TeamSlides: a Multimodal Teamwork Analytics Dashboard for Teacher-guided Reflection in a Physical Learning Space

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Advancements in Multimodal Learning Analytics (MMLA) have the potential to enhance the development of effective teamwork skills and foster reflection on collaboration dynamics in physical learning environments. Yet, only a few MMLA studies have closed the learning analytics loop by making MMLA solutions immediately accessible to educators to support reflective practices, especially in authentic settings. Moreover, deploying MMLA solutions in authentic settings can bring new challenges beyond logistic and privacy issues. This paper reports the design and use of *TeamSlides*, a multimodal teamwork analytics dashboard to support teacher-guided reflection. We conducted an *in-the-wild* classroom study involving 11 teachers and 138 students. Multimodal data were collected from students working in team healthcare simulations. We examined how teachers used the dashboard in 22 debrief sessions to aid their reflective practices. We also interviewed teachers to discuss their perceptions of the dashboard's value and the challenges faced during its use. Our results suggest that the dashboard effectively reinforced discussions and augmented teacher-guided reflection practices. However, teachers encountered interpretation conflicts, sometimes leading to mistrust or misrepresenting the information. We discuss the considerations needed to overcome these challenges in MMLA research.

CCS Concepts: • **Applied computing** → **Collaborative learning**; • **Human-centered computing** → *Collaborative and social computing*; *Visualization systems and tools.*

Additional Key Words and Phrases: teamwork analytics, team dynamics, visualisation, MMLA, dashboards, reflection

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1 INTRODUCTION

Working in face-to-face teams effectively is essential across various disciplines and professional sectors [41]. Effective teams should demonstrate a high level of communication, teamwork, and embodied strategies. This is particularly crucial in professions such as firefighting [14], healthcare [13], and strategic training [41], where the focus extends beyond mere communication to also encompass how team members physically coordinate to ensure safety and reduce errors [38, 41]. It is, therefore, critical for educational institutions to nurture students with the skills of highly effective teams by providing effective reflection mechanisms [41]. Yet, the effectiveness of this reflection often depends on teachers' observations. Various approaches, such as utilising video recordings combined with observations, have enabled evidence-based reflective practices, offering an accurate and actionable picture of recent events [23]. Yet, these approaches come with drawbacks: they can be time-consuming [40], may reflect only the teacher's subjective viewpoint [20], limiting the direct interaction between teachers and students [23].

Multimodal Learning Analytics (MMLA) presents a promising direction to aid effective team reflection. MMLA innovations have been used to study complex teaching and learning processes [13, 33], transcending analytics derived from clickstreams only [51], extending to analytics derived from multiple sensor streams including physiological [22], audio [36, 55], and spatial [3, 52, 55] data. The aim is to facilitate a comprehensive understanding of interactions in physical learning settings, enhancing both teachers' and students' capacities to reflect on their teaching and learning experiences [41]. Achieving this would entail creating user-friendly interfaces, such as MMLA dashboards, using multimodal data to deliver actionable insights, thus closing the learning analytics feedback loop [12, 51].

However, there are limited empirical studies investigating the use and impact of MMLA dashboards for collaborative team activities [2, 11, 54]. Some research has demonstrated their utility in enhancing individual students' physio-motor [15] and presentation skills [34]. Some MMLA dashboards have also been created to facilitate teacher reflection by offering insights into general classroom interactions [1]. Notably, although some MMLA dashboards have been prototyped to support reflection on teamwork practices, these have primarily been confined to controlled lab studies to investigate their potential and feasibility [16, 19, 29, 36]. There is a notable gap in our knowledge regarding the real-world use of MMLA dashboards. To the best of our knowledge, no study has yet reported how teachers use MMLA dashboards to support team reflection *in-the-wild* (this is, in an authentic learning setting). The limited research might stem from the challenges of implementing scalable MMLA solutions in classrooms [2, 54].

To address this gap, this paper reports on the findings of a classroom study that looked at the use of an MMLA teamwork dashboard in supporting teacher-led reflection. Specifically, we investigated the strategies teachers employed with the dashboard and analysed their actual experiences and perceptions of its benefits and challenges. Our findings contribute to the existing literature on MMLA by offering insights into its practical utility and reflecting on the challenges that can only be revealed when teachers use the dashboard live with students in an authentic educational setting.

2 BACKGROUND AND RELATED WORKS

2.1 Teamwork and Reflection Practices

Reflection is a crucial metacognitive ability, allowing individuals to critically evaluate their learning trajectory and the depth of their understanding [7]. One form of this is reflection-on-action, where students: 1) revisit a learning experience, 2) attend to feelings, and 3) critically reassess the experience. Engaging students in such reflective exercises can foster a deeper understanding of key concepts, facilitating knowledge transfer and nurturing both cognitive and applied skills [43]. To ensure the effectiveness of the reflection process, teachers play a vital role, especially in face-to-face teamwork reflection, where multiple events can unfold simultaneously, challenging students' ability to engage in accurate and reliable reflective practices [41]. Teachers often need to guide reflection, leveraging relevant materials and formulating reflective questions, ensuring students navigate the reflection journey with both direction and purpose [23].

However, guiding teamwork reflection can pose significant challenges for teachers. One challenge is balancing the evaluation of both technical skills, like specific procedures, and non-technical elements, such as teamwork and communication [41]. Moreover, ensuring reflections are valid, reliable, fair, sustainable, and developmental becomes particularly challenging in dynamic teamwork settings that closely resemble authentic contexts, as assessment can be complex due to diverse student reactions and the variety of resources required [10]. The nature of reflections largely depends on timely, quality feedback from teachers, which is commonly based on both their observations and students' self and peer assessments[23]. However, student assessments can sometimes be inaccurate, particularly for those who are low-performing [10, 23]. Sole reliance on teacher observations is not ideal, as their quality depends on the teacher's experience and understanding of learning objectives [20].

Video recordings have been a widely used technological tool to help teachers guide teamwork reflection and provide feedback in both medical training and teacher education [10, 23]. Using these recordings, teachers can showcase exemplar behaviours to students, an approach that enhances learning outcomes [40], particularly for students with limited previous knowledge [10]. Yet, these recordings are not ideal for real-time feedback immediately after learning activities. Teachers commonly face challenges in recalling and pinpointing specific student actions from the video while making systematic observations [20]. Viewing the entire recording during teamwork reflection can be time-consuming and disruptive, limiting the direct interaction between teachers and students [23]. This underscores the ongoing need for effective educational technologies that support immediate, evidence-based feedback in teamwork reflection [41].

2.2 Multimodal Learning Analytics

Advancements in MMLA may potentially support teachers in guiding teamwork reflection in practice. MMLA research harnesses intricate physical and physiological signals to gain insights into learners' metacognitive states, emotions, and learning behaviours [6, 33]. The maturity of sensing technologies, such as eye-tracking, position tracking, and physiological sensing, coupled with artificial intelligence from computer vision and natural language processing, has enriched MMLA research. For example, the growing ecological validity of MMLA was evidenced by the balancing between small-scale controlled lab studies and ecological studies that deploy sensors in real-world classrooms [11]. These studies illustrate the potential benefits of MMLA in enhancing research, refining pedagogy, and learning outcomes [46]. Among these benefits are MMLA technologies for automated evaluation and reflection in teamwork, support for teachers in classroom management, and feedback automation for oral presentations [34].

However, despite these promising research advancements, recent systematic reviews in MMLA indicated a predominant focus on creating novel methods and generating new insights for research purposes [54]. For instance, some studies aimed to comprehend cognitive load during online problem-solving [25] and to predict learning performance in game-based learning [22]. These studies generally gathered multimodal data and undertook post-hoc analyses to produce various forms of analytics. Nevertheless, many of these studies did not make MMLA immediately accessible and available to teachers during the learning process through dashboards or interfaces, limiting our understanding of their practical value [11, 35, 54].

