Modelling Spatial Behaviours in Clinical Team Simulations using Epistemic Network Analysis: Methodology and Teacher Evaluation

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ABSTRACT

In nursing education through team simulations, students must learn to position themselves correctly in coordination with colleagues. However, with multiple student teams in action, it is difficult for teachers to give detailed, timely feedback on these spatial behaviours to each team. Indoor-positioning technologies can now capture student spatial behaviours, but relatively little work has focused on giving meaning to student activity traces, transforming low-level x/y coordinates into language that makes sense to teachers. Even less research has investigated if teachers can make sense of that feedback. This paper therefore makes two contributions. (1) Methodologically, we document the use of Epistemic Network Analysis (ENA) as an approach to model and visualise students' movements. To our knowledge, this is the first application of ENA to analyse human movement. (2) We evaluated teachers' responses to ENA diagrams through qualitative analysis of video-recorded sessions. Teachers constructed consistent narratives about ENA diagrams' meaning, and valued the new insights ENA offered. However, ENA's abstract visualisation of spatial behaviours was not intuitive, and caused some confusions. We propose, therefore, that the power of ENA modelling can be combined with other spatial representations such as a classroom map, by overlaying annotations to create a more intuitive user experience.

CCS CONCEPTS

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

KEYWORDS

Epistemic Network Analysis, nursing, simulation, spatial behaviour, qualitative analysis

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1 INTRODUCTION

In healthcare education, students are often immersed in manikin-based team simulations (see Figure 1) designed to provide realistic scenarios that help them to practise a range of clinical procedures [14] and develop critical clinical skills that they will need in the workplace [4] to improve patient outcomes [21]. Specific *spatial abilities* are required for registered healthcare professionals [16], such as knowing when to keep close physical proximity to the patient [31] and to other team members [27]; and being able to accomplish a specific task through appropriate positioning and coordination in a specific location of the ward [44].

The use of evidence for *debriefing* after the simulation is a signature pedagogy in simulation-based healthcare education [7] that enables students to reflect on errors and for educators to engage in dialogic feedback with students. However, many spatial behaviours in physical spaces can easily become occluded due to the multiple tasks students have to accomplish, and the fact that there are typically 5-6 teams in action on the ward. Although video-based products to support student reflection exist, they are typically impractical for in-class use (it is too difficult for the teacher to cue up key moments from multiple teams, ready for a short 15-20 minute group debriefing session), and imprecise for generating evidence about positioning measures. In turn, healthcare students rarely reflect on such evidence to improve their spatial abilities [15]. Also teachers may commonly find it challenging to assess and support students' development of such spatial skills. This lack of evidence to inform reflective training practices has been identified as a persistent gap in healthcare education [22].

Indoor-positioning technologies can pervasively capture traces of student spatial behaviours which, if effectively curated, could be rendered visible for the purpose of supporting reflection and learning on spatial abilities. However, despite a growing interest in using positioning analytics in healthcare (e.g. [12, 23]) and in classroom

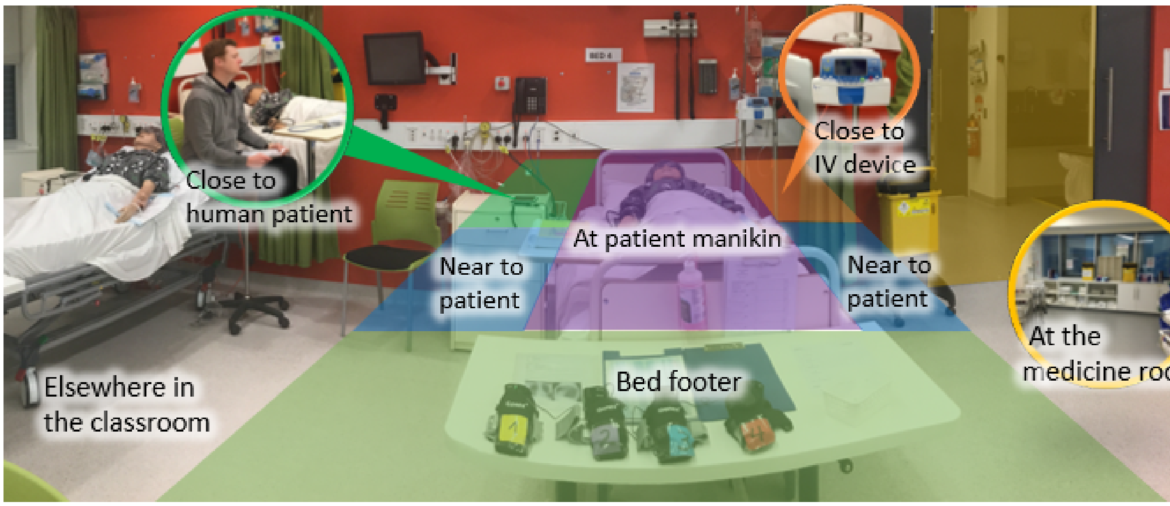

Figure 1: Healthcare simulation ward: meaningful *spaces of interest* as defined by teachers.

studies (e.g. [25, 33]) little work has focused on giving meaning to such low-level x/y coordinates beyond measuring proximity. To address this, we investigate the use of Epistemic Network Analysis (ENA) [37] as a means to imbue healthcare students' positioning data with the meanings that presence and movement in particular *spaces of interest* (Figure 1) signify during team simulations, and make these visible for discussion.

