RESEARCH-ARTICLE

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Proceedings of the ACM on Human-Computer Interaction, Volume 5, Issue CSCW1 (April 2021)
https://doi.org/10.1145/3449284
EISSN: 2573-0142

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Effective teamwork is critical to improve patient outcomes in healthcare. However, achieving this capability requires that pre-service nurses develop the spatial abilities they will require in their clinical placements, such as: learning when to remain close to the patient and to other team members; positioning themselves correctly at the right time; and deciding on specific team formations (e.g. face-to-face or side-by-side) to enable effective interaction or avoid disrupting clinical procedures. However, positioning dynamics are ephemeral and can easily become occluded by the multiple tasks nurses have to accomplish. Digital traces automatically captured by indoor positioning sensors can be used to address this problem for the purpose of improving nurses' reflection, learning and professional development. This paper presents; i) a qualitative study that illustrates how to elicit spatial behaviours from educators' pedagogical expectations, and ii) a modelling approach that transforms nurses' low-level position traces into higher-order proxemics constructs, informed by such educatos' expectations, in the context of simulation-based teamwork training. To illustrate our modelling approach, we conducted an in-the-wild study with 55 undergraduate students and five educators from whom positioning traces were captured in eleven authentic nursing education classes. Low-level x-y data was used to model three proxemic constructs: i) co-presence in interactional spaces, ii) socio-spatial formations (i.e. f-formations), and ii) presence in spaces of interest. Through a number of vignettes, we illustrate how indoor positioning analytics can be used to address questions that educators and researchers have about teamwork in healthcare simulation settings.

CCS Concepts: • **Human-centered computing → Human computer interaction (HCI)**; *HCI design and evaluation methods*; User models.

Additional Key Words and Phrases: indoor positioning sensors; teamwork; proxemics; learning analytics; spatial behaviours

ACM Reference Format:
Gloria Fernandez-Nieto, Roberto Martinez-Maldonado, Vanessa Echeverria, Kirsty Kitto, Pengcheng An, and Simon Buckingham Shum. 2021. What Can Analytics for Teamwork Proxemics Reveal About Positioning

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2573-0142/2021/4-ART185 $15.00
https://doi.org/10.1145/3449284

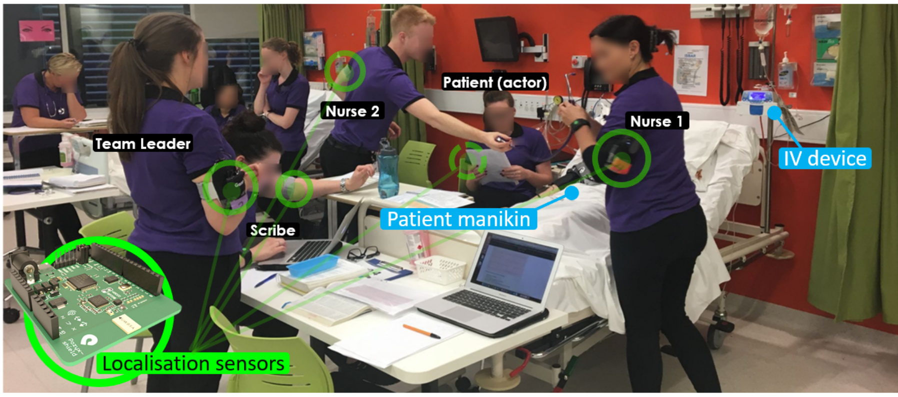

Fig. 1. A team of students wearing indoor positioning trackers in a simulated ward at a nursing classroom.

Dynamics In Clinical Simulations?. *Proc. ACM Hum.-Comput. Interact.* 5, CSCW1, Article 185 (April 2021), 24 pages. https://doi.org/10.1145/3449284

1 INTRODUCTION

Simulation-based learning strategies are designed to provide safe training spaces for students and professional practitioners to develop the critical clinical and teamwork skills they will need in authentic clinical placements [3]. In the case of nursing education, pre-service nurses are often immersed in simulated wards to practise a range of clinical procedures [16]. In these simulations, nursing students are commonly asked to enact different team roles according to a fictional scenario and to perform a variety of tasks with the purpose of improving the outcome of a simulated patient (i.e. a human manikin such as the one presented in Figure 1). These team training situations are complex, especially when unexpected events emerge and students are expected to perform pertinent actions, make decisions and communicate with others effectively and timely [36].

Some of the key skills students are expected to develop include recognised *spatial abilities* that are required of registered nurses, [18] such as knowing how and when to keep close physical proximity to the patient [66] and to other team members [55]; having the ability to position themselves appropriately in a specific location of the room to accomplish a specific task [90]; and adopting particular spatial arrangements to enable interaction or avoid disrupting others during certain collaborative procedures [29]. Yet, spatial behaviours in the physical space are ephemeral and can easily become obscured by the multiple tasks nurses have to accomplish [17].

Some researchers have focused on the study of these ephemeral yet important spatial behaviours (termed *proxemics*) in observational studies of teamwork in healthcare situations. These works have started to demonstrate a positive relationship between team member positions and eventual patient outcomes (i.e., patient satisfaction, status, and safety) [29, 49, 50, 56]. However, it remains less obvious how the analytical methods used in these studies can be used to support students as they reflect upon and improve their own practice. Some researchers have started to embrace the use of technology to automate the analysis of spatial behaviours in healthcare for both teamwork process improvement and educational purposes. For example, a manual mouse-tracking interface has been used to generate point-by-point positioning data from videos to visualise workflows of teams in trauma simulation scenarios [60]. This suggests that advances in sensing technologies and machine learning are likely to enable new ways to analyse teamwork proxemics.

The emerging area of indoor positioning analytics [4] is of particular interest to this work. Digital traces captured by indoor positioning sensors can be used to study and contribute to the enhancement of teamwork proxemics generally, and healthcare in particular. Aimed at supporting students and educators, positioning data can be pervasively captured and rendered visible for the purpose of improving nurses' reflection, learning and professional development. Curated representations of positioning data hold potential to help researchers address new questions on teamwork proxemics or speed up analysis cycles that currently depend solely on observations. Despite this promise, the bulk of research in indoor positioning analytics has focused on improving the accuracy of algorithms [51] usually with the aim of facilitating navigation [30], providing location-based services and alerts [4], or assessing team tactics in sports [67]. In the context of healthcare, proximity beacons and wearable trackers attached on nurses' robes have been proposed as potential solutions to track and automatically visualise nurses' movements in the physical space [12, 43]. Yet, an unexplored question remains: what kind of questions about teamwork dynamics can be addressed based on the analysis of large amounts of indoor positioning data?

This paper seeks to address this question by asking what analytics for teamwork proxemics reveal about positioning dynamics in clinical simulations. We present 1) a qualitative study that illustrates how to elicit the specific student spatial behaviours that educators expect according to the learning goals of a clinical simulation; and 2) an approach to model nurses' low-level positional traces into meaningful higher-order positioning constructs, according to such educators' expectations. To illustrate this approach, we conducted a study in 11 authentic nursing undergraduate practical sessions in a university, involving 55 students and five educators from whom indoor positioning traces were captured. Low-level *x-y* coordinates and body rotation data were modelled into three constructs: (i) *co-presence* of nurses in interactional spaces as a proxy of potential 1-1 communication among team members and the patient; (ii) *socio-spatial formations* (e.g., being around the patient or the team leader, or being side-by-side during a particular procedure); and (iii) presence in *spaces of interest* in which nurses could perform certain tasks (e.g., being at the foot of the bed or next to the patient). A number of vignettes are presented to illustrate how indoor positioning analytics can contribute to address the questions formulated by educators and to advance our understanding of teamwork in healthcare simulation settings.

2 BACKGROUND

2.1 Proxemics and Teamwork

Research on teamwork suggests that team performance is associated not only with the performance of individual team members, but also with the ways team members cooperate with one another, and how effectively they use the resources and space available [25, 83, 87]. This is partly why *proxemics* has been used as a lens to study complex and dynamic interactions among team members who are collocated, particularly in contexts where the use of the space is critical to complete certain tasks.

