool according to the activities for each week"* (T1). At the same time, the instructional design provides the context required for sense-making of the positioning data. T4, the coordinator in context C3, expressed this while inspecting the positioning data of his teachers, as follows: *"You know what's happening because you know what's supposed to happen".*

In context C1, teacher's positioning traces were strongly shaped by the distinct instructional designs enacted in each class with the same students. Figure 5 presents the indoor maps presented to T1 showing the data from classes A, C and D. For example, in class A, students were asked to focus on design work, with the teacher sitting at each table to provide feedback. While the teacher inspected her data (Figure 5, left) she explained: *"I think it is pretty accurate because I was standing in this, at the centre area (see Point A in Figure 5), and I was talking a lot at the beginning. Then, I tended to hang around near the students".*

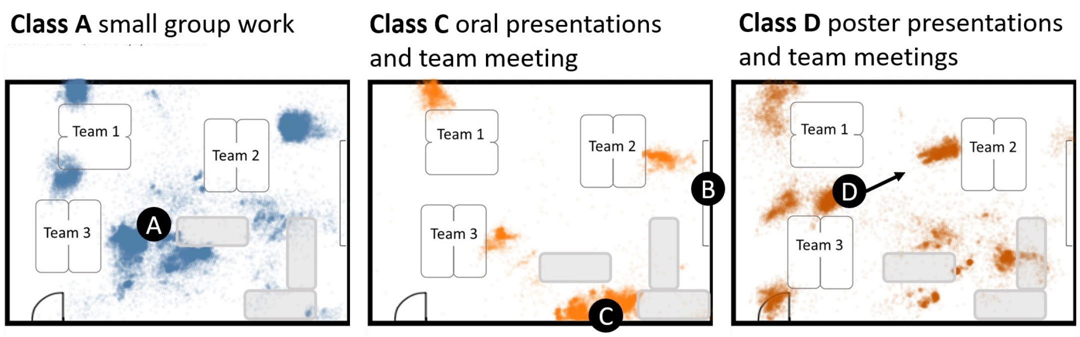

Fig. 5. Positioning data maps in the design context (C1). All classes were taught by teacher T1.

In contrast, in class C (Figure 5, centre), where students presented their work using the projector (Point B), the teacher commented: *"Here I am not so central. Why did I move further back? Oh! Students were doing presentations, so I sat down in the same spot for half of the class (see Point C). I think the data is pretty good. After the presentations I spent time with each group".* Finally, regarding class D (Figure 5, right), where students did a poster presentation, pinning materials on the walls for other students and the teacher to come closer, the teacher mentioned: *"I would like to justify my [data]. I spent more time with team 2 than what it seems, but because they were doing the presentations as a poster I was standing further away from their table"* (Point D). This suggests that the meaning of the positioning data and the proximity to students' spaces is strongly dependent on the classroom activity context (e.g. for class D the teacher was still paying attention to particular students' poster presentations from a longer distance compared to classes A and B).

Similar reflections emerged in context C3. The coordinator and teachers explained how students' task explains certain patterns observed in their positioning data. For example, the coordinator (T4) explained the differences between two instructional designs as follows: *"for [ID1] since all the groups are doing exactly the same, teachers basically move slowly around the tables, looking over the shoulder and making themselves available (e.g. see Figure 6, left). But for [ID2] teachers run around a lot, because students are running around a lot (...) since they bring their own projects (e.g. see Figure 6, centre). Students also need more space for experimental design. It's not like in [ID1] where the task has been prescribed".*

The teaching assistant (T7) explained how the instructional needs (e.g. the need for theoretical explanations in ID1) and the particularities of the task (e.g. the complexity of students' projects in ID2) strongly shaped the way teachers moved in the classrooms and the kind of instruction provided (e.g. being closer to the teacher's computer "lecturing" – see Point A in Figure 6 – or close to the students' experiments for the case of ID1 compared to the "more spread" classroom coverage in some instances of classes enacting ID2): *"For ID1, because each group was doing the same set of experiments, we had to make them understand the whole theory, we had to lecture. That's why*

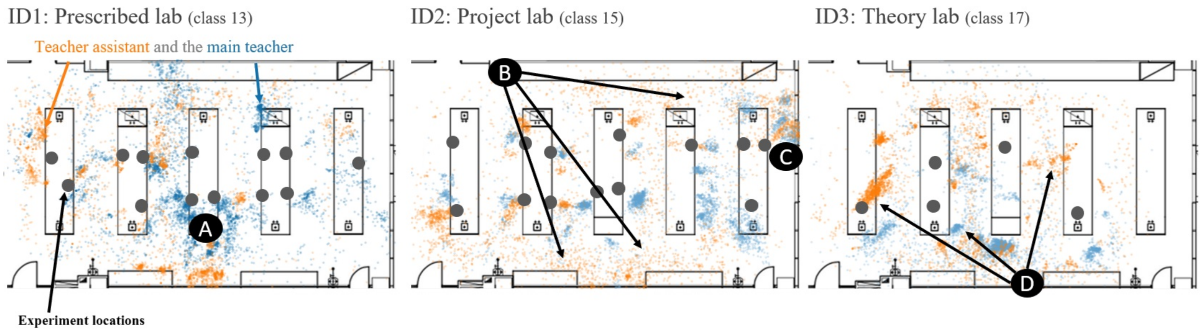

Fig. 6. Example positioning data maps in the science education context (C3). Classes taught by T6 (main teacher) and T7 (assistant).

we spent more time at each table. But for this one (ID2) it's not much theory, that's why we were spreading and just making sure everything was safe" – see Point B.

T4 explained that two types of patterns emerged from these two instructional designs, a *"staccato style type of scattered attention"* for ID1, and *"a lot more concentrated attention"* for ID2. Similarly, T5 explained that *"it is possible to know that [the instructional design] is different [between two maps] because the pattern is different"*. In contrast, regarding the classes enacting ID3, some spaces in the classroom were barely utilised since teachers set up 4-5 experiments in selected benches (see Figure 6, right) and students need to move from one experiment to the other. This explains why teachers concentrate in specific spaces and their role changes from lecturing and monitoring (in ID1 and ID2) to demonstrating. T4 explained why proxemics patterns were unique for ID3, as follows: *"For [ID1/ID2], the teachers go around, whereas for [ID3] they are demonstrators of the four experiments, some set up closer to the edges of the benches (e.g. see Point D). Students come in, and they know what they are going to do"*.