First, this paper contributes a better understanding of the potential for ENA representations to support reflection on spatial team behaviours, by presenting a qualitative study that examines teachers' perspectives on ENA representations of spatial behaviours. To generate these, positioning data was captured while teams of undergraduate nurses engaged in healthcare simulations. A set of spaces of interest, particularly relevant for the simulation tasks, were identified from previous co-research with teachers who designed and facilitated the experience. Based on these, positioning data was modelled, by following principles of Quantitative Ethnography (QE) to encode multiple sources of data [6] into higher-order meaningful codes, and were represented as epistemic networks to teachers. Second, this paper documents teachers' perspectives on such ENA representations, in terms of how they: (i) made sense of the ENA diagrams; (ii) envisaged potential uses of ENA to support their teaching; and (iii) proposed improvements to ENA diagrams to better support students in guided reflection.

The rest of the paper is structured as follows. Section 2 presents the foundations and related work in the areas of indoor positioning analytics in education and Epistemic Network Analysis. Section 3 introduces the simulation learning context. Section 4 describes how positioning data was collected and modelled, and how the epistemic networks of spatial data were generated and evaluated with teachers. Section 5 presents the results from such evaluations performed with five educators to examine their perceptions on spatial ENA representations. Finally, Section 6 discusses the results and presents potential avenues of future work. The paper finalises with some concluding remarks in Section 7.

2 BACKGROUND AND RELATED WORK

This section presents (i) current works exploring spatial aspects of learning using indoor positioning technologies and analytics; and (ii) foundations of Epistemic Network Analysis.

2.1 Indoor Positioning Analytics in Education

Recent developments in sensing technologies, and improvements in their accuracy, are enabling new ways to investigate complex processes that occur in physical learning settings (e.g. [30, 43]). The traces created by these technologies are opening up opportunities to examine the spatial behaviours of students in physical learning spaces, and so to support both researchers' investigations, and teachers' reflections. For instance, Sensei [33] and EduSense [1] equip classrooms with sensing technologies that enable automatic proximity tracking of teachers and students. Sensei relies on tiny proximity sensors embedded in shoes and other wearables to provide relative positions of students and teachers in a classroom. This enables the creation of basic visualisations that assist teachers to observe which areas of the classroom they visit more, which students they interact with, and for how long. EduSense is a computer vision system that detects the proximity of students and the teacher, also recognising kinaesthetic behaviours such as raising a hand, and facial features. While both technologies provide relative proximity rather than continuous position tracking, the data they capture holds promise for generating a deeper understanding of spatial behaviours.

Other researchers have used indoor positioning systems that enable tracking the locations of teachers and students point by point. For example, An et al. [2] and Martinez-Maldonado [24] created displays that alerted a teacher who appeared to have spent little time with certain students. Going beyond measuring proximity, Martinez-Maldonado et al. [25] describe *Moodoo*, a library to extract spatial metrics related to instructional behaviours which enables the analysis of how different learning designs impact upon the way teachers move in classrooms and approach students. However, most of these works have focused only on teachers' behaviours. Less work has focused on students working in teams, with some remarkable exceptions. These include work by Chng et al. [8] who used depth sensors to automatically identify if students were working individually or collaboratively in a maker-space, and then analyse how group strategies can impact individual student performance. Work by Echeverria et al. [12] also looked at nursing spatial behaviours, visualising the positions of nurses around a patient manikin using a combination of heatmaps and state diagrams. However, the visualisation in Figure 2, representing student transitions between locations, does not provide any indication of either the *frequency* of nurses movements, and critically, no indication of the *meaning* of nurses' presence in different locations.

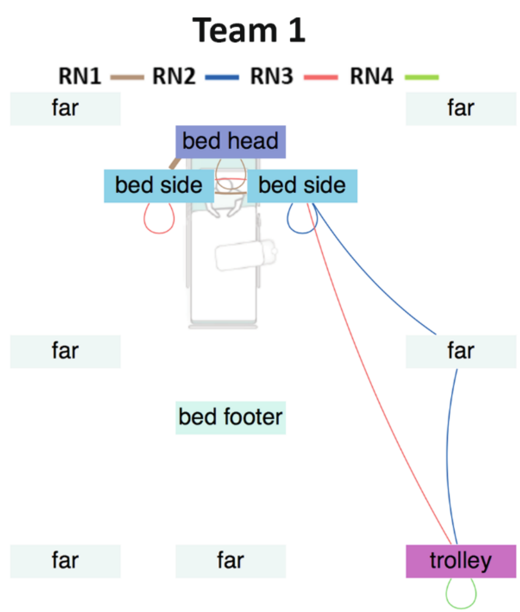

Figure 2: A visualisation of nurses' movements between positions as modelled by Echeverria et al. [12].

These examples demonstrate the growing interest in using indoor-positioning technologies to study spatial behaviours in physical learning spaces, however, most are limited to quantifying proximity information among teachers and students [8, 24, 33]. Although some metrics have been proposed to model the positioning or proximity traces to correlate them to instructional [25] or collaborative [8] behaviours, less work has focused upon giving meaning to such low-level x/y coordinates of students interacting in physical learning spaces for the purpose of supporting reflection and learning. We therefore go beyond these previous works, and particularly beyond the work of Echeverria et al. [12] in a healthcare setting, by exploring the opportunity of using epistemic network analysis (ENA) to imbue student positioning data with the meanings that certain spaces may have during a particular learning task.

In recent years, ENA has been gaining prominence in LA [40] and CSCL [10, 39] by virtue of the fact that it focuses on the relationships between codes in data, and generates visualisations that facilitate the comparison of datasets. Since we were interested in configurations of spatial relationships in students' positioning, and comparing student teams, ENA held promise as an analytic technique. However, modelling spatial data introduced new challenges, critically, how does one map from low level sensor x/y coordinates, to higher order codes (required for ENA modelling) that reflect the language and concepts used by nursing educators?