Proxemics can be broadly defined as the study of the ways people use physical spaces and interpersonal distances to mediate interactions according to their cultural context [23]. Foundations of proxemics have been applied to a variety of fields (such as robotics [14], architecture [24], education [48] and urban planning [26]) with the purpose of analysing people's spatial behaviours and mobility dynamics in both indoor and outdoor spaces [9]. For instance, peoples' interactions can be measured based on body distances and rotation to assess how the patient satisfaction is affected by non-verbal cues [54]. When proxemic constructs are integrated into the work of an ethnographer, it is possible to generate a better understanding of the peoples' physical dispositions that naturally emerge during interactions in relation group tasks and physical structures of the collaborative space [45]. These observations can lead to identifying spatial behaviours and tools that maximise connectivity and interaction possibilities [44].

In fact, the proxemics lexicon [5] defines the *constructs* that encapsulate different aspects of the study of space in social contexts. For example, Cristani et al. [7] used the notions of *interpersonal spaces and distances* to identify the establishment of social ties among group members. Setti et al. [73] focused on the proxemic construct of *formations or arrangements*, based on people's proximity and bodies dispositions, to examine how people establish conversation groups in informal settings. Martinez-Maldonado et al. [48] proposed the notion of *classroom proxemics*, to explore the meanings that certain spaces in the classroom take up according to the proximity of teams of teachers to students and classroom resources (e.g. desks, whiteboards and personal computers).

In short, proxemics has been used as a lens to analyse socio-spatial interactions in physical teamwork settings. We will refer to this particular application of proxemics as *teamwork proxemics*. In this paper, we build on the proxemics lexicon to identify critical *proxemic constructs* that can guide the modelling from indoor positioning data to meaningful representations of spatial team behaviours. Such constructs will be discussed in more detail in section 5.

2.2 Proxemics in Healthcare Team Situations

The study of proxemics in healthcare has caught attention in recent years, focusing in particular on identifying how effective teamwork can improve patient outcomes. For instance, video analysis has been used to demonstrate that the ways anesthetic teams' group dynamically around the patient can directly impact patient outcomes [29]. Also, questionnaires from patients have demonstrated that nurses' proximity to them can determine their sense of personal space and their rehabilitation outcomes [49]. Another study with professional nurses analysed the role of proximity to the patient and other team members as an indicator of sustained caring and nurse-patient interaction [66]. Similarly, systematic observations of teams (in admittedly small samples) have yielded positive results when teams of nurses perform a particular procedure in close physical proximity to newborns [50] and adults [56]. Zhang and Sarcevic [90] examined how nurses' position and movements during time-critical medical tasks, such as trauma resuscitation, can improve the coordination of teamwork and team awareness of the clinical situation.

Some other works have suggested the use of proxemics for training healthcare students and practitioners about spatial skills. For example, Cooper et al. [6] described the very serious consequences on the patient's health (e.g. failures in anesthesia management) when teamwork is not trained effectively to position themselves during anesthesia to minimise medical errors. Likewise, McLaughlin et al. [49] demonstrated that training nurses on proxemics, territoriality and awareness of personal spaces can improve the nurse-patient relationship and the patient outcomes in general.

Together these works have demonstrated the relevance of and sustained interest in studying the relationship between teamwork and proxemics in healthcare to i) better understand the effect of teamwork proxemics on patient outcomes, and ii) educate pre-service healthcare staff on the spatial skills they need to develop. However, the methods used (including systematic observations and self-report questionnaires) are impractical to provide timely feedback in training settings. For this reason, researchers are investigating the use of tracking technology to automate the analysis of positioning behaviours in teamwork, which we describe next.

2.3 Analytics for Teamwork Proxemics

Recent developments in sensing technologies, and improvements in computational image processing, are enabling the tracking of team spatial behaviours over time [8, 36, 38, 40]. Such infrastructure has been used to track people's positioning dynamics in two contexts relevant to this study: classrooms [71] and hospitals [28]. For example, computer vision systems have been used to detect proximity of people, as well as some kinesthetics behaviours, such as raising a hand, and facial gestures [1]. Automated and semi-automated video-based approaches have also been used to analyse students' postures during a lecture [63], to quantify interactions among teachers and students [81] or to support manual tracking of nursing teams' workflows [60]. An advantage of these studies is that people being tracked do not need to wear any device. The disadvantage is that video-based approaches depend on the position of static cameras which do not provide precise positioning, or precision in measuring distances between people over time, and are susceptible to occlusion, or failures to differentiate bodies [47, 71].

In contrast, wearable sensors can provide indoor positioning data with high (centimeter) precision. Rosen et al. [68] has called for methods and technologies to generate sensor-based measurement of teamwork in healthcare. Aligned to this, Olguín et al. [57] explored the opportunities of using sociometric badges to analyse social interactions based on close proximity of nurses. Kannampallil et al. [33] suggested that RID (Radio-Identification) sensors could be used to better understand clinicians' locations and interactions in critical workplace (e.g. trauma center). Similarly, Isella et al. [31] also used RID devices to track nurses in order to understand spread propagation patterns of infections, based on face-to-face contacts among individuals. The closest work to ours is that of Echeverria et al. [11, 12]'s who presented a small scale pilot study using indoor positioning trackers to generate a network graph representing nurses around a patient bed in a simulation.

The above work points to the development of indoor positioning analytics [58, 88]. However, it is still unclear how these digital traces, obtained either from computer-vision systems or wearables, can effectively contribute to address important questions about teamwork dynamics in healthcare settings. Our paper both contributes to this body of research, and goes beyond the related work presented in this section, by proposing a modelling approach that can transform the large amounts of data (generated through sensors and computer vision systems) into higher-order proxemic constructs. We will illustrate how these constructs can directly address the kinds of questions asked by educators, and so lead to the promotion of spatial skills development in nursing education.

3 THE EDUCATIONAL CONTEXT

The modelling approach to be presented in the next section will be illustrated through an authentic study conducted during regular classes of an undergraduate nursing practice course, in which healthcare simulations are an essential part of students' learning. These in-class simulations often start with a description of learning goals by an educator, followed by the simulation itself, concluding with an educator-led *debrief* aimed at provoking students' reflection on performance and errors made that is based on the expected goals of the session [37]. Although video-based products to support this reflection exist, they are commonly impractical for class use, which results in students rarely reflecting on such evidence [17] to improve their performance. This lack of evidence to inform reflective training practices has been identified as a persistent gap in healthcare education [42]. The proposed modelling approach is ultimately aimed at contributing to address it.

3.1 The Learning Situation

This paper focuses on 11 classes taught by five educators, conducted in Week 7 (of 12 weeks) in the unit of study Integrated Nursing Practice. Six of such classes were conducted in the 2018 term and five in the 2019 term. Around 25 third year students commonly attended each class. Each class was organised in teams of 4-6 students, each performing the simulation around a patient bed. One team in each of the 11 classes volunteered to participate and get their activity tracked. The average duration of the simulation was 69 minutes (std=14.35). A total of 55 students, 48 females and 7 males were part of the study (aged 20-45 years, mean=23.5, std=5.4). For the particular simulation under analysis, students are expected to learn how to work effectively as a team when a patient is experiencing an allergic reaction to a medication. Students are asked to play different roles, namely: a) the team leader, b) registered nurses (Nurse 1 and Nurse 2), c) a scribe nurse (who documents all the clinical procedures performed to provide a true and timely representation of what occurred), and d) the patient (enacting the voice of the patient manikin, see Figure 1). In addition, one educator in each class plays the role of the main doctor in the ward.