In sum, the instructional design strongly shapes teachers' proxemics, as evidenced in the teaching contexts where more than one instructional design was enacted. Moreover, individual teaching strategies were also visible (discussed in more detail in the next section). On the one hand these findings are hardly surprising – indeed it would be highly problematic if instructional design and teaching strategies were invisible in the proxemics data. So, this provides encouraging evidence that (i) the positioning data was of sufficiently high definition to reflect these instructional differences, and (ii) that the 'footprints' visualisation was intelligible to non-technical teachers, although the nuances of how they are interpreted are examined throughout this paper.

5.1.2 Differentiated instruction strategies between teachers. Differences between teachers were more evident in the healthcare context where the same instructional design was repetitively taught by two teachers. Figure 7 shows the resulting maps for T2 and T3 (left and right), which are representative of the rest of recorded sessions. Maps show two teaching strategies. T2 stayed at the teacher's desk (*"I used the area around the lectern initially to outline the class activities, learning objectives and give the handover to the students before the simulation begins"* – see Point A) and attended students very closely to patients' beds (Point B). T2 explained her teaching approach as follows: *"I usually make time to talk to each group, review their skills, answer questions and do some teaching close to them. I find that students are more comfortable to ask questions and clarify concepts at the bedside"*. In contrast, T3 placed a chair at the centre of the classroom (see Figure 7, right, Point C) and, although also moved about the patient beds, he was not as close to students as T2. T3 explained his pedagogical approach as follow: *"I use a* *'whole-of-class' approach, in a central space in the class, not at the lectern. From there I can observe all bed areas. The area between Beds 4 and 3 is another location where I can observe activities and interactions from another direction".*

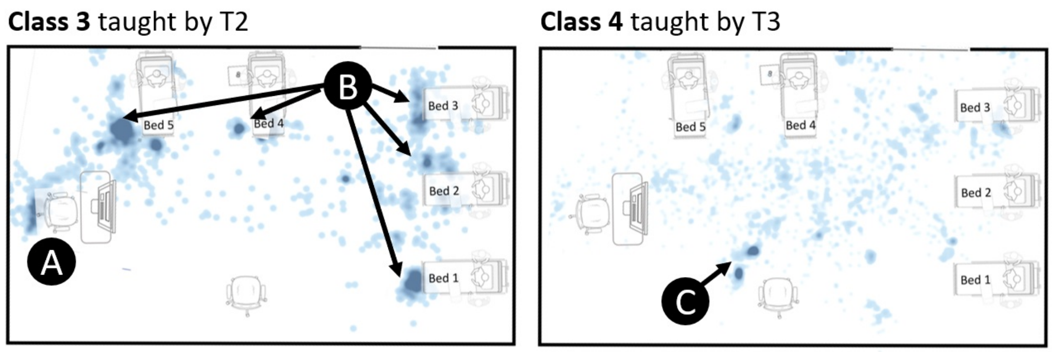

Fig. 7. Example positioning data maps in the healthcare education context (C2). Classes taught by T2 (left) and T3 (right).

When teachers looked at each other's data they wondered about the implications of the other's pedagogy. T2 showed interest in T3's teaching approach, as follows: *"It seems [T3] does a lot of his teaching at the front and then gets the students to do stuff. Whereas with me I'm part of the action all the time, playing the role of the doctor. Unless maybe he got the students to come to him. I never actually watched his labs. It would be interesting to see because this year I've got a lot of new tutors to run the simulations. It would be good to show them these"*. T3 also wondered about the difference of T2's approach as follows: *"It may relate to specific team needs in that class or simply different teaching styles"*. T3 added that his teaching approach was influenced by the particularities of the classroom interior design, as follows: *"I commonly locate myself outside the workspace at the foot of the beds. From a physical environment perspective, there is no space for me to be on the right side of Beds 5 or 3, and this is similar for the left side of Bed 1. For context, there may be students acting as a patient sitting on the right side of each bed; space in this room is problematic"*.

Differences among teachers also emerged in context C3, particularly for the case of the inexperienced teaching assistants. Figure 8, for example, shows two distinctive behaviours that were categorised by T4 and T5 as assistants being either *"helpful"* to students (left) or *"supervisory"* (right). T5 explained that the assistants T7, T8 and T10 displayed a similar teaching behaviour: *"not concentrating on one group, giving help to everybody. There is a marked difference here, specially this assistant (T7) is more helpful"* (e.g. see Point A). In contrast, T5 explained that the behaviour being made visible by the data depicted a concern he observed during the classes, as follows: *"I think [T9] doesn't do much because the dark patches are few. His movement is supervisory. In practice, this means he is not having enough time to give explanations. He's spending more time moving (pointing at B in Figure 8, right)"*.

In sum, although the instructional design is a critical factor that impacts the kind of observable patterns that can emerge from the teachers' positioning data (as illustrated in the previous section), differences in teaching approaches can break the 'expected' patterns.