The next section presents a brief introduction to ENA, and introduces the important question of how educators make sense of ENA representations.

2.2 Epistemic Network Analysis

Epistemic Network Analysis (ENA) is a relatively novel statistical method, motivated by Quantitative Ethnography (QE) [35], for constructing dynamic network models that quantify and visualise the structure and strength of connections among elements in coded data [36]. In ENA, *nodes* represent the codes used to analyse the data, and *edges* or links represent connections, which are weighted: thicker and more saturated lines suggest stronger connections, whereas thinner, less saturated lines suggest weaker ones. ENA was initially developed to model cognitive networks from discourse (e.g. chat or forum) data, for example, in collaboration and self-regulated learning (e.g. [13, 17, 32, 41]).

However, since its inception with discourse data, ENA has been used to extract insights from other sources of data. For example, Wooldridge et al. [42] modelled communication patterns of health care teams in both face-to-face and computer mediated settings. In this work, task allocation roles by medical staff (e.g. receivers and senders of task allocations) in physical and virtual spaces became the codes in the epistemic networks to identify communication patters. A further example is given by Collier [9], who applied ENA to fMRI (functional Magnetic Resonance Imaging) data from children to identify areas of the brain that are co-activated during numeracy tasks. Finally, Andrist et al. [3] applied ENA to model eye-tracking data to identify how dyads synchronise their gaze patterns to perform collaborative tasks.

However, we have identified two critical gaps in our understanding of ENA that our work seeks to address: (i) ENA's application to embodied learning, and (ii) teachers' perceptions of ENA. Firstly, despite the importance of face-to-face activity in myriad educational contexts, ENA has not yet been used to model student/teacher activity in a physical space. Secondly, ENA has to date been a tool for *researchers* to make sense of their data, which means that little evidence has been collected regarding *teachers'* perceptions of ENA's value to support their practice. An exception is the work of Herder et al. [20], who piloted a simplified ENA diagram as part of a sophisticated tool for high school teachers to monitor and assess students' progress during an online simulation. The ENA was generated in real time, from automated analysis of student actions. Of the three teachers who were studied, one valued the concept of the network diagram to show higher order integration between concepts, another was not confident about its coding classifications, and the third struggled to interpret it. All teachers were unfortunately overwhelmed by the demands of the teaching their class, and so did not have time to experiment with it more fully.

To the best of our knowledge, this is the first paper in applying ENA to model spatial behavioural data. As such, the two key contributions of this paper lie in its exploration of: (i) the potential of using ENA to imbue students' spatial data with the meanings that presence in particular *spaces of interest* signifies during a learning task; and (ii) teachers' perspectives on ENA representations of spatial behaviours of their nursing student teams.

3 CONTEXT

3.1 The Learning Situation

This paper focuses on five classes, part of a course on *Integrated Nursing Practice*, conducted during Week 7 (of a 12 week term) in 2019, with students in their third year at the [*Anonymous university*]. Approximately 25 students typically attend a class in the simulation ward, and they are organised in teams of 4–6 students, each working in a simulated training scenario around a patient bed. One team in each of the five classes volunteered to participate in this study and have their activity tracked, completing informed consent forms (ethics approval number ETH16-0582). The average duration of the simulation was 69 minutes (std=14.4). A total of 25 students (21 female) were studied (aged 20-45 years, mean=23.5, std=5.4). Five teachers were involved in teaching the five classes.

In this simulation, students took on various nursing roles to collaboratively care for a patient experiencing an allergic reaction to medication. The teacher played the role of the main doctor on the ward, and one student played the role of the patient, giving a voice to the manikin. According to the learning design, a highly effective team should carry out the following critical actions:

(1) Measure an initial set of vital signs;
(2) Administer the intravenous (IV) antibiotics;
(3) Take a second set of vital signs;
(4) Stop the IV antibiotic after the patient reacts with chest tightness;
(5) Perform an electrocardiography (ECG); and
(6) Call the doctor after stopping the IV antibiotic.

The simulation was therefore 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); *Phase 5:* patient recovery.

4 METHODOLOGY

4.1 Positioning Data

Students' positioning data was captured through wearable tags[1] carried in waist-mounted bags. The positioning system triangulates the exact location of each tag with reference to 8 anchors affixed to the classroom walls. The raw positioning data consists of x and y coordinates in millimeters captured at 2-3Hz but downsampled to 1Hz for normalisation purposes across teams.

4.2 Data Modelling

4.2.1 Identifying spaces of interest. Ward locations take on multiple meanings, based on the kind of activity unfolding, and the presence of teachers, students and objects (e.g. devices, furniture) [29]. Following Hall's analysis of proxemic behaviour [18] such spaces can be 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.

The meanings that presence and movement in these *spaces of interest* signifies for the particular learning design of the simulation under study have been identified during several years of co-research with the nursing academics who teach the students, through a combination of formal interviews and past prototyping (Echeverria et al. [12]). For example, these instructors have explained that in this simulation nurses usually gather around the *foot of the bed* where the documentation about the patient is commonly located, but that at least one nurse should remain *close to the patient* continuously after they complain about chest pain.

4.2.2 Modelling from positioning data to spaces of interest. Each fixed and semi-fixed space of interest was mapped as two-dimensional square regions in the tracker coordinate system to classify location (Figure 1). For the case of the dynamic spaces, proximity data between nurses and the teacher was used to dynamically identify when students were close to the teacher and where in the classroom this occurred.