According to the assessment criteria for this task (intervening during an allergic reaction), a highly effective team should carry out the following *critical actions*: i) measure an initial set of vital signs; ii) administer the intravenous fluid (IV) antibiotics; iii) take a second set of vital signs after the patient complains of chest tightness; iv) stop the IV antibiotic after the patient reacts with chest tightness; v) perform an ECG after the patient complains of chest tightness; and vi) call the doctor after stopping the IV antibiotic. Therefore, the simulation can be divided into 5 phases: *Phase 1:* patient assessment (from the beginning of the simulation to the moment nurses realise the patient needs IV antibiotic); *Phase 2*: IV fluid preparation; *Phase 3:* IV fluid administration; *Phase 4:* patient adverse reaction (since the patient starts complaining about the allergic reaction until the moment nurses stop the IV antibiotic); and *Phase 5:* patient recovery.

3.2 Low-level Positioning Data

Students' low-level positioning data was captured through wearable tags[1] at 2-3Hz. Tags, carried in waistbags or armbands, were worn by students during the simulation. The positioning system triangulates the exact location of each tag with reference to 8 anchors affixed to the classroom walls. Pozyx system accuracy for most of the location points is between 1 and 30 cm [89]. The raw data captured by the positioning tags consists of x and y coordinates in millimeters, and the body rotation of each nurse, relative to the position of the anchors, in degrees. Multiple data points in a single second were down-sampled to 1Hz (one data point per team member per second). Data points ware formatted as follows: *{tagId, timestamp, x, y, rotation}*. Body rotation data was only captured for the last 5 teams (teams 7-11) due to technology limitations.

Some student actions were automatically logged through the high-fidelity manikin[2], such as instances when students checked the vital signs, the pulse of the patient, and oxygen levels. Other actions performed by each student, including the *critical actions* (i-vi) and additional actions such as writing charts, stopping IV fluid, calling the doctor, were manually logged using a web application by an observer. For this particular study, a researcher acted as the observer. However, the actions could be also logged by a student taking the role of the scribe. All sessions were video recorded.

4 INTERVIEWS WITH EDUCATORS

4.1 Student Spatial Behaviours Expected by Educators

In order to design meaningful analytics, it is necessary to understand the range of spatial behaviours that matter for this simulation, and when they should occur. The five educators (females: 4, average years teaching: 12.6), who had taught the simulation beforehand, were interviewed to identify the spatial behaviours they expected from students in each phase. Each interview was recorded using an online video conferencing platform (i.e., Zoom) and had an approximate duration of 60 minutes. Following a semi-structured format, the interview was structured as follows: (1) educators were explained the purpose of the session, (2), then, they were presented with the phases of the simulation according to the learning design, and (3) they were asked to respond to the following question for each phase of the simulation: What spatial behaviours would you expect students

[1] www.pozyx.io
[2] Laerdal 3G

or certain roles to exhibit in phase X (X, ranging from 1 to 5), if any? The interviews were fully transcribed using a professional service.

The first author of this paper grouped and categorised educators' responses to identify the expected behaviours in relation to each phase using NVIVO. This resulted in a set of descriptions of the *expected spatial behaviours* of students for this specific simulation that were discussed by the rest of the research team. The team found consistent descriptions of expected behaviours across educators. Then, the first author conducted an inductive thematic analysis [69] across phases by searching emerging categories related to the types of spatial behaviours that could be tracked using positioning technologies. The following three categories emerged: *i*) *expected interactions* between specific roles or with the patient; *ii*) *expected social arrangements* during the simulation; and *iii*) *expected spaces* where a particular nurse should position herself/himself. The resulting categories were discussed with the rest of the co-authors and were mapped to proxemics lexicon [5].

Table 1 summarises the spatial behaviours that were expected for each phase, and extracted from the teachers quotes. For example, in phase 1, all nurses are expected to *gather around* the *team leader* to plan their activity (*i* - expected interactions between specific roles), usually at the *bed footer* where the documentation is commonly located (*iii* - expected spaces of interest). In phases 2, 3 and 4, at least two nurses should be in close proximity to each other while they prepare (face to face or side-by-side: *ii* - expected social arrangements), provide and stop (side-by-side for one nurse to monitor what the other is doing) the IV-antibiotic, as per current national guidelines [2]. The proxemic constructs associated with each of these categories will be fully described in Section 5.

Phase 1	Phase 2	Phase 3	Phase 4	Phase 5
- Nurses are expected to be around the patient most of the time. (i) - Nurses should be together, around the team leader. (i) - Nurses are expected to be close to the patient performing the initial assessment. (iii)	- The antibiotic preparation should be performed by two nurses. (ii) - Fewer people should be around the patient. (i) - Some nurses should be at the medicine room retrieving the antibiotic and IV equipment. (iii)	- The patient should not be alone during this phase. (i) - Nurses are expected to be near to the patient validating that the intubation is working properly. (iii)	- One nurse must be assessing vital signs, other doing the ECG, other calling the doctor, and one nurse with the patient. (iii) - The antibiotic stopping procedure should be performed by two nurses. (ii)	- Nurses should be together, around the team leader, writing a patient report. (i)
- At least one nurse should be assessing the patient vital signs every 10 minutes during the simulation. (ii) - The scribe can be next to the patient, or at the footer of the bed through the simulation. (iii)				

Table 1. Educators' expectations regarding the nurses' spatial behaviours in each phase, categorised as follows: *i*) expected *interactions* between specific roles or with the patient; *ii*) expected *social arrangements* during the simulation; and *iii*) expected *spaces* where a particular nurse should position herself/himself.

4.2 Spaces of Interest

The meanings that presence and movement in *spaces of interest* signify for a particular learning design of a simulation have been studied over the course of several years' co-research with the nursing academics, through a combination of formal interviews and prototyping (e.g. Echeverria et al. [12] and Martinez-Maldonado et al. [47]).

As part of the interview, teachers were asked to validate the *meaningful physical spaces* that were identified based on the characteristics of the simulation (allergic reaction to antibiotics) and the learning design. Then, these were mapped as a two-dimensional area using the coordinate system of the positioning tags. Figure 2, illustrates the meaningful physical spaces identified and validated with educators. For example, being in close proximity to the *bed* or the nurse enacting the role of the *patient* could indicate interaction with the patient. Furthermore, being close to the *IV device* could indicate that nurses are starting or stopping the IV fluids, which is critical for the simulation.

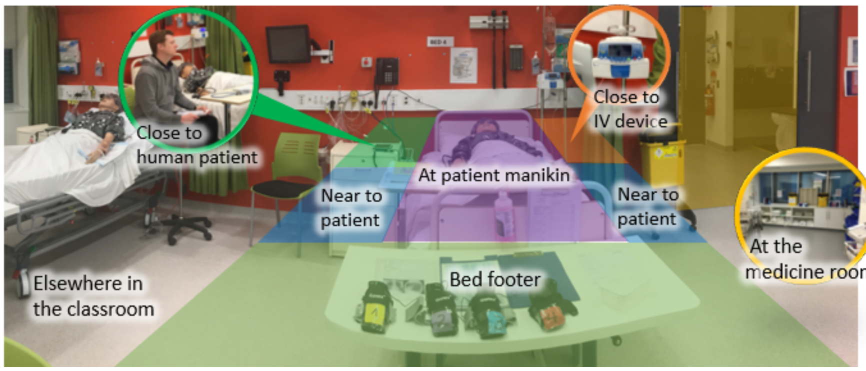

Fig. 2. Meaningful physical spaces of interest according to educators who conducted the simulation.

Also, as expressed by educators, the *bed footer* is where the nurses are commonly interacting with each other to analyse the current situation, looking for more information, or preparing the medicine brought from the medicine room. In addition, these physical spaces could be linked to the actions of a specific role, such as the team leader being *next to the bed footer* monitoring the team members activity. The physical spaces which educators recognised as meaningful for the simulation will be fully described below in section 5.1.3.

The next section describes our proposed approach to model student spatial behaviours, by transforming low-level positioning data into meaningful proxemic constructs based on the three categories that emerged from the study presented in this section.

5 MODELING APPROACH

Figure 3 depicts our proposed modelling approach for mapping from (1) low-level positioning data (described in the previous section) to (2) higher-order proxemics constructs, with the purpose of (3) addressing meaningful questions that an educator may formulate to engage with students in dialogical feedback, or (4) questions that could be interesting for researchers to analyse teamwork activity in general. The following subsections describe each of these components, instantiated in the context of healthcare simulations and the learning situation described in Section 3.1.