5.1.3 Identification of particularities of each class. Another critical factor mentioned by some teachers that influences the instructional proxemics is the uniqueness of each class. This was particularly highlighted by all the teachers in context C3, who inspected positioning data from several classes. For example, T5 said: *"Every class is different, even though the same teacher stays, the [positioning] pattern can be different"*. Teachers further explained that this can be due to a number of factors. The first factor mentioned by T6 was student's **preparedness**: *"From class to class all can be quite different. When you check [a group's] project plan, you can realise how much they are*

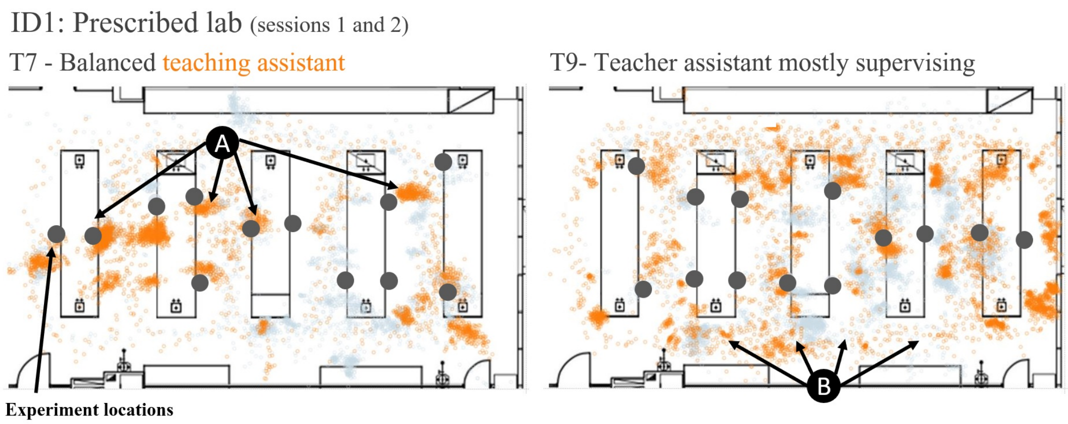

Fig. 8. Positioning data maps contrasting a "balanced" teaching assistant (T7, left) and a "supervisory" assistant (T9, right) in the science lab (C3).

prepared to do the experiment. I think that affects which groups need more or less of your time". A teacher assistant also explained how he had to adapt his typical circulation from one group to the other according to **students' support needs** besides not being prepared, particularly for groups facing challenges in their experiments. This was explained by T7 as follows: *"This group was having a difficult time understanding the 'stacking'. I helped them derive the mass formulas so that's why I spent more time over here".*

Teachers also pointed at factors not directly related with the learning tasks that made their positioning in some classes different. The first factor was related to the **time of the day**, particularly contrasting those classes taught in the morning and in the afternoon. For example, in the health context, T3 mentioned that the second class in the day tends to be more relaxed than the first,and her data may reflect this pattern: *"I knew [the positioning] would be like [more spread], because it's Monday, the first class. The second class is commonly a most relaxed one"* (and more clustered).

This was also observed by teachers in C3. For example, T7 pointed out the difference between two classes taught by the same teachers on the same day, with teachers staying longer near the teacher's desk in the afternoon classes. However, the same teacher explained that some of these 'clusters' of positioning data points may be explained by administrative issues present in particular classes. T7 explained: *"For this class (Figure 9, left) [T6] was assigning experiments for the next lab. That's why there's this deep coagulation of dots (Point A). He had the sheet in front of the desk and all students were coming here. But for this one (Figure 9, right) we had assigned experiments, that's why there was no coagulation (Point B)".*

In sum, multiple factors can make each class unique and this can be reflected in teachers' positioning data. The next two subsections describe two more kinds of patterns that teachers could see while inspecting the positioning data: territoriality in co-teaching and temporal dynamics.

5.1.4 Identification of territoriality in co-teaching. Territoriality is a concept closely related to proxemics and refers to behavioural mechanisms people use to communicate ownership or occupancy of spaces [74]. This notion was more evident in context C3 that involves co-teaching. For example, Figure 10 shows some examples of classes in which territoriality patterns emerged. The map in Figure 10 (left) shows one example similar to four other classes enacting ID1 in which teachers divided the classroom to focus mainly on certain students (e.g. the assistant focused on the first two benches, from the left, and the main teacher on the remaining benches). In a

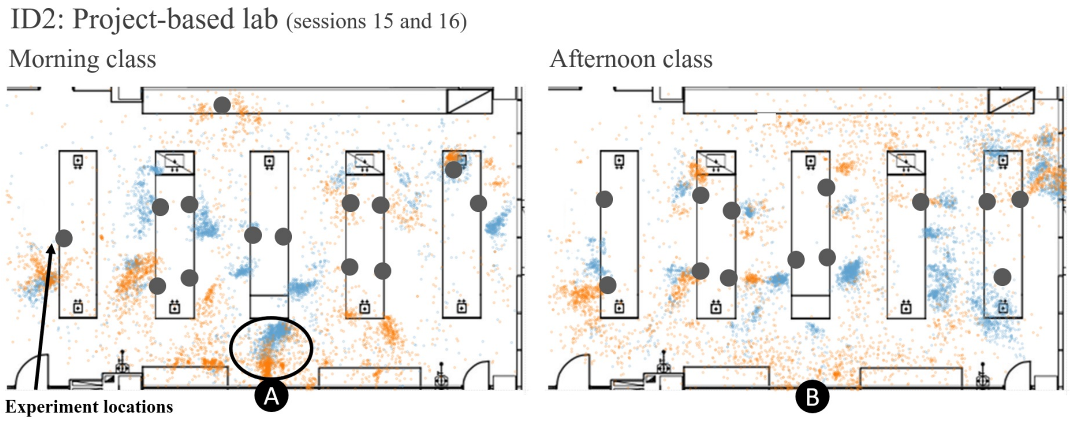

Fig. 9. Positioning data maps contrasting a morning and afternoon classes taught by the same teachers (T6 and T7) in the science education context (C3).

way, this is expected, because the coordinator of the unit stated: *"That's the instruction they get. I tell them the main teacher [T5 or T6], you get an assistant and employ [him/her] in the best way, maybe you split up the tables with that assistant"*.

However, in some classes, this was just an emerging territoriality pattern instead of being an explicit instruction. T5 explained this as follows: *"If I see the other [teacher] focused on the other two benches, then I just concentrate more on the other side of the room"*. T7 also reflected about how he adapted his behaviour based on the other teacher to keep the attention balanced, even if he received direct instruction to only focus on some groups of students, as follows: *"I was assigned these two lab tables, but when [T6] moved to my side, I moved to his side. So, we tried making sure there was a balance between all the tables"*. However, territoriality patterns did not emerge in all the classes. This mainly occurred for the classes enacting the instructional design ID2 (e.g. see Figure 10 right). T5 identified this absence of clear territoriality boundaries as follows: *"This is interesting, as they move on, the blue and the orange, they go over the place [for ID2]. Whereas here, for sessions in [ID1] there is still a separation. We don't see that here in the authentic experiment (ID2), it's much more spread"*. The coordinator suggested that the characteristics of ID1 allow teachers to distribute the attention they provide to students since all the groups are performing the same task. In contrast, for ID2, in which each group has a different project, some groups may even need feedback from both teachers, *"particularly, if they chose an experiment that is more difficult"*.