As described in section 4.2.1, spaces of interest for this simulation were elicited during an extensive process of co-research with nursing academics, and are summarised in Table 1. For example, the only *fixed* space for this simulation was *the medicine room* which is a well defined area with medical instruments and supplies (Table 1, row 1). *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 defined as any area in which a nurse and doctor were in close proximity ($\leq$1.5 m) to each other. Thus, if a nurse was close to the teacher and they both were *elsewhere in the classroom*, this was coded as *asking for help* (row 8). 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* (row 9). All the remaining positions in the classroom were coded as *elsewhere* in the classroom. Consequently, each datapoint of each nurse in the dataset is associated with a *space of interest*, possibly in conjunction with *asking/receiving help*.

To encode indoor positioning data and the spaces of interests into a higher-order level of meaning we followed the *Multimodal Matrix* (MM) methodology [6]. Building on the MM, this paper's novel contribution is documenting how to drive the modelling of learners' positioning data from teachers' pedagogical intentions, and coding *fixed*, *semi-fixed* and *dynamic* spaces of interest within a physical learning space. Figure 3 shows a simplified representation of the modelling performed on the positioning data. The MM is a data structure in which each code m is represented by a n column

[1] www.pozyx.io

Row	Space of interest (codes)	Meaning	Example expected behaviour in current simulation	Type
1	At the medicine Room	Here, nurses commonly get medicine and equipment they require for the patient care.	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.	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 signs (e.g. pulse, hart rate) (right)	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).	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 1: Codes for the meaningful spaces of interest.

of the matrix. For example, Figure 3 (A) shows the raw data and the *spaces of interest*.

Based on QE, *segments* [38] (m rows) are the smallest units considered for analysis. For sensor data, each row can represent a time window (e.g. one second in our studies) of the team activity (Figure 3, B). This way, the content of each cell expresses an attribute of a given team member at that moment. In our study, we represented the presence or absence of a student in one or more spaces of interest at a given moment (i.e., each second). Finally, segments can be grouped into *stanzas* to represent meaningful associations. In discourse analysis, a stanza might correspond to a number of utterances before or after a particular incident [11]. In our study, the phases of simulation (see section 3) can serve to group the segments into stanzas (Figure 3, C).

4.2.3 Generating epistemic networks from spatial data. The output of the modelling described above was processed using the online ENA tool[2] for the duration of the simulation. In the resulting epistemic networks, each node represents the codes for *fixed, semi-fixed and dynamic spaces of interest*, and the activities of *asking for and receiving help*, and each edge represents transitions between two spaces of interest, possibly in conjunction with help seeking/receiving. The positioning of nodes does not correspond to actual positions on the floorplan (a key point to which we will return when we report teachers' responses). Instead, ENA automatically places the nodes in fixed positions to facilitate visual comparison of networks (for details of the algorithm, see Shaffer [34]). From the 5 teams, we selected the ENA diagrams of *Team 1* (Figure 4a) and *Team 3* (Figure 4b) for our study, because they were the more contrasting teams (see Figure 5).

4.3 Evaluation of ENA diagrams with educators

The qualitative study in this paper used a retrospective reflection technique [19] to investigate the Nursing educators' responses to the ENA diagrams of their students' activity. Five teachers (T1-T5) were interviewed, each of whom had taught the simulation beforehand, to preserve the authenticity and value of the study. The discourse analysis of five experts is sufficient to identify salient patterns and is effective for identifying most usability problems with prototypes [28]. Our study sought to address three research questions:

- RQ1: What insights can teachers gain from visual representations of nursing teams spatial behaviours using ENA?
- RQ2: What potential uses of ENA for supporting teaching and reflection on nurses' spatial behaviours are envisaged?
- RQ3: If potential uses are identified, then what improvements are needed for making ENA representations for special data into effective reflection tools for nurses?

4.3.1 Interview protocol. The interviews were conducted as approximately 20 minute online video conferences via Zoom, structured as follows: (1) *Explanation of the ENA diagram.* The researcher showed a floorplan to explain the spaces of interest, and then showed the ENA for Team 1 (Figure 4a) to show how they corresponded to the node labels. It was emphasised that node locations bore no correspondence to the floorplan, the meanings of edges and thickness were explained as reflecting the number of transitions between locations, but no explanation was given about why nodes were positioned as they were (this was judged to be too complex to explain quickly). (2) *Interpretation of ENA (RQ1).* Educators were asked to think aloud while inspecting the connections presented in the three ENA diagrams shown in Figure 4. The prompt question was *"According to this diagram, can you explain how TEAM 1 transitions between the Spaces of Interest?"* (3) *Eliciting envisaged usage (RQs 2 and 3).* After viewing the three ENA diagrams, teachers were then asked about the potential value of ENA for student and teacher reflections, and about any improvements to the ENA design that might help to support their teaching practice.

4.3.2 Video analysis. The interviews were video-recorded, fully transcribed, and coded using NVivo. Two researchers were present in each session. We examined participants' statements and their actions exploring the prototypes. Following Mcdonald et al. [26], and given the direct alignment between the study protocol and the analysis themes, statements of interest were jointly coded [5] by two researchers according to the pre-set themes of the study protocol: (a) teachers' interpretations of ENA visual representations of spaces of interest; (b) anticipated usage strategies; and (c) opportunities to improve ENA to support reflection. Resulting coded statements were examined by the authors who had several discussions to select

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

Multimodal observation	LOW-LEVEL POSITIONING DATA					PRESENCE IN SPACES OF INTEREST							
						Fixed spaces	Semi-fixed			Dynamic-spaces			
A	Time	Team	Role	X	Y	At the medicine room	Close to IV device	Elsewhere	...	Close to doctor	Asking for help	Receiving help	
	Measure an initial set of vital signs												Stanza
	00:29	1	Nurse 1	10	12	1	0	0		1	0	1	C
	00:30	1	Team Leader	11	15	0	0	1		1	1	0	
Segment	...	...	...	..	...	0	0	1		0	0	0	
	Administer the intravenous (IV) antibiotics												
B	05:02	2	Nurse 2	12	15	0	1	0		0	0	0	
	05:03	2	Nurse 3	12	15	0	1	0		1	0	1	

Figure 3: Schematic showing the application of the Multimodal Matrix modelling technique to two phases in the simulation activity.

