

The Multimodal Matrix as a Quantitative Ethnography Methodology

Simon Buckingham Shum¹, Vanessa Echeverria^{1,2} and Roberto Martinez-Maldonado¹

¹ Connected Intelligence Centre, University of Technology Sydney,
PO Box 123, Broadway, Sydney, NSW 2007, Australia

² Escuela Superior Politécnica del Litoral, ESPOL
Campus Gustavo Galindo Km 30.5 Vía Perimetral, Guayaquil, Ecuador
FirstName.LastName@uts.edu.au

Abstract. This paper seeks to contribute to the emerging field of Quantitative Ethnography (QE) by demonstrating its utility to solve a complex challenge in Learning Analytics: the provision of timely feedback to collocated teams and their coaches. We define two requirements that extend the QE concept in order to operationalise it such a design process, namely, the use of *co-design methodologies*, and the availability of *automated analytics workflow* to close the feedback loop. We introduce the *Multimodal Matrix* as a data modelling approach that can integrate theoretical concepts about teamwork with contextual insights about specific work practices, enabling the analyst to map between higher order codes and low-level sensor data, with the option add the results of manually performed analyses. This is implemented in software as a workflow for rapid data modelling, analysis and interactive visualisation, demonstrated in the context of nursing teamwork simulations. We propose that this exemplifies how a QE methodology can underpin collocated activity analytics, at scale, with in-principle applications to embodied, collocated activities beyond our case study.

Keywords: multimodal, learning analytics, teamwork, CSCL, sense making

1 Introduction and Background

Quantitative Ethnography (QE) is a methodological approach that respects the insights into specific cultural practices gained from the interpretive disciplines developed in ethnographic and other qualitative traditions, but seeks to apply the power of statistical and other data science techniques to qualitatively coded data, such as observational fieldnotes, interviews, or video analysis [36]. To date QE has been exemplified primarily by the development of the Epistemic Network Analysis (ENA) tool, to examine the relationships between coded data elements (e.g. [9, 16, 35]).

In this paper, we propose that a modelling methodology and analytics workflow, developed to process and visualise multimodal data from nursing team simulations, also exemplifies QE principles. The intended contribution is thus twofold: (i) an articulation of two key requirements in order to operationalise QE for a learning analytics

application, and (ii) a demonstration of QE's value in implementing a multimodal learning analytics pipeline and end-user tool, which has been piloted with nursing academics and students. While Herder et al. [19] have described the full automation of ENA from *online* student teams' interaction data, generating a real-time dashboard for teachers, to our knowledge, this is the first time that QE has been applied to the analysis of multimodal sensor data, combined with human observational data, to generate a feedback visualisation about *collocated* teamwork.

In the next section we introduce the challenge of ascribing meaning to multimodal traces of learning activity. Section 3 introduces the specific educational challenge driving this work, namely, how to better inform the debriefings for collocated nursing teams on a simulated hospital ward. Section 4 provides a definition of our requirements in order to operationalise QE for such a learning analytics application. Section 5 introduces the *Multimodal Matrix*, inspired by QE principles in combination with a teamwork activity theory, illustrating its application to the nursing context, and briefly describes the visualisations it enables, informed by co-design. Section 6 summarises progress to date, and outlines some future work trajectories.

2 From Clicks and Data Streams, to Constructs

An important challenge in the fields of learning analytics (LA) and educational data mining (EDM) is to provide more timely, useful evidence to aid teachers in pedagogical decision-making, and students in understanding what actions they can take to maximise their opportunities of learning, e.g. [2, 15]. While there has been substantial interest in creating visualisations and dashboards to communicate data to different stakeholders, recent reviews question the impact of these learning analytics interfaces [4, 20, 25]. Clearly, at the user interface level, the representations need to be intelligible to users [1] but the problems in fact go deeper into the infrastructure [17]. On what basis can low-level system logs serve as proxies for higher order constructs? Once that relationship has been established, data can then be rendered in ways that are intelligible to people without a strong analytical background. Imbuing data with contextual meaning brings key stakeholders (such as teachers and students) into the sensemaking loop, whereas until quite recently, analytics for human activity remained the preserve of researchers.

This is fundamentally a modelling problem, long recognised in assessment science, and now manifesting in LA and EDM in various forms. In assessment science for technology-enabled learning such as educational gaming, we find techniques such as Stealth Assessment [37] and Evidence-Centred Design [3, 26]. In an LA context, this challenge has been dubbed as mapping “from clicks to constructs” [6, 39].

One particular strand of research within EDM focuses on adding meaning to student data *before* doing any data processing, through the use of *alphabets* to encode sequences of logged interactions. One example of this was presented by Perera et al. [30], who use alphabets as rules to encode low-level events from an online system into items representing a higher level of abstraction. This is performed as a pre-processing step before conducting sequence pattern mining to facilitate the interpretability of the

results. A similar methodological approach was suggested by Martinez-Maldonado et al. [22] who used different alphabets to interrogate a multimodal educational dataset (speech acts and actions on a shared device by groups of students) to find sequential patterns that differentiated cohorts of students. The limitation reported by authors in these studies is that an item can only contain a certain amount of contextual information. The more that information is associated with a particular logged action, the more complex the task to mine useful partners becomes.