5.1.5 Temporality aspects and segmentation of positioning data. Another key aspect highlighted by teachers was related to proxemics and temporality while inspecting their data divided into quartiles. This served for teachers to interpret their positioning data according to **students' task progress**. For example, T7 explained: *"For the first quarter of the class I was just standing by the [teacher's desk] because students were just setting up their experiments. I was waiting for them to set up. For the second half of the class, students faced more problems, so I was much more spread"*. Surprisingly, T6 explained how he reacted differently to the same temporality aspect of the class: *"It seems in the first half of the class, I went more to the tables because they were in the beginning of doing the experiment. Then, gradually, they got more 'okay' with their set ups, and then I didn't go to the tables that much"*. Although this emphasises two opposite teaching approaches, it points at the importance of considering task progress as a key factor for interpreting the positioning data.

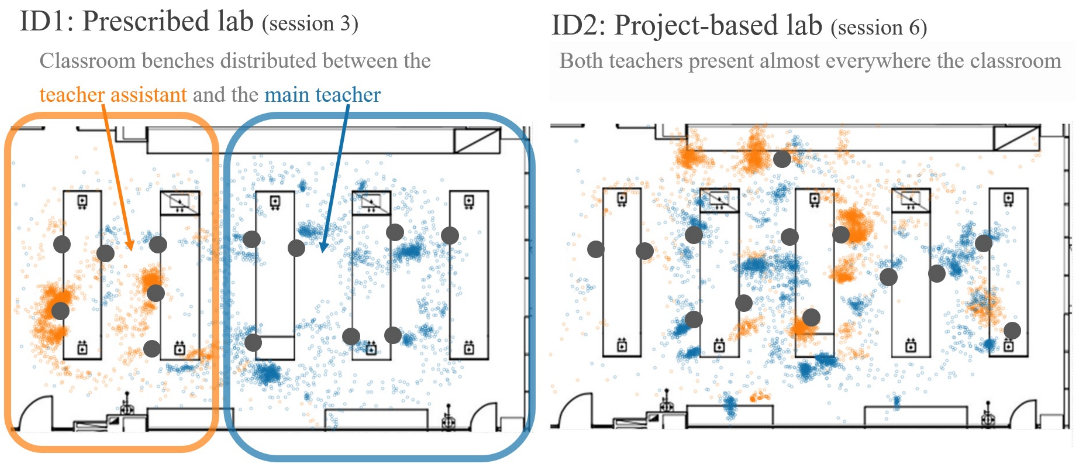

Fig. 10. Positioning data maps contrasting a territoriality pattern emerging in a particular instructional design (ID1- left) versus positioning traces of teachers more spread in the classroom in another learning design (ID2- right) in classes taught by the same teachers (T5 and T10) in the science context (C3).

Teachers in context C1 and C2 emphasised that different patterns are expected in different **phases of the class macro-script**. For example, T3 in context C2 specified the phase in which positioning data would be relevant: *"It is useful to only include data from the actual simulation time (phase 2), not briefing (phase 1) and de-briefing (phase 3) periods"*. Finally, all teachers indicated that presenting the positioning data presented as **consecutive segments** added value for reflection about the progress of their teaching in a class. For example, T1 reflected on her teaching for class A, divided into quartiles (q1-4) as follows: *"At the beginning (q1), I am at the centre of the classroom talking to all students. Then (q2), look at that! The attention is pretty even. I kind of moved around for [q2] and [q3]. For q4 I guess I was just talking and moving a bit to hear the conversation of the top group again"*.

In sum, temporality aspects such as the task progress, the identification of tasks in which the positioning data is relevant and the way the data is split in time emerged as three key important aspects to be considered to facilitate interpretation of the positioning data.

5.1.6 Summary of results and implications. Table 2 summarises results regarding **visibility**. The interpretation of the positioning data was clearly enriched based on teachers' deep knowledge about the expected learning tasks (Table 2, 1.1). Emerging tools that have been built with the intention to provide instant feedback on classroom positioning (ClassBeacons [5] and a tablet-based dashboard [53]) have not yet considered the characteristics of the instructional design as an input to adjust this feedback (Table 2, 1.2), using instead fixed distance parameters as a proxy of student-teacher interaction (1.6 and 2.5m for [5] and [53], respectively). Teachers emphasised other factors that shape proxemics, including the teaching approach (1.4, 1.5) and also the uniqueness of each class (e.g. due to particularities of students – 1.6 – and administrative tasks [67] - 1.7). Providing teachers with the ability to identify emerging territoriality patterns (1.8) over time (1.9) during a class or across classes was also suggested by the results.

5.2 Awareness: potential uses of positioning data for teaching

The previous section focused on how teachers interpreted their positioning data and the potential added value of doing this to inform their practice. This section focuses on the envisaged uses of these data once is made visible.

Table 2. Summary of results in terms of visibility

Visibility - RQ1) Is there any (and what is the) added value of making instructional positioning data visible to teachers?	
Emerging sub-themes	Design implications
i) Interpretation of positioning data based on the instructional design	1.1 **Meaning** can be given to positioning data based on *the tasks that students are expected to do.* 1.2 One-size-does-not-fit-all: A potential *instructional proxemics* support tool should be **calibrated** according to the *instructional design.* 1.3 The *personal distance* between the teacher and students (to be considered as a **potential interaction** between them) varies according to the classroom task.
ii) Differentiated instruction strategies	1.4 Positioning data can help unpack different **teaching strategies** followed by *experienced* teachers to approach the same content. 1.5 Positioning data can help identify potential **poor instruction practices**.
iii) Particularities of the classes that affect instructional proxemics	1.6 Positioning data can help teachers reflect on how **characteristics of the students** affect their positioning strategies, including: extent of *preparedness* and *particular support needs.* 1.7 Positioning data can help teachers to reflect on how **other factors**, such as the *time of the da* in which the class is held and *administrative tasks*, can affect the classroom dynamics.
iv) Territoriality	1.8 Positioning data can help teachers identify explicit or emerging **territoriality patterns** in certain instructional designs, particularly in co-teaching contexts.
v) Temporality aspects and segmentation	1.9 Positioning data, divided into meaningful or arbitrary **segments**, can help to identify particular positioning patters according to: students' tasks *progress*, and the *class macro-script.*

Three sub-themes emerged regarding awareness and potential uses of positioning data, namely, i) supporting professional development; ii) classroom management in real-time; and iii) informing classroom interior design and seating arrangement.

