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FATE in MMLA: A Student-Centred Exploration of Fairness, Accountability, Transparency, and Ethics in Multimodal Learning Analytics

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Abstract

Multimodal learning analytics (MMLA) integrates novel sensing technologies and artificial intelligence algorithms, providing opportunities to enhance student reflection during complex, collaborative learning experiences. Although recent advancements in MMLA have shown its capability to generate insights into diverse learning behaviours across various learning settings, little research has been conducted to evaluate these systems in authentic learning contexts, particularly regarding students' perceived fairness, accountability, transparency, and ethics (FATE). Understanding these perceptions is essential to using MMLA effectively without introducing ethical complications or negatively affecting how students learn. This study aimed to address this gap by assessing the FATE of MMLA in an authentic, collaborative learning context. We conducted semi-structured interviews with 14 undergraduate students who used MMLA visualizations for post-activity reflection. The findings highlighted the significance of accurate and comprehensive data representation to ensure visualization fairness, the need for different levels of data access to foster accountability, the imperative of measuring and cultivating transparency with students, and the necessity of transforming informed consent from dichotomous to continuous and measurable scales. While students value the benefits of MMLA, they also emphasize the importance of ethical considerations, highlighting a pressing need for the LA and MMLA communities to investigate and address FATE issues actively.

Notes for Practice

- Research in fairness, accountability, transparency, and ethics (FATE) can foster the design of multimodal learning analytics (MMLA) systems that are equitable, responsible, and trustworthy, assuring that they benefit a broad spectrum of students without reinforcing biases or discrimination.
- This paper presents the first evaluation of student perceptions of FATE in a large-scale MMLA deployment, providing empirical evidence from an in-depth qualitative study from a student-centred perspective to identify a set of specific FATE issues that need to be addressed in future MMLA studies and practices.
- The paper highlights the need for fair and transparent data representation, multilevel data access, clarity in data collection and analysis processes, and measurable informed consent, advocating for research and practices that are ethically robust, student centred, and accountable in addressing FATE issues.

Keywords:
Multimodal learning analytics, fairness, accountability, transparency, ethics.

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1. Introduction

Multimodal learning analytics (MMLA) remains a relatively novel approach in learning analytics (LA), focusing on diverse data collection methods to examine complex learning processes (Blikstein, 2013; Worsley et al., 2021). Rather than solely using clickstreams and keystrokes, MMLA encompasses other modalities like gestures (Worsley & Blikstein, 2015), body movements (Zhao et al., 2022), eye movements (Schneider et al., 2018), facial expressions (Sümer et al., 2023), hand motions (Spikol et al., 2017), voice (D'Mello et al., 2015), and physiological responses (Azevedo & Gašević, 2019). Recognizing the multifaceted nature of student interactions, MMLA offers insights for creating personalized, adaptive learning environments (Cukurova et al., 2020). By leveraging diverse data, educators and researchers can design systems that address individual student needs while considering different factors that influence learning (Sharma & Giannakos, 2020).

Despite the promise of MMLA, there are concerns about the technologies used and unforeseen practices that may arise (Prinsloo et al., 2023; Cukurova et al., 2020; Worsley et al., 2021; Ochoa, 2022). Challenges include the intricacies of multichannel modelling, such as mapping diverse data to educational constructs (Ochoa, 2022; Martinez-Maldonado et al., 2020), and logistical issues like complex technical infrastructure impacting MMLA scalability (Yan et al., 2022; Ouhaichi et al., 2023). Systematic reviews consistently point out socio-technical and ethical challenges when transitioning MMLA from research settings to classrooms (Prinsloo et al., 2023; Yan et al., 2022; Alwahaby et al., 2022; Crescenzi-Lanna, 2020). Specifically, using advanced sensors in learning spaces may threaten student privacy (Prinsloo et al., 2023). While more data modalities can refine modelling (M. N. Giannakos et al., 2019), this does not guarantee fairer analytical results (Deho et al., 2022). Additionally, research in authentic classrooms remains scarce, leaving a gap in understanding how to use MMLA effectively while addressing the emerging fairness, accountability, transparency, and ethics (FATE) concerns in artificial intelligence (AI) (Memarian & Doleck, 2023). Despite being highlighted in the MMLA literature (Alwahaby et al., 2022; Cukurova et al., 2020; Worsley et al., 2021; M. Giannakos et al., 2022), authentic MMLA deployments have yet to thoroughly examine these FATE issues.

Researching FATE in LA and MMLA is vital (Memarian & Doleck, 2023; Khalil et al., 2023). It can foster the design of LA systems that are equitable, responsible, and trustworthy, assuring that they benefit a broad spectrum of students without reinforcing existing biases or accentuating discrimination (Khalil et al., 2023). Similarly, studying FATE in MMLA is essential to identifying the boundaries of MMLA in an authentic learning setting (Prinsloo et al., 2023). Previous studies have emphasized that understanding students' perceptions of FATE issues can aid in informing the creation of analytics technologies and the strategies surrounding their ethical use (Kasinidou et al., 2021; Memarian & Doleck, 2023), as well as addressing potential threats to acceptance and adoption (Hakami & Leo, 2020). This paper makes inroads into this area by exploring FATE issues in the context of an authentic large-scale MMLA deployment.

Our paper provides the first evaluation of students' perceptions of a real-life MMLA dashboard deployment in an authentic learning environment. Previous literature has rarely evaluated MMLA systems within real-world, physical learning environments (Ochoa & Dominguez, 2020; Schneider et al., 2024). This limitation has been particularly evident in MMLA studies investigating FATE-related issues, where most evaluations were conducted either in controlled laboratory settings (Kasepalu et al., 2021) or without direct engagement with students (Mangaroska et al., 2021). By embedding our study within the course curriculum, we were able to collect high-quality data from students actually using the MMLA dashboard, ensuring a robust and valid evaluation of FATE-related issues in ecological conditions. The main contribution of this work to both the FATE and MMLA fields lies in providing valuable insights from learners' perspectives in an authentic/ecological learning setting. These findings can potentially provide essential information for improving the design and implementation of future MMLA solutions in real physical classrooms by balancing and prioritizing various dimensions of FATE. Ultimately, we aim to answer the call of Cukurova and colleagues (2020) by moving MMLA research toward ecologically valid studies that contribute insights into tackling the multifaceted challenges of ethics, practices, and methodologies.

2. Background

2.1 Fairness, Accountability, Transparency, and Ethics (FATE)

Over the past decade, research and discussion around the FATE of data-intensive educational systems have become more prevalent in LA (Khalil et al., 2023) and AI (Memarian & Doleck, 2023; Khosravi et al., 2022) in education communities. While LA and AI have brought forth numerous possibilities for optimizing learning and improving educational outcomes, they have also introduced or intensified several critical issues that could undermine the ethicality and beneficence of education, such as eliciting bias and discrimination and diminishing student privacy and agency (Ungerer & Slade, 2022; Holstein & Doroudi, 2019; Pardo & Siemens, 2014). Before exploring prior FATE-related works, especially in MMLA, we first defined each FATE element by synthesizing the findings of a recent systematic review of FATE in AI and higher education (Memarian & Doleck, 2023) and prior discussions of FATE in LA (Khalil et al., 2023; Holstein & Doroudi, 2019; Deho et al., 2022; Slade & Prinsloo, 2013; Prinsloo et al., 2023).

