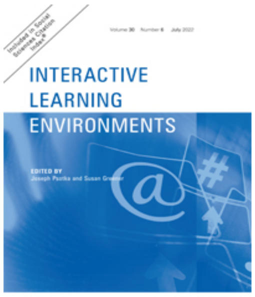

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Designing translucent learning analytics with teachers: an elicitation process

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ABSTRACT

Learning Analytics (LA) systems can offer new insights into learners' behaviours through analysis of multiple data streams. There remains however a dearth of research about how LA interfaces can enable effective communication of educationally meaningful insights to teachers and learners. This highlights the need for a participatory, horizontal co-design process for LA systems. Inspired by the notion of *translucence*, this paper presents LAT-EP (Learning Analytics Translucence Elicitation Process), a five-step process to design for the effective *use* of translucent LA systems. LAT-EP was operationalised in an authentic multimodal learning analytics (MMLA) study in the context of teamwork in clinical simulation. Results of this process are illustrated through a series of visual proxies co-designed with teachers, each presenting traces of social, physical, affective and epistemic evidence captured while teams of student nurses practised clinical skills in a simulated hospital setting.

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Introduction

Learning Analytics (LA) systems can offer new insights into learners' behaviours through the analysis of multiple, often intertwined, sources of data collected from the interaction of learners with educational technologies (Gašević, Dawson, & Siemens, 2015), or from the physical learning environment (Chua, Dauwels, & Tan, 2019). As the number of available LA interfaces rise however, their impact on learning is becoming increasingly questionable (see reviews by Bodily & Verbert, 2017; Jivet, Scheffel, Specht, & Drachsler, 2018; Matcha, Gasevic, & Pardo, 2019).

Designing effective LA interfaces is a complex task that requires careful understanding of the critical stakeholders (and their relationships), and the contexts in which those systems will function (Buckingham Shum, Ferguson, & Martinez-Maldonado, 2019; Chen & Zhu, 2019). Yet, there remains a dearth of research about how LA interfaces can effectively communicate educationally meaningful insights for teachers and learners (Echeverria, Martinez-Maldonado, Granda, et al., 2018), a key challenge to be tackled in order to facilitate a wider and sustained adoption (Ferguson et al., 2014; Prieto, Triana, Maldonado, Dimitriadis, & Gašević, 2018). A critical problem with many LA interfaces is that they are commonly designed following a top-down process (Prieto-Alvarez, Martinez-Maldonado, & Anderson, 2018). This is, researchers and developers make most of the design decisions in behalf of teachers and learners. Moreover, it is becoming clear that general purpose interfaces – not particularly tailored to support certain students or learning situations – cannot be easily used

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to support learning (Teasley, 2017). This makes more evident the need for a participatory, horizontal co-design process for LA systems.

There is consequently emerging interest in involving students, teachers and other stakeholders in the design of LA innovations (Dollinger & Lodge, 2018), understanding the values that must be endorsed by these (Chen & Zhu, 2019), and keeping teachers in the "design loop" (Rodríguez-Triana, Prieto, Martínez-Monés, Asensio-Pérez, & Dimitriadis, 2018). In the past 30 years, disciplinary practices in the broader area of human-centred design (Gasson, 2003; Giacomin, 2014) have demonstrated the value of bringing the voices of end-users into software design to increase the possibilities of successful appropriation (Carroll, 2004). A specific strand of work is the discipline of *co-design*, in which researchers and designers tackle the complex task of translating diverse voices into design requirements (Sanders & Stappers, 2014). However, including multiple stakeholders adds complexity to the design process (Prieto-Alvarez, Martinez-Maldonado, & Anderson, 2018). Previous work has explored ways to co-design educational systems or curricula with teachers (e.g. Roschelle & Penuel, 2006) and students (various examples in DiSalvo, Yip, Bonsignore, & DiSalvo, 2017). Yet, more specific work in the area of LA is needed to guide researchers and designers in engaging non-data experts to understand basic "analytics" related concepts, and to build mutual understanding of educational constructs.

Inspired by the notion of "translucence" (Niemantsverdriet, Broekhuijsen, van Essen, & Eggen, 2016), this paper presents the Learning Analytics Translucence Elicitation Process (LAT-EP) for involving teachers in the co-design of analytics representations of learner data, and strategies to embed these into their practice. To illustrate how LAT-EP can be operationalised in an authentic setting, results of a multimodal learning analytics (MMLA) study are presented in the context of teamwork in clinical simulation. MMLA interfaces can be much more complex than regular LA systems as teachers and learners need to make sense of multiple sources of data. Four visualisations were co-designed with the aim of serving as proxies of social, physical, affective and epistemic aspects of activity captured while teams of students practised clinical skills in a simulated setting.