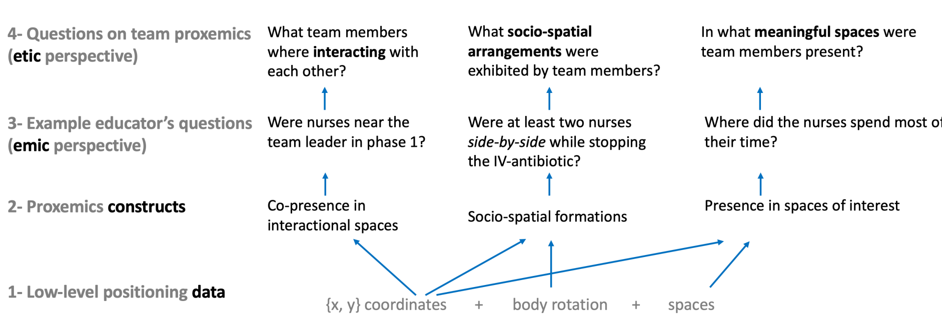

Fig. 3. An approach to model from (1) nursing students' low-level positional data (coordinates, body rotation and spaces of interest) to (2) higher-order proxemics constructs aiming at (3) addressing contextual questions by educators or more (4) general questions about teamwork activity.

5.1 Proxemics Constructs

Informed by the expected spatial behaviours which were derived from the interviews with educators (in section 4.1), the emic language used by educators, we specified three proxemic constructs that can be modelled using low-level positioning data (informed by the etic perspective): i) *co-presence in interactional spaces,* ii) *socio-spatial formations,* and ii) *presence in spaces of interest.* In this section, we will ground their definitions in the literature, and detail the data used to model each of them.

5.1.1 Co-presence in interactional spaces.

The concept of *interactional space* was defined by Mondada [53], and refers to the dynamic use of the physical space which enables verbal interactions between people. The interactional space is constituted by people mutually adjusting the arrangements of their bodies to enable close proximity and mutual attention to each other, and the objects they manipulate. This is aligned to Hall's classic work [22] which outlined four types of distances, each commonly used by people for a certain type of interaction. These are: i) *intimate* (0-0.46m), where the presence of the other person is unmistakable and can be overwhelming [5]; ii) *personal* (0.46-1.2m), where the majority of intensive and delicate interpersonal transactions occurs [5]; iii) *social* (1.2-3.7m), where verbal transactions can occur, but it is generally considered as a distance from which strangers commonly interact [77]; and iv) *public* (3.7+), where the other person's presence is not well-defined and it can be either acknowledged or ignored [5]. Although these exact distances vary across cultures, most interpersonal interactions with acquaintances tend to occur under 1.5m [77].

These types of distances are critical to identify situations in which team members may be interacting with each other. Based on classic proxemics work [22, 46] and empirical work in healthcare [50, 56], the co-presence of two nurses within their intimate or personal spaces can be indicative of some verbal interaction or awareness of each others' actions. Similarly, if a nurse is close to the patient it can be indicative of nurse-patient interaction or care giving.

The construct of co-presence in interactional spaces was thus modelled by measuring the distance between the x, y coordinates among each team member and the patient (either the manikin or the nursing student playing the role of the patient), per second. We identified instances of close proximity (intimate or personal distances) using the parameter d= 1.2m which, according to Martinec [46], is an appropriated distance to enable direct interaction and also accounts for the (commonly 91cm) width of the patient bed (according to current standards [84]) that may be between two nurses. This parameter can be adjusted depending on the team context or the simulation.

5.1.2 Socio-spatial formations.

The notion of socio-spatial formation or *facing-formations (f-formations)* was originally defined by Kendon [34] referring to the ways people cluster so that they can have direct and equal access to one another (for example in side-by-side, face-to-face, in a circle or L-shapes: see Figure 4), and exclude a designated outer space behind them. F-formation analysis has enabled HCI and CSCW research to understand how teams coordinate and communicate to achieve tasks including collaborative information-seeking [45], healthcare [52], and even cooking [59]. This construct has also been useful to design systems that enrich collocated groupwork with context-aware interfaces that adapt the way content is displayed according to how group members orient themselves [44].

Three concepts characterise an f-formation: the *o-space*, which is the joint interaction territory to which team members in the formation have easy access; the *p-space*, the narrow strip of space that surrounds the o-space which is occupied by the team members; and the *r-space*, which is the area that surrounds the o-space and p-space. Figure 5 (left) illustrates these spaces and the kind of data that would be needed to automatically model the f-formations: positioning coordinates and the angle of approach of each person. For example, in the healthcare context, nurses collaborating

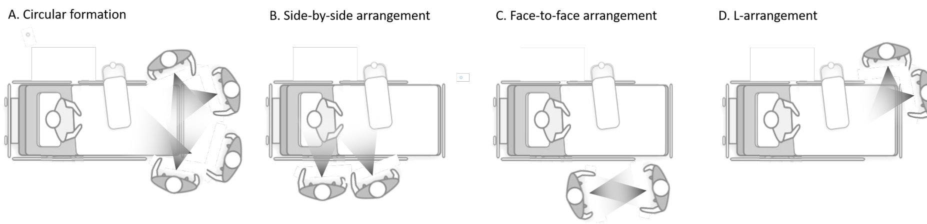

Fig. 4. Illustrative examples of some f-formations in the context of our healthcare team simulation study.

while preparing the IV antibiotic might require an appropriate f-formation, having the clinical instruments located at the o-space, to equally and effectively complete the task.

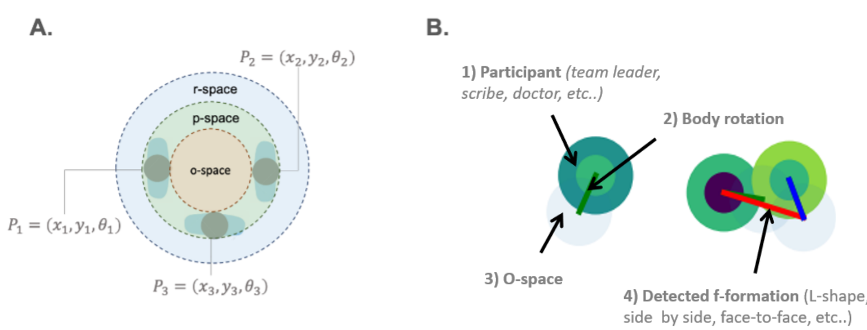

Fig. 5. Left: Social spaces in an f-formation: o-space, p-space and r-space. Three individuals (P), with position (x, y) and a rotation angle (θ) Right: visual output of the GCFF algorithm that automatically detect f-formations.

We used the Graph-Cuts for f-formations (GCFF) method [73] to automatically model this construct based on the positioning data. GCFF has been previously used to detect f-formations in static images. GCFF detects when two or more individuals' o-spaces intersect. This intersection is defined as the *transactional segment*, which is the area in front of the body that can be reached easily, and where hearing and sight are most effective between individuals. Thus, given the x and y coordinates of an individual or a group of individuals (see B.1 in Figure 5-right) and their *rotation* (B.2), GCFF calculates the probability of each individual occupying a specific *o-space* (B.3) (and thus, a f-formation) when their transactional segments overlap (e.g. see B.4).

5.1.3 *Presence in spaces of interest.*

Certain spaces in the classroom can have multiple meanings based on the kind of activity unfolding on the site and the relative proxemics among teachers, students and objects (e.g. devices, furniture) [61]. For Hall [21], such spaces are of three types: *fixed spaces*, which have their shape and size determined by the presence of objects that cannot easily be moved (e.g. walls or screens; *semi-fixed spaces* which are established by movable features in the environment (e.g. tables, beds, curtains and clinical trolleys) that only remain unmoved and unrearranged during peoples' interactions; and *dynamic spaces*, which are formed solely by the spacing and orientation of individuals as they interact with each other.