2.1.1 Fairness

The fairness of LA is crucial as it can affect decisions related to students' learning pathways, interventions, academic success, and overall well-being (Deho et al., 2022; Holstein & Doroudi, 2019). This terminology is a complex concept involving both descriptive and technical dimensions (Memarian & Doleck, 2023). Descriptively, fairness seeks to establish a landscape in education that rectifies unjust practices and mitigates biases, ensuring that algorithmic processes do not produce discriminatory outcomes (Shin et al., 2021; Islam et al., 2022). From a technical viewpoint, fairness can be achieved through rigorous statistical and mathematical approaches during various stages of the machine learning pipeline, emphasizing metrics such as statistical parity, equalized opportunity, and accuracy parity (Jiang & Pardos, 2021; Kim & Cho, 2022). Addressing fairness also involves recognizing and tackling different types of biases and employing strategies ranging from pre-processing techniques to post-process approaches (Barbierato et al., 2022). In the context of LA, fairness should extend beyond ensuring that the analysis and algorithmic processes result in unbiased and non-discriminatory analytics (Holstein & Doroudi, 2019) to assuring the equitable and impartial reporting and visualization of these analytics in dashboards or other user-facing interfaces (Verbert et al., 2020).

2.1.2 Accountability

Accountability is a multifaceted concept that includes the responsibility and answerability of individuals, institutions, or systems for actions, decisions, and outcomes they produce (Memarian & Doleck, 2023). Specifically, some researchers associate accountability with explicability and consider a system or process that can be explained as accountable (Bezuidenhout & Ratti, 2021). Others see accountability as a measure to hold providers of automated systems answerable for their algorithmic decisions, including both system developers and data suppliers (Pagallo, 2017). This lack of clarity about who should be held accountable is further complicated by the debate between human accountability and human–AI shared accountability when considering the implications of AI systems in education (Memarian & Doleck, 2023). In this sense, the accountability of LA is beyond a particular individual or party but distributed among multiple relevant stakeholders (Prinsloo & Slade, 2017), including but not limited to institutions, teachers, students, researchers, and technology providers. For example, the technology infrastructure department of an institution may be held accountable for data security, while developers of the algorithms and dashboards might be responsible for ensuring algorithmic and reporting fairness (Pardo & Siemens, 2014). In MMLA, accountability is also associated with data access, as these analytics could be used by different stakeholders for multiple purposes (e.g., feedback, reflection, and potentially assessment; Kasepalu et al., 2021; Mangaroska et al., 2021). Therefore, understanding access to learner data is essential for holding different parties accountable.

2.1.3 Transparency

Transparency in data-driven technologies is closely linked to accountability; for these technologies to be accountable, they must be transparent (Tsai et al., 2019). From an algorithmic point of view, transparency means that algorithms are understandable, either in technical terms or in simpler language (Ungerer & Slade, 2022). On the other hand, from a process-oriented viewpoint, transparency extends to clarity around data usage, consent mechanisms, and recourse options, aligning with standards like Europe's General Data Protection Regulation (GDPR; General Data Protection Regulation, 2016). Chaudhry and colleagues (2022) introduced a transparency index for educational AI systems, classifying it into three tiers: transparent to algorithmic experts (e.g., AI researchers and practitioners), transparent to domain experts (e.g., educational technology experts and enthusiasts), and transparent to educational stakeholders (e.g., educators and students). Based on these prior works, transparency in LA could be defined as the articulation and comprehension of data-driven insights and methods and the implications of analytics-driven interventions, ensuring that stakeholders, particularly students, can understand, trust, and engage with the analytics (Tsai et al., 2019; Ungerer & Slade, 2022).

2.1.4 Ethics

Ethics in LA is a broad concept that focuses on the principles and values guiding the collection, analysis, and use of data, often overlaid with some aspects of fairness, accountability, and transparency (Ungerer & Slade, 2022). Specifically, ethical research in LA often focuses on investigating issues related to privacy, informed consent, data security, and the broader impact of analytics on society (Tzimas & Demetriadis, 2021; Rubel & Jones, 2016). Of these, informed consent is critical and a prerequisite for conducting any LA research, as such mechanisms are essential for ensuring student privacy and autonomy (Slade & Prinsloo, 2013). Achieving informed consent in practice is often complex (Prinsloo et al., 2023). For example, providing students with explanatory statements and asking for their consent often implies their awareness of the collection, usage, and storage of their data (Tsai et al., 2020). However, given the length of these statements, it is probable that students do not read them and thus consent without being fully aware of the situation (Prinsloo & Slade, 2016). Additionally, in MMLA studies, the use of advanced sensing technologies adds another layer of complexity, such as students' level of comprehension regarding how their data will be collected, processed, and analyzed by these sensors (e.g., positioning tracking, computer vision, and wearable biometrics sensors; Prinsloo et al., 2023; Beardsley et al., 2020). This issue becomes particularly vital in low-risk MMLA research that adopts an opt-out consenting approach, whereby participants are given explanatory statements and need to actively opt out to withdraw their participation and data (Junghans et al., 2005). Understanding the intricacies of opt-out consenting is essential for advancing the ethicality of LA (Sun et al., 2019).

2.2 FATE in MMLA

MMLA has advanced rapidly over the past decades with the overarching goal of extending LA research not only beyond computer-mediated contexts but also to hybrid and physical learning settings (Ochoa, 2022; Cukurova et al., 2020). Specifically, this subfield of LA strives to derive data-driven insights concerning learners' metacognitive and emotional states, alongside their learning behaviours, by using fine-grained physical and physiological signals (Blikstein, 2013; Ochoa, 2022). This endeavour has become increasingly realized with the advancement in sensing technologies such as computer vision algorithms for gesture and posture detection, wearable positioning tracking, and physiological sensors (Crescenzi-Lanna, 2020; M. Giannakos et al., 2022; Sharma & Giannakos, 2020). While the integration of advanced sensing capabilities has empowered MMLA with the ability to capture a range of different modalities (e.g., video, audio, heart rate, positioning, and gaze; Cukurova et al., 2020; Worsley et al., 2021), many concerns have also been raised regarding the FATE of MMLA (Alwahaby et al., 2022; Yan et al., 2022). For example, in a systematic literature review of MMLA research, Alwahaby and colleagues (2022) identified several ethical issues around the design and use of MMLA systems, including privacy, informed consent, data management, and ethical clearance. While these issues have been briefly mentioned, either in the introduction, background, or discussion sections, they have yet to be formally investigated as the main research objective of an MMLA study. Likewise, in another review, Yan and colleagues (2022) further illustrated the lack of understanding of the fairness and the potential risks associated with existing MMLA solutions. Both reviews advocated for the immediate need for FATE research in MMLA, especially from a human-centred instead of an algorithm-focused perspective, which has been the primary focus of prior FATE research regarding data-intensive educational systems (Khalil et al., 2023; Memarian & Doleck, 2023).