2.3 Related Works, Research Gaps and Research Questions

2.3.1 Related Works. In Learning Analytics, dashboards are visual interfaces that aggregate and present information about learning processes or behaviours, aiming to support teaching and learning practices [49]. Dashboards facilitate reflective practices by making information accessible to students and teachers, allowing them to review insights that can inform immediate intervention [50]. In MMLA, there has been progress in deploying dashboards across various learning spaces, both online (i.e., virtual classrooms, [56]) and physical (i.e., classrooms, labs [30]).

Some studies have made MMLA dashboards available to teachers or students in physical spaces. For instance, Ochoa and Dominguez [34] used RAP, an MMLA dashboard, to give immediate feedback on students' oral presentations. This dashboard analyses video, audio, and slides using AI to assess student performance across five dimensions. A randomised evaluation showed its positive effect on enhancing students' presentation skills. Recent studies have explored the potential of MMLA dashboards for teacher reflection. For instance, An et al. [3] examined ClassBeacons in the wild, using a tangible user interface and focusing on its ability to offer insights into teachers' movements in the classroom. Their findings emphasised the potential to provide visual cues to teachers to support reflection on their practice and adjust future strategies accordingly. For a similar purpose, Ahuja et al. [1] introduced Edusense, a system to monitor classroom interactions between teachers and students and support teacher reflection practices. Yet, while authors presented promising high-fidelity data-driven prototypes, there was a noticeable absence of empirical validation with teachers. Further, Lee-Cultura et al. [27] assessed an MMLA dashboard that tracks student interactions in a physical learning setting by interviewing teachers to validate a dashboard prototype. Teachers found it useful for understanding learning dynamics to potentially provide timely feedback but raised issues about understanding the data's complexity.

Focusing on teamwork, Martinez-Maldonado et al. [29] validated a layered MMLA dashboard prototype that visualised teamwork dynamics using a retrospective reflection approach with teachers. While teachers saw its potential value in capturing evidence for provoking deeper reflections and revising instructional designs, they also expressed concerns about data misuse and privacy. In related studies, Fernandez Nieto et al. [19] [18] reported a validation study to explore the potential use of a set of different MMLA visual representations for teamwork using high-fidelity prototypes, also emphasising their role in reflection and feedback provision.

2.3.2 Research Gaps. These above studies highlight both the potential benefits and challenges of creating and deploying MMLA dashboards. However, most of these studies have primarily documented such potential based on controlled validation studies [18, 19, 27, 29]. Furthermore, there is a gap in research specifically addressing teamwork [11, 35]. Given the limited empirical research in authentic in-the-wild classroom settings, the potential benefits of dashboards for teaching and learning in such environments remain unexplored [2]. It is important to understand how teachers can interpret and use information from multimodal data through ecological studies, especially since these MMLA teamwork dashboards should be designed to present information that non-experts could easily interpret in a limited time [51]. Furthermore, deploying MMLA teamwork dashboards in real-world contexts can help identify challenges not just limited to logistics and privacy but also encompassing interpretation conflicts and mistrust [2, 54]. Gaining insights into how teachers address these challenges can offer valuable guidance to other researchers and practitioners.

2.3.3 Research Questions. We address the above gaps through the following questions in the context of a multimodal teamwork dashboard deployed *in-the-wild*: **RQ1.** How can a multimodal teamwork dashboard be utilised in an authentic learning setting to aid teacher-guided reflection? **RQ2.** What values do teachers attribute to the use of the multimodal teamwork dashboard? **RQ3.** What challenges do teachers face when using the multimodal teamwork dashboard?

3 METHODS

3.1 Learning Scenario

High-fidelity healthcare simulations provide an opportunity for students to practice ***prioritisation, teamwork*** and ***communication*** skills. These high-fidelity simulations often occur in a fully immersive, simulated environment, replicating clinical scenarios that students might face in their professional practice, using high-fidelity manikins instead of real patients [10]. In these, students commonly play a role and are presented with a clinical problem to solve as a team, followed by a reflective *debrief*. A senior teacher is usually the primary debriefer and guides students to decompress their feelings and reflect on their performance and learning opportunities [23, 43].

Our study was conducted in the context of a third-year unit of the Bachelor of Nursing Program at Monash University, in which students are required to take part in high-fidelity team simulations. These simulations run in a three-hour class session. The simulation is structured into three segments: i) an in-class pre-brief (10 minutes), ii) the clinical scenario (approx. 20-30 minutes), iii) and a post-scenario class-wide debrief led by the teacher (approx. 30 minutes). Two consecutive simulations are conducted in each class, focusing on prioritisation, teamwork and communication skills. Two rooms are used to facilitate these learning scenarios: the *simulation room*, furnished with hospital beds, high-fidelity mannequins, and medical equipment, and the *debrief room*, equipped with a projector screen and educational materials for conducting the debrief sessions.

Students are organised into teams of four to play the roles of graduate ward nurses. Those students not participating in the role-play serve as observers in the debrief room, where the ongoing clinical scenario is live-streamed. The scenario is divided into three primary phases: **Phase 1:** Two nursing students, playing primary graduate ward nurses, enter the ward and receive ***handover information*** for four patients. One of these patients begins to deteriorate, prompting the students to call for help. **Phase 2:** Additional students, also playing ***graduate ward nurses enter the scenario*** to assist in caring for the patients. **Phase 3:** Following a Medical Emergency Team (MET) call initiated by the students, a ***doctor enters*** the ward to offer additional support.

3.2 Multimodal Sensor-based Data and Apparatus

We collected spatial and audio data streams using a ***positioning indoor system***[1] and ***wireless lapel microphones***, respectively, for each team member participating in the clinical scenario. All the data is captured and synchronised with our multimodal data capture system [2]. Before the simulation begins, each student is given a belly bag containing a positioning sensor to track their *x-y coordinates* within the learning space (see Fig. 1 - top) and is asked to wear a wireless lapel microphone to capture their *audio*. Each student is also assigned a colour based on their role (i.e., blue and red for primary nurses – PN1 and PN2 –, respectively, and green and yellow for secondary nurses – SN1 and SN2 –, respectively), generating de-identifiable data streams. The simulation room comes pre-equipped with built-in video cameras, and an additional 180-degree video camera was added to the setup for enhanced coverage. During the clinical scenario, an observer —either a researcher or a teacher— logs the *main phases* of the scenario and their respective timestamps using our observation tool, aiding in the contextualisation of the multimodal data [17].