As described in section 4.1, spaces of interest for this simulation were elicited from educators, and are summarised in Table 2. For instance, the only *fixed* space for this context was *the medicine room* which is a well defined area with medical instruments and supplies (row 1). In contrast, *semi-fixed* spaces were determined by different areas depending on the position of the IV device (row 2), the student acting as the patient (row 3), and the patient's bed (rows 4-6), meaning that these spaces could change depending on the classroom or lab where the simulation is being enacted. Finally, *dynamic spaces* were driven by areas where the close proximity between people (e.g. nurse, doctor) could occur and are not attached to a specific location, but instead depend on participant availability. For example, the teacher acting as the doctor moves from bed to bed, and creates dynamic spaces with different nurses as she moves. Based on educators' interviews, if nurses come close to the doctor outside of the semi-fixed spaces it is commonly for the purpose of *asking for help* (row 8) and if the educator comes closer to nurses' work area, then she is either just supervising or nurses are *receiving help* (row 9). Rows 8 and 9 are the only ones which do not represent actual physical spaces. These spaces are dynamic because they depend both on the proximity between educators and students and the location of their encounters. The labels used to represent these spaces indicate how such encounters are commonly interpreted by educators. All the remaining positions in the classroom were coded as *elsewhere in the classroom.*

Row	Space of interest (codes)	Meaning	Example expected behaviour in current simulation	Type
1	In the medicine room	Here, nurses commonly get medicine and equipment they require for the patient care.	In phase 2, nurses are expected to be at the medicine room retrieving the antibiotic and IV equipment.	Fixed
2	Close to IV device	From here, nurses can check, start and stop the IV device.	After noticing the patient is having an allergic reaction nurses are expected to be close to the IV device to stop it.	Semi-fixed
3	Close to the human patient	Nurses being close to the student enacting the patient can indicate that verbal assessment of the patient is taking place.	In phase 1, nurses are expected to be close to the patient performing the initial assessment.	Semi-fixed
4	Near to patient	At these spaces nurses validate the intubation device (left) and assess vital sings (e.g. pulse, hart rate) (right)	In phase 3, nurses are expected to be near to the patient validating the intubation is working properly.	Semi-fixed
5	At the patient manikin	Being very close to or on top of the patient bed can indicate the patient is being attended. Certain clinical procedures require nurses to lean over the patient's bed.	After noticing the patient is having an allergic reaction nurses should attach the ECG device to the manikin.	Semi-fixed
6	At the bed footer	From here, the team leader monitors and delegates tasks; and nurses coordinate, read charts or write observations.	The scribe should be next to the patient, or at the head/footer of the bead.	Semi-fixed
7	Elsewhere in the classroom	Nurses can be in other spaces interacting with other nurses, finding books (e.g. the Monthly Index of Medical Specialities) validating medication, or looking for the doctor (teacher).	In phase 4, nurses have to notify the doctor that the patient had an allergic reaction.	Semi-fixed
8	Asking for help	Nurses asking for help to the doctor (teacher)	Nurses spending time elsewhere in the classroom and close to the doctor.	Dynamic
9	Receiving help	Nurses receiving help from the doctor (teacher)	Nurses being close to the teacher in any space of interest but elsewhere in the classroom.	Dynamic

Table 2. Codes for the meaningful spaces of interest construct.

This construct is modelled by mapping the (x and y) coordinates to fixed and semi-fixed areas identified above. The dimensions (width and height) and shapes (e.g. rectangle areas) of each fixed and semi-fixed space were mapped as two-dimensional areas to assess if a positioning data point was in any of the spaces of interest. Additionally, proximity data between nurses and the teacher was used to identify the dynamic spaces (rows 8 and 9). More specifically, if a nurse was close to the doctor and they both were elsewhere in the classroom, this was coded as asking for help. If they were both present in any of the semi-fixed spaces of interest (i.e. rows 2-6), this was coded as receiving help. This way, each datapoint of each nurse in the dataset is associated with one or two codes of spaces of interest. If more than one team is tracked in the classroom at the same time, the coordinate mappings of the semi-fixed spaces would be defined with reference to the patient bed each team is working at.

5.2 Questions on Team Proxemics (educator and researcher perspectives)

To examine what analytics for teamwork proxemics can reveal about positioning dynamics in clinical simulations, we associated our three proxemic constructs with the kinds of questions that educators and researchers bring to making sense of teamwork. We use the notion of the *emic perspective* [32] to refer to the kinds of questions that can be addressed with positioning data from the *insider's* perspective, who would raise questions according to the culture of the healthcare education context. For example, these are questions that nursing educators may have about students' activity in order to provide informed feedback, such as the categories that emerged from the study presented in section 4.1. The positioning behaviours that educators expected for this sim (presented above in Table 1) can be formulated as a very specific question, such as: *Were at least two nurses side-by-side while stopping the IV-antibiotic?* In contrast, the *etic perspective* reflects *outsider* questions (e.g. CSCW researchers and team scientists) studying positioning dynamics, using different, more analytical constructs. In our case, instead of a local question about the particular simulation, a question from the etic perspective could be: *What are the socio-spatial arrangements exhibited by high-performing teams?*

In the next section, we illustrate through a number of 'data vignettes' what questions analytics for teamwork proxemics helps to address, with examples focusing primarily on the educators' (emic) perspective. We suggest potential avenues of research that could address broader question about teamwork (the etic perspective) in the Discussion (section 7).

6 ILLUSTRATIVE STUDY

This section illustrates the modelling approach presented in the previous section, through a series of data vignettes. These were selected because they respond to authentic educators' questions and serve to show how positioning data can help in telling data-informed stories about nurses' proxemic behaviour. Each group of data vignettes includes: a) the educator question being addressed (the emic perspective) about the nurses' spatial behaviours as expected in each phase (see Table 1); b) an illustrative analysis of positioning data from one or more of the 11 teams who participated in our study; and c) a set of insights that can be gained from the modelling of a specific proxemic construct.

6.1 Co-presence in Interactional Spaces

6.1.1 Data vignette 1: the interactional space between nurses and the patient.

a. Context and the educators' question. The data vignettes presented in this subsection address the educators' question: *Were nurses around the patient during the simulation?* Throughout the simulation, nurses should assess the status of the patient regularly because strong medication is being administered. Moreover, close proximity to the patient is associated with effective communication and reassures the patient that they are being cared for, which is critical to patient-centred hospital practice [82].

b. Analysis. For this illustrative example, social network analysis (SNA) was performed on the output from the modelling of co-presence in interactional spaces described in section 5.1.1. This is the aggregated time nurses spent in close proximity with both one other and the patient (manikin plus human role-player). SNA is a tool that is commonly used to investigate social structures represented using nodes (team roles and the patient in our case) and links (representing social ties of some sort) [27]. For this purpose, SNA can be an effective analysis technique to model presence of nurses in the patient's interactional space (i.e. connections between student roles and the patient based on physical proximity). For this particular vignette, the *links* represent the average time that students spent in interpersonal proximity to the patient, thus serving as a proxy for close patient care. Thick (dark blue) links indicate longer periods of time in close proximity (>50% of the phase duration). Red (thin) links indicate shorter periods of time in close proximity (<=50%).

Two kinds of interpersonal social graphs can be generated: *full proximity networks*, portraying physical proximity among all team members (Figure 6, left); and *role-centred ego networks*, revealing personal proximity between roles in relation to a central role (i.e. the patient) and the focus of these data vignettes (right). All networks were normalised based on the weighted time average of co-presence to enable comparison among phases and teams.