Of the few studies that have investigated FATE-related issues in MMLA, most were conducted in controlled laboratory settings and have yet to evaluate MMLA solutions in authentic learning settings. For example, Kasepalu and colleagues (2021) investigated teachers' trust in an MMLA dashboard for monitoring students' collaboration and identified a relationship between trust and the level of transparency in data processing. In their study, teachers did not actually use the dashboard in practice. Instead, they were shown an 8-minute video of a 30-minute recording and evaluated the dashboard accordingly. Likewise, Mangaroska and colleagues (2021) evaluated students' perspectives on the accessibility of their multimodal data collected during a lab study. The results illustrated a mixed perspective on data sharing, where some students were comfortable with sharing anonymous and aggregated data with educators, while others demonstrated concerns over the unequal power relations that multimodal data may introduce, potential usage in data profiling, and pervasive surveillance, especially with physiological data. However, the study by Mangaroska and colleagues (2021) focused merely on the data collection process, without illustrating and evaluating MMLA with students, which could affect the outcomes as the utility of these data remains unclear for students. To the best of our knowledge, none of the existing MMLA studies have evaluated students' perceptions of the FATE of an MMLA solution after a practical implementation in authentic learning settings, where the MMLA solution has actually been used by students during learning activities. Understanding these perceptions is crucial. It can provide valuable insights for future MMLA research, aiming to create solutions that are fair, accountable, transparent, ethical, and, most important, beneficial for enhancing the learning experience (Gašević et al., 2014).

This study addresses this gap by examining students' perceptions of FATE issues regarding the use of MMLA visualizations in an authentic collaborative learning setting. Specifically, the following research questions were investigated: In an authentic MMLA deployment, **RQ1**, how is *fairness* perceived by students, especially regarding the representation of their data; **RQ2**, how is *accountability* perceived by students, especially regarding the access of their data; **RQ3**, how is *transparency* perceived by students, especially regarding the data collection and analysis processes; and **RQ4**, how is *ethics* perceived by students, especially regarding the opt-out informed consent?

3. Methods

3.1 The Authentic Learning Context

The study was conducted in the context of high-fidelity healthcare simulations that enable students to practise prioritization and teamwork skills. In these, students play the role of nurses and address a clinical problem while focusing on patient care

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management. Third-year students in the bachelor of nursing program at Monash University engaged in these simulations, each spanning between 20 and 30 minutes. Students are grouped into teams of four, taking the roles of two primary and two secondary nurses. The scenario involves three phases: **Phase 1:** Two primary nurses receive handover information for four patients, with one patient deteriorating. **Phase 2:** Two secondary nurses are called to assist with patient care. **Phase 3:** Following a medical emergency team (MET) call by a nurse, a teacher, acting as a doctor, offers support. Immediately after the scenario, all students engage in a teacher-guided debrief session.

3.2 The MMLA System

An MMLA system[1] was used during the debrief of the simulations. This comprises (1) the data collection component, which captures, synchronizes, and stores data from different sensors and devices (i.e., audio, positioning, video) (see Section 3.2.1), and (2) the visualization component, which is responsible for generating analytics and visualizations (see Section 3.2.2).

3.2.1 Multimodal Data Collection

Each student received a belly bag with a positioning sensor to monitor their ***x-y* coordinates** and **body orientation** in the learning space. They also wore a wireless headset microphone for **audio** recording. Students were assigned colours according to their roles: red and blue for primary nurses (PN) 1 and 2, and green and yellow for secondary nurses (SN) 1 and 2. These helped create anonymous data streams. Additionally, a 180-degree camera was used to **video**-record the simulations and an **observation tool** enabled teachers to tag and annotate relevant phases and events.

3.2.2 Visualizations

Teachers used a set of four visualizations to prompt reflections right after the simulations, capturing task prioritization, teamwork, and communication behaviours (see Figure 1). Over nine months, the MMLA visualizations were designed through a co-creation with nursing teachers and a research team that consisted of software developers, interaction design experts, and LA researchers, guided by LATUX workflow (Martinez-Maldonado et al., 2016). In a focus group discussion, we began by **exploring opportunities and challenges** on how LA can be integrated into their current teaching practice to support post-simulation reflection. In the second stage, the teaching team generated **low-fidelity paper-based prototypes**. In the third stage, the research team developed and tested **higher-fidelity prototypes** collaboratively and iteratively with teachers through three **pilot studies** over six months. These visualizations were then integrated with the existing LA system in the physical classroom and used in 64 simulation sessions. The details about the visualizations will be open-sourced in our repository[2].

Furthermore, we evaluated the visualizations with students using the Evaluation Framework for Learning Analytics (EFLA) for individuals' understanding of data, awareness, reflection, and the impact on the learner through an eight-item questionnaire (Scheffel et al., 2017). Complete results were detailed in our previous study (Yan et al., 2024), revealing that students perceived visualizations as effective in providing clarity on the data collected, stimulating reflection on, and adaptation in, their learning behaviours. Additionally, students highlighted the importance of data accuracy, transparency, and privacy protection to maintain user trust. Therefore, in this paper, we emphasize exploring student reflections on FATE through these visualizations of their data.

A: Prioritization Chart Based on students' **position data**, and drawing from proxemics literature (Hall, 1971) and teacher insights (Yan et al., 2023), we identified five prioritization behaviours. We checked if **students were collaborating** by seeing if two or more were close (within 10 metres) for over 10 seconds. Otherwise, they were deemed to be **working individually**. We also discerned if students were involved in a **primary** or **secondary task** by dividing the learning space into respective areas. The primary task pertained to the patient named Ruth, who needed prioritization, while the secondary task involved the other three patients. Finally, we tracked if students **moved around the beds** when away from the main beds or other students. Using *x-y* coordinates, we tagged each student's behaviour every second into one of the five behaviours. We then aggregated the time the team dedicated to each behaviour, visualized in a bar chart (see Figure 1A).

B: Ward Map We integrated *x-y* coordinates with students' speech presence/absence data. Using a voice activity detector (VAD)[3], we labelled speech utterances from individual students' audio recordings, producing timestamped instances indicating speech presence or absence. These instances were merged with *x-y* coordinates to determine each student's location per second. The final matrix for each student included timestamps, audio presence (0/1), and *x-y* coordinates. We depicted these spatial and audio data on a hexbin map[4] to display the spatial-audio relationship. The *x-y* coordinates were adjusted to fit the physical learning space layout. Data points were grouped in hexagons, each representing an area in the ward map. Students were

[1] https://github.com/Teamwork-Analytics/teamwork-visualiser-dashboard
[2] https://github.com/orgs/Teamwork-Analytics/repositories
[3] https://github.com/wiseman/py-webrtcvad
[4] https://d3-graph-gallery.com/hexbinmap.html