3.3 TeamSlides Design

We followed a human-centred design approach [9, 31] to design a multimodal teamwork analytics dashboard. A two-year partnership with the *senior teaching staff* (the coordinator and three main teachers) from the Bachelor of

[1]https://www.pozyx.io
[2]https://github.com/Teamwork-Analytics

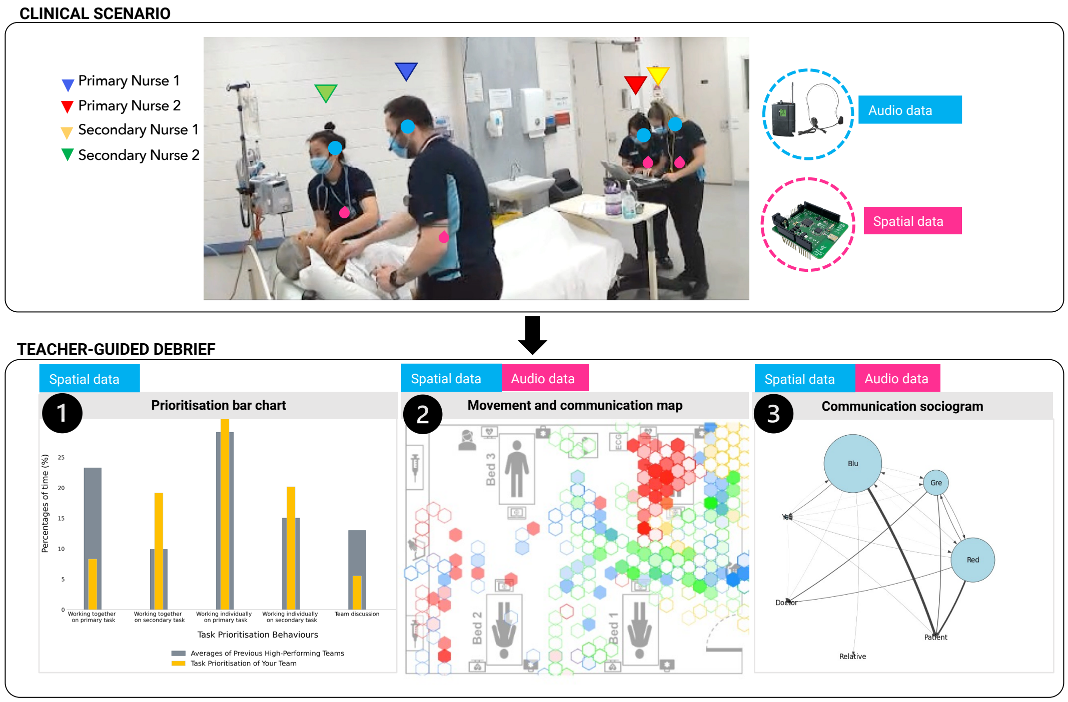

Fig. 1. Top: The clinical scenario depicts four student nurses (blue, red, green, and yellow) attending to a deteriorating patient. We collected audio and spatial data from each student nurse. Bottom: The dashboard used during the teacher-guided debrief. It contains three visualisations: 1) prioritisation bar chart, 2) movement-communication map and 3) communication sociogram.

Nursing program led to designing a multimodal sensor-based solution to support the post-scenario debrief to foster evidence-based reflection. Next, we detail our three-stage design process of TeamSlides.

Stage 1: Gathering multimodal data: In the first year (2021), we adopted a data-driven approach to gathering a multimodal dataset, identifying potential analytics and visualisations related to teamwork and evaluating the feasibility of generating visualisations and deploying an MMLA solution in-the-wild. Thus, we collected multimodal data, using the apparatus described in Section 3.2, from 208 students (196 females) distributed in 52 teams of 4 students.

Stage 2: High-fidelity prototype design: Multimodal data from Stage 1 enabled us to generate an initial set of visualisations representing the key behaviours of interest, as emphasised in the learning design of the clinical scenario (Section 3.1) while considering the feasibility of collecting data in authentic classrooms.

Stage 3: Prototype validation: In the second year (2022), two months before the study, we engaged the senior teaching staff (T1-T4) in three design workshops to validate an initial set of visualisations. In the first workshop, we showcased three initial visualisations. These were inspired by prior works (detailed below). We posed questions to validate the teachers' understanding of the underlying visualisation (i.e., *What is your understanding of this visualisation? Is the information presented clear?*). We also sought feedback on possible changes in data representation and visual elements (i.e., *Would you like to modify the current version to improve your understanding?*). In the following two workshops, we revised the improvements made to each visualisation, focusing on seeking feedback on potential changes (*i.e., Would you like to modify the current version to improve your understanding?*). All workshop sessions were video-recorded via Zoom and transcribed for analysis.

During the workshops, two researchers documented teachers' observations. Later, both researchers analysed the transcripts and complemented their observations. Based on the teachers' observations, the entire research team decided on the necessary changes. We present the final design that the teachers agreed to use during the teacher-guided debrief. We developed *TeamSlides*, a multimodal teamwork analytics dashboard consisting of 1) a team's prioritisation bar chart, 2) a teamwork movement and communication map, and 3) a team's communication interaction sociogram (See Fig. 1 - bottom). The dashboard was built as a web application showing the visualisations as a slideshow. Teachers could select the desired visualisation based on the key learning point being discussed. Next, we explain the design rationale and the analytics derived from the multimodal data for each visualisation.

3.4 Team's Prioritisation

Design Rationale – A previous study [53] used Epistemic Network Analysis (ENA) [45] to show teachers students' prioritisation behaviours. While teachers understood the ENA visuals, they found them too complex for real-time reflection. They wanted a simple representation to quickly understand team behaviour and compare it with both high- and low-performing teams. Hence, we opted for *bar charts*, a common chart in K-12 education and media [26].

Analytics and Visualisation – We used positioning data to generate analytics on team prioritisation, identifying six key behaviours based on the learning design of the simulation. First, the simulation room was divided into primary and secondary task spaces to differentiate prioritisation tasks according to clinical scenarios. The primary task centred on Bed 4, and the secondary task included Beds 1, 2, and 3. A 1.5 m radius around each bed covered essential equipment and defined these task spaces (See Fig. 1 - top). Second, we defined teamwork and individual behaviours that could serve as proxies of resource allocation in prioritisation. We calculated ***working together*** as two students within one meter for over 10 seconds to filter out unintended or casual interactions [5]. Those not meeting this criterion were classified as ***working individually***. Instances of potential ***team discussion*** were associated with prolonged student interactions, specifically when two or more students met outside designated primary and secondary task spaces for more than 10 seconds. Finally, we defined ***task transition*** as instances where a student was alone outside primary or secondary task areas, potentially indicating a lack of focus [38]. We used *x-y coordinates* to categorise each team member's behaviour (i.e., primary nurse 1 and 2; secondary nurse 1 and 2) every second into one of the six behaviours described above. We then calculated the total percentage of time the team spent on each behaviour. For comparison, we also calculated the average percentage of high-performing teams identified in the dataset collected in 2021. These percentages are shown as yellow and grey bars in Fig. 1 - bottom ❶.

3.5 Teamwork Movement and Communication

Design Rationale – To address the challenge of visually representing two modalities, movement and communication, we explored spatio-temporal designs that capture both the location and timing of events, ideal for analysing dynamic events over time [4]. Spatio-temporal visual analytics, including hexbin maps [42] and heatmaps [52], have been used to visualise teachers' classroom movements. Dandelion diagrams have also been used to depict two data modalities – body orientation and trajectory – and visualise teacher's movement strategies [18]. However, it remained challenging to integrate communication traces and their physical positions in the same visualisation. Therefore, our work aimed to leverage *hexbin maps*, which aggregate data into hexagonal bins, to visualise students' spatial and audio data.

Analytics and Visualisation – We combined *x-y* coordinates with non-verbal (presence/absence) speech data per student. We detected and labelled speech utterances using a voice activity detector (VAD) [3] from individual students'

[3]https://github.com/wiseman/py-webrtcvad

audio data. This pre-processing step yielded timestamped instances where individual students were talking or not (absence/presence). We then merged these instances with *x-y* coordinates and their respective timestamps to infer the location of each student per second. A final matrix is then calculated per student, where each row has: the timestamp (per second), presence/absence (0/1) of audio, x coordinate, and y coordinate).