The rest of this paper is organised as follows. The next section provides an overview of recent work in the area of human-centred learning analytics and co-design, foundations of the concept of translucence, and an overview of the state-of-the-art related to the illustrative scenario, at the intersection of collaborative learning and MMLA. The following section describes the proposed elicitation process and how it was operationalised in an authentic case, aimed at understanding the information needs of teachers and their perspectives on a set of previously co-designed visualisations on multimodal healthcare activity data. The paper concludes with reflections on the future of this work and implications for researchers and practitioners.

Background and related work

Co-design and human-centred learning analytics

Human-centred learning analytics is a term recently proposed to the subcommunity of LA researchers and practitioners interested in utilising the body of knowledge and practice from design subcommunities, such as Participatory Design (PD), User-Centred Design (UCD) and Co-Design, into data-intensive educational contexts (Buckingham Shum et al., 2019). Work in this area is embryonic, with some researchers advocating rapid prototyping with teachers (Martinez-Maldonado et al., 2015) and interviewing students to understand their disciplinary perspectives on data (McPherson, Tong, Fatt, & Liu, 2016).

The first adaptations of various co-design techniques were to identify teachers' data needs and build prototypes of awareness tools with them (Holstein, McLaren, & Aleven, 2017, 2018). In fact, teachers, in both secondary and tertiary levels, have been the most commonly involved stakeholder in LA co-design studies. Dollinger, Liu, Arthars, and Lodge (2019) discussed implications for the use of participatory semi-structured interviews with teachers in long-term LA projects. Wise and Jung (2019) combined LA interface walkthroughs and transcript analysis to make design decisions for a teacher dashboard. Holstein, McLaren, and Aleven (2019) featured a number of co-design techniques, namely card sorting, directed storytelling, semi-structured interviews, prototyping and behavioural mapping, to co-design a classroom analytics innovation with teachers. Some examples of LA design processes engaging with students are only now beginning to emerge (Chen & Zhu, 2019; de Quincey, Briggs, Kyriacou, & Waller, 2019; Prieto-Alvarez, Martinez-Maldonado, & Buckingham Shum, 2018).

In summary, these studies illustrate a growing interest in co-designing LA systems with students, and particularly with teachers. However, none of these reports proposed the steps that other researchers or designers can use as a guide to structure co-design sessions; and to move from the design of interface features to understanding critical aspects of the use and orchestration of the envisaged LA tool. This paper addresses this need by operationalising an LA elicitation process, based on the concept of translucence.

Foundations of translucence

The term social *translucence* was originally proposed by Erickson et al. (1999) to refer to the characteristic of collaborative systems that use social information to compensate for the loss of *visibility* (of socially significant information), *awareness* (of others' actions) and *accountability* (of people's own actions) as a result of moving group activities from physical spaces to a fully digitally mediated format. The notion of translucence foregrounds the intention of making some aspects of the activity visible but not fully transparent (Erickson & Kellogg, 2000). This is a critical concept for the design of LA systems since it is commonly said that a key goal of LA systems is making learning visible and actionable (Buckingham Shum & Ferguson, 2012), within the boundaries of a framework that endorses the ethical use of learners' data (Slade, Prinsloo, & Khalil, 2019). The notion of translucence is of particular importance for MMLA innovations, use of sensors may raise privacy concerns, with significant personal information easily and pervasively collected (Ochoa, 2017).

Translucent systems involve the use of proxies. These are minimalist visualisations representing some aspect(s) of group activities (Erickson et al., 1999). The original idea of social translucence has been embraced and further developed as an analysis framework for eliciting design requirements (Niemantsverdriet et al., 2016). The work presented in this paper builds on this approach, providing a process to engage with teachers in understanding the context of usage of visualisations of multimodal evidence using a translucence lens.

Collaboration and multimodal learning analytics

This sub-section presents an overview of studies in the area related to the illustrative scenario of this paper: collocated collaboration analytics.

There is a small but growing interest in building a new generation of monitoring, awareness and reflection tools for collocated learning activities (Rodríguez-Triana et al., 2017). One promising approach is to capture multimodal behavioural traces from co-present activities using sensors and logging capabilities of educational interfaces, analyse them, and create feedback mechanisms to support reflection and evidence-based practice (Blikstein & Worsley, 2018). Although the concept of creating "group mirrors" is not new in online learning platforms (e.g. Jermann & Dillenbourg, 2008), the term *collocated collaboration analytics* has been proposed to refer to those innovations aimed at mining digital traces that can convert face-to-face group work, from an ephemeral activity that is commonly studied via direct observations and annotations, into a phenomenon that can be modelled computationally (Martinez-Maldonado, Kay, Buckingham Shum, & Yacef, 2019). For example, recent works have highlighted the unique opportunities of making traces of co-present activities visible for aspects that are not constrained by the cognitive realm such as the manipulation of physical objects (Davis, Schneider, & Blikstein, 2017), physical/gaze synchronisation (Schneider & Pea, 2017), gestures (Spikol, Ruffaldi, & Cukurova, 2017) and arousal states (Malmberg et al., 2018).