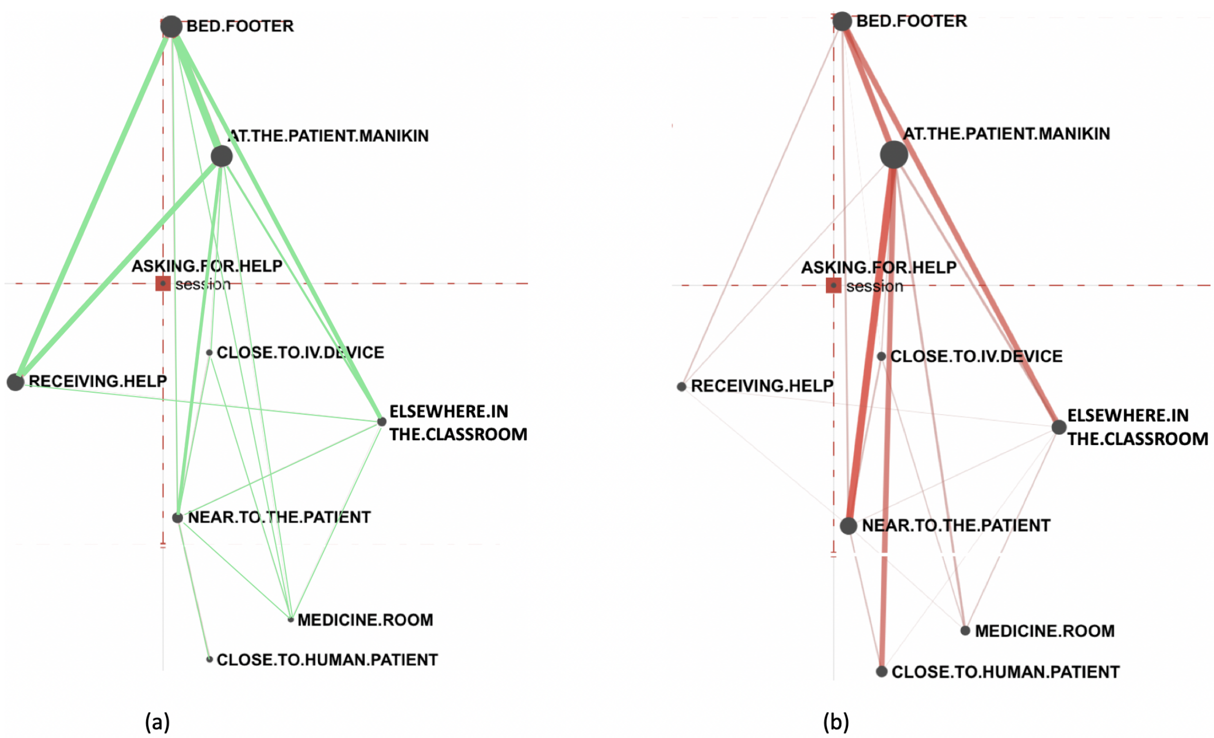

Figure 4: Presence of nurses in spaces of interest around the patient and in the classroom during the healthcare simulation using Epistemic Network Analysis for Team 1 (a) and Team 3 (b).

instances that illustrate the opportunities and concerns raised by the teachers.

5 RESULTS

This section presents the results of the analysis organised around the three questions motivating these studies.

5.1 RQ1: Teachers' Interpretations of the ENA Diagrams

Strong connections. Four of the five teachers were immediately able to start interpreting the ENA diagrams of both teams (see Figure 4, a and b respectively) focusing on the visually salient, strongest connections (thicker edges). However one teacher found them very confusing and could not volunteer any reading of them. When interpreting the ENA diagram for team 1, teachers first mentioned the strong connection between the nodes *bed footer* and *at the patient manikin*. According to teachers, the meaning of this connection is associated with the patient-care construct (e.g. students assessing the patient vital signs). By focusing on the other two edges forming a triangle with the node *receiving help*, one of the teachers explained that *"the most common behaviour of nurses in team 1 was moving from the head of the bed to the footer, because they [focused on] assessing the patient, and then they were receiving help from the teacher, probably because they needed guidance to achieve the task"* (teacher T1). For team 3, teachers highlighted the connections between the nodes *at the patient manikin*, *near to the patient* and *close to the human patient*. For example, teacher *T2* described that *"these students seem to have started at the patient manikin more than anything else, then going close to the human patient, students did interact with the patient, with the person and the actual manikin"*. Similarly, teacher *T4* confirmed this as follows: *"it looks like team 3 was doing more of communication with the actual human patient as well"*. Regarding other strong connections, teachers explained the meaning of nurses using those spaces, for example, nurses being *elsewhere in the classroom* suggested that nurses may have gone to