The challenge of developing multimodal learning analytics can be seen as an extreme case in which the aim is to capture rich contextual information in a learning situation [28]. These innovations offer exciting opportunities for educational research and practice through the analysis of multiple, intertwined streams of learner data (e.g. related to gestures, physical positioning, gaze, speech and physical manipulation of objects). Consequently, the user interfaces resulting from these multimodal innovations can be even more complex than regular LA systems [33] as they may pose serious challenges for teachers and students in terms of sense making of multiple sources of evidence. In fact, a recent review [10] identified that most current multimodal learning analytics tools are aimed at helping *researchers* to annotate multiple data streams to identify patterns of meaningful learning constructs. The current multimodal analytics prototypes, presented by Echeverria et al. [12, 13] and Ochoa et al. [29], are initial attempts to map low-level data with higher order constructs in the user interface. Worsley [40] proposed the use of the concept of epistemological framing [34] as a potential way for understanding human cognition through multimodal data. In this case, the epistemic frames can serve to typify of certain high-level activity (e.g. a person is discussing) based on a combination of low level behaviours that can potentially be detected via sensors (e.g. prolific gestures, an up straight posture, gaze at peers and animated talk and facial expressions).

In sum, there is a growing interest in mapping from low-level data to meaningful constructs, and related attempts have been made in the areas of EDM, data-driven assessment and multimodal LA. In the next section we introduce the applied challenge that has motivated the need to integrate theoretical concepts about teamwork with contextual insights about specific work practices, to enable the mapping of low-level sensor data with codes that could be used to operationalise meaningful constructs.

3 Timely Feedback on Nursing Teamwork Simulations

Nursing simulations play an important role in the development of teamwork, critical thinking and clinical skills and prepare nurses for real-world scenarios. Students from the UTS Bachelor of Nursing experience many hypothetical scenarios across different stages of their professional development. In these scenarios students, acting as Registered Nurses (RNs), provide care to a patient, who has been diagnosed with a specific condition. Manikins, ranging from newborn to adult, give students the opportunity to practise skills before implementing them in real life. Simulations are sometimes recorded and played back to students so that strengths and areas for improvement can be observed in facilitated debriefing sessions [18].

The manikin (“Mr. Lars”) was programmed by the teacher to deteriorate over time, dividing the task into two phases. In phase one a group of four students assess and treat Mr Lars for chest pain. These RNs in different roles communicate with Mr. Lars, apply oxygen, assess his pain, perform vital sign observations, administer Anginine according to the six rights, connect him to an ECG, identify his cardiac rhythm, document appropriately and call for a clinical review. In phase two, the same group of students takes over Mr. Lars’s care at which point he loses consciousness due to a fatal cardiac rhythm, and the team must perform basic life support. Each simulation lasted an average of 9.5 minutes. Fuller procedural details are provided in [12, 14].

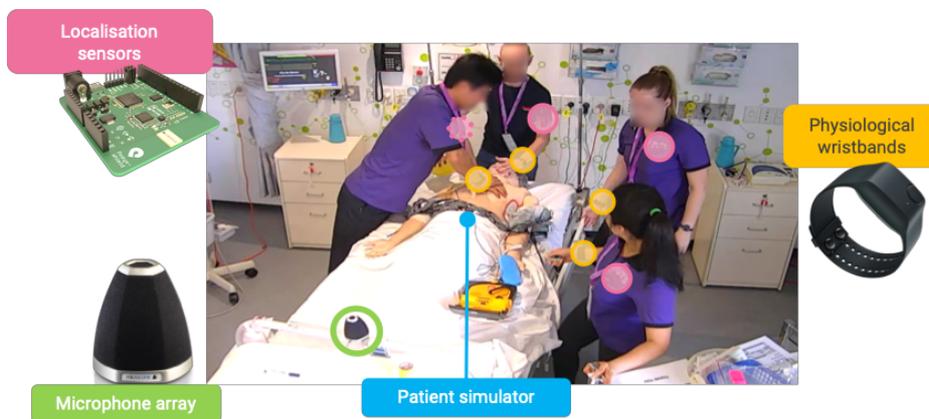


Fig. 1. Data collection from a nursing simulation in a lab scenario, using a range of sensors.

3.1 Instrumenting Simulations to Detect Teamwork

Several sensors and equipment were utilised to track interactions, summarised below:

Indoor localisation: Students’ movement around the manikin was captured automatically through ultra-wideband (UWB) wearable badges (Pozyx.io¹). This system is composed of a set of anchors to sense the physical space, which are mounted on the walls, and several wearable tags or badges attached to people or objects (such as the resus trolley). Figure 1 illustrates the distribution of the anchors across the simulation room (blue squares).

Patient Simulator: Some student and patient actions were automatically logged by the high-fidelity Laerdal SimMan 3G² manikin including placing the oxygen mask, setting oxygen level, attaching blood pressure monitor, reading blood pressure, administering medicine, attaching the ECG device, starting CPR, and stopping CPR. Proprietary Laerdal Software exported the actions and their timestamp in a .txt file.