Whilst these examples show the potential of MMLA for investigating links between theory and collocated collaborative learning activity, recent MMLA research have identified the continuing gap between complex multimodal data and strategies to operationalise these to enable measurable impacts on learners or the orchestration of learning tasks (Di Mitri, Schneider, Specht, & Drachsler, 2018; Echeverria, Martinez-Maldonado, & Buckingham Shum, 2019; Ochoa, 2017). The current paper indirectly contributes to this underexplored area with a five-step elicitation process to *design-for* the effective use of LA systems illustrated through an MMLA study in the context of collocated collaboration.

LAT-EP: the Learning Analytics Translucence Elicitation Process

The design process proposed by Niemantsverdriet et al. (2016) was conceived as a generic tool for developing multi-user translucent systems in the built environment. It particularly focused on providing designers and researchers with a process for eliciting *information needs*, and the implications in terms of interaction, to afford *visibility*, *awareness*, and *accountability* for each role played by the stakeholders of a system. This process was enriched with steps recommended by three human-centred approaches from recent literature, purposed to proactively engaging teachers (Rodríguez-Triana et al., 2018) and other stakeholders (Prieto et al., 2018; Prieto-Alvarez, Martinez-Maldonado, & Anderson, 2018) in the process of co-designing learning analytics; as described below:

(1) The "the teacher in the loop" approach by Rodríguez-Triana et al. (2018) suggests a step in which teachers' inquiry can enrich the design of effective MMLA systems by explicitly stating the *pedagogical questions* (*hypotheses*) to be addressed by data automatically collected via sensors.
(2) The OrLA framework (Prieto et al., 2018) considers design implications that may affect *orchestration* aspects (e.g. tasks such as designing for, monitoring, managing and adapting the learning activities) as a result of adopting a learning analytics tool at a classroom level.
(3) Prieto-Alvarez, Martinez-Maldonado, and Anderson (2018)'s approach highlights the identification of the *roles* that stakeholders in the system may play, and the *power relationships* that may shape learning analytics use and adoption.

Table 1 presents the LAT-EP process and exemplar questions for each step, articulating teachers' questions, orchestration aspects and particular learning analytics co-design constructs into the following steps:

Step 1 – Stakeholder definition: Identify individuals in the classroom ecology and the key roles they can play, beyond traditional roles of teacher, students or administrator. This involves identifying their overlapping/multi-faceted roles (Niemantsverdriet et al., 2016) and the particular characteristics and orchestration functions (Prieto et al., 2018) associated with each.

Step 2 – Influence and power: Once the roles have been identified, it is critical to understand the relationships of power and influence (Niemantsverdriet et al., 2016). In educational settings, the relationship between the teacher and students is commonly hierarchical, in which teachers aim to positively influence students to maximise their opportunities of learning. Importantly, people with apparently similar roles may have different sub-roles, goals, responsibilities and needs. For example, in higher education some teachers also coordinate other teachers, or some have more or less involvement in shaping the learning design.

Step 3 – Inquiry: Given the complexity of the multimodal data, it is critical for people who will MMLA systems to define the pedagogical questions, hypotheses or expectations to be addressed using the evidence generated (Rodríguez-Triana et al., 2018). This is critical for designing any learning analytics tool aimed at connecting low-level data with meaningful constructs (Echeverria, Martinez-Maldonado, Buckingham Shum, et al., 2018).

Step 4 – Translucence: This step embeds the core contribution of the translucence paradigm for designing MMLA interfaces, foregrounding three constructs: visibility, awareness and accountability.

Table 1. LAT-EP: a five-step elicitation process to design for effective use of translucent MMLA systems.