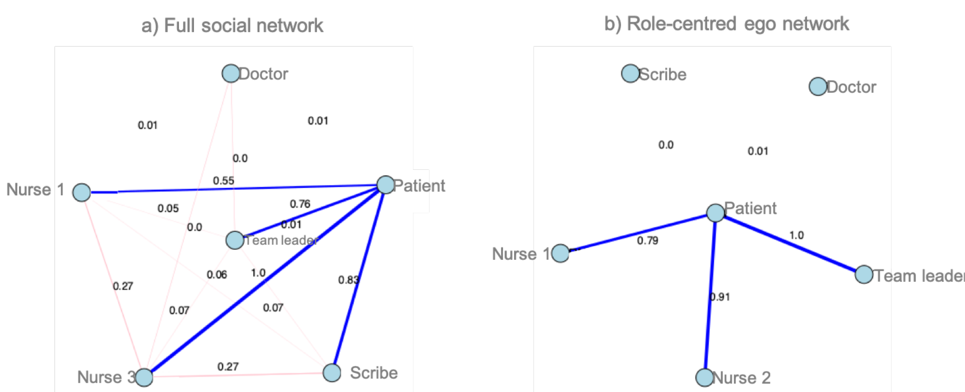

Fig. 6. Example of social networks representing mutual presence in interactional spaces during phase 1: a) a full proximity network of team 4 (left) and b) role-centred ego networks focused on the patient in team 4 (right). The labels near each edge indicate the proportional amount of time two people were in close proximity to each other.

c. Exemplar insights. Since the patient is central according to educators, patient-centred ego networks can be used to identify the presence of team members in the patient's interactional space. Figure 7 depicts social ego networks for teams 1 and 2 for phases 1-4 of the simulation. Nurses in team 1 (Figure 7, top) were strongly connected to the patient. During all phases, at least one of the nurses enacting active roles (i.e. the team leader and nurses 1 and 2) were at the interactional space of the patient. Although the scribe nurse, on average, spent most of her time in close proximity to the patient, she was acting as an observer and it was not intended to be performing an active role. As a result, the fact that two active nurses were always close to the patient while having an adverse reaction (with the exception of phase 2) suggests this team was effective when providing patient-centred care.

In contrast, Figure 7 (bottom) demonstrates that the patient-centred ego network for team two had a weak presence of active nurses in the patient's interactional space. The only strong presence of active nurses near the patient occurred during phase 1 (nurse 2) and close to the end of the simulation (nurse 2 and the team leader). In fact, phases 2 and 3 show only the scribe close to the patient (i.e. none of the active nurses). Compared to team 1, these networks suggest a weaker patient-centred attention. Moreover, the lack of connections between nurse 1 and the patient might be an indicator of disengagement of nurse 1 with the patient.

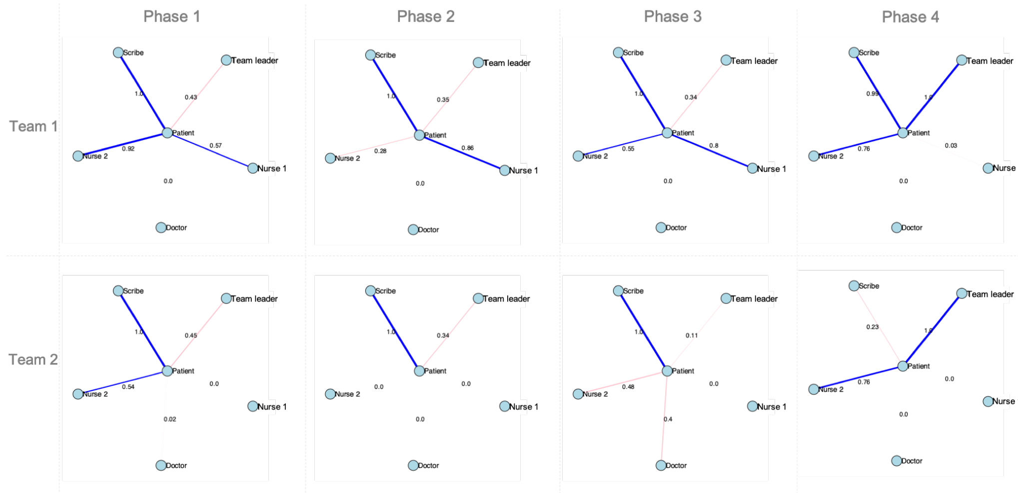

Fig. 7. Patient-centered ego network for teams 1 and 2 from phase 1 to 4.

Overall, responding to the educators' question (were nurses around the patient during the simulation?), five out of the eleven teams failed in being close to the patient in at least one of the phases, which means during that phase none of the team members were in interpersonal proximity with their patients. This is a potential area to be improved by these pre-service nurses, which was automatically highlighted by the analytics.

6.1.2 Data vignette 2: positioning of the team leader.

a. Context and the educators' question. Educators expect the leader to play a central role in phase 1 of the current simulation, because this is when the team is assuming the responsibility of taking care of a new patient. Because of that, educators may raise the question: *were nurses together (around or close) to the team leader during phase 1?*

b. Analysis. Similar to the previous vignette, SNA can also be used to model proximity ties among nurses. To analyse whether team leaders in various teams played a central role in phase 1, a full social network representing co-presence in interactional spaces can be used for comparison. These networks were also normalised to enable team comparison. From SNA, the metric *degree of centrality* was used to identify the most connected role in each team in phase 1 [39].

c. Exemplar insights. Through the following data vignettes we compare two teams, *team 2* and *team 5*, which exhibited contrasting spatial behaviours in relation to the team leader. The leader from team 2 was not surrounded by other team members (low weighted centrality= 1, considering ties >0.5%). By contrast, the leader from team 5 played a central role during this phase (higher centrality= 3). These two teams are representative of 3 and 8 other teams in which the team leader also showed a low or high centrality, respectively.

Figure 8 (left) shows these contrasting behaviours in more detail during phase 1. Although the team leader was in close proximity to the scribe during the whole phase, he/she only was in close proximity to the main nurses 1 and 2 during 0.04% and 0.27% of the time. This team leader was not close to the patient to a great extent either (0.15% of her time) making it reasonable to expect this nurse to have called the other nurses to come closer during phase 1 to coordinate their work for the rest of the simulation.

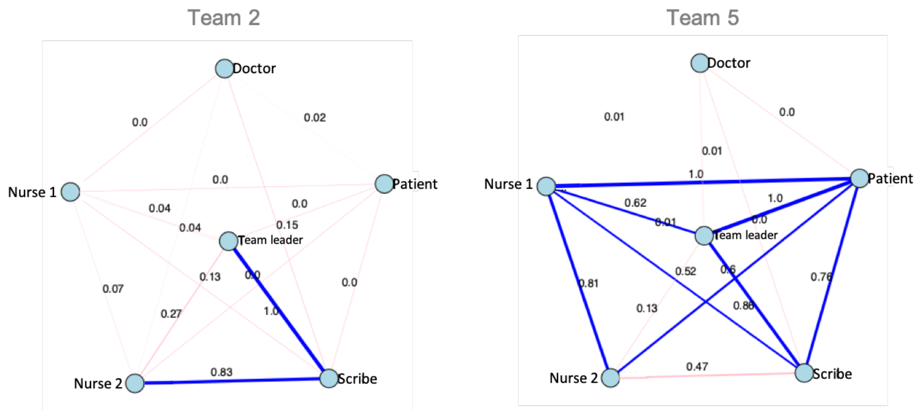

Fig. 8. Full social networks for teams 2 and 5 during phase 1.

By contrast, Figure 8 (right) shows multiple similarly thick links between all the nurses, which are also connected to the patient. In fact, the team leader was in close proximity to the patient during the whole phase and his/her time of co-presence in other nurses' interactional spaces was 0.62%, 0.52% and 0.86% for nurses 1, 2 and the scribe, respectively.

Although this would be an expected behaviour from an effective team, this was not ideal either, since it is not recommended that the patient listens to nurses' talking about their case as they are planning an intervention. In short, a leader that is too close could result in patient discomfort.