5.2.1 Professional development. Teachers saw value in using their positioning data *"to reflect on [their]teaching"* (T1), *"improve the delivery"* of their classes (T5), and as *"formative feedback for improving practice"* in general (T2). These and other similar teachers' reflections point at the potential use of their positioning data for supporting professional development. T1 suggested that teachers can use positioning evidence for **self-reflection** without further guidance. For example, she explained she was able to reflect on her positioning based on the data as follows: *"I should not necessarily embed myself within the group as opposed to put myself at the front of the room when talking to all the students for students to feel that I am spending equal time with all of them".*

Another strategy highlighted by some teachers (T1, T3, T5 and T6) in all the contexts was for coordinators to use these data to **facilitate team meetings** to improve classes delivery, paying special care not to point at behaviours of specific teachers. T1, the coordinator in context C1, stated this as follows: *"As the unit coordinator, if I had these data, I would use it for our weekly meetings with my tutors. But I think I'd have to be very cautious about how to show the data. If I was one casual academic, I may feel like I am not doing my job properly or that I am being tracked".* Similarly, teachers in C2, who are both coordinators of different units, highlighted the potential use of the positioning data as *"a de-briefing tool for the teaching team"* (T3). However, T2 suggested that although she agrees that the data may be very useful for teachers to reflect *"after the class", this should be done "in private first before showing the data to others".*

The coordinator in context C3 emphasised the potential benefit for coordinators to look at these data to make **high-level decisions**, since they *"manage the class and are responsible for the teaching approach"*. T4 explained the critical role of the coordinator to gain insights about the teaching and class dynamics, and communicate these to teachers delivering the classes. T4 expressed this as follows: *"The coordinator can explain the expected dynamics and show to the teachers: bang! These are the two or three things that are currently happening, and this is how I expect them to happen. For instance, we have to find a pedagogy to remedy the way students are attended in some classes in [ID1]"*. T5 also explained he would prefer to see these data *"straight after the class"* to *"get the full picture, once everything's gone, to learn how to improve the next class"*. Finally, the assistant (T7) in context C3 also agreed that he would need some **guidance** from a more experienced teacher to know how to improve his practice, given that *"each teacher looking at the positioning data may have its own perception on the data"*.

All the teachers emphasised the particular usefulness to train **novice teachers** or **casual academics**. For example, T1 explained this as follows: *"I think it would be good to show this to casual academics, who are probably less experienced. This would be a quick way to show them how to work the room and how to be conscious about how to spend the time"*. T3 in context C2 explained how *"sample data from other tutors"* could be used to generate instructive materials *"particularly useful for less experienced lab tutors who may benefit from seeing data of more experienced teachers, with narrative context provided"*. This suggest that the positioning data should be **curated to identify best practices** or those particularly sought by the unit coordinators. In the science context (C3), teachers T4, T5 and T6 also supported the idea of using these *"real data for facilitating the induction of new teachers every semester"* (T5). However, T5 suggested that it would be good to correlate different instructional proxemics patterns with students' outcomes (e.g. *"using their final mark of that of their experiments"*). Then, T5 explained: *"this way when I get a new person, next time, you can show the correlation between outcome and positioning input"*.

5.2.2 Real time support. Although most teachers positively commented on the usefulness of the data for real-time classroom use, most had mixed feelings about how information would be communicated. Teachers mentioned that having access to these data in some form during the class would have *"immediate effect"* (T5) so teachers could take **corrective actions** and make sure *"they don't miss a group"*. Most positive teachers were those in context C3 because they had to attend more than 10 groups of students per class, while keeping awareness of the complexity of co-teaching. T6 explained the potential benefit of having access to these data in real time: *"[the teacher] would realise how much time she has spent at each group of the students in the lab. This could make her think about her performance as well. For example, if she realised that she has not spent that much time on the side tables, then she can give more attention to those students immediately or in the next lab"*. Even the teacher in the smallest classes in our sub studies (T1) explained that real-time access to the data in each class would make her *"aware of how much time I am spending with each group"* which is something sometimes she forces herself to do by programming *"a timer on [her] phone because sometimes it is easy to get carried away by interesting conversations, then needing to rush towards the end"*.

However, some teachers did not like the idea of having the data available in real time (T2, T3) and others explicitly stated it would be *"a kind of **distraction"*** (T4, T5 and T7). T4 and T5 suggested that teachers could be notified if something was automatically detected that they should pay attention to; i.e. with a *"subtle beep or a wake-up call"* (T5).

5.2.3 Interior design and seating arrangement. Some teachers (T4-7) mentioned these data would also be useful for stakeholders who can **make design decisions** on the university learning spaces. However, they all raised concerns regarding how this could be achieved. For example, T6 explained: *"It would be useful for assessing the learning space but I think these data would need to be supplemented with other parameters like the type of learning activity, where the experimental set ups (and students) were located"*. T5 was very concerned that some stakeholders could try to over-optimise the use of the space without clearly knowing the teaching needs. For example, he explained: *"We've got to be careful giving this to business people. The educational people, okay, but business people no. Because they can easily say: this table is not being used, you don't need it, eliminate it"*.