Microphone array: A six-channel high-quality USB microphone array (Microcone) was located at the base of the patient’s bed to detect nurses’ conversations. Microcone

¹ Pozyx developer kit and a multitag-positioning system: <https://www.pozyx.io>

² Laerdal simulation manikins: <https://www.laerdal.com/nz/products/simulation-training/emergency-care-trauma/simman-3g>

Recorder application for MacOS was used to automatically track multiple people speech. Six .wav files were saved at the end of each session, one per channel. In addition, the application generated a .csv file including the total duration of the session, start and end timestamps where speech was detected and the person who was speaking (previously configured in the application).

Physiological wristbands: Empatica E4³ wristbands included a photo plethysmography (PPG) sensor to measure Heart Rate continuously, an electrodermal activity (EDA) sensor to measure skin conductance, a 3-axis accelerometer to detect movement and activity, and an optical thermometer to sense physical activity. Each wristband exported an EDA.csv file containing the timestamp when the Empatica started to capture data and EDA values; and an ACC.csv file with x , y and z accelerometer values.

In addition to these sensors and equipment, all the sessions were recorded by the video camera system installed in the lab room, comprising three fixed cameras and several microphones in the ceiling.

Two researchers and a teacher were present in each session. Besides the data outlined above, other data gathering included observation notes and recordings of the group debriefing. These were transcribed for analysis. Data analysis involved two researchers independently screening the video recordings of the sessions looking for moments of interest that could serve to derive multimodal observations for further analysis. More details on the context and instrumentation are provided elsewhere [12].

4 Defining Requirements for QE Enabled Feedback

In his presentation of the QE concept, Shaffer [36] set the goal of designing ways to model and analyse data that harmonise qualitative and quantitative methodologies. Clearly there are many facets to the QE concept, but in our reading, of particular importance is the requirement that *all analysis techniques can read from, and write to, a common data representation*. This emphasis seems to us to be distinctive, clearly moving beyond mixed methods, and pivotal to enabling ethnography, and the social sciences more broadly, to move into data science and real time analytics. Building on this, we introduce two additional requirements (points 1 and 4 below) to specify the design process and enabling infrastructure required to deliver timely, analytics-driven feedback:

Using QE to inform the design of timely, analytics requires:

1. *Co-design with stakeholders in order to gain insights into current and envisioned work practices.*
2. *These insights inform the modelling and analysis of qualitative and quantitative data.*
3. *Analysis techniques can read from, and write to, a common data representation.*
4. *This is executed by an automated analytics workflow.*

³ Empatica wristbands: <https://www.empatica.com/en-int/research/e4>

We emphasise *co-design* because we are developing feedback tools for use by real users (educators and students), so simply from sound user-centred design principles, this is good practice: we need to understand what feedback will be of most value. Moreover, human-centred design goes deeper than good user interfaces: it shapes the data we gather, and how we model it. The analytics challenge requires us to devise a way to model the sensor data in ways that respect, and will enable, culturally meaningful interpretations of work practices when visualized. Co-design provides us with a way to understand work practices in great specificity.

Secondly, we emphasise *automated analytics workflow* because this is the only way to make sense of large data sets sufficiently quickly to serve our purposes, namely, to close the feedback loop to educators and students in a timely manner for post-simulation debriefings. We turn now to the question of how we bring the insights from co-design to the modelling of multimodal data, and automate visualisation generation to inform the team debriefing.

5 The Multimodal Matrix as a QE Modelling Methodology

In order to address the above requirements, we have developed a modelling approach and data representation named the *Multimodal Matrix* (Figure 2), comprising the following conceptual elements: *dimensions of collaboration*, *multimodal observations*, *segments*, and *stanzas*, which are elaborated in subsequent sections.

		Dimensions of collaboration											
		Physical				Epistemic			Social		Affective		
Stanzas	Time	RN1_next	RN1_patient	RN1_intensity	Check_pulse	CPR	RN1_talking	Patient_talking	EDA peak
	Phase 1	00:01	1	0	low		0	0		0	1		0
00:02		1	0	low		1	0		0	1		0	
00:03		1	0	low		1	0		1	0		0	Segment
00:04		1	0	low		1	0		1	0		0	
Phase 2	12:23	0	1	high		0	1		1	0		0	
	12:24	0	1	high		0	1		0	0		1	
	12:25	0	1	high		0	1		1	0		1	
	12:26	0	1	moderate		0	0		0	0		0	
....													

Fig. 2. Schematic design of the Multimodal Matrix, from [12]

This matrix provides the common, integrating representation to hold data and analysis results from qualitative and quantitative methods: it can be populated with categorical data *automatically* from a full sensor/analytics pipeline, *semi-automatically* in which human input augments the analysis and/or workflow, or manually from conventional qualitative or quantitative data analysis. Qualitative codes are modelled by combining events from multiple sources (columns) into *segments*, and by combining multiple segments. Temporally dependent codes can be modelled into meaningful *stanzas* by combining *segments* (rows of events).