6.2 Socio-spatial Formations

6.2.1 Data vignette 3. F-formations while stopping IV-antibiotic.

a. Context and educators' question. From an educators' perspective, students are expected to follow official guidelines while preparing, administering or stopping medications. One of such guideline emphasises the need to perform these tasks, at least, in pairs, with one nurse monitoring what the other nurse is doing. For this, the data vignette in this subsection illustrates how positioning data could help educators to confirm the following question: *How was the team physically arranged while stopping the IV-antibiotic? Were at least two nurses engaged in the stopping task?*

b. Analysis. The GCFF algorithm has been specifically developed to automatically identify f-formations from static images. For this reason, GCFF was applied to automatically identify overlaps in transactional segments of two or more people (presented in subsection 5.1.2). The algorithm automatically identifies if nurses were in a f-formation and graphically represents a detected formation.

c. Illustrative insights. Figure 9 depicts the visual outputs from the GCFF algorithm of four teams (8 to 11) while stopping the IV fluid during phase 4. Team 8 did not exhibit any specific formation as nurses were at different sides of the bed while nurse 2 stopped the IV antibiotic. Although this does not necessarily suggest an ineffective teamwork behaviour, it can signal that one nurse was probably stopping the IV by herself, which can lead to errors and unexpected patient outcomes, particularly during procedures with the patient medication. With this information, educators could provide informed feedback during debrief sessions and help nurses reflect on why they did not comply with specific guidelines.

In contrast, the visual outputs of teams 9, 10 and 11 show particular f-formations during the IV-fluid stopping task. Teams 9 and 11 exhibited the expected behaviour: one nurse is providing the medication and the second is monitoring. Based on their body rotations, nurses were side-by-side (team 9) or assuming an L-shape (team 11) formation, which both enable manipulation of the IV device. For the case of team 10, the algorithm detected a side-by-side formation between the team leader and nurse 2, but other team members were in close proximity to them, suggesting they were also aware of their actions before and after stopping the IV-antibiotic. These insights can be useful for educators not only to assess whether at least two nurses engaged in stopping the IV medication but also to visualise how nursing students approached the task and to discuss with them any challenges they may have faced.

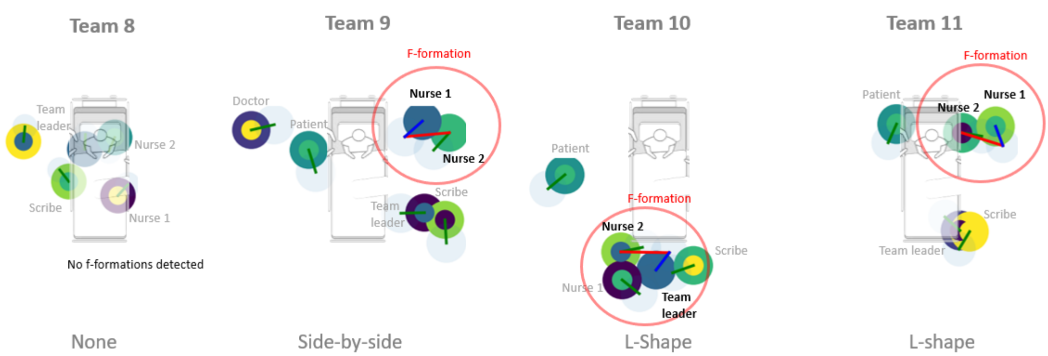

Fig. 9. Detected formations in teams 9, 10 and 11 while stopping the IV-antibiotic.

6.3 Fixed, Semi-fixed and Dynamic Spaces of Interest

6.3.1 Data vignette 4. How different teams used the spaces of interest.

a. Context and educators' question. Here, we are interested in how nurses from different teams used the physical spaces in the classroom for the same team task. This problem is related to the following questions from an emic perspective: *Where did nurses spend most of their time during the simulation? Did nurses spend too much time at the medicine room? Were at least some team members near the patient during the event?*

b. Analysis. In this case, the interest is in giving meaning to individual team members' coordinates at a higher level of abstraction. SNA can be used to model interpersonal ties based on proximity data but it does not incorporate the particular places where nurses actually were. For this reason, we used Epistemic Network Analysis (ENA) to analyse nurses' presence in fixed, semi-fixed and dynamic spaces of interest (as described in section 5.1.3). ENA is a novel method used for identifying connections among elements in coded data and for representing such connections through dynamic network models [74]. ENA was originally conceived as a tool to quantify and model qualitatively coded discourse data. Yet, the method has recently been used by several data scientists to model other forms of coded data, such as social connections (e.g. [86]) and digital tools usage (e.g. [75]), in various group settings. We believe that our work is the first to use ENA to model physical spaces.

The output of the modelling described in section 5.1.3 was processed using an online ENA tool[3]. In the resulting epistemic networks, each node represents fixed, semi-fixed and dynamic spaces of

[3]http://www.epistemicnetwork.org/

interest (see Table 2), and each link represents the co-presence or transitions between two spaces of interest. In addition, networks are weighted: thicker and more saturated lines suggest stronger connections, whereas thinner, less saturated lines suggest weaker connections [76]. The positioning of nodes does not correspond to the actual positions of the spaces of interest on the floorplan. Instead, ENA automatically places the nodes in fixed positions to allow for meaningful comparison of patterns of connection between two or more team networks.

c. Illustrative insights. Figure 10 shows ENA diagrams for teams 7 and 9, mapping transitions between spaces of interest for the whole simulation.

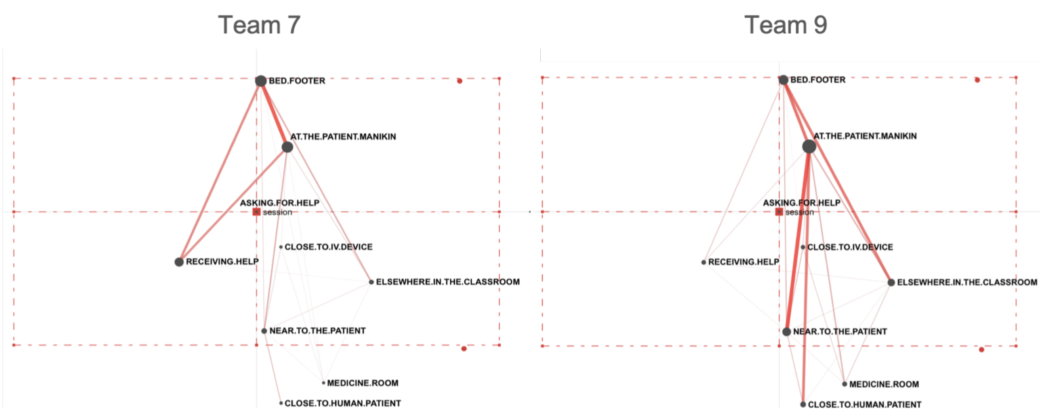

Fig. 10. Epistemic Networks showing the spaces of interest. Team 7 (left) received help from the teacher, while Team 9 (right) was more independent.

Figure 10 (left) shows the epistemic network of a team transitioning between the bed footer and the patient manikin most of the time (see thick edge between nodes: *at the bed footer* and *at the patient manikin*). Moreover, this team received some help from the teacher mostly in these two semi-fixed spaces (see edges going to node *receiving help*). In contrast, although members of team 9 also remained very close to the patient manikin and at the bed footer (Figure 10, right), they occupied other meaningful spaces during the simulation. For instance, edges going to the nodes *near to the patient* and *close to human patient* suggest that team members also occupied the space further apart of each other but around the patient manikin, and close to the student role-playing the patient. This can be indicative of patient-centred care. Moreover, this team displayed a more independent and proactive behaviour, as team members commonly were elsewhere in the classroom and only received little help from the teacher (see thick edges connecting the node *elsewhere in the classroom* and thinner lines connecting the node *receiving help*).

7 DISCUSSION

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

7.1 Implications for Supporting Team Learning and Reflection (the Emic Perspective)

The CSCW field has contributed rich insights into the value of reflective practices for improving team performance [10], fostering purposeful learning [78], the development of professional practices [41], and the re-design of group work practices [62]. In the particular context of healthcare training, team-based reflection on past group activity is considered by some authors to be the most crucial element in simulation-based training [13, 72]. It is through reflection that team members identify their learning gaps, and develop strategies for improving them. From a teaching and learning perspective, the use of evidence, conveyed via appropriate visualisations, is critical for providing feedback to students, particularly if they come from different backgrounds and perspectives as in interprofessional medical teams [70]. Our ultimate aim is to provide evidence from the analysis of large amounts of indoor positioning data to support this reflection on teamwork dynamics.