We visualised spatial and audio data using a hexbin map[4], grouping data into hexagonal bins to show the spatial-audio relationship (see Fig. 1 - bottom ❷). The *x-y* coordinates were scaled and rendered according to the size of a layout image of the physical learning space. Each data point was mapped into a hexagon, representing a small area in the ward map. Each student was colour-coded (primary nurses in blue and red; secondary nurses in green and yellow), with colour intensity indicating speech activity. For example, a ***fully filled hexagon*** implied active speaking, while ***grey fill*** indicated silence. Teachers could filter the data by student colour and key phases of the learning design.

3.6 Team's Communication Interaction

Design Rationale – In previous studies, non-verbal speech metrics, such as individual and group speaking times, have offered invaluable insights into collaboration patterns [35]. Sociograms can depict speaking participation and turn-taking, revealing complex collaboration and roles [21]. These visuals have been used in both online [56] and in-person learning [16, 36]. Building on this, we used *sociograms* to visualise student speech interactions.

Analytics and Visualisation – An f-formation occurs when multiple participants maintain a spatial and orientational relationship in close proximity, such that they can enable effective communication among the individuals [24]. We identified these f-formations using students' *x-y* coordinates and body orientation, specifically seeking those in close proximity as proxies for ongoing communication interactions. After detecting the f-formations among participants, we used the VAD to extract utterances and their duration and time of occurrence. We categorised their verbal interactions as follows: 1) If an utterance occurred within an f-formation that coincided with or is closely followed by another utterance, it would be considered an instance of verbal interaction with all individuals within this f-formation. Otherwise, this utterance would be considered an instance of verbal interaction with patients if a patient is close. 2) Regarding utterances that occurred outside an f-formation, they would be considered instances of verbal interaction with patients.

We visualised verbal interactions as a directed sociogram (see Fig. 1 - bottom ❸) with seven nodes: one for each student (named by their colour) and one for the relative, doctor, and patient. Node size reflected each student's total speaking time. Weighted, directed edges represented the duration of interactions between participants. Edge width corresponds to the cumulative duration. We excluded outgoing edges from the doctor, relative, and patients, fixing their node sizes to focus on student interactions.

4 IN-THE-WILD CLASSROOM STUDY

We conducted an in-the-wild classroom study. In-the-wild studies have been adopted at a larger scale and uncover the usage and impact of new technologies in non-controlled conditions [31, 39]. Teachers used *TeamSlides* in post-scenario debriefs to discuss team performance with students. The study, approved by the Monash University Human Research Ethics Committee, took place over one month in the second semester of 2022. One week before commencing the classroom study, all teachers participated in a training session to become familiar with the dashboard.

4.1 Data Collection and Analysis

4.1.1 Multimodal Data and Visualisations. We collected spatial and audio data using our MMD system (Section 3.2). Capturing these data is considered non-intrusive and consistent with standard practices in nursing simulations [44].

[4]https://d3-graph-gallery.com/hexbinmap.html

Students could choose to consent either to multimodal data collection during the clinical scenario, and/or to the use of *TeamSlides* during post-scenario debriefs. The visualisations shown in *TeamSlides* (see Section 3.3), were automatically generated and used by teachers in the debriefs without the researchers' involvement. The study included 11 teachers and 139 students (114 females) from 54 teams. Two researchers were on-site to address technical challenges.

4.1.2 Debrief sessions. Teacher-guided debriefs while using *TeamSlides* were audio-recorded. Teachers consented to be audio-recorded and wore a lapel microphone to capture their speech. Recordings were made only for teams where all members consented to the study. Therefore, of the 54 teams, we obtained recordings from 30 sessions. Eight were invalidated due to missing audio. The remaining 22 sessions were transcribed using Whisper. We split the transcripts into 577 meaningful utterances for analysis. We performed a thematic analysis of the utterances using an inductive approach [8]. One researcher initially reviewed ten debrief sessions and annotated key ideas in each utterance. Similar ideas were then grouped to identify emerging themes, which a second researcher reviewed. Both researchers agreed on the final themes and split the analysis of the remaining sessions [32]. Additionally, we recorded the time teachers spent using each specific visualisation in each session.

4.1.3 Post-hoc teachers' interview. After the classroom study, we interviewed the four senior teaching staff (T1-T4) using a semi-structured protocol to understand their experiences and challenges with *TeamSlides*. We asked questions about the perceived value (i.e., *Did the dashboard assist you during debriefs? How?*) and challenges (i.e., *Did you face any challenges when using the dashboard?*). We organised two interview sessions, each with two teachers, lasting roughly 60 minutes. All interviews were video-recorded and transcribed for analysis. We conducted a thematic analysis [8], using a deductive approach (i.e., question-driven approach) to identify instances that shed light on teachers' perceived values and challenges. To address RQ1, we identified themes from the debrief sessions that showcased teachers' nuanced strategies in using *TeamSlides*. For RQ2 and RQ3, we identified themes that captured teachers' values and challenges in using *TeamSlides*, supplemented by insights from the interviews.

5 RESULTS

In this section, we highlight the main themes for each RQ. For clarity, we will call the prioritisation chart, movement-communication map, and communication sociogram the three "visuals" in TeamSlides. Here, N is the number of sessions that support a certain finding, and SN refers to the session number connected to a specific quote.

5.1 RQ1 – *TeamSlides* Usage in-the-wild to Support Teacher-guided Reflections

5.1.1 Usage time and order of usage: Over the four-week classroom study, teachers spent an average of 6.8 minutes (ranging from 1.9 to 12.4 minutes) during each debrief using *TeamSlides*. They spent about 3.5 minutes on the prioritisation bar chart, 1.5 minutes on the movement-communication map, and 1.7 minutes on the communication sociogram. Audio recordings revealed that teachers typically used *TeamSlides* towards the debrief's end, in their slideshow order (as presented in Figure 1 - bottom ❶ - ❷ - ❸).

5.1.2 Explaining the meaning of the data to students. In every session (N=22), teachers clearly explained the data points and the meaning of each visual element and then interpreted the data for the students. For example, in SN-5, the teacher explained that the *"data we collect is around the positioning [prioritisation chart], so this is around our task prioritisation working together on the primary task"*. This was also seen in SN-21 when the teacher explained what the data represented: *"the coloured in squares [representing communication] are when you're talking, and the grey ones are* *when you're not talking, but we can separate them according to who was who [referring to the colour]"*. The teachers generally then interpreted the data, for example: *"You can actually see your footprint of what you did in that scenario. The darker, brighter colours are where you're actually talking. You can see a lot of conversation happening around [patient]"* (movement-communication map; SN-14) and *"the bigger the dot means, the more talking you were doing. We would expect the primary nurses to be bigger"* (communication sociogram; SN-8).

5.1.3 Combining visualisation insights with prior observations. Teachers often used *TeamSlides* to point out individual or team behaviours, aligning the visuals with their prior observations to discuss students' actions more deeply. Next, we outline this approach across the three visualisations.

In nearly all sessions (N=19), teachers used the prioritisation chart to primarily focus on the team's strategies, delegation, and transitions between tasks. Teachers commonly identified insights within the bar chart and then provided explanations, drawing from their observations during the clinical scenario. For instance, a teacher discussed the team's primary task based on the dashboard before elaborating on her observations of the secondary task: *"A significant amount of time was allocated to [patient]. As we also discussed, this meant that less time was available to attend to the other patients. Despite dealing with Jessie [relative], it appears that Bailey [patient] was not adequately attended"* (SN-18).

For the movement-communication map, teachers often (N=20) started discussions by highlighting specific behaviours. They described how these related to roles, task distribution, prioritisation, and communication approaches. One teacher, for instance, commented on the time allocated to a secondary task as an area to improve: *"More time should've been with [patient], the priority. [Student] might've stayed on the secondary task. It's crucial to identify this. One might not always be aware of time allocation, but this [visualisation] offers clarity. Future actions should be around understanding priorities and being mindful of where time is spent"* (SN-9). Another teacher explained students' movements and communication centred on the primary task, noting its alignment with effective teamwork and communication strategies: *"We can observe movement at different points. The coloured dots clearly show that most communication happened around bed 4, which is precisely what we observed and expected"* (SN-2).