The matrix thus seeks to provide a representation to help make sense of low-level sensor data through the introduction of qualitative coding derived from top-down (theory) and bottom-up (context-specific phenomena) sources:

Theory: a framework for collaborative activity (ACAD) was used to define key constructs for combining lower level events into higher order codes (see below). Obviously, this could be replaced by any other theory/framework that served the analyst's interests and stakeholders' needs. The Multimodal Matrix enables us to introduce theoretical perspectives. We draw on the Activity-Centred Analysis & Design (ACAD) framework [24], which defines *physical*, *epistemic* and *social* dimensions as critical, as follows (p.2065):

- “*the set (physical) component* – which includes the place in which participants' activity unfolds, the physical and digital space and objects; the input devices, screens, software, material tools, awareness tools, artefacts, and other resources that need to be available
- *the social component* – which includes the variety of ways in which people might be grouped together (e.g. dyads, trios, groups); scripted roles, divisions of labour, etc.
- *the epistemic component* – which includes both implicit and explicit knowledge-oriented elements that shape the participants' tasks and working methods.”

To these three dimensions we add *affective* states of engagement, worry or anticipation, this being particularly important in the healthcare professions. It will be seen below how these broad categories help to make sense of the data.

Insights into work practices: multiple sources: (i) insights from nursing professionals about what makes a nurse's position meaningful when performing different tasks; (ii) information from staff and students regarding they would like to see captured to inform post-simulation debriefing (informing which sensors are deployed); and (iii) information that staff and students said would assist post-simulation debriefing (from co-designing visualization prototypes). Co-design sessions provided insights into the experiences of UTS students and academics in the specific simulations run in the Health faculty's facilities. We detail elsewhere how we have adopted, and in some cases adapted, well known co-design techniques to gain these insights [11, 31, 32].

5.1 Application of the Multimodal Matrix to Nursing Team Simulations

Each data stream captured by the sensors and devices listed above was encoded into columns in the multimodal matrix based on meaning elicited from subject matter experts, the learning design, or literature. The data streams were manually synchronised at 1 Hz, down-sampling data streams from sensors that had a higher frequency. The multimodal observations used in our studies, and their relationship with the dimensions of collaboration, are depicted in the edited excerpt from a nursing teamwork simulation in Table 1.

Table 1. Edited excerpt from a nursing teamwork simulation encoded in the Multimodal Matrix

	Physical						Epistemic			Social					Affective		
time	RN1.patient_bed	RN1.next_to_patient	RN1.around_patient	RN1.bed_head	RN1.trolley_area	RN1.physical_intensity	RN1.check_pulse	RN2.check_pulse	RN1.compressions	RN1.speaking	RN2.speaking	patient.speaking	RN1.listening	RN2.listening	patient.listening	RN1.EDA_peak	RN2.EDA_peak
3:22.0	0	1	0	0	0	L	0	0	0	0	0	1	1	1	0	0	0
3:22.1	0	1	0	0	0	L	0	0	0	0	0	1	1	1	0	1	0
3:22.2	0	1	0	0	0	L	0	0	0	0	0	1	1	1	0	0	0
3:22.3	0	1	0	0	0	L	0	0	0	0	0	1	1	1	0	0	0
3:22.4	0	1	0	0	0	L	0	0	0	0	0	1	1	1	0	0	0
3:22.5	0	1	0	0	0	L	0	1	0	0	0	0	0	0	0	0	0

5.2 Multimodal Observations

From the data collected, we were now in a position to associate multimodal observations, optionally in combination, with one or more dimensions of collaboration. Space precludes a very detailed description, but our goal in this paper is to convey the way in which the coding of data works.

Segments: Segments are considered the smallest unit of meaning. Thus, for this particular example in teamwork nursing simulations, we took a segment of one second. This small value was selected because we needed to analyse moment-to-moment critical reactions from nurses during the performance of the activity, this being a high-stakes activity.

Stanzas: Segments can be grouped according to criteria to show meaningful relationships. In the nursing simulations, stanzas were defined to capture key phases in the collaborative task (e.g. see rows grouped by phase in Figure 2). For this particular example, two stanzas were defined, based on two critical actions in the learning design: i) when the patient asks for help and ii) when the patient loses consciousness.

The major column headings in Table 1, drawn from the ACAD framework, are described next.

ACAD Physical dimension. Embodied strategies during high-stakes teamwork scenarios are critical in healthcare education [23]. This provides an example of how qualitative insights into the work practice shape the quantitative modelling: *what makes position meaningful, for these stakeholders, in this simulation?* In other simulations, position might take on other significances, or with more advanced students (for instance) there might be other learning outcomes, which will focus on other key behaviours. Based on interviews with four nursing teachers [14], we identified five meaningful zones which are associated with a range of actions nurses must perform: i) *the*

patient's bed, for cases in which nurses were located on top of or very close to the patient; ii) *next to patient*, for cases in which nurses were at either side of the bed; iii) *around the patient*, for cases in which nurses were further away from the bed, from 1.5 to 3 metres away of the bed); iv) *bed head*; which is an area where a nurse commonly stands to clear the airway during CPR; and v) *trolley area*, for cases in which nurses were getting medication or equipment (a localisation badge was attached to the trolley). Indoor localisation data was automatically encoded into these meaningful zones (Fig. 3).