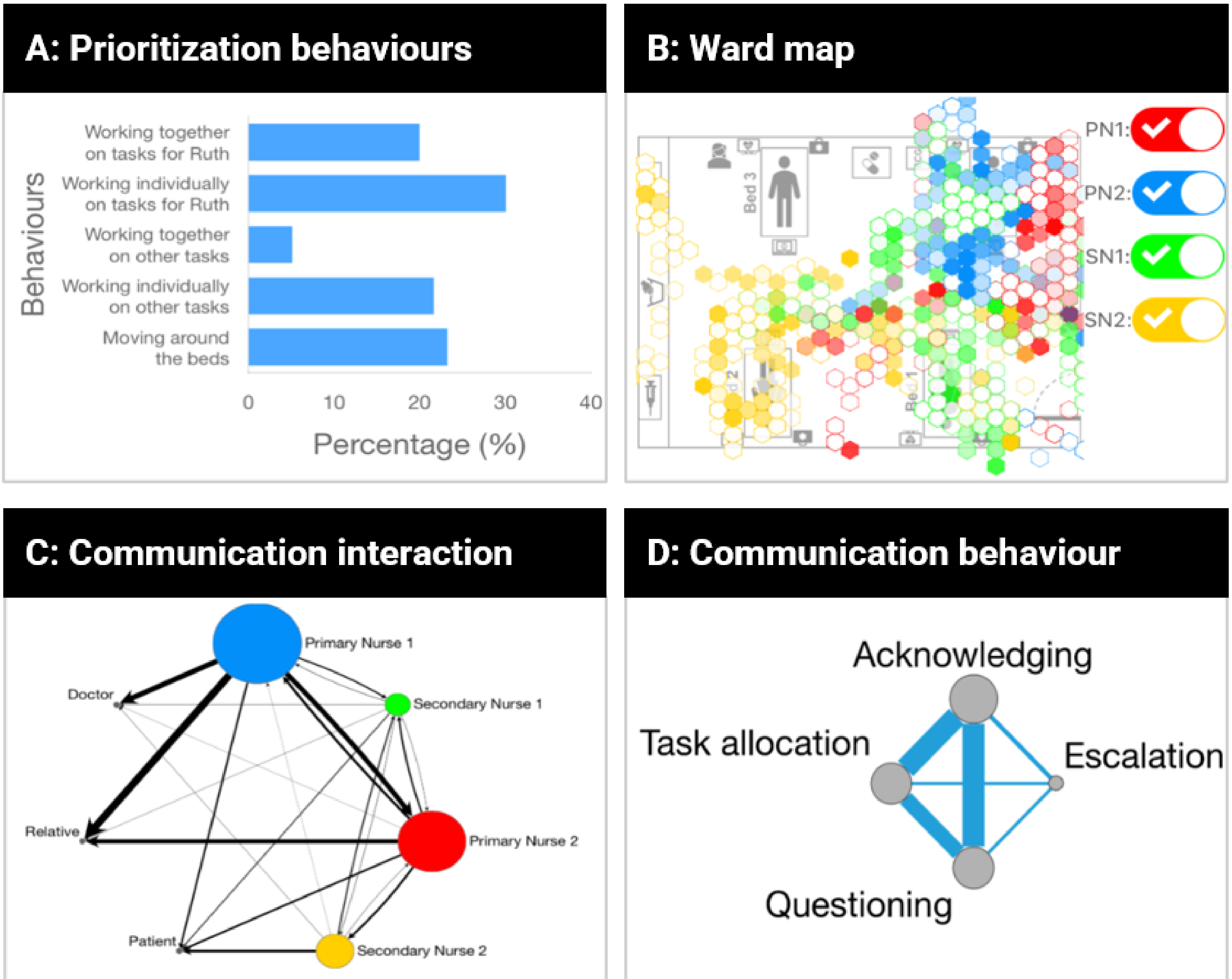

Figure 1. A set of four visualizations used by teachers to guide reflection on collaboration dynamics in the classroom based on a combination of positioning (A, B, C, and D) and audio (B, C, and D) data.

colour-coded (Section 3.2.1), with colour intensity reflecting speech activity. As shown in Figure 1B, a **fully filled hexagon** signified active speech, while **no fill** denoted silence.

C: Communication Interaction Diagram We combined students' positioning and audio data to visualize communication interactions. We identified f-formations—when two or more students were physically in close proximity—using individual *x*-*y* coordinates and body orientation. Using the VAD, we extracted speech segments and their lengths. We inferred conversations between students or other participants (e.g., doctor, patient, relative) if speech happened within an f-formation (Zhao et al., 2022). For example, if PN1 (red) spoke within proximity of PN2 (blue), we assumed that PN1 was conversing with PN2. We computed each student's speaking time and visualized interactions through a node-link graph. As illustrated in Figure 1C, nodes represent participants engaged in the simulation, and arrows illustrate the direction of speaking. The node size represents the student's total speaking time, while the arrow width represents the interaction duration between two students. Nodes were colour-coded to preserve de-identification.

D: Communication Behaviour Diagram We adapted a coding scheme on healthcare teamwork and communication behaviours (Zhao et al., 2023) to analyze students' dialogue content. This was achieved by combining audio and positioning data. We used the VAD to identify when students spoke in the audio, providing us with corresponding timestamps. These timestamps were used to extract the voiced audio segments, which were subsequently transcribed using the OpenAI Whisper large model[5].

[5]https://github.com/openai/whisper/tree/main

Moreover, by combining the timestamps and positioning data, we identified moments when two or more students conversed while in close proximity, forming dialogue segments. We then coded each utterance (i.e., a turn of talk) within a dialogue segment using the adapted coding scheme. Following a similar approach used by Zhao and colleagues (2023), each utterance can be assigned multiple codes. For visual representation, we developed a simplified epistemic network graph as shown in Figure 1D. This network was implemented referring to the data-processing algorithm of epistemic network analysis (Shaffer et al., 2016). Each node symbolizes a code, and the lines between them indicate co-occurrences of codes within students' dialogue segments (i.e., similar to in epistemic network analysis; Shaffer et al., 2016). The thickness of the lines represents the extent of co-occurrences observed throughout the simulation.

3.3 Study Design

This study, approved by the Monash University Human Research Ethics Committee, spanned four weeks in 2023's second semester as part of a compulsory unit of a bachelor of nursing degree at Monash University. We conducted a follow-up semi-structured interview to delve into FATE within MMLA visualizations used in debriefs, structured as follows:

(i) Initial explanation: Despite prior exposure, we first clarified the data in each visualization.

(ii) Understanding of the information: Students interpreted their data visualizations, with opportunities for clarification.

(iii) FATE questions: Introducing a potential assessment tool scenario, we prompted discussion on LA's educational future. Queries covered fairness (e.g., "Do you think all students in your team are fairly represented in the visualizations? How?"), accountability (e.g., "Any concerns about data misuse in these visualizations?"), transparency (e.g., "Do you understand the data collection and transforming process?"), and ethics (e.g., "Would you prefer the 'opt-in' or 'opt-out' consent method? Why?"). These questions drew from FATE research in human-computer interaction, LA, and AI in education (Mangaroska et al., 2021; Prinsloo et al., 2023; Hakami & Leo, 2020; Khalil et al., 2023; Memarian & Doleck, 2023). The complete list is available at https://anonymous.4open.science/r/FATE_in_MMLA-DC16/.

3.4 Participant Recruitment

At the request of the teaching team, an opt-out consent method was adopted, as the MMLA system became an integral part of all regular teaching sessions. An explanatory statement was provided to students, including the essential information about the study. Position and audio data were collected from all students, deleting those who opted out immediately after their sessions. Data from 60 teams (each comprising four students) was captured during the simulations. Typically, each teaching session allows two teams to participate in the simulation. Teachers then used the visualizations for the debrief (Section 3.2.2), so students viewed these visualizations during their team discussions. After class, students were invited to participate in a semi-structured interview to explore the research questions using their data. An opt-in consent approach was chosen for the interviews, and participants received a $40 voucher as appreciation for their time. Conducted via Zoom, these interviews were video recorded and took place a week after the simulation experience, with a single researcher facilitating each session. Following the principle of saturation and guided by Guest and colleagues (2006)'s recommended sample size, we recruited 15 students for the interviews. After conducting a pilot session and refining our questions based on feedback, the analysis focused on responses from 14 students (12 females, avg. age: 22 years, std. dev: 1.6) who participated in the subsequent interviews.