Some teachers also highlighted how these data could be useful to make decisions in terms of finding more effective and pedagogical ways to use the current space. Notably, T7 explained how he would **recommend more effective seating arrangements** if he finds sub-optimal spaces in the classroom. He explained this as follows: *"From the data, if there is any space where students are consistently receiving less attention, I would recommend the students not to sit there. I would just ask them: 'can you sit in this area?'"*. In fact, this points at T6's comment regarding how students sitting closer to the teacher's desk could be receiving more attention across classes: *"I think naturally you are more concentrated on [the groups in the middle] because you're more constantly walking there and you can just stop more often"*.

Finally, T4 asked to also track his activity and that of others **in other learning spaces** to identify how the same teachers make use of different spaces. For example, he suggested to track activity in *"traditional lecture theatres"* because *"there are some teachers who just stay in one position"* or in regular tutorial classes because *"so many things can happen and there is complexity like in the laboratory classrooms"*.

5.2.4 Summary of results and implications. Table 3 summarises results regarding **awareness**. Teachers suggested several potential ways their data could be used to enhance their practice. The potential to support professional development was evident and strategies were proposed (2.1-2.3), some particularly tailored to novice teachers (2.4-2.5). This is relevant for pre-service teaching programs [12] or for assistants in HE who commonly lack pedagogical training [26, 30]. In contrast, potential design implications and concerns were raised in terms of showing positioning data in real-time. Although punctual alarms could be triggered to warn teachers while corrective actions can still be made (2.6, i.e. attending a neglected group of students), interfaces that continuously provide information for teachers may not be easily adopted by teachers (2.7). This suggests that current solutions that provide public alarm-displays [5] or live-heatmaps [53] may not be effective in the long run. Finally, teachers emphasised the possibility to assess the learning space (which has been suggested as a gap in the literature [56]) and how other institutional stakeholders could use the data to optimise current learning spaces (2.8, 2.10). This points at the broader field of learning space design in which other stakeholders could bring a critical voice to the design and use of learning spaces.

5.3 Accountability: implications of sharing positioning data

This section focuses on the implications of making teachers' positioning traces visible to others. Three sub-themes emerged pointing at concerns and potential coping strategies in terms of i) sharing teachers' positioning data with other stakeholders; ii) using these data to assess teachers' performance; and iii) how to address the incompleteness of positioning traces by capturing other sources of data.

5.3.1 Implications of sharing. All the teachers agreed that it would be useful to share their positioning data with **peer teachers**. For example, T5 optimistically expressed the following: *"I think everybody should look at it. The other teaching members"*. T2 more specifically explained why she thought sharing teachers' positioning data with others would be beneficial: *"to give others some insight into the overall teaching methods, their interactions with students, to improve their teaching style and to learn from one another"*. However, some teachers mentioned that some could feel embarrassed so they should be asked first before sharing the information with others by allowing them to *"look at their data in private first"* (T2) and share the data *"not without information about the context"* (T3) in which it was captured. T7 suggested that teachers should be able to decide to *"share their data anonymously"*. This teacher summarised the envisaged added value of sharing his data with others but also emphasising how the data should be shared: *"I would be definitely confident and fine with sharing my 'footprints' with other tutors if it helps them improve [their teaching] in the future, as long as the teacher's name is confidential [because] someone*

Table 3. Summary of results in terms of awareness

Awareness - RQ2) What are the anticipated uses of these data for teachers and their visual representations to support teaching?	
Emerging sub-themes	Design implications
i) Supporting professional development	2.1 Positioning data can be used to provoke **self-reflection** on positioning strategies. 2.2 Positioning data can be used to facilitate **team meetings** aimed at enhancing instruction. 2.3 Positioning data can be used to make data-informed **high-level decisions** by coordinators. 2.4 Positioning data can be used to train **novice teachers** or **casual academics**. 2.5 Teachers suggested that positioning data needs to be curated by experienced teachers to **communicate best teaching practices**.
ii) Providing support in real-time	2.6 Positioning data can be used in real time for teachers to take **corrective actions**. 2.7 Teachers were concerned about positioning data becoming a **distraction**, suggesting minimalistic ways to communicate critical events through *subtle alarms*.
iii) Informing classroom interior design and seating arrangement	2.8 Positioning data can be used by relevant stakeholders to **make institutional design decisions** on the configuration of learning spaces. 2.9 Positioning data can be used to **optimise seating arrangements**. 2.10 Teachers suggested assessing the **impact of different learning spaces** on instruction.

might come up with some judgement, like maybe this tutor is not attending these groups much so he's not doing it right".

All teachers agreed that **coordinators** would be the best stakeholders, besides peers, to gain access to these data because they could directly *"advise teaching assistants in the next session"* (T7) or, *"plan better [learning tasks], case studies or the learning materials"* (T2), and gain understanding of the *"general performance of the delivery of the classes"* (T6). T3 in C2 explained that the coordinator can have a key role in the *"interpretation of [positioning] data, because this will depend on the type of clinical scenarios being used"*. T7 added that the coordinator could *"identify if there is any pattern that may result in better student feedback provision, then, [s/he] could make a decision and advise the teachers to follow [this pattern]"*.

Some teachers also commented on the potential benefit of sharing teachers' positioning data with **teaching support staff and university decision makers** to assess the use of the teaching space for optimisation purposes. For example, T7 mentioned that they could identify *"underutilised spaces within the classroom and decide to remove or add benches"*. As noted above, in the health context (C2) T3 identified a lab room that was *"problematic"* to effectively provide feedback to some groups. However, as also mentioned above, other teachers (e.g. T4 and T5) raised concerns in sharing these data to non-academics that may not understand the pedagogical needs of the teachers.

Finally, all teachers commented that, although these data could be shared with **students**, *"they may not be interested"* (T1, T4, T6). In the health context (C2), the data may have some relevance since the teacher is playing a role in the simulation activity of the students. T3 explained that automatically identifying teacher's interventions *"could be used during the de-briefing, for example indicating when a teacher (enacting the role of a doctor) may have approached the bedside to correct an unsafe practice"*. Other teachers, particularly in the science context (C3) raised concerns in terms of sharing their positioning data with students, partly because students can misunderstand the teacher's approach (since they do not have expertise in pedagogy) and complain about not being attended. This was explained by T5 as follows: *"Students probably will not look at these data. But if they do, it would be a bit scary because I've dealt with them so much. If they find out about it, it can stir trouble. If I say, 'you don't need to see it', then they will say 'I really need to see it' and they could complain"*. T7 suggested that these data are critical for making informed pedagogical decisions and this is the main reason why students may gain little value from these data as follows: *"it is teachers who should decide what groups may need more attention, rather than the student deciding themselves that I should sit there to give them more attention"*.