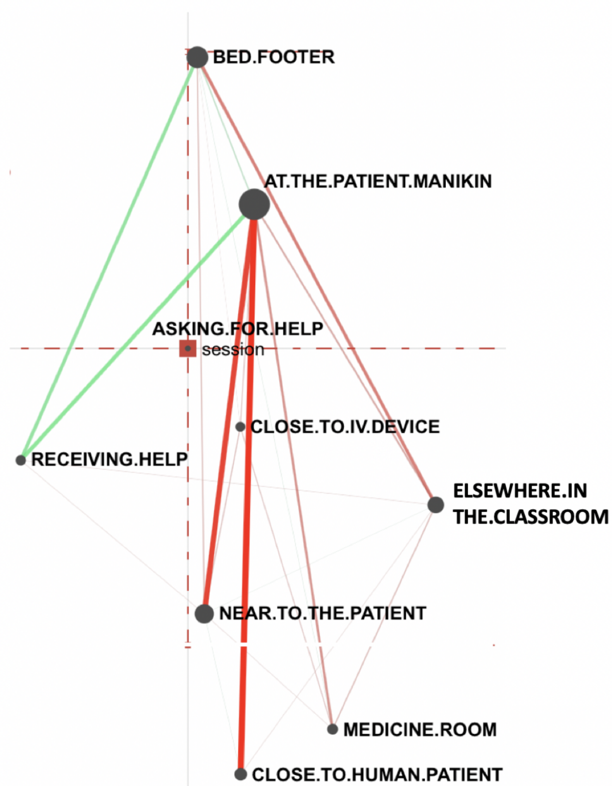

Figure 5: The *comparison* network shows the difference between teams: green edges where Team 1 is stronger, red edges where Team 3 is stronger.

find additional help (e.g. books), or the ECG device to assess the patient.

In sum, all educators agreed that team 1 was receiving significant help from the teacher, which for this simulation was not expected, because this is an immersive simulation and the students were meant to be addressing critical incidents independently as a team. Team 3 was much more focused on the patient, as expected. This suggests that teachers associated strong connections to the predominant spatial behaviours of students.

Weak and missing connections. Teachers also interpreted thinner edges. For example, regarding the node *close to IV devices* in team 1, teacher *T1* explained that *"the [team members] do not need to be there very often [in that space], they are there just for preparing the medicine and then they give the medicine so that is fine, instead they need to be closer to the patient"*. Also, teacher *T5* explained that this weak connection occurred *"probably because students first tried to figure out what was going on with the patient"*, which according to this teacher is the explanation of the presence of some connection to the node *receiving help*.

Regarding identified missing connections, three out of the five educators agreed that team 1 was generally not as close to the patient as was expected for this simulation. For example, the teacher *T3* explained that *"there was not a lot of contact with the human patient and it is a procedural problem of team 1"* (note just one thin edge connected to the node *close to human patient*. However, teacher *T1* argued that, although not ideal, team 1 could still assess the human patient because *"students can still talk to the human patient from the other side of the bed. So they may have done a lot assessment on the actual manikin and then maybe just talked to the human patient from the other side of the bed"*. The principal insight from the ENA representation for team 3, that all teachers agreed with, was that students were generally far from the teacher, neither asking nor receiving help. For instance, teacher *T1* explained that *"this team was autonomous because they look like they asked less for help, even when they may have received some help, it seems they did not depend on it"*. Teacher T5 described this behaviour from the spatial traces as follows: *"probably this team was in a more advance level of expertise or was more confident with the work they were doing"*. This suggests that, based on missing connections, teachers were also able to identify the nurses' lack of presence in spaces of interest, which pointed to qualities and also potential areas of improvement for the teams.

Comparing networks. Four out of five teachers suggested that this visual comparison (Figure 5) confirmed what they interpreted from the individual ENA representations. For example, teacher *T4*, suggested that *"this [comparison visualisation] just reinforces what I was talking about before, there is a correction to be made for team 1 or a couple of corrections in terms of performance. More interaction to the patient is needed and they should avoid receiving too much help from the teacher. Whereas, team 3, was much more engaged with the patient"*. Likewise, teacher *T5* reflected on this comparison, suggesting that *"students in team 1, which is the green one, were more keen to ask for more help from the teacher than team 3, which was more independent, and tried to figure it out by themselves what to do"*. Finally, only one of the educators interpreted other connections apart from the more prominent edges. Teacher *T2* explained that *"Team 3 went to the medication room a little bit more* *than the other team"* and associated this to the more independent and active behaviours of team 3.

5.2 RQ2: Anticipated Pedagogical Uses

Regarding the potential use of ENA representations for supporting their teaching practice, four out of five of the teachers agreed that this tool could be very useful for nursing students to reflect on aspects like patient-care and team autonomy. For example, *T2* suggested that this tool could be used *"during the debrief session to focus on teams that might have required specific interventions, such as team 1"*.

Teacher *T4* also highlighted the potential of using the ENA representations for teachers to reflect on their own practice. This teacher explained how she focused on the extent to which she provided help to the students, as follows: *"for me as a teacher if I am doing an immersive simulation, I am expected to let students to figure out the situations or try to address the simulation scenario by their own without my help"*.

Moreover, *T1* explained that ENA representations can be very useful for teachers because they normally want to compare teams at a glance, *"it is good that you can see the comparison because then you can see the differences among different teams"*. Additionally, teacher *T2* mentioned that whether or not students receive or request help *"can also indicate that they had to receive a kind of additional support or instruction to address the simulation, it might suggest possible changes in the learning design"*.

In sum, teachers recognised the contribution of ENA diagrams to: identify teams' spatial behaviours, compare teams, interrogate their own practice (regarding to what extent they affected the immerse character of the sim), and to revise the learning design.