Through the data vignettes presented above, we have illustrated the potential of automatically generating evidence about positioning strategies to address authentic questions that educators have when monitoring, assessing and reflecting on nursing team simulations. For example, the analysis associated with the data vignette related to co-presence in interactional spaces (section 6.2.1) facilitates the rapid comparison of team performance in terms of patient-centre care, and the central role that the team leader should play at critical moments. With such analytics in place, this approach could enable the provisioning of automated feedback which could be used to spark reflection in a post-simulation debrief.

The automated detection of f-formations could be useful to detect clinical errors that should be minimised by following effective collaborative practices. As illustrated in section 6.2.1, the common error of not having another team member to validate the administration of medication can be addressed in training. A report based on this vignette could help educators, who may be monitoring various teams simultaneously, to assess which teams of students may not be following the national guidelines. Medication errors are still prevalent in professional nursing practice, and thousands of people die each year as a result of such errors [19] which makes this contribution highly significant in its potential to solve a widely acknowledged problem. Moreover, automatically identifying how teams use the space during critical situations, and the transitions among such spaces (as illustrated in subsection 6.3.1), could contribute to recent interest in mapping nurses' workflows in emergency wardrooms for the purpose of improving clinical practice [60], or improving the architectural design of the wardrooms [43]. There are opportunities to use these analytics to support reflection. For example, this approach could help educators to identify teams that require more support, or for students themselves to reflect on how they use simulation spaces and available equipment within the context of their assigned roles.

In sum, team reflection commonly occurs under the guidance of a facilitator or educator [79], but this can be highly challenging for educators to provide. Debriefings are dependent on expert educators' observations (but often stretched over multiple teams), and the partial (sometimes stressed, and always biased) memories of students. This is perhaps why healthcare educators and students are increasingly recognising the added value of capturing objective evidence of collocated activity and rendering it visible to support debriefing after a team simulation [11, 47]. We envisage that both the elicitation of key teamwork spatial behaviours expected by educators and the modelling approach presented in this paper, will contribute to the creation of team-facing interfaces that could be used in conjunction with the educator to engage in evidence-based reflection on spatial behaviours.

7.2 Implications for Team Research (the Etic Perspective)

In their review of 25 years of CSCW research in healthcare, Fitzpatrick and Ellingsen [15] emphasised that a critical contribution of CSCW research is in generating a deeper understanding of micro mobility, spatial arrangements of patients, healthcare staff, resources and information on the wards and in hospital settings. Our paper contributes to this call from a methodological point of view. For example, although social network analysis (SNA) has been used to identify proximity among team members (e.g. using sociometric badges [35] or infrared tags [54] in CSCW research), modelling indoor positioning data as proxemic constructs can enable the generation of more complete models that not only identify proximity between two or more team members, but also considers: the context in which they encounters one another, where precisely these interactions occur, the locations where individuals perform work, and micro mobility aspects (such as f-formations) that can provide more nuanced indicators of team behaviours. Although our vignettes focused on addressing authentic questions that educators might have about a particular simulation, we see potential for our modelling approach to answer broader questions in healthcare (the researchers' etic perspective). For example, indoor positioning data could provide much more accuracy, enable longitudinal studies and accelerate researchers' cycles in identifying relationships between team proxemics and patient outcomes, which is an area that has only been investigated via direct observation [49, 50, 56]. Furthermore, the modelled proxemic constructs could also be used to meaningfully analyse teamwork within other contexts where positioning data have been or are starting to be considered as an important source of evidence of team performance. For example, modelling co-presence could support the investigation of how multiple teachers interact with students (co-teaching) in the classroom as recently explored by Martinez-Maldonado et al. [48]. Similar space-time team dynamics could be modelled for the case of team-sport events (e.g. see positioning visualisations of basketball matches in [20]). Modelling f-formations continuously and automatically has been explored for the purpose of designing interactive systems (e.g. [64]). Coupling f-formation data with the presence of team members in meaningful spaces could also be extended to training settings, such as: team firefighting [80], where indoor positioning has also started to be used; and workspace analysis [65], that seeks to understand how interior elements and displays influence the collaborative behaviors of office workers.

In sum, while our modeling approach originated from a clinical simulation scenario based on prior CSCW research, we see significant potential for its use across a broad range of teamwork settings. This would meaningfully facilitate evidence-enhanced professional training, data-enabled workplace optimization, and fundamental research into professionalization.

7.3 Limitations and Future Work

From a usability and effectiveness perspective, we recognise that our data vignettes only illustrate what is now in principle possible (i.e. to provide visualisations that address educators' questions). The raw outputs from SNA, GCFF and ENA are not intended to serve as end-user interfaces. More work is therefore needed to create interfaces that can be easily understood by people without formal data analysis training. The next step in our research program is to conduct empirical evaluations of curated interface prototypes, first with educators, and (most likely after further iterations to refine the designs), with students.

From a modelling perspective, we should highlight that the spatial behaviours expected by the educators are context and task-dependent, which means they will change depending on the simulation. Consequently, some of the modelling techniques presented in section 5.1 might not be applicable to address questions in new contexts.

From a data integrity perspective, the software may not have identified some f-formations due to abnormal values in the rotation data captured. These abnormalities were caused by some nurses adjusting the waistbags containing their positioning trackers, and so altering the rotation values. Their data was manually corrected after inspecting video footage of the simulations, but future work should consider this as a potentially disruptive factor for automatic analysis, particularly for in-the-wild settings.

From an automation perspective, in our study, researchers still played an important mediating role in helping identify the kinds of questions to answer, and analysing spatial behaviors. Yet, to realise the ultimate goal of providing feedback to students right after the end of the simulation, both technical and educational challenges need to be addressed (e.g. post-processing of eye-tracking data [85]). Sensing technologies and their interfaces are rapidly evolving, making it difficult to plug multiple sensors into the same system. More work in this area is thus needed to create infrastructures that enable smooth sensor interoperability and data fusion, specially if positioning data is enriched with other contextual information such as student actions. Moreover, even if the technical challenges can be addressed, further research should explore how educators can express their educational intentions to the system and how both educators and students can effectively incorporate data practices into the curricula and their professional practices.

8 CONCLUSION

Movement and orientation sensors, combined with analytics and visualization, open new opportunities to make visible people's positioning behaviours, and to provide insights into team proxemics in complex settings. This paper's core contributions are twofold. First, the extraction of educators' expected spatial behaviours from the qualitative study, along with their contextualized implications in regard to learning goals. Second, the development of a modelling approach to transform low-level data of nurses' positioning traces into higher level constructs, grounded in prior work on proxemics and social spatial formations, in the professional learning context of clinical simulation. Guided by educators' pedagogical intentions and questions (the emic perspective), three proxemics constructs were identified in the proxemics literature and modelled using sensor data, namely: i) *co-presence in interactional spaces,* ii) *socio-spatial formations,* and iii) *presence in spaces of interest.* Through a number of data vignettes, we illustrated how this enables the generation of visualizations to address clinical educators' questions about the positioning behaviours of nursing teams. We have discussed the implications of this modeling approach for CSCW and team research, and envisioned its potential utility for data-driven, evidence-based analysis of positioning dynamics in healthcare and other team contexts. In conclusion, our approach shows promise for opening up a valuable new avenue of research in proxemics, one that will help us to resolve low level positioning data into educationally meaningful constructs.

9 ACKNOWLEDGMENTS

Gloria Fernandez Nieto gratefully acknowledges the University of Technology Sydney for PhD Scholarship support. Roberto Martinez-Maldonado's research is partly funded by Jacobs Foundation.

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Received October 2020; revised January 2021; accepted January 2021