5.3.2 Assessing teaching performance. All teachers raised concerns regarding the use of positioning data to summatively assess their performance. The teacher who was the most positive regarding this (T6) clarified that more information would be needed to fully understand what teachers were doing at the different spaces of the classroom: *"I think that these data can be useful to assess teachers' performance, but more parameters are required: where the groups of students were located, what were their set ups, and the nature of each lab. All these parameters must be studied all together and only then it can be used for assessing the teachers' performance"*. T3 said that assessment should not be performed *"without context"* and that *"moving around does not mean a sound and appropriate interaction between teachers and learners"*. Other teachers similarly explained that the way they were 'assessing' their own data was always relative to the particular learning task of the session (e.g. T7 said that their own assessments are "very dependant to students' type of experiment") and that these data *"would be great to give formative feedback to tutors to improve practice"* (T2). T1 briefly summarised the reason why most teachers could be concerned in terms of being assessed quantitatively, as follows: *"I think we are tested enough on how we perform through surveys. I think [our positioning data] should be used as a teaching aid to make you become more aware but it would be too imposing to be used to track your performance"*.

Some of the concerns raised in terms of using positioning data to track teaching performance also point to the limitations of such data, which is the focus of the next emerging sub-theme.

5.3.3 Limitations of positioning data. Teachers mentioned other sources of evidence that would enrich their classroom positioning data to build richer models of their teaching that could be shared. For example, T3 was concerned about relying only on positioning data to reflect his teaching approach, as follows: *"I'm not convinced the heat map 'proximity' correctly captures teacher-student interactions I interact with students in a whole-of-class approach at certain times during the class, while I am located in central position"*. Some teachers suggested specific sources of evidence to capture the teaching strategies such as the detection of teacher-student conversations (T7), or whether the teacher is looking at specific groups even if not interacting with them (T1). T6 also suggested the capture of physiological data, particularly to support novice teachers develop copying mechanisms to deal with stress while interacting with students, as follows: *"Some people may be stressed, but manage very well when they teach. Having these data may show some patterns. Maybe the more stressed teacher walks more too. A more relaxed one is just observing them and when he realises they need help he just approaches to them. It would be interesting to explore these patterns"*.

Emerging pilot studies have been investigating multimodal traces of teaching, without considering positioning traces [67]. However, wearable sensors, such as microphones, cameras and mobile eye-trackers, may raise privacy concerns that were highlighted by some teachers. T7 explained: *"although I think it would be helpful to know if a teacher may be discussing with some students I don't think all the teachers or the students would be comfortable with that and it's also difficult to do it in practice. You need to take consensus of each student coming in, but there're about 30 to 40 students in our classes, so it's a bit difficult, I guess"*.

5.3.4 Summary of results and implications. Table 4 summarises results regarding **accountability**. The potential benefit of sharing teachers' data with other academics was not contested (3.1). However, sharing the data with non-academic stakeholders raised potential concerns since they may not fully understand teaching needs (3.2). Sharing these data with students could also spark potential issues such as complaints if teachers' attention is not

Table 4. Summary of results in terms of accountability

Accountability - RQ 3) What is the potential impact of sharing instructional positioning data to other stakeholders on teachers' accountability?	
Emerging sub-themes	Design implications
i) Sharing positioning data with other stakeholders	3.1 Teachers agreed it can be useful to share their positioning data with **peer** and **coordinators**. 3.2 Teachers partly agreed it can be useful to share their positioning data with **teaching support staff** and **university decision makers** but some raised *concerns* about sharing their data with *non-academics*. 3.3 Teachers raised *concerns* about sharing their positioning data with **students**.
ii) Assessing teacher's performance	3.4 Teachers raised *concerns* about the potential use of positioning data to **assess teachers' performance** due to *limitations* of the data and others not fully understanding their *meaning*.
iii) Limitations of positioning traces	3.5 Teachers suggested enriching positioning data with **multimodal sources** (e.g. audio and eye-trackers). 3.6 Teachers raised *concerns* about **indirectly capturing students' data** pervasively.

egalitarian (3.3) or generating disruption, as it has been reported in the studies with ClassBeacons [5]. Teachers' concerns about using these data for summative assessment of performance (3.4) are justified. There is a global raising concern among teachers in terms of surveillance and datafication of modern teaching practice [14] which can also impose limitations on the capture of additional contextual data (3.5) due to privacy issues (3.6).

6 DISCUSSION

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

6.1 Implications of the results

This paper responds to the emergence of classroom sensing technologies (e.g. Sensei [70] and EduSense [2]) and also emerging solutions aimed at communicating positioning information to teachers in real-time using tangible [5] and surface devices [53]. We addressed the divide between these ubiquitous technology developments and the lack of understanding of what added value positioning data offers teachers, what they could do with positioning data analytics, and the implications of making such positioning data visible, with the potential for erroneous interpretation. This is aligned with recent interest in human-centred design approaches applied to data-intensive educational contexts, coined as human-centred learning analytics [15]. One of the implications of showing data to teachers is the potential support to make informed decisions, which can lead to changes in current pedagogies.

As illustrated through our studies, indoor positioning data can spark several potential innovative uses to support teaching and learning. Although the provision of real-time support can be an exciting area to explore, teachers in our studies emphasised that indoor analytics might help them in their professional development through reflective practices, institutional support and as part of a community of practice. In order to improve their own teaching practices and classroom pedagogy, teachers must know what is happening in a given learning situation, as we have observed throughout the interviews. However, teachers have less data about their behaviours compared for what they have about their students [51]. Hence, lack of teachers' data and course meta-data limit educator's opportunities to reflect on their teaching activities, pedagogical practices, the quality of the learning content, and the interactions, making it hard, almost impossible, to improve the cycle of teaching without these data.