5.3 RQ3: Improvements to ENA Diagrams

During the interviews teachers expressed concerns about the complexity of the visual representations to interpret. For example, *T3* stated that he recognised the value of the tool for reflection but *"it is a bit difficult to interpret, and there should be some clear guidelines to go to the clinical staff and students for them to understand what the visualisation means"*. In fact, we acknowledge that an accurate explanation of the ENA representation (codes and connections) is needed to avoid teachers' misinterpretations, specifically regarding the position of codes and its independence with the actual floor position. This because, all teachers confused the node positions with a floor position.

A number of improvements were suggested, which reflected the distinctions being made between codes (nodes). Three teachers recommended simplifying the ENA representations by combining the codes for the *patient-manikin* and the *human role-playing the patient* (which counter-intuitively, were not next to each other in the diagram): *"the patient manikin and the person playing the role of the patient represent the same entity for the simulation, both might refer to patient-care" (T1)*; *"even when (the human patient and the manikin) are located at different spatial data points, it would be worthwhile to combine them because that's the composite" (T3)*.

However, in another instance, the nodes were not making an important distinction. *T3* suggested splitting the code *near to the patient* into two different codes: *"there is a left side to the patient and a right side to the patient. There will be different procedures being performed at each side. I think it may be worthwhile to consider separating those ones out"* [...] *"the right hand side of the patient will be predominantly where students will be doing clinical assessment, checking vital signs, and talking to the patient. Whereas the left side in this scenario is where the IV-device is, having both might bring additional insights about the nurses behaviours"*.

Finally, other recommendations were related to the inclusion of additional elements to support interpretations. For example, the *T3* suggested that the ENA representations *"could just have some legend down the side or some explanatory notes linked to the edges"* to explain the meaning of the connections. Alternatively teachers requested more contextual information regarding what was happening during a particular period of time, for example, when critical clinical procedures were occurring, or focused the analysis pf differentiated spatial behaviours according to the specific roles enacted by students such as the *team leader*.

6 DISCUSSION

Revisiting the research questions (Section 4.3), we can summarise the teachers' interviews as follows: (RQ1) teachers could interpret strong and weak connections in individual teams, and were able to characterise and assess spatial behaviours in relation to learning outcomes such as *effective patient-care* and *team autonomy*. The teams *difference diagram* was considered helpful, and reinforced their initial interpretations; (RQ2) teachers envisaged the use of ENA diagrams to identify teams' spatial behaviours, interrogate their own practice and to support interventions; (RQ3) teachers requested additional contextual details regarding tasks and roles to assist ENA interpretation, and proposed both node *fusion* to hide unnecessary distinctions, and node *fission* to bring out important distinctions that were masked.

Reflecting on these findings, several points merit discussion. Learning to read ENA requires the ability to first *decode* the visual language, before being able to *interpret* it. We found that four of the five teachers, following a few minutes' guided walkthrough from the researcher, could decode the language, and could construct consistent narratives about what it signified in terms of student and teacher behaviour. It was noticeable that after the initial strangeness of the first exposure to an ENA diagram, narrative interpretations flowed much more quickly from the teachers when they moved onto the Team 3 diagram.

We did find that using ENA to visualize *spatial behaviours* introduced additional complexities not found when modelling non-spatial activity. One teacher found it very confusing and could not give any interpretations of it. Several teachers needed ongoing reminders that node positions were independent of floorplan position. One teacher thought the ENA seemed upside-down, since the medical room was at the bottom. Another teacher appeared to interpret an edge that passed close to a node as meaning students were literally close to that location. ENA's quadrants added visual noise, but no meaning to the teachers. Everyone found it incongruous that the ENA node for the manikin patient was positioned a long way from the human role-playing the patient's voice, when conceptually they are the same thing, and physically adjacent in the room (in fact, they wanted them merged).

