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Stepping Outside the Ivory Tower: How Can We Implement Multimodal Learning Analytics in Ecological Settings, and Turn Complex Temporal Data Sources into Actionable Insights?

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Abstract: The field of Multimodal Learning Analytics (MMLA) is expanding, allowing researchers to capture rich, fine-grained data on learning processes in a variety of learning environments. High-quality process data can open the door for new insights on how people learn, creative interventions to support them, and build the foundation for personalized learning platforms. There is, however, a growing recognition that there is a lack of ecological implementations in MMLA (Cukurova, Giannakos & Martinez-Maldonado, 2020): the vast majority of projects are lab-based, which limit the generalizability and impact of multimodal sensing in education. This symposium brings together researchers who have used MMLA methods in the wild. The panel will discuss obstacles to the use of multimodal data in real-world settings, share lessons learned from current projects, and propose productive next steps for the field to become more ecologically relevant.

Introduction

Multimodal Learning Analytics (MMLA; Blikstein, 2013) is a field of research that involves analyzing and interpreting data from diverse sources to understand and improve the process of learning and instruction. The term "multimodal" refers to the various modes of communication (such as speech, text, eye-movement, gestures, facial expressions, etc.) and interaction (like physical artifacts, technological interfaces, etc.) that are taken into account. The aim of MMLA is to provide meaningful insights into the learning process by integrating and examining data from multiple dimensions. It seeks to understand how different modalities contribute to learning, how they intersect and influence each other; and helps in designing effective learning environments. It applies various methods and techniques such as machine learning, data mining, and artificial intelligence to process, organize, and interpret complex data. MMLA has substantial implications for personalizing learning experiences, improving teaching methodologies, providing real-time feedback, and promoting successful learning outcomes.

Researchers, however, are recognizing that there is a need for more ecological validity and impact from MMLA: "there is a clear need for further work in the implementation of MMLA systems in authentic spaces where learning occurs (e.g., homes, classrooms, museums), an endeavor that is already acknowledged as challenging (Baker, Ocumpaugh, & Calvo, 2015). It is clear that this line of work has not yet reached its full capacity, and proper in situ setups hold the potential to bridge data quality and ecological validation..." (Cukurova, Giannakos & Martinez-Maldonado, 2020). In a literature review on the scalability of MMLA, Yan, Zhao, Gasevic and Martinez-Maldonado (2022) found that more than half (51%) studies were conducted in laboratory settings. In a related field (Multimodal Collaboration Analytics, MMCA), Schneider et al. (submitted) have reviewed 147 studies that have used multimodal sensing to capture collaborative processes. They found that only 24 (16%) of them took place in ecological settings.

In short, there is growing evidence that MMLA can be helpful in capturing learning processes in controlled environments; but there is a need to generalize these results to practice. This symposium brings together five perspectives to discuss the challenges of using MMLA in ecological settings. Each researcher presents a project below, with lessons learned and proposed solutions to facilitate the use of multimodal data in education. The symposium will discuss a wide range of issues, such as data privacy, ethics, validity, setting up complex data collection pipelines, data fusion (i.e., synchronizing and integrating different data streams), data analysis (i.e., finding signal in the noise), the role of theory in MMLA, replication in educational research, and more. The outcome of the symposium is to draft a preliminary list of Grand Challenges in MMLA and a research agenda to address them.

Contribution #1: Multimodal learning analytics to support learning and teaching in constructionist learning environments

Bertrand Schneider

Project description

Constructionist learning environments, such as makerspaces and digital fabrication labs, are ideal training grounds for cultivating 21st century skills. These environments are inherently student-centered and project-based, through tasks that carry real-world relevance. However, the very nature of such open-ended spaces, where each student follows a unique learning trajectory, presents significant challenges, making the measurement of learning progress complex. To tackle this issue, we have instrumented our makerspace with eight cameras capturing both pose and gaze data (Figure 1; the left image shows the 3D pose and gaze data mapped onto a floorplan of the makerspace; the right side shows the field of view of a camera where the same two students are collaborating while another one is working at the laser cutter). This approach has generated millions of observations, offering an alternative glimpse into students' learning processes and interactions. Our current challenge is to make sense of this rich dataset and use it to enhance both learning and teaching. We are considering different data-driven interventions to support learners and teachers. This includes the development of a dashboard (Guillain & Schneider, 2021), which, despite its potential usefulness, has been underutilized, as well as explorations in the use of GPT-based feedback systems (Sung, Guillain & Schneider, 2022). These efforts aim to translate that data into practical tools and feedback that can improve teaching and improve students' learning outcomes using multimodal sensing data.