3.5 Analysis

All interviews were transcribed for analysis. We conducted a deductive-inductive thematic analysis approach (Fereday & Muir-Cochrane, 2006). First, using a deductive method, we sorted instances based on FATE concepts. Then, we used an inductive method to identify emerging themes within each concept. One researcher analyzed the first three interviews following this approach. A second researcher then reviewed the findings, and the two came to an agreement on the identified themes (McDonald et al., 2019). After this, they analyzed the remaining interviews in an iterative manner to reach saturation of themes and full agreement (Ando et al., 2014).

4. Results

4.1 Fairness (RQ1)

Students' perspectives on the fairness of the MMLA visualizations at reflecting their individual and team performance were mixed: six participants (P1, P3, P4, P9, P10, and P12) agreed, four (P2, P7, P8, and P11) disagreed, and four (P5, P6, P13, and P14) found the visualizations to be "somewhat fair." Their responses comprised four themes, covering positive and negative student perspectives of fair representation and potential improvements for assessment.

4.1.1 Accuracy of Reflection

The participants ($n = 7$) felt that the MMLA visualizations accurately reflected simulation events. Those who saw them as a *fair* representation noted a clear alignment between the visualizations and their experience. P1 felt that it was an "accurate representation of what happened," while P3 confirmed the visualization's representation of roles, observing that "Secondary Nurse 2 had the smallest role to play . . . that was also true within the simulation." P4 mentioned the visuals: "Even though we were doing different roles, it demonstrates what actually happened in that scenario pretty well." The visualizations, capturing both communication and movement, were further commended. P9 noted about the communication interaction diagram (Figure 1C) that the dot size "reflects how much we were speaking." Coupled with the ward map (Figure 1B), P9 found that it showed that while the primary nurse spoke the most, they moved the least, concluding that it "reflects physically moving around and communication fairly."

4.1.2 Inadequate Analysis and Visualization Design

A prominent theme was the lack of consideration in the decision-making process of data selection, analysis, reporting, and visualization, raising concerns about fair representation. Two sub-themes were identified as follows.

Visualization Not Representing the Full Context and Nuances The limitations of data visualization in capturing the depth and context of communication were highlighted by students ($n = 5$). P11 remarked on the challenge of illustrating individual contributions, arguing that, "It's quite difficult to show how each team member participated or contributed to this scenario." P5 noted that, as a secondary nurse, visualizations might misrepresent their level of engagement: "You can see that we don't communicate a lot because we were doing that task." P8 critiqued the communication behaviour diagram (Figure 1D) for its lack of context, stating that it merely "recognizes that people were asking questions and giving answers, not actually [providing] any context of what they were [saying]." P7 expressed reservations about the ward map, pointing out that the data is in aggregate form as it does not "show how we moved minute by minute." Furthermore, P6 emphasized the system's limitations in capturing the "quality and effectiveness of communication," for example, "a nurse was talking but they were taking quite some time to get to their point . . . which would be contributing to the ward map and communication interaction," and the lack of recognition for "each person's communication style," whether they are more passive, active, or direct.

Individual Contributions and Role Differentiation Differentiating individual contributions during simulations, especially between primary and secondary nurses, proves challenging. P3 noted that the communication behaviour diagram mainly shows team interactions, stating, "The communication behaviour . . . you can [only] see if the team overall did a lot of acknowledging and questioning. It might just be two people going back and forth. So that's harder to differentiate each role." From a role perspective, P10 observed, "I guess the primary nurses are more expected to do task allocation and escalation, whereas it's . . . more expected for the job of acknowledging and questioning to be for the secondary nurses." P10 further suggested that it would be beneficial to see "which roles were doing most of those communication behaviours." P6's comments highlighted potential biases, noting that one might assume "red [with bigger circle] is doing a lot . . . they deserve a higher grade compared to green and yellow." while the ward map suggests "green and yellow is not moving around a lot. That means they're not doing anything."

4.1.3 Flawed or Incomplete Data

Another theme from the interviews was the misrepresentation of information, mainly attributed to missing data or technology flaws. P7 observed inconsistencies between their perceived communication levels and the visual representation, stating, "I think we talked a lot . . . in my opinion, my arrows from me as a Primary Nurse 1 to Primary Nurse 2 should be bigger." Similarly, P13 pointed out the visual omission of a secondary nurse's communication, mentioning that "having no arrows coming out shows that they weren't communicating to anyone other than the patient, which I do not think was accurate." P5 suggested that these discrepancies might be due to "technical difficulties, like if there was some problem with the mic." Additionally, the exclusion of non-healthcare professionals like patients' relatives impacts the accurate interpretation of events. P4 noted that the system failed to capture their "interaction with the patient's relative in Bed 3." With no data for the patient's relative, the ward map suggested inactivity, making it seem "like we weren't doing anything." In an extreme case, P2 highlighted the unfairness of evaluating based on incomplete data, pointing out the complete omission of Secondary Nurse 1 from the ward map: "She doesn't even exist there, so I feel like it's not fair in that aspect."

4.1.4 MMLA Visualizations for Assessment

In this subsection, we report students' views on the use of MMLA visualizations for *fair assessment* of individual and team performance. Students' opinions were divided. Only P3 supported the idea without any strings. Some students ($n = 5$; P1, P4, P10, P12, P13) felt that MMLA visualizations could be used fairly for assessment under certain conditions, while the majority ($n = 8$; P2, P5–9, P11, P14) believed it would be unfair. Beyond the aforementioned themes, students provided suggestions to enhance the visualizations for assessment. Many highlighted the need to incorporate video and audio data. P2 viewed them as a

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"collection of memory," and P4 felt that they could "help better understand what's happening in the scenario." P9 emphasized their ability to "capture body language." Other suggestions included multiple trials and role rotations, as proposed by P7 and P8, to identify consistent performance trends and enhance assessment accuracy.

4.2 Accountability (RQ2)

In this subsection, we focus on data security as a lens to investigate students' perceived accountability in data access, potential misuse, and consequences, as well as the measures to mitigate such risks.

4.2.1 Data Access

We summarize the results by the types of stakeholders mentioned, namely students (e.g., whole and other classes), educators (e.g., coordinators and teachers), and third parties (e.g., researchers and admins).

Students A majority of the participants ($n = 12$) believed that the whole class should have access to their data, primarily for self-reflection and collaborative learning purposes. P7 saw the benefits in self-improvement, stating that students could "reflect on their own performance" and identify areas of strength or needed growth. P6 felt that the data should be available "right after the simulation just for reflection," helping students quickly understand their actions. P5 noted the data's value in reviewing team dynamics. However, P3 and P11 felt that access should be limited to the four students participating in the same simulation scenario. For example, P3 said, "not necessarily the whole class . . . you were able to reflect on your experience without comparing." Only six participants felt that it would be appropriate to share data access with students from other classes. The main concern, as voiced by P6 and P13, was fostering competitive or negative attitudes and the risk of judgment from peers. P10 expressed concerns about comfort, noting that some students might be "scared of judgment from other people," which could discourage them from participating actively. On the other hand, some participants, like P4 and P14, saw data sharing as a learning opportunity. P4 believed that younger students, in particular, could benefit as they might not have had much hands-on experience, suggesting that it could be valuable for those who "haven't had that much experience on placement and other scenarios."