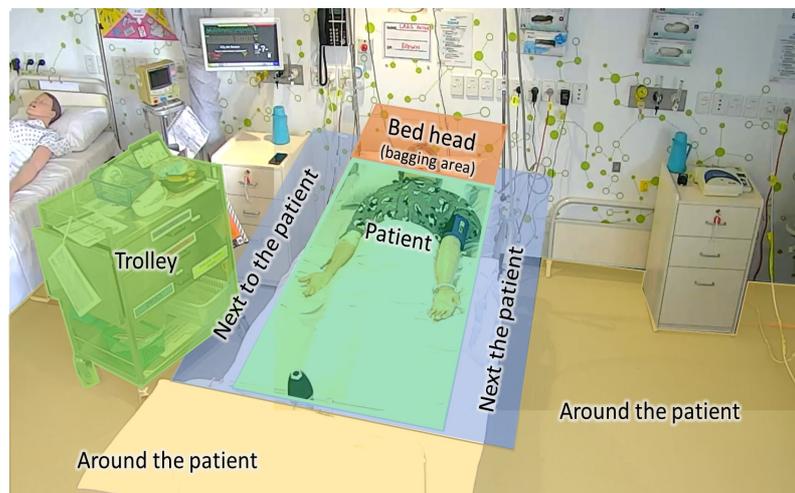


Fig. 3. Nurses' positions were classified into zones, reflecting insights from subject matter experts regarding what makes position significant in teamwork [12]

A Kalman filter was applied to remove noisy data points, and a cluster analysis was performed ($k=16$) to assign one meaningful zone to each point. The first five columns in the Physical dimension group from Table 1 illustrate the meaningful zones for RN1 (e.g. RN1.patient_bed). Each cell has a value of "1" if that zone is occupied, or "0" otherwise. For instance, the row in the first second [0,1,0,0,0] means that RN1 was next to the patient. In addition to movement, nurses' *physical intensity* is studied in the literature [8], ranging from low (e.g. walking, talking, manipulating medical tools) to high (e.g. performing a CPR). We defined *low (L)*, *medium (M)* and *high (H)* levels, where high = performing CPR. The last *Physical* column shows that RN1's physical intensity at 03:22.0 was low (L).

ACAD Epistemic dimension. In the matrix, each column represents who performed an action (e.g. RN1.check_pulse). For example, the first column in the Epistemic dimension group is RN1.check_pulse = 0, meaning that RN1 did not check the pulse at time 03:22.0, while RN2.check_pulse = 1 at 03:22.5.

ACAD Social dimension. Verbal communication plays an important role in the management and coordination of patient care and teamwork strategies [41]. From the video recordings, we manually transcribed and synchronised the speech for each nurse and

the patient using NVivo software. Start and ending points were annotated, along with the speaker and listener identification to further model the interactions. With this information, we created a sparse matrix, with 1's when a nurse was speaking/listening at a specific time, or 0 otherwise. The first column in the Social dimension group shows RN1.speaking, RN2.speaking and patient.speaking, and the following three columns are listening interactions. We can observe how the patient-nurse speaking-listening interaction is represented for the first four seconds: row [0,0,1]; [1,1,0] means that the patient is speaking while RN1 and RN2 are listening.

Affective dimension. Physiological data can be effectively used to aid nurses in recalling confronting experiences in order to develop coping strategies [27]. An increase in EDA, specifically, is typically associated with changes in arousal states, commonly influenced by changes in emotions, stress, cognitive load or environmental stimuli. We automatically identified peaks in EDA data as a minimum increase of $0.03 \mu\text{s}$ [5], using EDA Explorer [38]. Each cell contains a value of “1” when a peak in that timeframe was detected. For example, the RN1.EDA_peak column shows that RN1 had an EDA peak at 03:22.0.

We should emphasise that the primary classification of an atomic event under one of the four column headings should not be read as a rigid constraint. For instance, common sense tells us that “social” actions may also have physical attributes. An arbitrary number of codes can be defined as combinations of any events, constrained only by the analyst's interests.

Judgements about whether an attribute is, for instance, “High / Medium / Low” are again, modelling decisions, which may be based on theory, evidence or intuition (see the above example rationale for setting activity peak thresholds for EDA data). Binary 0 / 1 variables are required, but apply only for the specified duration (row labels). For instance, if higher definition tracking of certain columns is required than in the above example, one could sample every 0.1 seconds to detect changes.

To summarise, the Multimodal Matrix provides a ‘container’ to make modelling decisions explicit. The merits of those decisions derive from the integrity of the underlying assumptions about the structure of the phenomena, and how they can be modelled. In the concluding section, we reflect on the commitments that this approach is itself requiring on behalf of the analyst.

5.3 Generation of Visual Feedback

We are now ready to return to the applied outcome, namely, to improve learning by providing better feedback to the nursing teams and teachers. Thus, the final step is to generate representations that offer insights. Figure 4 shows examples of the visualisations that are now being evaluated with the academics and students, informed by the initial co-design sessions. See [12] for a fuller design rationale behind these, and the results of user trials.