The study in the health context (C2) also emphasised the opportunities for materialising varied teaching strategies, with the possibility of provoking meaningful discussions among the teaching team. The study in the science context (C3) illustrated the potential of these data to explore how multiple teachers coordinate and interact to deliver classes as a team. These results have implications for team teaching, which is becoming a common pedagogical approach from elementary [75] to higher education [76]. Finally, results from the study contribute to address the identified need for automated approaches to provide evidence to assess the use of physical learning spaces [48, 53, 57]. Teachers' reflections pointed at potential uses of these data to indirectly influence teaching and learning such as supporting the design and configuration of existing and new learning spaces, identifying optimal furniture arrangements and measuring the impact of the space on learning. Yet, special attention should also be placed on identifying the implications of disclosing these data. The ethical and practical implications of bringing sensors to capture multimodal data in learning spaces is still an area that is not well understood [62], which deserves a human-centred stance to it.

6.2 Sensemaking of positioning and multimodal data

Teachers in our studies engaged in a deep sensemaking process in which they brought their previous experience, their pedagogical expertise and their expert knowledge of the particular educational contexts to give meaning to the positioning data. As suggested by Lim et al. [48], multimodal approaches are needed to understand what is actually happening in the different spaces where the teacher is in the classroom. However, this points at an emerging issue in human-computer interaction related to how mapping from low-level data traces to higher-order constructs could be meaningful for human decision-making [24]. A critical question is how to give meaning to the growing amounts of sensory data that can be captured from the learning spaces that could make sense for improving teaching and learning. A theoretical stance, such as instructional proxemics, can help guide the mapping of meaningful instructional zones in the classroom with the evidence that can be ubiquitously computed. In sum, much more work needs to be done to reduce the complexity of sensory data into constructs that teachers, students or decision-makers could understand.

6.3 Ethics, data privacy and pervasive surveillance

The risks of pervasive surveillance are evident. Although offering greater efficiency and accountability has been one of the promises of ubicomp systems in the last years, the field has also emphasised the critical importance of data protection and fair information practices to deal with sensor data [17]. This includes challenges regarding how insights from the *ubicomp data* are inferred; who gains access to the data, in which form and for what purpose; and how people can express their privacy preferences [16]. Indeed, teachers in our study were not necessarily concerned with who their data would be shared with but also for what purpose. In the field of learning analytics several codes of ethics have emerged to address concerns like this (see review in [43]). For example, under one of these it is stated: *"data generated from learning analytics* ***will not be used to monitor staff performance****, unless specifically authorised following additional consultation"* (University of Edinburgh, principle 7). When applied to pervasive data collection, such as indoor positioning tracking, this not only points at the need for clear limits in the usage of such data, but also at the need to horizontal practices to design for data-intensive innovation in intelligent physical spaces (e.g. see participatory surveillance [4]), including the voice of the teacher.

6.4 Limitations

The studies presented in this paper have some limitations. The authentic nature of the studies limited the number of teachers participating in the interviews. For example, not all the teaching assistants in the science context (C3) were available to be interviewed due to personal time availability. Moreover, while the studies involved three very distinctive classroom layouts, other regular classroom configurations could have been explored (i.e. a lecture room). As a result, the sample size is insufficient for statistical measurement and the authenticity of the learning situations make it hard for controlling variables that could enable exploring the presence of generalisable patterns. Although the aim of the studies was to generate an in-depth understanding of what indoor positioning can reveal about instructional proxemics, exploring the presence of instructional proxemics patterns that reflect effective teaching would constitute a major breakthrough in teaching and learning practice. For this to be achieved, larger scale studies should involve more teaching situations, and teachers with various levels of experience and from different disciplines. At the same time, future studies can focus on exploring the impact of certain characteristics of the learning space on instructional proxemics.

Another acknowledged limitation of our study is that teachers interacted with their data through a simple, static representation (presenting all indoor positioning data points in a classroom floor map). The purpose of this design decision was to be able to generate similar representations across the three different contexts. However, this points to a wider problem in localisation research. Various authors have pointed to the dearth of research in indoor localisation analytics (e.g. [52, 61]), which includes the design of effective visualisations of positioning data and metrics that could provide more precise indicators that could minimise bias. Teachers in our study did not report major problems while inspecting their positioning maps, but interpretability issues can emerge due to occlusion of data points and a lack of quantitative references. Yet, more work needs to be done to create more effective indoor localisation analytics particularly tailored to educational environments.

6.5 Implications for future systems in education, and beyond

In Karl Weick's terms, visualisations such as these serve as "sensemaking support tools", designed to help stakeholders construct "plausible narratives" [81]. From the evidence gathered to date, we are framing such tools strongly as *formative feedback tools* (not summative, judgemental audits). In this role, their function is to provoke deeper, more productive reflections and conversations about how to improve teaching practice, by making available empirical data for the first time. The quantification of instructional proxemics makes ephemeral, embodied, contextualised activity into one or more persistent representations, with all the advantages and disadvantages that such snapshots bring. Like all images of rich, human activity, there is not always a single, unambiguous truth to discern, so attaching high stakes outcomes to the conclusions about 'what a map is saying' is fraught with risks. The idea that at some point, automated judgements might be made about such maps is therefore even more misguided, however attractive the economic argument might be to administrators. This cautionary framing is as relevant to other application domains seeking to infer complex qualities about humans from activity traces (e.g. "people analytics" in organisational human resource management) as it is to education and learning analytics.

7 CONCLUSION

This paper has documented data-driven teachers' reflections provoked by basic visual representations of classroom positioning data in three different educational contexts. The results of applying the same elicitation protocol across the studies have implications for designing ubicomp systems deployed in the classroom and also for the use of positioning data to improve classroom teaching. The relevance of the results goes beyond the use of a specific indoor positioning technology given the recent emergence of various classroom tracking systems. This paper contributes to much more work that needs to be done to create human-centred analytics solutions to enhance collocated teaching and learning in physical spaces. Future work will include the design and deployment of positioning technology to support teacher's training and professional development, and real-time classroom interfaces, considering the concerns rose by teachers in this paper.

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