For the communication sociogram, teachers initiated discussions (N=16) about communication dynamics among roles and how they aligned with effective strategies. For instance, a teacher discussed the overall communication patterns and then highlighted a student's limited interaction with the doctor as a potential improvement area, as follows: *"There's lots of good communication between the whole team. But, there seems to be minimal communication with the doctor. I was looking for [Student] to hand over to the doctor, but you appear to have not communicated with the doctor. As we've observed, in terms of communication, that's an area that could have improved"* (SN-18).

5.1.4 Prompting conversations with students. Teachers engaged with students to verify if the dashboard's data reflected their behaviour (N=7). At the end of the debrief, they often sought confirmation with questions like *"Does it feel like what you experienced?"* (SN-14) and *"Was that indicative of what happened?"* (SN-11). Teachers also posed reflective questions based on key insights from the dashboard about the team's performance (N=5). These questions touched upon primary tasks (e.g., *"What could have been done in hindsight?"* – SN-6), secondary tasks (e.g., *"What was happening with the other patients then?"* – SN-4), teamwork (e.g., *"What does that tell us about teamwork?"* – SN-17), and communication (e.g., "*What do you take from that?"* – SN-19). Additionally, teachers sought student confirmation to ensure they understood the data's meaning (N=5), asking, for instance, *"Does that make sense?"* (SN-4).

5.1.5 Augmenting emotional support. Students frequently felt dismayed or frustrated after simulations. In such cases, the dashboard was used to emphasise good performance, aiming to alleviate the frustration or stress produced by the simulation (N=8). As a teacher explained: *"You've provided great examples of strong communication and really effective teamwork [...] It's often helpful to see the visuals, especially when you might feel disheartened after a scenario"* (SN-19).

5.2 RQ2 – Teachers' Values when Using *TeamSlides*

5.2.1 TeamSlides provided evidence-based insights. During the debriefs (N=8), teachers verbalised the assumed 'objectivity' and reliability of the data (e.g., *"Data is objective, you can't go wrong with data"* – SN-5). They also highlighted how the dashboard provided 'compelling' evidence of the team's behaviours, valuing the ability to *"show evidence of actions and see the footprint of what you did in the scenario"* (SN-14). Teachers used the dashboard to confirm prior observed behaviours (e.g., *"it's what you really did"* – SN-18). During the debriefs (N=14), teachers highlighted the capacity of using the dashboard for mirroring and validating the team's performance. Teachers commented: *"it's really cool to see that's what we would expect and that's what happened"* (SN-7) and *"that's precisely what we aimed to see"* (SN-1 & SN-18); *"that's a reflection of what you did"* (SN-16)

During the interviews, teachers recognised that the dashboard offered evidence-based insights and discussed the difference between subjective interpretations and 'objective' data. T4 mentioned how teachers might inadvertently focus on specific students or activities, potentially skewing their perception of the team's performance and introducing bias into the discussion. However, the data presented a more 'objective' *"black and white"* perspective, being *"less subjective"* (T4). T3 also valued the role of the dashboard as a form of *"triangulation"*, especially when verbal feedback may not be sufficient for some students. Teachers also found the dashboard useful in presenting concrete evidence and for reinforcing the discussion. T3 expressed that the dashboard provided concrete visual confirmation to students about their performance: *"The way we used it was to unpack the learning outcomes and linked them to the visualisation"*. T2 noted that the dashboard *"backed up the discussion"* and revealed clear reasons for specific outcomes, such as patient deterioration. T4 echoed this view: *"certainly reinforcing the debrief and reassuring students learning"*.

5.2.2 Positive reactions when using the movement-communication map and communication sociogram. We found the movement-communication map was more positively received than the other two visualisations. During debriefs (N=10), teachers described it as *"interesting"*, *"cool"*, and *"great"*. This visualisation was particularly valued for facilitating discussions on task prioritisation and communication (described in Section 5.1.3). One teacher verbalised this positive feeling and reflected on the team's prioritisation: *"It's a great visual, isn't it? This is actually where [student] spent time. Now [let's] reflect: was it good to spend time there could it have been spent in a different way?"* (SN-9). Teachers also appreciated the communication sociogram but to a lesser extent (N=5). During debriefs, comments included *"It's so really cool to watch how you're communicating in a different amount"* (SN-11) and *"what a fantastic example and visual display of the great communication which we've seen between the two of them in the scenario"* (SN-19).

In sum, all teachers valued the dashboard for debriefs, especially the movement-communication map, and the communication sociogram. Regarding the former, T3 noted, *"it highlighted the significance of teamwork and communication during a MET call"*, while T2 remarked regarding the latter: *"it effectively showcased the extent of communication."* Yet, there were some reservations about the prioritisation bar chart, which we will discuss next.

5.3 RQ3 – Teachers' Challenges when Using *TeamSlides*

5.3.1 Mismatch between the data and teachers' expectations. In the debrief, there were instances where data in the dashboard diverged from teachers' expectations. In such cases, teachers highlighted the data's limitations and then explained what happened in the simulation. This inconsistency was evident when teachers compared the values of the observed team (yellow bars) with high-performing teams (grey bars) (N=7). They often attributed the misalignment to the system's inability to accurately discern between individual and team behaviours as one teacher explained: *"Partly, that's a limitation of the data; it's challenging to discern what was a team and an individual activity since all of you were on the bed"* (SN-17). Inconsistencies were also linked to team strategies, such as using a 2:2 task split, which differed from the approaches of high-performing teams (N=6). This was seen as a limitation in the data representation. One teacher explained, *"I'm not quite sure why this is reading so high unless it's because of the 2:2 split"* (SN-8). In such cases, sometimes teachers acknowledged that the team performed well. Teachers also highlighted cases of data incompleteness due to sensor issues, resulting in fewer students being tracked than anticipated (N=8) (e.g., *"the data hasn't tracked very well"* – SN-2). This could lead to skewed representations, potentially affecting interpretation (*"There were only three of you, so that might be why working together on the secondary task is very low."* – SN-22)

In the interviews, teachers indicated discrepancies between the dashboard's information and their expectations influenced their trust, making them question its reliability: *"There were differences in what we're discussing. I thought, 'I wonder how reliable this is?'"* (T1). Their trust increased as they became more familiar with the dashboard, explaining inconsistencies to students using prior observations: *"As we got more familiar, we were able to explain to students why their data represented something different"* (T2). Their trust increased over time (*"I think our trust developed over time"* – T4), despite the difficulty in understanding the data during the first week: *"I did trust it in the later weeks for sure."* (T3). Teachers preferred a complete data set over incomplete data to build trust and understanding. An entire team's data (four students) gave a holistic view of performance. In contrast, incomplete data, especially from only two students, required added explanations and could be misleading. T1 mentioned, *"If you don't go through it, they don't understand what they're looking at later."* While T3 chose only to use the dashboard with complete data, other teachers found merit when the data were from three students, suggesting that it still provided valuable insights. However, additional explanation is required: *"Using it with three [students] was still relevant, because you got most of the scenario, and you could talk about how a fourth person might have changed that"* (T1).