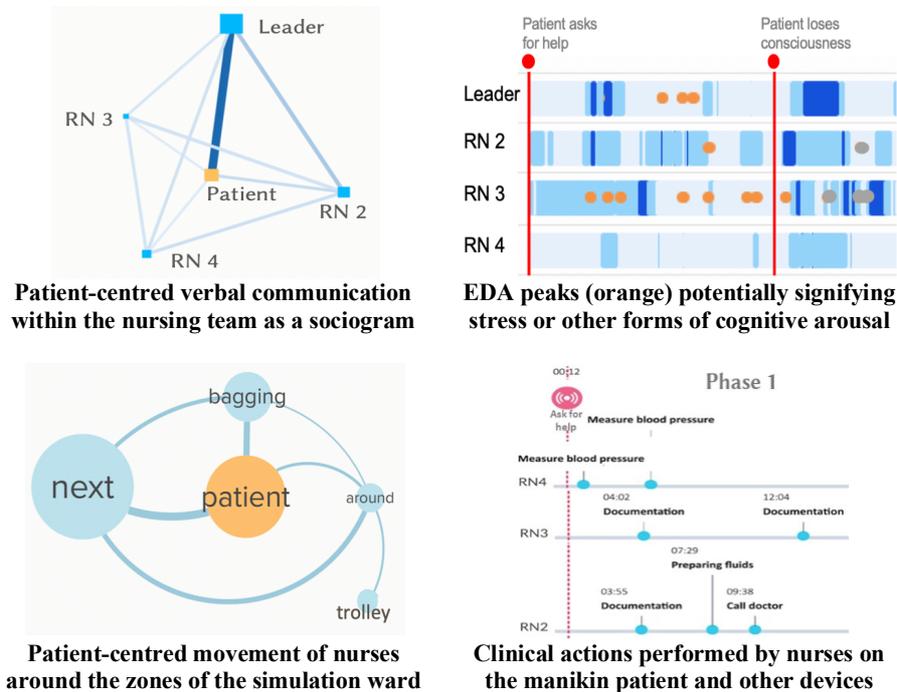


Fig. 4. Example visualisations generated from the multimodal teamwork activity data

6 Summary and Future Work

In this paper, we have proposed a Quantitative Ethnographic methodology and analytics platform, to tackle the problem of making multimodal data streams meaningful for interpreting collocated teamwork. We accomplish this using a data representation called the Multimodal Matrix, which organises quantitative data in relation to codes derived from two sources: qualitative insights from stakeholders into their work practices (i.e. undertaking and coaching nursing simulations), plus theoretical insights into how collaborative teamwork can be analysed (ACAD framework). Rows in the matrix may be populated automatically or semi-automatically, and additionally with results from manual data analyses. This modelling approach thus enables us to build a principled bridge between multimodal logs generated from sensors, and higher order constructs such as a curriculum outcome (e.g. *'competence in patient-centred teamwork'*), and its constituent skills (e.g. *'patient-centred talk'*; *'correct positioning during CPR'*). When those signals are combined meaningfully, they may serve as proxies for these competencies, and once visualized, may provoke deeper reflection and discussion in debriefing sessions.

To deliver real-time, scalable feedback to nursing teams, we have highlighted the need not only for an integrative representation, but also *co-design processes* that provide stakeholders with voices to shape the design, and an *automated workflow* capable

of generating feedback representations sufficiently quickly. The analytics workflow is now sufficiently automated (there remain a few manual elements) to generate visualizations for student debriefs within a few minutes of completing a simulation, and the Multimodal Matrix has provided the database to generate visualizations to meet stakeholders' requests for debriefing support, which are now being evaluated with staff and students, with promising results [12].

Fuller workflow automation must overcome challenges such as identifying who is performing an action and connecting siloed data sources from different products (e.g. manikin and wristband data) before the scripts can integrate and visualize them. Although not the focus of our work to date, attempts to automate other forms of qualitative analysis — e.g. attending to what, how or when utterances are made — does of course present complex challenges, requiring different kinds of textual content analysis, sequence analysis [22], location analysis [21], speech content analysis [7], and so forth, which are the focus of multimodal learning analytics research. Analyses of how space is used can draw additionally on knowledge of team roles, and hence power. For instance, knowing that a nurse is the team leader leads one to expect different activity from that role at a critical moment. We are interested to learn of other examples in which positional data might be combined with other data classes in order to quantify phenomena that qualitative analyses have concluded are significant.

We believe that this is the first application of a QE approach for *collocated teamwork*, working from multimodal data streams rather than clickstreams. The principles underpinning Quantitative Ethnography, codified in the Multimodal Matrix, have assisted us in making significant advances in tackling an extremely complex challenge: delivering timely analyses and feedback on embodied groupwork.

To conclude, we would want to reflect critically on the Multimodal Matrix as a lens. It is agnostic both theoretically and empirically, in the sense that it can be used to structure data about any form of temporal activity, with columns labelled according to any constructs of interest, and myriad visualisations can be generated from this. On that basis, we envisage that it should be of service for analysing diverse forms of human activity. That being said, no symbol system is completely neutral, but always privileges certain information, and ignores others. All symbol systems require the structuring of thought and data in particular ways: writing has different affordances to oral communication, visual representations vary in their perceptual affordances from each other, multimedia adds new dimensions, and so forth. It is possible that the tabular representation used in the Multimodal Matrix, in which rows represent time windows, and columns discrete streams of data, may prove problematic for certain forms of ethnographic or other qualitative analysis. Since we have highlighted that a hallmark of QE is the ability for quantitative and qualitative methods to read and write a common representation, we welcome commentary on whether this representation is indeed sufficiently expressive to meet the needs of other QE approaches.