Process step	Example questions to be asked by the designer, researcher or facilitator
Step 1 – Stakeholder definition: To identify the people who are part of the classroom ecology, by describing the different roles/stakeholders (Niemantsverdriet et al., 2016; Prieto-Alvarez, Martinez-Maldonado, & Anderson, 2018)	• Who are the *stakeholders* in the learning situation? • How many different kinds of *roles* are actually active during the (classroom) activity? • Can a stakeholder have more than one role, or are they mutually exclusive?
Step 2 – Influence and power: To map the influence of all roles on interaction/activity (Niemantsverdriet et al., 2016; Prieto-Alvarez, Martinez-Maldonado, & Anderson, 2018; Rodríguez-Triana et al., 2018)	• For every activity carried by each role, is there an *influence on other people*? • What is the explicit *power hierarchy*? • How is the learning design crafted and implemented? Who has an *influence on the learning design*? • Who has a major *influence on the adoption* of the learning analytics innovation?
Step 3 – Inquiry: To define the questions to be answered by the learning analytics solution or hypotheses/expectations that can be tested with evidence (Rodríguez-Triana et al., 2018)	• What are the common *classroom dynamics* that can be observed in regular classes? • What are the particular *collaborative learning constructs* that learners are aimed to develop and how can these be assessed? • What *questions* can be elaborated on aspects of the classroom that are currently hard to see? • What *hypotheses* can be confirmed or rejected based on evidence captured and modelled through the learning analytics.
Step 4 – Translucence: To define the information different roles require for the classroom activity (Niemantsverdriet et al., 2016; Prieto et al., 2018)	• What information is currently available (*visible*) for the different roles? What kind of information should be made available? How should it be visualised? What kind of metrics would be interesting to see? What other sources of information would you like to see? • Which information is needed for every role to create *awareness* of other people? What information would be useful for the teacher/students to have before/during/after the collaborative learning activity? • Which information is needed for every role to be held *accountable* for actions? Who do you think should look at the information? Should the data be made available to different roles (e.g. teachers, novice teachers, students, sub-roles amongst students, coordinators, learning units)? Do you think this information can be used for assessing performance? How do you think we can ensure students' privacy?
Step 5 – Design for orchestration: To translate the required information that lead to enhanced classroom translucence and orchestration (Niemantsverdriet et al., 2016; Prieto et al., 2018)	• What would you *do* with the information? • What information can *trigger changes* in current teaching and learning practices? • How can the required information be translated into *interaction aspects*? • Should the information be available *centrally*, *locally*, *or both*? • Considering user *privacy*, is all information necessary in its current form?

Visibility and *awareness* needs should be identified for each role and the spatiotemporal context, including the data sources and metrics that would be useful and how to represent them. As *accountability* tensions may become more evident, this step also includes developing an understanding about who will have access to certain information, in which forms and for what purpose(s).

Step 5 – Design for orchestration: Information needs can be translated into design aspects, either prompting changes in the visualisation tool or the orchestration strategies. For example, information needs for every role to be held accountable can be translated into privacy configurations or a certain information architecture.

The following section shows how this elicitation process was operationalised in an authentic project using a combination of semi-structured interviews based on the questions suggested in Table 1.

Study

This section presents a study in which a series of visualisations of multimodal data were co-designed with teachers and students. The section includes: (1) an overview of the learning context; (2) the multimodal data and setup utilised; (3) the visualisations generated; (4) a description of the study with teachers; and (5) results from this study.

Context of the study

The design case presented in this paper is part of an ongoing project being conducted in the Bachelor of Nursing at an Australian University. The overarching aim is to provide automated feedback to students working with patient manikins engaged in clinical simulations (see Figure 1). Learning tasks are conducted as practice laboratory sessions in classrooms equipped with five basic manikins in hospital beds that provide indicators of a patient's health, respond to actions, and can be programmed to deteriorate over time. The duration of these simulation sessions ranges from several minutes (e.g. emergency response scenarios) to a couple of hours (e.g. nursing shifts scenarios). Students collaborate and practice their knowledge and healthcare skills. Teachers commonly lead a whole-class reflection (debrief) activity at the end of each session.

A number of co-design tools have been used with nursing academics and students in the last three years to identify meaningful feedback mechanisms that can provoke reflections on practice. Five teachers and over 20 students have partnered in the design of this MMLA innovation. This overarching co-design process was conducted in three stages as depicted in, and illustrates how LAT-EP can be operationalised.

Stage 1 included the exploration of data needs and the co-design of low-fidelity prototypes with nursing students and educators. General purpose co-design techniques (Prieto-Alvarez, Martinez-Maldonado, & Anderson, 2018) were used in this first stage in (eight) individual and (five) group sessions with teachers and learners respectively (see, Stage 1). These co-design tools included card sorting (Fincher & Tenenberg, 2005), a technique that was used to identify the main needs that teachers and students face during healthcare simulation; focus groups (Gibbs, 1997), which helped to identify the main requirements for a set of tools that could support reflection on the simulation during the post-activity debrief; and low-fidelity prototyping (Virzi, 1989), which led to a series of visual characteristics that a learning analytics tool should contain for students to reflect on their actions after the simulation. An initial set of prototypes of proxy visualisations of multimodal learning

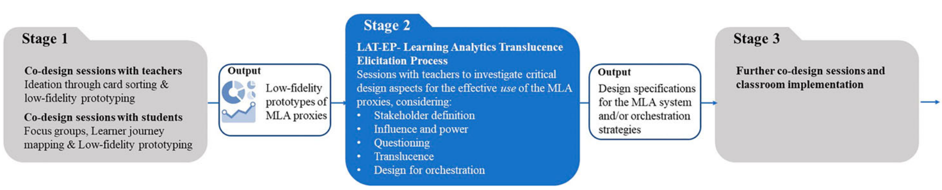

Figure 1. Diagram representing the overarching co-design process, highlighting where in the development lifecycle can LAT-EP be used, for co-creating MMLA interfaces in the context of the healthcare simulation analytics project.

data to be used during the nursing debrief was produced (see, Output – further detail in the next section). Particularities of these sessions go beyond the scope of this paper but can be found elsewhere (Echeverria et al., 2019).