Educators Most participants ($n = 10$; $n = 13$) supported granting data access to the unit coordinator and other teachers to enhance teaching and assessment methods. P13 saw the visualizations as an "overall snapshot" that could highlight areas for teaching improvement, which could serve as a "reflection tool for future courses." While P2 and P6 highlighted the value for teachers assessing student performance, P7 believed that teachers could use the data to pinpoint student "weakness" but was hesitant about sharing with the unit coordinator due to concerns about fairness in assessment. Some participants, like P8 and P11, were cautious about unrestricted access. They preferred differentiating access levels between video, audio, and visualizations. P8 felt that teaching staff should be among the "few people" with access to video and audio, whereas others should see only anonymized visualizations. P11 advocated for a more limited approach, suggesting that staff access only the graphs to avoid potential bias or judgment, for example, "one student was having a bad day, or they're really stressed just before the scenario, they may perform poorly, and that may pose some judgment."

Third Parties Four participants emphasized the value of researchers accessing their data. P6 outlined the broader potential of such data, suggesting that it might be "useful in the general sense of a study like what you're doing right now. If it's proved to be efficient and accurate, it could also go further into a health organization's research and study and overall in our country. And potentially, if it gets that far could be international as well." Only three students felt that university administrative staff need access to their data. P3 reasoned that the admin team should "have their hands on everything" to support teaching staff effectively. P10 expressed trust in the institution's protocols and the integrity of administrative staff, believing that they would uphold student privacy and adhere to the organization's code of conduct. They felt assured that measures would be in place to protect students, stating, "I would trust staff would have procedures in place to keep students safe."

4.2.2 Misuse of Data and Consequences

Four sub-themes are summarized as follows.

Judgment and Critique A primary concern among participants was the potential for judgment and critique from others, including students, teachers, or outsiders without a nursing background. P5 emphasized the simulation as "a safe place" for learning and worried that outsiders might misunderstand situations and use them negatively. P6 raised concerns about potential misrepresentation, where outsiders might create a "false story" and link it to unrelated adverse medical outcomes, so that "someone might make up a false accusation of a particular hospital or particular person." This participant also recalled an instance where past student videos were used in teaching, leading to critiques, which made them wary about their own data being "potentially critiqued." P1 expressed concerns that students could be "disempowered or lose motivation to pursue learning," compromising their learning experience and outcomes.

Privacy Concerns Many participants voiced concerns about the exposure of personal identity, especially from video and audio collected during the simulation. P4 articulated the discomfort as follows: "I would be concerned, 'cause I don't feel comfortable having my face ... exposed to others who aren't meant to have access to it." P7 pointed out the problem, in essence, summarizing, "because our pictures are there. So people can identify us easily." Moreover, P4 and P5 pinpointed their perceived nature of data misuse as "breach of privacy" and "breach of confidentiality." Lastly, P2 warned about the danger of using AI for malicious intent. "I think nowadays like AI ... is on a very big hike. So I think it could make, for example, an AI of me saying something. [Because] my face is there, my voice is there," and remarked, "Technology nowadays is scary."

Impact on Future Career Some students also stressed the potential consequences on their employment prospects if data was made accessible to future employers. P8 conveyed the anxiety that "what if your future employer ... [has] a look at your performance?" Such concern can be linked to judgment. As P11 suggested, "it could be misused in regards to judging a student's or a participant's performance when they didn't know they would be judged in a way ... A potential employer might use that and discriminate against us." P10 further elaborated that organizations might find fault in students' actions from the video and audio, which may affect "their willingness to employ us later."

Academic Integrity Finally, students were worried that leaked videos could compromise the authenticity of subsequent learning scenarios, leading to academic integrity issues. P5 pointed out that if students from other classes viewed the simulations in advance, "it's not an actual reaction anymore." P4 validated this sentiment by imagining another scenario where "a past student has given a current student access to the videos and the visualizations so that they can get a better score ... they've breached academic integrity and policies."

4.2.3 Delineation of Accountability

Students delineated accountability for data misuse between institutional and individual levels. Institutions, particularly universities and research teams, are seen as the primary custodians of data, bearing the responsibility for its safeguarding and ethical handling. P2 stressed the role of the "Director of the program, the uni as a whole [is] responsible ... they should really ensure that this sort of stuff is encrypted." P12 reiterated this trust in institutions, believing that the university "should be responsible." P7 emphasized the importance of the research team and university implementing consistent privacy policies, suggesting that anyone handling the data should protect the privacy of those in the videos, especially when sharing with third parties. At the individual level, responsibility for data extends to all who interact with, access, or disseminate the data. Teachers, as the bridge between data and its pedagogical implications, were particularly highlighted. P1 believed that teachers "should be responsible for like how they communicate with the student" and their conveyed judgments. Additionally, any individuals, including students, who misuse the data, either deliberately or accidentally, should be held accountable. P4 pinpointed that "the person who gave the information, as well as a student who had the intent to use it for to cheat essentially would get in trouble." P9 further emphasized the seriousness of unauthorized data sharing, stating that "whoever would be sharing this video ... should have to suffer the consequences for it."

4.2.4 Prevention of Data Misuse

Participants provided insights into the measures that should be in place to protect data from misuse. First, participants like P2 highlighted strict access control, noting the importance of "encryption" coupled with "limiting access" to the data. P9 further elaborated that students should access the data "indirectly" where they "saw once on the screen," with P7 suggesting that students could "see the videos on a centralized platform" for a limited time. Moreover, P10 suggested measures like ensuring a secure online environment, relying on existing platforms like Moodle, while P11 introduced a novel concept of using "blockchain encryption," inspired by its application in healthcare, as a potential measure to ensure data integrity. Lastly, P3 emphasized anonymity, suggesting that "the quality [of videos shouldn't be] good enough to do facial recognition" yet they should retain enough detail for those in the simulation to recognize their participation.

4.3 Transparency (RQ3)

4.3.1 Data Collection and Tools

Students' understanding of data capturing and the tools used was a prominent theme. Participants noted the multimodal data collection methods in the simulation. P2 summarized the multimodal nature of the tools, stating, "I do understand that the belly bag was for the sake of positioning, the microphone for the sake of audio obviously, and the cameras in the room also help with the positioning." P12 linked the tools directly to the visualizations, observing how the microphones and belly bag collected data for the ward map. However, not all students clearly understood how and what data was collected. P4 assumed that the data was mainly from "audio and video," while P6 believed that cameras played a primary role in "generating the ward map and prioritization behaviour chart [Figure 1]." In fact, the positioning data for both visualizations was captured by the positioning sensor inside the belly bag. This misconception was evident when P7 questioned the communication interaction diagram, wondering "how you really know to whom we talk." There was a gap between students' perceived and actual understanding. P9, discussing the prioritization chart, felt that the combination of tools captured data, even though the chart relied solely on the indoor positioning system. Despite this, the student believed their understanding was "adequate, maybe not a hundred percent."