References

1. Alhadad, S. S. J. Visualizing Data to Support Judgement, Inference, and Decision Making in Learning Analytics: Insights from Cognitive Psychology and Visualization Science. *Journal of Learning Analytics* 5(2): pp. 60-85 (2018).
2. Bakhshinategh, B., Zaiane, O. R., Elatia, S., Ipperciel, D. Educational data mining applications and tasks: A survey of the last 10 years. *Education and Information Technologies* 23(1): pp. 537-553 (2018).
3. Behrens, J. T., Dicerbo, K. E., Foltz, P. W. Assessment of Complex Performances in Digital Environments. *The Annals of the American Academy of Political and Social Science* 683(1): pp. 217-232 (2019).
4. Bodily, R., Verbert, K. Trends and issues in student-facing learning analytics reporting systems research, in *Proc. International Learning Analytics and Knowledge Conference, LAK'17* pp. 309-318 (2017).
5. Braithwaite, J. J., Watson, D. G., Jones, R., Rowe, M. A guide for analysing electrodermal activity (EDA) & skin conductance responses (SCRs) for psychological experiments. *Psychophysiology* 49(1): pp. 1017-1034 (2013).
6. Buckingham Shum, S., Crick, R. D. Learning Analytics for 21st Century Competencies. *Journal of Learning Analytics* 3(2): pp. 6-21 (2016).
7. Chandrasegaran, S., Bryan, C., Shidara, H., Chuang, T.-Y., Ma, K.-L. TalkTraces: Real-Time Capture and Visualization of Verbal Content in Meetings, in *Proc. SIGCHI Conference on Human Factors in Computing Systems, CHI'19* pp. 577:571--577:514 (2019).
8. Chappel, S. E., Verswijveren, S. J. J. M., Aisbett, B., Considine, J., Ridgers, N. D. Nurses' occupational physical activity levels: A systematic review. *International Journal of Nursing Studies* 73(August): pp. 52-62 (2017).
9. Csanadi, A., Eagan, B., Kollar, I., Shaffer, D. W., Fischer, F. When coding-and-counting is not enough: using epistemic network analysis (ENA) to analyze verbal data in CSCL research. *International Journal of Computer-Supported Collaborative Learning* 13(4): pp. 419-438 (2018).
10. Di Mitri, D., Schneider, J., Klemke, R., Specht, M., Drachsler, H. Read Between the Lines: An Annotation Tool for Multimodal Data for Learning, in *Proc. International Conference on Learning Analytics and Knowledge, LAK'19* pp. 51-60 (2019).
11. Echeverria, V. Designing and Validating Automated Feed-back for Collocated Teams Using Multimodal Learning Analytics. PhD in Learning Analytics. University of Technology Sydney (UTS), Sydney, Australia (In prep.).
12. Echeverria, V., Martinez-Maldonado, R., Buckingham Shum, S. Towards Collaboration Translucence: Giving Meaning to Multimodal Group Data, in *Proc. SIGCHI Conference on Human Factors in Computing Systems, CHI'19* pp. 39, 31-16 (2019).
13. Echeverria, V., Martinez-Maldonado, R., Chiluiza, K., Shum, S. B. Dbcollab: Automated Feedback for Face-to-Face Group Database Design, in *Proc. International Conference on Computers in Education, ICCE'17* pp. 156 - 165 (2017).
14. Echeverria, V., Martinez-Maldonado, R., Power, T., Hayes, C., Shum, S. B. Where Is the Nurse? Towards Automatically Visualising Meaningful Team Movement in Healthcare Education, in *Proc. International Conference on Artificial Intelligence in Education, AIED'18* pp. 74-78 (2018).
15. Gašević, D., Dawson, S., Siemens, G. Let's not forget: Learning analytics are about learning. *TechTrends* 59(1): pp. 64-71 (2015).
16. Gašević, D., Joksimović, S., Eagan, B. R., Shaffer, D. W. SENS: Network analytics to combine social and cognitive perspectives of collaborative learning. *Computers in Human Behavior* July(2018): pp. (2018).