Stage 2 consisted of using LAT-EP with teachers to identify the design aspects that are critical for the effective *use* of visualisations of MMLA data. The study presented in this paper focuses on Stage 2. Stage 3 consists in implementing and deploying the mechanisms for the proxies to be used and orchestrated in authentic classroom sessions (not reported in this paper).

Multimodal data and setup

Multimodal data used for generating a set of group visualisations (proxies) were automatically collected as part of a program run by one of the teachers in 2017. Three groups of students participated in a 15–20 minutes cardiac arrest scenario divided into two phases: (1) assessment of a patient suffering chest pain, and (2) resuscitating the patient after he loses consciousness. For these sessions, the environment was equipped with a range of sensors (a microphone array, indoor localisation badges, physiological wristbands) to track different aspects of the activity, including who is speaking, where nurses are in the space, arousal states and actions performed on the manikin. Figure 2 illustrates the setup.

Proxy visualisations of multimodal collaboration data

Examples of resulting prototypes of the proxy visualisations of a group of four nurses (RN1 – team leader, RN2, RN3 and RN4) are shown in Figures 3 and 4, and include:

- *A social proxy*, indicating the amount of verbal communication between each nurse and the patient (enacted by the teacher remotely located) in the scenario. This visualisation is aimed at portraying the patient-centred care construct (Stewart, 2001) of (simulated) registered nurses (RNs and the Leader nodes in Figure 3, left) interacting with the patient (the central node of proxies). Communication among nurses and the patient are represented as edges between the nodes, reflected by the presence of human voice recorded by wearable microphones or the microphone array.

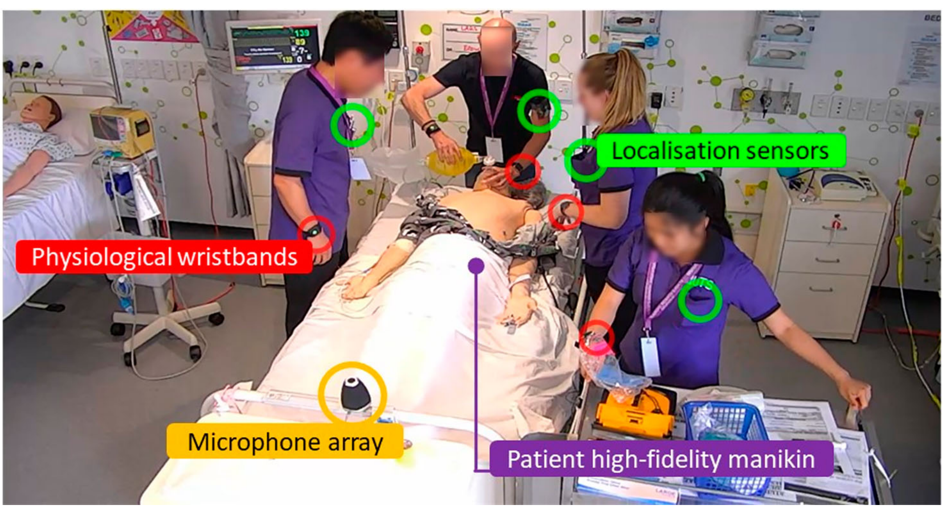

Figure 2. Students (Team A) in a simulated healthcare scenario.

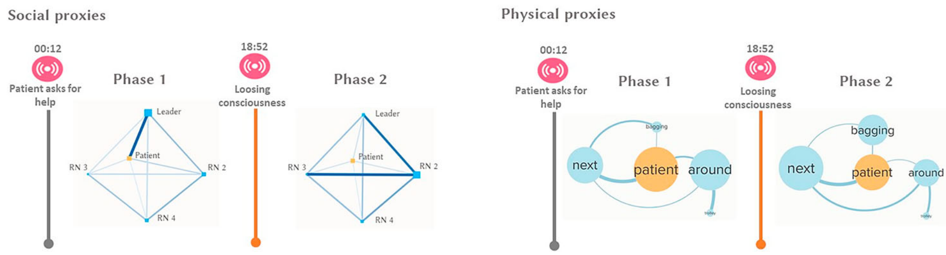

Figure 3. Proxies for Team A. Left: social proxies, the central node represents the patient and the rest of the nodes the nurses. Edges represent verbal communication among these. Right: physical proxies, circles represent areas around the patient's bed.