4.3.2 Data Processing and Analysis

While most participants ($n = 11$), except P1, P2, and P14, attempted to explain their understanding of data processing, many relied on guesswork. Several believed data was synthesized to create the visualizations. P3 presumed, "All of my data would be put into one thing, and then it would be shuffled around like in Excel, and then you create graphs." P5 thought the system "gathers the thoughts from the simulation, and grabs it into the different visualizations," highlighting a general lack of clarity around data processing. The complexity and volume of data may have contributed to this confusion. P11 observed that while the collected information seemed "complicated," its presentation was "rather easy to interpret." P12 was puzzled by the rapidity of data processing, wondering "how exactly that was transformed so quickly," noting that the visualizations appeared almost immediately post-simulation. A lack of data and AI literacy could be another factor. Some students, like P6 and P13, believed data was manually analyzed by researchers. P6 thought that the creation of a communication behaviour diagram required human interpretation, while P13 assumed that researchers filled hexagons on the ward map based on student movement and speech. In contrast, P7 suggested that "maybe AI" was involved, while P11 envisioned an automated process with "an algorithm processing positioning data and transcribing" speech.

4.3.3 Motivation to Learn

Expanding on these misconceptions and lack of understanding, we asked students about their motivations for learning more details about data collection and processing. Out of the 14 students, only P3 showed no interest as long as they could use and reflect upon the visualizations. In contrast, P8 found that "it's interesting . . . helps me understand the charts a bit better." Further, P13 felt that "seeing how it [visualization] was achieved" could help them to "better understand how accurate it is." Notably, P14 highlighted that understanding "how the data was processed" can contribute to "how much you'll be able to trust those [visualizations]."

4.4 Ethics (RQ4)

This subsection focuses on investigating and making sense of students' decisions and preferences regarding consenting methods. We present the findings in three parts, corresponding to the questions we asked in the interview.

4.4.1 Informed Consent and Explanatory Statement

By inquiring about students' awareness and engagement with the explanatory statement, we examined their understanding of the provided information in the decision-making process. While all participants were aware of the statement and their rights to opt out, only five (P5, P9, P10, P12, P14) fully read it. The remaining nine had various reasons for not doing so. P1 expressed a carefree attitude, saying, "I didn't read it or anything. But I didn't really mind if stuff [data] was used." P3 was enthusiastic, noting, "I didn't read it in full. But that's because I was already ready to engage and happy for this data [to be used]," suggesting trust in the data usage. P6 felt that it was too lengthy, remarking, "Because I never read the terms and conditions, it's just too long," despite the fact that the document was just over two pages. Additionally, reading the document did not guarantee full comprehension, with P10 admitting they "skimmed over it pretty quickly" and P14 not reading "it word by word."

4.4.2 Motivation for Participation

We also explored the motivation for students to stay in the study and allow their data to be used for research. A prominent factor was the belief in the values and benefits of their contribution to research, education, and even practice. P1 trusted the authenticity of the research, noting, "If you guys are doing it for research, I know that you'd be doing it for something cool or good." P2 believed that their participation might "benefit someone [a PhD or Master's student] and help them graduate." P8 saw the potential for their data to benefit the development of "better education and learning tools," and P12 initially felt that it was "daunting at the start because I knew everybody's watching" but later believed that the data could enhance future practices. P3 viewed their participation as both a personal learning opportunity and a means to improve patient care, hoping that "this [participation] is one little thing that I get benefit out of, and a lot of other people can get benefit out of." Trust in the institution also played a role. P11 said, "I did trust the university to use my data in a way that is responsible." Similarly, P10 felt "comfortable" that the data would not be used to judge them.

4.4.3 Opt-Out versus Opt-In Consent Method

When discussing the preference between opt-out and opt-in consenting, 11 participants (P1–4, P6, P8–10, and P12–14) favoured the opt-out approach used in the study. In contrast, three participants (P5, P7, and P11) preferred the opt-in method. For those preferring the opt-out method, the primary reason was the ease of participation and little effort required by this approach. P12 found it "easier," and P1 believed many students tend to avoid extra steps, observing, "knowing my cohort, people are kind of lazy . . . if you want data, give them the choice to opt out." P6 felt that "if I need to opt in, I probably wouldn't have been participating." This student also suggested that employing the opt-in method would require "more effort" to recruit the same number of participants, whereas using the opt-out approach, "if there are people that disagree with their data being collected, they would take action." Similarly, P13 anticipated a higher participation rate "with the opt-out approach, maybe get more people to be using the study and it's still made very clear to the people who definitely don't want to be in it, that it is an option. So I just reckon it works better." Nonetheless, some pinpointed the importance of clear communication about their options to exit the study before the simulation started. P10 advocated for an "informed opt-out" to ensure that students know that "they can opt out and what it means if you don't opt out." P4 reinforced the importance, expressing that confusion between participating in the simulation and the research was not clarified "until right before when I got given the headset and the belly bag." Conversely, proponents of opt-in valued the autonomy and control it offered. P7 appreciated that it gave people "autonomy," and P11 sought "more control and more informed choice." P5 felt that the opt-in method would prevent misunderstandings, ensuring that students knew that they were "participating in this study."

5. Discussion

5.1 Main Findings

In this study, we uncovered students' perceptions of FATE issues of MMLA visualizations in an authentic learning setting. The majority of students equated **fairness (RQ1)** with the accuracy of visualizations, aligning with previous studies on LA dashboards, which emphasized the equitable and impartial reporting and visualization of LA (Verbert et al., 2020). This accurate reporting could be particularly challenging for MMLA. Apart from ensuring algorithmic fairness, MMLA, reliant on sensing technologies, can encounter technical challenges, leading to **flawed or incomplete data** during the collection process, leading to biased and unfair representation, echoing prior logistical concerns (Yan et al., 2022; Ouhaichi et al., 2023). Likewise, students also attributed their concerns to the lack of consideration in the decision-making process during data selection, analysis, reporting, and visualization, resonating with prior works on algorithmic fairness (Jiang & Pardos, 2021; Kim & Cho, 2022) that understanding and addressing fairness issues is a holistic and multistage process (Barbierato et al., 2022). Specifically, in MMLA, selective data handling could lead to potential biases such as **lack of depth and context of communication** and **failure to account for individual contributions**. Additionally, students' perceived fairness of the visualizations is also context dependent, emphasizing the need to differentiate the individual challenges, for example, setting role-based rubrics when their grade is at stake. As the goal of LA is to optimize learning, fairness should not be limited to algorithms but also extend to a student-centric process where the decisions related to reporting and visualization are also considered (Verbert et al., 2020).

Regarding **accountability (RQ2)**, most students supported sharing their data within their class for collaborative learning and reflection but were cautious about sharing with other classes, fearing judgment. Educators, particularly unit coordinators and teachers, were largely supported to access the data to improve teaching methods, though some students advocated for differentiated access levels. For third parties, some participants recognized the potential value for researchers, while only a few felt university admin staff should have access. These views align with Mangaroska and colleagues (2021)'s findings, showing students' willingness to share anonymous data with educators. However, concerns were raised about potential misuse, including judgment, privacy breaches, impact on future career prospects, and academic integrity. These issues are particularly evidenced in identifiable personal data such as audio and video, echoing past studies (Mangaroska et al., 2021; Prinsloo et al., 2023; Liu & Khalil, 2023). Lastly, students believed accountability for data misuse should lie both with institutions, such as universities and research teams, and with individuals, especially teachers and those misusing the data. These findings resonate with prior works that accountability is beyond an individual person but distributed across multiple parties (Prinsloo & Slade, 2017; Pardo & Siemens, 2014).