5.3.2 The prioritisation bar chart was challenging. Teachers occasionally found the prioritisation bar chart challenging. Negative comments such as *"weird"*, *"bit confusing"*, and *"hardest thing to describe"* were expressed during debriefs (N=7). In the initial week, teachers struggled to explain certain data labels on the chart, such as 'task transition', with one teacher remarking, *"I get a bit confused about 'task transition' – is it the time taken to switch tasks?"* (SN-11). However, their understanding and confidence improved with time and familiarity, leading to clearer explanations for students.

Teachers' comments during the interviews were consistent with what we observed from the debriefs. The difficulty of understanding the data presented in the bar chart was evident. T3 and T1 highlighted confusion when explaining 'task transition', mentioning it often did not align with their observations, which impacted the depth of their discussions: *"I'm still unsure about explaining the 'task transition' as it doesn't always correlate to the scenario,"* (T3). As for the 'task discussion', the unclear data generation led to varied interpretations during debriefs, as noted by T1: *"I initially thought it was about discussions near the patient, but after consulting the research team, I learned it referred to discussions elsewhere."*

6 DISCUSSION

6.1 Research Questions

Regarding **RQ1**, teachers developed a series of strategies to appropriately use the MMLA dashboard in their teaching practice. These included using the analytics towards the end of the reflective debrief to scaffold discussions about team performance and augmented their own observations with insights from the dashboard to provoke discussions and pinpoint areas for improvement. Moreover, they actively engaged students in discussions to validate the data's understanding, promote reflection, and provide emotional support. Teachers were transparent about the meaning of data and their limitations, which is especially important given that students were not familiar with such analytics. Teachers cultivated an environment of trust with students in light of using analytics [47, 50]. These strategies not only resonate with *teaching with analytics practices* [50] but also align with best reflection practices in nursing education [23] and teamwork reflection practices [41]. This suggests the potential of using analytics to augment this kind of signature pedagogy where team sessions are followed by in-depth reflection-on-action [7].

Concerning **RQ2**, our findings highlighted that teachers valued the visualisations for providing evidence-based insights, sparking discussions, and supplementing observations with other data sources. These results corroborate earlier teachers' views on the potential uses of MMLA dashboards, as described in prior controlled studies [18, 19, 29], through real-world deployment. Yet, the use of evidence-based dashboards is not without challenges. While data can provide valuable insights, over-reliance on data might detrimentally influence learning due to misinterpretations, leading to biased decisions [48]. For example, due to imperfection in MMLA systems [33, 54], there is a risk of unfair judgements, misinforming teachers or students [22]. Teachers' strategies to overcome these biased decisions and misinterpretations due to data limitations are discussed in RQ3. Teachers also valued the dashboard for mirroring the team's behaviour and considered it a source of what they termed *'objective'* evidence. However, as Tsai et al. [48] pointed out, *"numbers are subjective"*. It is important to consider the subjectivity that can be introduced during data processing, influenced by developers' and designers' decisions. Moreover, teachers' interpretation of the data, shaped by their previous knowledge and expertise, further introduces subjectivity. This highlights the potential overconfidence teachers might place in the data and emphasises the importance of recognising their subjectivity.

Nonetheless, teachers valued the movement-communication map and the communication sociogram visualisations, receiving positive reactions during debriefs and interviews. They explained that the former, in particular, could effectively foster an understanding of teamwork and communication dynamics during discussions about the team's performance. While prior studies have considered various visual design approaches for effectively communicating multimodal data [16, 19, 29] (noting that these methods were validated in controlled studies), our findings suggest that the movement-communication map offers a promising avenue for visualisation research that integrates positioning and voice data.

Regarding **RQ3**, our study identified two main factors affecting teachers' trust in using the dashboard. First, discrepancies arose between the displayed data and teachers' expectations, stemming from incomplete data or unaccounted strategies that deviated from typical high-performing team behaviours. MMLA systems, being imperfect [33, 54], can sometimes provide unreliable data. This unreliability can cause discomfort among teachers, potentially disrupting their teaching flow. To counteract these issues and build trust, teachers adopted a transparency strategy. They openly discussed data limitations and potential inaccuracies with students, aligning with best practices in LA [48].

Focusing on the visualisations, the prioritisation bar chart presented particular challenges due to uncertainties in the analytical process. This highlights two primary considerations. First, while teachers may understand the visualisations in principle (Section 3.3), it is only when they see them *come alive* in the authentic use and student engagements that they may appreciate the strengths and weaknesses that were not recognised before. This depth of understanding is best learned in authentic deployments [31, 39]. Second, increasing transparency in data processing can help teachers better navigate potential discrepancies [2, 13].

6.2 Implications for MMLA Research and Practice

Integrating Multimodal Learning Analytics (MMLA) systems and dashboards into classrooms presents opportunities and challenges for researchers and teachers. While these innovations have shown promise [13, 33], potential ethical and practical barriers must be addressed and studied in the wild [2, 54]. While our MMLA dashboard proved valuable in guiding teachers' reflection practices, it also presented challenges concerning data trust and reliability, which are more prominent in MMLA research [54]. Addressing these challenges requires several strategies. In addition to refining algorithms and models for better reliability, it is imperative to provide clear explanations for missing data. This could be achieved through explanatory approaches [29] by incorporating data quality indicators. Furthermore, promoting *"algorithm transparency"* [13] by revealing data processing steps, from raw data to final visualisations, will be beneficial. Such strategies can foster teachers' confidence in these dashboards, particularly during early adoption, ensuring the dashboards are used optimally without fostering undue distrust or overconfidence [19, 47, 48].

Teachers' experiences have highlighted trust concerns with the MMLA dashboard due to disparities between the displayed data and their own expectations. Although human-computer design principles often advocate intuitive design [9], the unique complexity of MMLA dashboards suggests the importance of additional training sessions [28]. Providing teachers with a comprehensive understanding of the multimodal data, their visual representations and technological limitations can mitigate potential misunderstandings and misuse. Complementing these practices, adopting in-the-wild studies combined with human-centred approaches and design methodologies [e.g., 37] can effectively uncover and potentially address the complexities and challenges inherent in MMLA systems.

6.3 Limitations and Future Work

Our study has important limitations. First, the dashboard and analytics were specifically designed for teamwork in physical spaces, such as nursing education, which might limit its applicability in this context. While other researchers might use this solution in comparable team-based settings, significant adaptations would be necessary. Further research is needed to compare the findings in different contexts. Second, the teachers participating in our study were actively engaged during the whole design and were particularly skilled at leading debriefs. This expertise and engagement might introduce selection bias: teachers are keen to use the dashboard due to their involvement in the whole design. Future iterations should also include the view of novice teachers. Third, our study focused on teachers' use and perspectives. We did not report students' views on the dashboard's adoption, data interpretation, and its impact on their learning. We aim to address this in future studies for a comprehensive evaluation.

7 CONCLUSION

Few studies have explored the use of MMLA dashboards in real-world settings. This paper presented *TeamSlides*, a dashboard with three visualisations derived from audio and positioning data. Teachers validated the dashboard to ensure alignment with key prioritisation, teamwork, and communication behaviours. Our in-the-wild study showcases teachers' dashboard usage, offering empirical insights into MMLA dashboards' potential. This paper provides empirical evidence of the dashboard's real benefits while highlighting some challenges that, although discussed in prior literature, have not been empirically evidenced. MMLA researchers can draw from these findings to enhance their solutions for real-world learning scenarios.