- *A physical proxy*, indicating the positions occupied by the nurses around the patient's bed area. Some critical positions around the patient have been identified in previous work for resuscitation scenarios, namely: being *next* to the patient (less than half a metre at the sides of the bed), at the *bagging* area (near the bed head), near the resuscitation *trolley*, *around* the patient (further away or at the bed footer) and above the *patient* (for performance of cardiac compressions in a resuscitation scenario) (Echeverria, Martinez-Maldonado, Power, Hayes, & Buckingham Shum, 2018). Figure 3 (right) shows the proxies, in the form of state diagrams, corresponding to how the nurses in a team occupied these five positions before and after the simulated patient lost consciousness during the clinical scenario.
- *A proxy of nurses' arousal*, indicating peaks of electrodermal activity (EDA). This visualisation is aimed at triggering reflection on students' stress response based on electrodermal arousal; a construct of growing interest in medical education (Duffy, Lajoie, & Lachapelle, 2016), automatically measured using the physiological wristbands. Figure 4 (left) presents the proxy of a team that includes one horizontal band per team member. Each band contains blue-coloured sections. The darker the shade of blue for a section the more intense the nurse was moving according to the accelerometer contained in the wristband. Dots correspond to peaks (Skin Conductance Responses – SCRs) automatically detected using the EDA explorer package (Taylor et al., 2015). A dot was coloured in orange or grey colour if low or high movement intensity was detected in parallel, respectively.
- *An epistemic*, *timeline proxy*, showing the actions each nurse performed during the simulated scenario (Figure 4, right). This provides a detailed account of the particular actions that each nurse performed during the simulation; for example, administering a medication to the patient, calling the doctor, preparing intravenous fluids and attaching an oxygen device to the simulated patient (manikin). These actions can be automatically detected by the manikin, via sensors or logged by an observer.

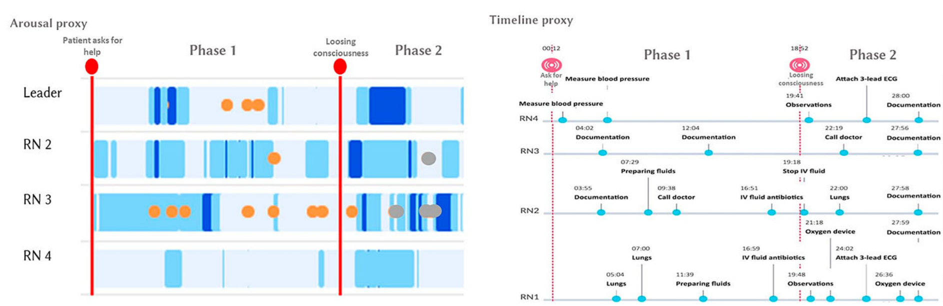

Figure 4. Proxies for Team A. Left: arousal proxy indicating: EDA peaks (orange dots); physical intensity (low, medium, high – represented by shades of blue); and EDA peaks affected by physical activity (grey dots). Right: the team epistemic, timeline proxy, depicting each student's actions in the simulation.

This paper goes beyond the visual aspects explored in our previous work (Echeverria et al., 2019) by applying the translucence elicitation process with teachers to understand critical aspects that influence the effective use of these visualisations in their practice, including: power/influence relationships, visibility, awareness, accountability, orchestration, and the questions that can be addressed based on the multimodal evidence.

Study design

Participants

Four active teachers and subject coordinators (T1, T2, T3 and T4) participated in the study. All teach using simulated scenarios in their subjects or had experience as Director, Health Simulation at a faculty level. Only one teacher had been involved in providing design requirements for the MMLA representations, but none had inspected the visualisations shown in the previous figures before.

Method

A 60-minute semi-structured interview was conducted with each teacher in private following the translucence elicitation process. Besides the questions shown in Table 1 (column 2), a 30-minute exploration task was added between Steps 3 and 4 in which teachers carefully inspected three sets of proxies corresponding to three teams of students (Teams A, B and C). Figures 3 and 4 show the set of proxies corresponding to Team A. Video recordings were captured during the interviews for further analysis.

Analysis

Recorded responses were transcribed and analysed by two researchers. Using the questions provided in Table 1. Responses were grouped by the five-step process and each passage (related responses by the same teacher) was thematically analysed using the social translucence (visibility, awareness, accountability) and educational concepts (teachers' questioning/hypotheses, orchestration aspects), by both researchers. The researchers discussed their two independent analyses to reach an agreement.

Results

Steps 1 and 2. Stakeholder definition/influence and power.