17. Gibson, A., Martinez-Maldonado, R. That dashboard looks nice, but what does it mean?: towards making meaning explicit in learning analytics design, in Proc. Australian Conference on Computer-Human Interaction, OzCHI'17 pp. 528-532 (2017).
18. Green, A., Stawicki, S. P., Firstenberg, M. S. Medical Error and Associated Harm-The Critical Role of Team Communication and Coordination. In: Vignettes in Patient Safety. IntechOpen, London, UK, pp. 1-13 (2018).
19. Herder, T., Swiecki, Z., Fougat, S. S., Tamborg, A. L., Allsopp, B. B., Shaffer, D. W., Misfeldt, M. Supporting teachers' intervention in students' virtual collaboration using a network based model, in Proc. International Conference on Learning Analytics and Knowledge, LAK'18 pp. 21-25
20. Jivet, I., Scheffel, M., Specht, M., Drachsler, H. License to evaluate: Preparing learning analytics dashboards for educational practice, in Proc. International Learning Analytics and Knowledge Conference, LAK'18 pp. 31-40 (2018).
21. Martinez-Maldonado, R. I Spent More Time with that Team: Making Spatial Pedagogy Visible Using Positioning Sensors, in Proc. International Conference on Learning Analytics & Knowledge, LAK'19 pp. 21-25 (2019).
22. Martinez-Maldonado, R., Dimitriadis, Y., Martinez-Monés, A., Kay, J., Yacef, K. Capturing and analyzing verbal and physical collaborative learning interactions at an enriched interactive tabletop. International Journal of Computer-Supported Collaborative Learning 8(4): pp. 455-485 (2013).
23. Martinez-Maldonado, R., Echeverria, V., Santos, O. C., Dos Santos, A. D. P., Yacef, K. Physical learning analytics: A multimodal perspective, in Proc. International Conference on Learning Analytics and Knowledge, LAK'18 pp. 375-379 (2018).
24. Martinez-Maldonado, R., Goodyear, P., Kay, J., Thompson, K., Carvalho, L. An Actionable Approach to Understand Group Experience in Complex, Multi-surface Spaces, in Proc. SIGCHI Conference on Human Factors in Computing Systems, CHI'16, pp. 2062-2074 (2016).
25. Matcha, W., Gasevic, D., Pardo, A. A Systematic Review of Empirical Studies on Learning Analytics Dashboards: A Self-Regulated Learning Perspective. IEEE Transactions on Learning Technologies: pp. in press (2019).
26. Mislevy, R. J., Behrens, J. T., Dicerbo, K. E., Levy, R. Design and discovery in educational assessment: Evidence-centered design, psychometrics, and educational data mining. Journal of Educational Data Mining 4(1): pp. 11-48 (2012).
27. Müller, L., Rivera-Pelayo, V., Kunzmann, C., Schmidt, A. From Stress Awareness to Coping Strategies of Medical Staff: Supporting Reflection on Physiological Data, in Proc. International Workshop on Human Behavior Understanding pp. 93-103 (2011).
28. Ochoa, X. Multimodal Learning Analytics. In: The Handbook of Learning Analytics. SOLAR, Alberta, Canada, pp. 129-141 (2017).
29. Ochoa, X., Chiluiza, K., Granda, R., Falcones, G., Castells, J., Guamán, B. Multimodal Transcript of Face-to-Face Group-Work Activity Around Interactive Tabletops, in Proc. CROSS-MMLA workshop on Multimodal Learning Analytics across Spaces pp. 1-6 (2018).
30. Perera, D., Kay, J., Koprinska, I., Yacef, K., Zaïane, O. R. Clustering and sequential pattern mining of online collaborative learning data. IEEE Transactions on Knowledge and Data Engineering 21(6): pp. 759-772 (2008).
31. Prieto-Alvarez, C., Martinez-Maldonado, R., Shum, S. B. Mapping Learner-Data Journeys: Evolution of a Visual Co-Design Tool, in Proc. ACM Australian Computer-Human Interaction Conference, OzCHI'18 pp. 205-214 (2018).
32. Prieto-Alvarez, C. G., Martinez-Maldonado, R., Anderson, T. D. Co-designing learning analytics tools with learners. In: Learning Analytics in the Classroom: Translating Learning Analytics for Teachers. Routledge, London, UK, pp. 93-110 (2018).

33. Sarter, N. B. Multimodal information presentation: Design guidance and research challenges. *International Journal of Industrial Ergonomics* 36(5): pp. 439-445 (2006).
34. Scherr, R. E., Hammer, D. Student behavior and epistemological framing: Examples from collaborative active-learning activities in physics. *Cognition and Instruction* 27(2): pp. 147-174 (2009).
35. Shaffer, D. W. Epistemic frames for epistemic games. *Computers & Education* 46(3): pp. 223-234 (2006).
36. Shaffer, D. W. *Quantitative ethnography*. Cathcart Press (2017).
37. Shute, V. J., Ventura, M. *Stealth assessment: Measuring and supporting learning in video games*. MIT Press (2013).
38. Taylor, S., Jaques, N., Chen, W., Fedor, S., Sano, A., Picard, R. Automatic identification of artifacts in electrodermal activity data, in Proc. Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBC'15 pp. 1934-1937 (2015).
39. Wise, A., Knight, S., Buckingham Shum, S. (In Press) Collaborative Learning Analytics. In: U. Cress, Rosé C, Wise A, Oshima J (eds) *International Handbook of Computer-Supported Collaborative Learning*. Springer
40. Worsley, M., Blikstein, P. A multimodal analysis of making. *International Journal of Artificial Intelligence in Education* 28(3): pp. 385-419 (2018).
41. Zhang, Z., Sarcevic, A. Constructing Awareness Through Speech, Gesture, Gaze and Movement During a Time-Critical Medical Task, in Proc. European Conference on Computer Supported Cooperative Work, ECSCW'15 pp. 163-182 (2015).