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REFERENCES

[1] K. Ahuja, D. Kim, F. Xhakaj, V. Varga, A. Xie, S. Zhang, J. E. Townsend, C. Harrison, A. Ogan, and Y. Agarwal. 2019. EduSense: Practical classroom sensing at Scale. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 3, 3, Article 71 (2019), 26 pages. https://doi.org/10.1145/3351229

[2] H. Alwahaby, M. Cukurova, Z. Papamitsiou, and M. Giannakos. 2022. *The Evidence of Impact and Ethical Considerations of Multimodal Learning Analytics: A Systematic Literature Review.* Springer, 289–325. https://doi.org/10.1007/978-3-031-08076-0_12

[3] P. An, S. Bakker, S. Ordanovski, R. Taconis, C. L. Paffen, and B. Eggen. 2019. Unobtrusively enhancing reflection-in-action of teachers through spatially distributed ambient information. In *Proc. of the 2019 CHI conference on human factors in computing systems.* 1–14.

[4] N. Andrienko, G. Andrienko, and P. Gatalsky. 2003. Exploratory spatio-temporal visualization: an analytical review. *Journal of Visual Languages Computing* 14, 6 (2003), 503–541. https://doi.org/10.1016/S1045-926X(03)00046-6

[5] T. Ballendat, N. Marquardt, and S. Greenberg. 2010. Proxemic Interaction: Designing for a Proximity and Orientation-Aware Environment. In *ACM Intl. Conference on Interactive Tabletops and Surfaces* (Saarbrücken, Germany). ACM, 121–130. https://doi.org/10.1145/1936652.1936676

[6] P. Blikstein. 2013. Multimodal Learning Analytics. In *Proc. of the 3rd Intl. Conference on Learning Analytics and Knowledge* (Leuven, Belgium). ACM, 102–106. https://doi.org/10.1145/2460296.2460316

[7] D. Boud, R. Keogh, and D. Walker. 2013. *Reflection: Turning experience into learning.* Routledge.

[8] V. Braun and V. Clarke. 2012. Thematic analysis. In *Research designs: Quantitative, qualitative, neuropsychological, and biological.* APA handbooks in psychology., Vol. 2. American Psychological Association, Washington, DC, US, 57–71. https://doi.org/10.1037/13620-004

[9] S. Buckingham Shum, R. Ferguson, and R. Martinez-Maldonado. 2019. Human-Centred Learning Analytics. *J. of Learning Analytics* 6, 2 (2019), 1–9. https://doi.org/10.18608/jla.2019.62.1

[10] O. Chernikova, N. Heitzmann, M. Stadler, D. Holzberger, T. Seidel, and F. Fischer. 2020. Simulation-based learning in higher education: A meta-analysis. *Review of Educational Research* 90, 4 (2020), 499–541.

[11] Y. H. V. Chua, J. Dauwels, and S. C. Tan. 2019. Technologies for automated analysis of co-located, real-life, physical learning spaces: Where are we now?. In *Proc. of the 9th Intl. Conference on Learning Analytics & Knowledge* (Tempe, AZ, USA). ACM, 11–20. https://doi.org/10.1145/3303772.3303811

[12] D. Clow. 2012. The Learning Analytics Cycle: Closing the Loop Effectively. In *Proc. of the 2nd Intl. Conference on Learning Analytics and Knowledge* (Vancouver, British Columbia, Canada). ACM, 134–138. https://doi.org/10.1145/2330601.2330636

[13] M. Cukurova, M. Giannakos, and R. Martinez-Maldonado. 2020. The promise and challenges of multimodal learning analytics. *British J. of Educational Technology* 51, 5 (2020), 1441–1449. https://doi.org/10.1111/bjet.13015

[14] S. S. Dawes, A. M. Cresswell, and B. B. Cahan. 2004. Learning From Crisis: Lessons in Human and Information Infrastructure From the World Trade Center Response. *Social Science Computer Review* 22, 1 (2004), 52–66. https://doi.org/10.1177/0894439303259887

[15] D. Di Mitri, J. Schneider, K. Trebing, S. Sopka, M. Specht, and H. Drachsler. 2020. Real-Time Multimodal Feedback with the CPR Tutor. In *Artificial Intelligence in Education.* Springer, 141–152.

[16] V. Echeverria, R. Martinez-Maldonado, and S. Buckingham Shum. 2019. Towards Collaboration Translucence: Giving Meaning to Multimodal Group Data. In *Proc. of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland UK). ACM, 1–16. https://doi.org/10.1145/3290605.3300269

[17] V. Echeverria, R. Martinez-Maldonado, L. Yan, L. Zhao, G. Fernandez-Nieto, D. Gašević, and S. B. Shum. 2023. HuCETA: A Framework for Human-Centered Embodied Teamwork Analytics. *IEEE Pervasive Computing* 22, 1 (2023), 39–49. https://doi.org/10.1109/MPRV.2022.3217454

[18] G. Fernandez-Nieto, P. An, J. Zhao, S. Buckingham Shum, and R. Martinez-Maldonado. 2022. Classroom Dandelions: Visualising Participant Position, Trajectory and Body Orientation Augments Teachers' Sensemaking. In *2022 CHI Conference on Human Factors in Computing Systems.* 1–17.

[19] G. M. Fernandez Nieto, K. Kitto, S. Buckingham Shum, and R. Martinez-Maldonado. 2022. Beyond the Learning Analytics Dashboard: Alternative Ways to Communicate Student Data Insights Combining Visualisation, Narrative and Storytelling. In *Proc. of the 12th Intl. Learning Analytics and Knowledge Conference* (Online, USA). ACM, 219–229. https://doi.org/10.1145/3506860.3506895

[20] K. L. Fraser, M. J. Meguerdichian, J. T. Haws, V. J. Grant, K. Bajaj, and A. Cheng. 2018. Cognitive Load Theory for debriefing simulations: implications for faculty development. *Advances in Simulation* 3, 1 (2018), 1–8.

[21] D. Gašević, S. Joksimović, B. R. Eagan, and D. W. Shaffer. 2019. SENS: Network analytics to combine social and cognitive perspectives of collaborative learning. *Computers in Human Behavior* 92 (2019), 562–577. https://doi.org/10.1016/j.chb.2018.07.003

[22] M. Giannakos, M. Cukurova, and S. Papavlasopoulou. 2022. *Sensor-Based Analytics in Education: Lessons Learned from Research in Multimodal Learning Analytics.* Springer Intl. Publishing, Cham, 329–358. https://doi.org/10.1007/978-3-031-08076-0_13

[23] K. Hall and K. Tori. 2017. Best practice recommendations for debriefing in simulation-based education for Australian undergraduate nursing students: An integrative review. *Clinical Simulation in Nursing* 13, 1 (2017), 39–50.

[24] A. Kendon. 2010. *Spacing and Orientation in Co-present Interaction.* Springer, 1–15. https://doi.org/10.1007/978-3-642-12397-9_1

[25] C. Larmuseau, J. Cornelis, L. Lancieri, P. Desmet, and F. Depaepe. 2020. Multimodal learning analytics to investigate cognitive load during online problem solving. *British Journal of Educational Technology* 51, 5 (2020), 1548–1562. https://doi.org/10.1111/bjet.12958

[26] S. Lee, S.-H. Kim, and B. C. Kwon. 2016. Vlat: Development of a visualization literacy assessment test. *IEEE transactions on visualization and computer graphics* 23, 1 (2016), 551–560.

[27] S. Lee-Cultura, K. Sharma, and M. Giannakos. 2023. MultiModal Teacher Dashboards: Challenges and Opportunities of Enhancing Teacher Insights through a case study. *IEEE Transactions on Learning Technologies* (2023), 1–19. https://doi.org/10.1109/TLT.2023.3276848

[28] L. Lim, S. Dawson, S. Joksimovic, and D. Gašević. 2019. Exploring Students' Sensemaking of Learning Analytics Dashboards: Does Frame of Reference Make a Difference?. In *Proc. of the 9th Intl. Conference on Learning Analytics & Knowledge* (Tempe, AZ, USA). ACM, 250–259.