For **transparency (RQ3)**, while participants understood the multimodal nature of tools, they held misconceptions about data capture specifics. Many students showed uncertainty about data processing and analysis, with varied guesses ranging from manual analysis by researchers to automated AI systems. Such misconceptions and lack of understanding resonate with prior studies of transparency in higher education (Tsai et al., 2019). Specifically, transparency might be more challenging to achieve in students than in teachers, where teachers may have more theoretical and contextual knowledge for comprehending the data analysis (Kasepalu et al., 2021). Yet, most students were keen to understand the data collection and processing, as such information could foster their trust in the technology and visualizations. This finding suggested the need to develop measures and mechanisms to evaluate and cultivate students' comprehension of the data collection and analysis processes, especially in MMLA studies where multiple sensors that might be unfamiliar to students could be used to capture physical or physiological data (Cukurova et al., 2020; Prinsloo et al., 2023). Similar to the transparency index for AI in education (Chaudhry et al., 2022), the field of MMLA also needs a transparency evaluation framework to account for the unique challenges of this field.

In terms of **ethics (RQ4)**, specifically examining the consenting methods, all participants were aware of the explanatory statement, but only five fully read it due to reasons ranging from carefree attitudes to perceptions of lengthiness. These perceptions align with prior concerns regarding consenting without full comprehension (Prinsloo & Slade, 2016; Li et al., 2022). This finding supports the imperative need to scrutinize our conception of informed consent from a dichotomous view to a continuous scale that captures different levels of comprehension and the importance of developing practical tools to measure such differences, such as an informed consent comprehension test (Beardsley et al., 2020). Most participants favoured the opt-out approach for its ease, anticipating a higher participation rate. However, the importance of clear communication and understanding of their options was emphasized. Conversely, those preferring the opt-in method valued the greater autonomy and control it provides, ensuring that participants are more informed and conscious of their choice to participate. This preference for the opt-out approach resonates with prior works, which reported similar results (Junghans et al., 2005; Li et al., 2019). Regardless of the consent method, clear communication and ensuring autonomy are essential for all participants, further supporting the need to transform the current consenting practices to ensure informed participation in LA and MMLA initiatives (Li et al., 2022; Beardsley et al., 2020; Sun et al., 2019).

5.2 Implications

The findings have several **implications** for future research and practices. Firstly, there is a need to ensure the fairness of visualizations by addressing algorithmic, technical, and representation challenges (Verbert et al., 2020; Ouhaichi et al., 2023; Barbierato et al., 2022). This necessitates a student-centred approach that prioritizes transparent and equitable data representation and decision-making processes, ensuring the alignment between researchers' selective representation of learner data and students' learning needs (Gašević et al., 2014). However, achieving a balance among these objectives—student-centred approaches, transparency, equitability, and accurate model representation—poses significant challenges. It is crucial to acknowledge that while striving for an ideal integration of these aspects, compromises may be inevitable. For example, the issue of fairness due to incomplete representation observed in the current study represents a compromise made to balance data richness and technical feasibility (Martinez-Maldonado et al., 2023; Chejara et al., 2023). Future research should aim to develop frameworks that optimize these competing priorities, ensuring that no single objective disproportionately undermines the others.

To provide a more practical perspective, it is important to consider how to prioritize these four objectives depending on the specific learning context. For instance, in a formative assessment scenario, the focus might lean more toward student-centred approaches and transparency (Bose & Rengel, 2009; Yan et al., 2024). Here, providing students with clear, understandable data visualizations that help them reflect on their learning progress is crucial (Alfredo et al., 2024). In this situation, while equitability and model accuracy are still important, they may take a secondary role to ensure that the students' immediate learning needs and comprehension are met. Conversely, in a summative assessment context where the stakes are higher, the emphasis might shift toward ensuring model accuracy and equitability (Darabi Bazvand & Rasooli, 2022). Accurate representations of student performance are critical to fair outcomes, and transparency about how these assessments are conducted can help maintain trust in the system (Carless, 2009; Dolan et al., 2019). In such cases, while it is still important to consider student-centred approaches, the primary focus may need to be on the integrity and fairness of the assessment process. For collaborative learning environments, the balance might be more evenly distributed. Equitability in data representation ensures that all students have fair access to collaborative tools and resources, while transparency helps students understand how their data is being used and shared (Chaudhry et al., 2022). At the same time, maintaining a student-centred approach ensures that the tools and visualizations used are genuinely beneficial for their collaborative efforts (Friend Wise et al., 2021), and model accuracy and explainability ensure that the insights provided are reliable and trustworthy (Khosravi et al., 2022).

Secondly, while students appreciate the benefits of sharing data for reflective and collaborative learning, they remain cautious about the broader dissemination, particularly when personal identifiers are involved. This highlights the importance of differentiated access levels and robust protocols to safeguard students' data, where different parties can be held accountable in case of data misuse (Prinsloo & Slade, 2017; Pardo & Siemens, 2014). Furthermore, the evident misconceptions about the data collection and analysis processes underline the urgency of fostering transparency (Tsai et al., 2019), potentially through developing transparency evaluation frameworks for MMLA and tailoring educational interventions to cultivate student comprehension (Chaudhry et al., 2022). Lastly, the complexities surrounding informed consent warrant a shift from traditional dichotomous views to more nuanced, continuous scales that accurately reflect comprehension levels. As such, future studies should prioritize the development of mechanisms that facilitate in-depth understanding, coupled with flexible consent options that respect student autonomy (Beardsley et al., 2020; Li et al., 2022). Collectively, these insights motivate a call to action for the LA and MMLA communities to devote more research initiatives to focusing on FATE, ensuring that the field remains student centred and ethically robust.

5.3 Limitations and Future Works

Several **limitations** should be considered when interpreting the current results. Firstly, FATE is a multidimensional concept; in fact, each aspect of FATE is a multifaceted concept that covers a range of implications from technical to socioeconomic.

Consequently, our exploration might not capture all the nuances and complexities. We predominantly focused on students' perceptions, which, while insightful, may not represent the views of broader stakeholders, such as educators, administrators, and tech developers. Secondly, the context of the study, being situated in an authentic collaborative learning setting and as part of formative assessment, may not be generalizable to other educational contexts, such as during self-regulated learning or in summative assessments where students' grades are at stake. Thirdly, students' perspectives on FATE may also be limited to the sensors and technology we deployed. For example, there could be differences in students' perspectives when more personal data, such as heart rate, is used for the visualizations, where they might be more hesitant to share such data (Mangaroska et al., 2021). Lastly, there is a selection bias, where we only investigated the perspectives of a sample of students who were willing to participate. Future studies should consider using a more diverse set of methodologies and including a broader range of participants to provide a more comprehensive understanding of FATE issues in LA and MMLA. Additionally, further exploration into the underlying reasons behind the personal differences in students' perspectives could provide valuable insights about ensuring the efficacy of the MMLA solution in addressing the needs of a diverse student population and understanding the role of FATE in educational practices.

6. Conclusion

In this study, we delved into students' perceptions of FATE issues of MMLA visualizations within an authentic collaborative learning setting. The findings highlight the significance of ensuring fairness in data visualization, the nuanced complexities surrounding data sharing, the imperative of transparency in data processes, and the ethical intricacies of informed consent. While students value the benefits of MMLA, they also emphasize the importance of ethical considerations, highlighting a pressing need for the LA and MMLA communities to actively investigate and address FATE issues. As technology and educational paradigms continue to advance, it becomes critical for LA researchers and practitioners to prioritize a student-centric approach, fostering a balance between innovation and ethical responsibility.

Declaration of Conflicting Interest

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