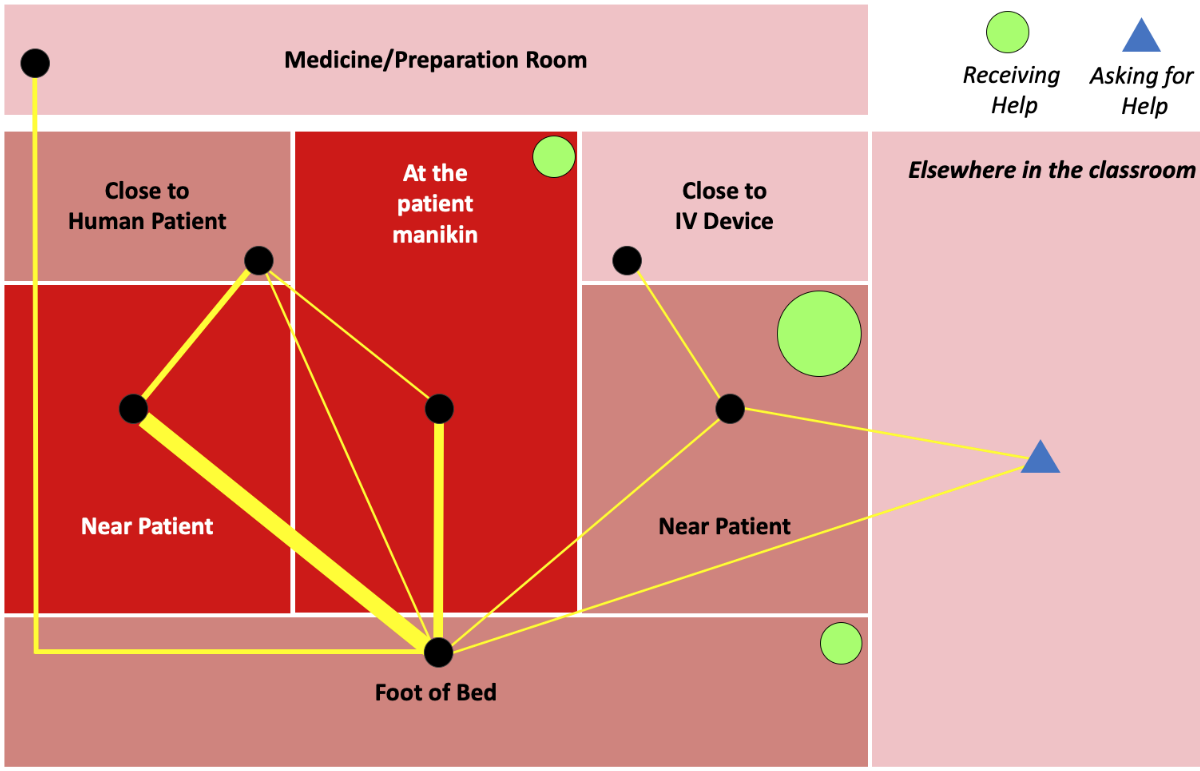

Figure 6: Design concept for visual feedback to educators and students. A map of the simulation ward is overlaid with annotations from the ENA modelling, translating node/edge weights into a heatmap, movement trajectories, and icons for different activities (e.g. circle or triangle).

However, the four teachers who engaged with ENA were not confused by the fact the nodes in the diagrams represented both *spaces of interest* and *activities* (requesting/receiving help). Thus, depending on which nodes were being connected, edges could represent transitions between two spaces, or the space in which an activity occurred. They found it very natural to interpret (for instance) *Team 1 received help at the bed footer.*

The key insight from this initial trial is that most of the teachers could learn to read ENA, but not all aspects were intuitive, especially since it describes spatial behaviour. ENA excelled visually in showing at a glance the most salient nodes and transitions, and enabling team comparison. Noting that making sense of nodes' relative positioning is challenging for *researchers* who understand the underlying algorithm, we made no attempt to explain this to the teachers, since this was deemed irrelevant. However, the disconnection between ENA positioning and the floorplan is strange, and leads us to reflect on whether teachers should be exposed to ENA directly.

We propose that much of the valuable information in ENA diagrams can be decoupled from the particular network visualisation generated by the current tool. ENA can be used to enrich other spatial visualisations, that make more sense to educators and students, such as the familiar floorplan of the simulation ward. Our thinking, therefore, has returned to the kind of visualisation developed by Echeverria et al. [12] (Figure 2), but annotated with the information from the *spaces of interest*-based ENA modelling that teachers gave such positive feedback on. Figure 6 shows an interface mockup, in which *ENA edge size* is translated into edges overlayed directly onto a floorplan, *ENA node size* is translated into colour saturation to create a heatmap, which at a glance shows which spaces of interest were most frequently occupied, and *asking/receiving help* nodes are translated into differentiated icons of different sizes in the relevant location. Clearly, modelling could include other weighted activity-based icons, and their weighted interconnections, with controls to view/hide different layers. This map still facilitates comparisons between teams, but is, we suggest, much more intuitive than ENA's abstract representations, designing out the possibility of the interpretive confusions that the teachers showed.

7 CONCLUSIONS

This paper makes two contributions, one methodological, and the other, a learning analytics infrastructure for an authentic educational challenge (improving feedback in clinical team simulations). Methodologically, we have documented the use of Epistemic Network Analysis (ENA) to model and visualize nurses' positioning during clinical simulations, by coding the contextual meanings that different *spaces of interest* take on. To our knowledge, this is the first application of ENA to the analysis of spatial activity. It has enabled analysis within teams, and comparison across teams. Given the importance of face-to-face activity in diverse educational settings, this is a valuable step. This also demonstrates the value of Quantitative Ethnography for learning analytics, in which a *qualitative* understanding of the meanings that spaces and locations take on is critical, in order to *quantitatively* model low-level sensor data from a complex activity, in a manner that respects how stakeholders understand this activity.

Secondly, we are conducting this work in order to provide new insights to improve the value of clinical teamwork simulations. We have documented preliminary evidence that Nursing academics could make sense of the ENA diagrams, seeing them as provocations to productive reflection and discussion among themselves as teachers, and for use with nursing students. After a few minutes' orientation from the learning analytics researcher, most could read the diagrams (i.e. were able to construct appropriate narratives about what the ENA signified about performance within a team, and team differences). However, we have also documented the complexities that an abstract spatial map such as this introduces when describing spatial behaviours. This led us to reflect on how the strengths of ENA as a conceptual representation, which received strong validation, can be preserved but more intuitively visualized, through *ENA annotation* of a map of the space where the teaching and learning activity takes place.

Future work will involve further design iterations to evaluate the proposed visualisation with teachers, and once they have validated it, to introduce it to students. The focus in this paper has been on ENA modelling of spatial behaviours, but data from other kinds of sensors can clearly be added (e.g. speech-to-text; use of equipment), in combination with more conventional kinds of conceptual activity codes for which ENA was originally developed. These could in turn, of course, make the visualisations more complex, leading to further design iterations.

In conclusion, this research program seeks to develop a learning analytics infrastructure that not only has *representational integrity* (the model is expressive enough to reflect important conceptual distinctions in the real world), but also *communicative integrity* — enabling the sensemaking needed to close the feedback loop not only to researchers, but to educators, and ultimately, to students. This paper's contributions have advanced our understanding of how to address these dual concerns.

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