Teachers identified the roles of people influencing the enactment of simulation classes. The teaching team in each subject commonly includes the subject coordinator, the assessor (which helps with administrative tasks) and class tutors. The coordinator commonly delivers lectures and coordinators and tutors lead simulation-based classroom sessions. Yet, more than half of the tutors are commonly on a casual contract or have never taught the subject previously, making it challenging for the coordinating team to train new staff. From Teacher 3 (T3): "new casuals involve lots of 1-to-1 training on how to handle the class, mark assignments and conduct the debrief". This is a potential threat to adoption since, although the coordinator plays a key role in integrating the MMLA innovation into the learning design (T3), casual teachers act as the final users that need to appropriate any MMLA tool but may have limited time and expertise. The role of Director, Health Simulation would also play a key role in adoption at a program level. For this study, the focus was on the coordinator (T3) and assessor (T1) of a nursing subject, and a former Director, Health Simulation (T2).

Step 3. Inquiry

Each teacher was asked to formulate hypotheses for each of the aspects of the group activity that was modelled (oral communication, physical positioning, arousal and actions) before looking at any proxy. Overall, the hypotheses by the teachers were similar because there are well-specified protocols that nurses are expected to follow. For example, in terms of oral communication, T1 stated that "Everyone needs to listen to the team leader, so things can run smoothly" (aligned with the evidence from teams, e.g. see Figure 3, left, Phase 1); and added "In the CPR part (Phase 2) whoever is managing the airway should lead the communication". For this later case, the evidence in the visualisations did not support this hypothesis (e.g. see RN2 leading the communication in Figure 3, left, Phase 2). As a result of later inspecting the proxies, the teacher reflected that "In this case there were prescribed roles. If roles wouldn't have been allocated things may have unfolded differently". This is the kind of evidence-based inquiry that this step is aiming to provoke (Rodríguez-Triana et al., 2018).

Overall, the formulation of hypotheses served to guide the exploration and the sense-making process while teachers inspected the proxies, after Step 3. In terms of the physical aspects of the group activity, teachers reflected on the meaning of spaces around the bed (e.g. "once the patient goes into cardiac arrest, someone would look at the airway, this person should be at the head of the bed", T3 – see larger circle in Figure 3, right, Phase 1 compared to Phase 2 labelled as *bagging*). In terms of physiological arousal sensing, teachers formulated a number of hypotheses explaining why a nurse would or would not be aroused during a simulation. T4 summarised this as follows:

> I would expect some spike in student's arousal when the patient falls into cardiac arrest. If nurses don't show any spike I guess it may mean there is some sort of detachment or that they don't know what to do.

This kind of hypotheses was later useful for teachers to reflect on the proxies of arousal. See for example in Figure 4 (left) that only RN3 (the most engaged nurse in the team) had peaks in arousal before and after the patient lost consciousness (orange and grey dots in the third bar). Finally, T2 drew on their experience to predict how the timeline of actions of an appropriate performance would look like, as follows: "If you have a really good team you will see them doing a lot of things at the same time. Unfortunately, what commonly happens is that they act in turns". Figure 4 (right) shows an example of a team with multiple actions in parallel.

Step 4. Translucence

Teachers then thoroughly explored the three sets of proxies, confirming or rejecting their initial expectations, and were asked questions associated with the three constructs of social translucence. First, in terms of *visibility*, all teachers agreed that the visualisations served as summaries or proxies of activity that may not be easy to understand without having a dedicated teacher analysing the simulation (e.g. "there may be things that the teacher picked up [during the simulation] but there may be things that the teacher didn't pick up. This is the value added by these visualisations", T1) and to support reflection (e.g. "[they] would help students reflect on their practice to see how they could improve it. When you are in the scenario it is very hard to think quickly and efficiently", T3). All teachers also highlighted the need to go beyond these representations, for example, by "combining the physical and the social proxies" to "to detect anomalies, such as assessing whether the nurse speaking more with the patient is the one that is further away" (T2), which is not ideal. In terms of *awareness* of the group dynamics, all teachers expressed that the timeline of actions (epistemic proxy) would assist them most in provoking reflection. T4 described her reasoning as follows: "the timeline is the best visualisation to use because it would give people an indication of what they were doing at what time in the scenario, and time is critical, at least for this particular scenario".