[29] R. Martinez-Maldonado, V. Echeverria, G. Fernandez Nieto, and S. Buckingham Shum. 2020. From Data to Insights: A Layered Storytelling Approach for Multimodal Learning Analytics. In *Proc, of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA). ACM, 1–15.

https://doi.org/10.1145/3313831.3376148

[30] R. Martinez-Maldonado, V. Echeverria, O. C. Santos, A. D. P. D. Santos, and K. Yacef. 2018. Physical Learning Analytics: A Multimodal Perspective. In *Proc. of the 8th Intl. Conference on Learning Analytics and Knowledge* (Sydney, NSW, Australia). ACM, 375–379.

[31] R. Martinez-Maldonado, A. Pardo, N. Mirriahi, K. Yacef, J. Kay, and A. Clayphan. 2015. LATUX: An Iterative Workflow for Designing, Validating, and Deploying Learning Analytics Visualizations. *J. of Learning Analytics* 2, 3 (2015), 9–39.

[32] N. McDonald, S. Schoenebeck, and A. Forte. 2019. Reliability and Inter-rater Reliability in Qualitative Research: Norms and Guidelines for CSCW and HCI Practice. *Proc. of the ACM on Human-Computer Interaction* 3, CSCW (2019), 1–23. https://doi.org/10.1145/3359174

[33] X. Ochoa. 2022. Multimodal learning analytics - Rationale, process, examples, and direction. *Handbook of Learning Analytics* (2022), 54–65.

[34] X. Ochoa and F. Dominguez. 2020. Controlled evaluation of a multimodal system to improve oral presentation skills in a real learning setting. *British Journal of Educational Technology* 51, 5 (2020), 1615–1630. https://doi.org/10.1111/bjet.12987

[35] S. Praharaj, M. Scheffel, H. Drachsler, and M. Specht. 2021. Literature review on co-located collaboration modeling using multimodal learning analytics—can we go the whole nine yards? *IEEE Transactions on Learning Technologies* 14, 3 (2021), 367–385.

[36] S. Praharaj, M. Scheffel, M. Schmitz, M. Specht, and H. Drachsler. 2022. Towards Collaborative Convergence: Quantifying Collaboration Quality with Automated Co-Located Collaboration Analytics. In *Proc. of the 12th Intl. Learning Analytics and Knowledge Conference* (Online, USA). ACM, 358–369.

[37] P. Reimann. 2016. Connecting learning analytics with learning research: the role of design-based research. *Learning: Research and Practice* 2, 2 (2016), 130–142. https://doi.org/10.1080/23735082.2016.1210198

[38] D. T. Risser, M. M. Rice, M. L. Salisbury, R. Simon, G. D. Jay, S. D. Berns, M. R. Consortium, et al. 1999. The potential for improved teamwork to reduce medical errors in the emergency department. *Annals of emergency medicine* 34, 3 (1999), 373–383.

[39] Y. Rogers, P. Marshall, and J. M. Carroll. 2017. *Research in the Wild.* Springer. https://doi.org/10.1007/978-3-031-02220-3

[40] M. Sablić, A. Mirosavljević, and A. Škugor. 2021. Video-based learning (VBL)—past, present and future: An overview of the research published from 2008 to 2019. *Technology, Knowledge and Learning* 26, 4 (2021), 1061–1077.

[41] E. Salas, D. L. Reyes, and S. H. McDaniel. 2018. The science of teamwork: Progress, reflections, and the road ahead. *American Psychologist* 73, 4 (2018), 593.

[42] N. Saquib, A. Bose, D. George, and S. Kamvar. 2018. Sensei: Sensing Educational Interaction. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 1, 4 (2018), 27 pages. https://doi.org/10.1145/3161172

[43] D. A. Schön. 2017. *The reflective practitioner: How professionals think in action.* Routledge.

[44] M. Seropian and R. Lavey. 2010. Design considerations for healthcare simulation facilities. *Simulation in Healthcare* 5, 6 (2010), 338–345.

[45] D. W. Shaffer, W. Collier, and A. R. Ruis. 2016. A tutorial on epistemic network analysis: Analyzing the structure of connections in cognitive, social, and interaction data. *J. of Learning Analytics* 3, 3 (2016), 9–45.

[46] K. Sharma and M. Giannakos. 2020. Multimodal data capabilities for learning: What can multimodal data tell us about learning? *British Journal of Educational Technology* 51, 5 (2020), 1450–1484.

[47] A. Shibani, S. Knight, and S. B. Shum. 2020. Educator perspectives on learning analytics in classroom practice. *The Internet and Higher Education* 46 (2020). https://doi.org/10.1016/j.iheduc.2020.100730

[48] Y.-S. Tsai, A. Whitelock-Wainwright, and D. Gašević. 2021. More Than Figures on Your Laptop: (Dis)trustful Implementation of Learning Analytics. *J. of Learning Analytics* 8, 3 (2021), 81–100. https://doi.org/10.18608/jla.2021.7379

[49] K. Verbert, E. Duval, J. Klerkx, S. Govaerts, and J. L. Santos. 2013. Learning Analytics Dashboard Applications. *American Behavioral Scientist* 57, 10 (2013), 1500–1509. https://doi.org/10.1177/0002764213479363

[50] A. F. Wise and Y. Jung. 2019. Teaching with analytics: Towards a situated model of instructional decision-making. *J. of Learning Analytics* 6, 2 (2019), 53–69.

[51] M. Worsley, R. Martinez-Maldonado, and C. D'Angelo. 2021. A New Era in Multimodal Learning Analytics: Twelve Core Commitments to Ground and Grow MMLA. *J. of Learning Analytics* 8, 3 (2021), 10–27.

[52] L. Yan, R. Martinez-Maldonado, B. G. Cordoba, J Deppeler, D. Corrigan, G. F. Nieto, and D. Gasevic. 2021. Footprints at School: Modelling In-Class Social Dynamics from Students' Physical Positioning Traces. In *Proc. of the 11th Intl. Learning Analytics and Knowledge Conference* (Irvine, CA, USA). ACM, 43–54. https://doi.org/10.1145/3448139.3448144

[53] L. Yan, R. Martinez-Maldonado, L. Zhao, S. Dix, H. Jaggard, R. Wotherspoon, X. Li, and D. Gašević. 2023. The role of indoor positioning analytics in assessment of simulation-based learning. *British Journal of Educational Technology* 54, 1 (2023), 267–292.

[54] L. Yan, L. Zhao, D. Gašević, and R. Martinez-Maldonado. 2022. Scalability, Sustainability, and Ethicality of Multimodal Learning Analytics. In *Proc. of the 12th Intl. Learning Analytics and Knowledge Conference.* ACM, New York, NY, USA, 13–23. https://doi.org/10.1145/3506860.3506862

[55] L. Zhao, L. Yan, D. Gasevic, S. Dix, H. Jaggard, R. Wotherspoon, R. Alfredo, X. Li, and R. Martinez-Maldonado. 2022. Modelling Co-Located Team Communication from Voice Detection and Positioning Data in Healthcare Simulation. In *LAK22: 12th International Learning Analytics and Knowledge Conference* (Online, USA). ACM, 370–380. https://doi.org/10.1145/3506860.3506935

[56] Q. Zhou, W. Suraworachet, S. Pozdniakov, R. Martinez-Maldonado, T. Bartindale, P. Chen, D. Richardson, and M. Cukurova. 2021. Investigating students' experiences with collaboration analytics for remote group meetings. In *Proc. of the 22nd Intl. Conf. of Artificial Intelligence in Education* (Utrecht, NL). Springer, 472–485.