In terms of *accountability*, unanimously, all teachers expressed certain concerns about summative assessment of students and instead offered several ideas about how they would incorporate the proxies into guided self-reflection tasks. This was clearly summarised by T3 as follows: "these data should be used for reflection. I think simulation in general should not be used for [summative] assessment. The whole point of simulation is to help people reflect and improve on their practice". Teachers T2, T3 and T4 suggested they would like to use the proxies in the classroom, with some strategies suggested to preserve privacy, such as "avoiding identifying people" (T2), "pixelating faces if video was shown" (T2) or "aggregating data from all teams" (T3). Most concerns, however, were about singling out groups (e.g. students analysing data from other groups). T3 suggested that once the proxies become mainstream, there would be less privacy concerns, as follows: "if the whole class is participating maybe we don't need written consent because it becomes part of the learning activity for everybody. Maybe we can have verbal consent before starting the reflection activity". T1 added that showing visualisations "does not go beyond what's currently done in nursing" since it is a common practice for students to be recorded during simulations and reflect on pre-recorded scenarios. Evidently, this does not necessarily apply to other educational contexts (Greener, 2019).

Step 5. Design for orchestration

Teachers suggested three strategies to orchestrate the use of the proxies in their subjects. First, T1 suggested to use the current proxies as case studies to design a reflective online task. T1 expressed this as follows:

> it would be interesting to format these for online delivery. It could be done in [the LMS] and ask questions such as: what do you see here? What would be your interpretation of this situation comparing team A versus B. [Students] could write a full response or select amongst certain fixed responses and I could have a look at them.

Similarly, T2 suggested she could visual representations for guiding reflection based on aggregated data so students would not be able to point at specific students making mistakes.

Alternatively, T3 suggested the proxies could be used during the debrief of particular groups with the teacher (e.g. "the arousal visualisations would be very interesting to use. For example, I would like to know what was going on with the nurse without arousal markers: so, were you guys nervous? were you worried? I think it would be really interesting to explore this with them", T3); and for students' self-reflection. T1 added that some "curation of the data would be needed to aid interpretation for online delivery".

Interestingly, teachers pointed at other potential uses besides supporting student activities directly. This included revising the learning design. For example, Teacher 1 stated that "there is some useful information [in the proxies] in terms of how we should setup [the simulation] for this particular scenario or other scenarios". Additionally, Teachers T1 and T2 suggested potential use in their nursing education research. This was explained by T1 as follows: "There is some information here that I think it would be useful to a broader audience, also for a simulation conference or to use this information in a manuscript".

Finally, Teachers T2 and T3 highlighted that certain data literacy challenges would need to be addressed in order to adopt these proxies into their regular practice. For students, T2 suggested the following:

> If we start exposing students to these in the first year, for example the first time they do CPR, they may gradually start unpacking the evidence. By the time they get to third year they would be understanding how it should be.

T3 added that the casual teaching staff would need to "be trained about how to guide the debrief", and that "you as a teacher need to use your emotional intelligence to pick up how students would react, particularly if they confront the evidence".

Concluding remarks

This paper presented LAT-EP, a five-step elicitation process to design for effective use of *translucent* MMLA systems, and how it was operationalised it to generate understanding of teachers' perceptions on the use of proxy visualisations generated from multimodal data automatically captured during team-based healthcare simulations. The visualisations sparked numerous ideas in terms of orchestration, their potential pedagogical value to support reflection (critical in nursing education) and, more broadly to make traces of nurses' activity visible to revise the learning design or support research in nursing. T1 summarised the spectrum of possible applications and uses as: "These [proxies] would be extremely useful for so many different reasons".

Although the study presented in this paper focused on visualisations of multimodal, teamwork data, the elicitation process and findings are relevant to a broader audience of educational researchers and practitioners interested in facilitating effective ways to use data for improving their teaching practice. For example, the suggested set of questions in terms of accountability allowed teachers to move beyond identification of privacy issues into the formulation of strategies to overcome these. Moreover, in nursing education it is common to review and reflect on past actions. Hence, this particular area of teaching and learning has already devised privacy policies that can potentially serve as exemplars to incorporate MMLA innovations in other learning contexts.

Methodological limitations are noted for the study presented here. First, although the LAT-EP is used in other projects to understand how teachers and students can interact with classroom data (Martinez-Maldonado, 2019), other case studies are needed to explore the different ways in which the elicitation process can be implemented into practice, including the stages in which it can be more or less useful. Second, the different steps of LAT-EP can be conducted at different times, in different sessions and with different stakeholders. In the study presented in this paper, the first two steps were partly conducted during preliminary sessions with teachers and the last three steps were conducted in the elicitation sessions. This work should therefore be seen as part of much more research that is needed for the Learning Analytics community, and the broader community interested in designing smart learning environments, to embrace human-centred approaches and identify the best design practices that may be followed by researchers and designers of data-intensive educational innovations.

Future work will investigate some requests proposed by the teachers in this study, including transposing some of the multimodal data into the video stream of the session to facilitate its revision; unpacking verbal communication by automatically identifying key phrases or questions that nurses are expected to say; and providing explanatory feedback to aid students during the debrief.

Disclosure statement

No potential conflict of interest was reported by the authors.

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