Figure 1
The Makerspace is Equipped with 8 High Resolution Cameras used to Extract Multimodal Data.

Challenges

We had to overcome several challenges during this project. The first was to capture accurate data from the makerspace. We first tried to build our own platform based on Microsoft Kinect sensors. Unfortunately, cleaning the data took a significant amount of time because we had to connect different datasets, remove duplicates, connect tracks, and manually clean up corner cases. We then moved to a self-contained package (openptrack.org), which is now deprecated and resulted in a dataset that was too noisy to be usable. Finally, we partnered with the Montessori Wildflower schools and used their 3D reconstruction algorithm, which worked well in our setting (github.com/WildflowerSchools/poseconnect).

The next major challenge was to persuade the institutional review board (IRB) and students that decreasing data privacy would result in new insights and increased learning outcomes. We were careful to frame this project as a way to improve the quality and frequency of formative feedback for learners and improve data-driven decision making for teachers. We specified that the data would never be used for summative assessment, or impact students' learning experience. Additionally, we did not collect audio data to avoid a situation where students would feel spied on. We devised an opt-out procedure, where students could ask us to discard their data. Finally, we showed them the final anonymized dataset (i.e., the stick figures on the left side of Figure 1). This resulted in an environment where students were comfortable having their data recorded.

Once the data is generated, however, you need to analyze it and make sense of the results. Using theory (Wise & Shaffer, 2015) helped us generate meaningful metrics and validate them (Chng, Seyam, Yao & Schneider, 2022). A final challenge was to use quantitative methods on such a small dataset (~20 students). To produce meaningful results, we had to run the same course 2-3 times over 2-3 years. This generated a dataset of 40-60 students, which took considerably longer to collect than some other types of studies.

Lessons learned

Even though this project is ongoing, we learned several lessons that apply to other learning environments and MMLA implementations: 1) if possible, find partners who are working on the same problem (instead of reinventing the wheel); 2) work with students to understand their level of comfort with data collection tools, and which measures need to be taken to create a safe and trusted learning environment; 3) avoid collecting data that impacts privacy (e.g., speech), especially if it's not crucial for answering research questions; 4) as much as possible, adopt participatory design methodologies to create useful platforms for learners and teachers (e.g., Guillain & Schneider, 2021); 5) don't underestimate the technical know-how and infrastructure required to collect and process multimodal data; 6) focus on formative (and not summative) assessment; 7) use theory to guide data analysis (e.g., Chng, Seyam, Yao & Schneider, 2022); 8) replicate results across different cohorts, especially when working with small sample sizes.

Contribution #2: Obstacles facing adoption of (MM)LA for formative assessment in higher education

Richard Lee Davis

Project description

What will it take to bring MMLA out of the research world and into practice? What obstacles and challenges should we expect to face? We have explored these questions by carrying out a series of qualitative studies investigating the adoption (or lack thereof) of learning analytics tools in higher education. In interviews with instructors and teaching assistants we have uncovered a set of needs that indicate that there is a place for learning analytics tools in classroom practice. At the same time, we have identified a number of concerns and constraints that help explain why adoption in practice has been low, and which suggest that the path to adoption is substantially more difficult than previously acknowledged. We have advanced a theoretical framework to support the adoption of LA in practice and anticipate how these insights might inform efforts to utilize MMLA for formative assessment in higher education.

Challenges, lessons learned, next steps

We have identified obstacles to both adoption and use of LA in higher education. To help make sense of the obstacles to adoption, we have developed the TACT framework (Technology Adoption Costs and Tolerances) (Davis et al., 2023) which theorizes that teachers' willingness to adopt new LA technologies is a function of two things: the adoption costs of a technology and the teacher's tolerances to those costs. When an LA tool fits with a teacher's existing practices and meets perceived needs, tolerances to adoption costs are high. Otherwise, tolerances, and prospects for adoption, are low.

MMLA systems are likely to impose very high adoption costs because they typically require new forms of classroom instrumentation and generate novel types of data. To ensure that teachers are willing to tolerate these costs, it is essential for MMLA systems to mesh with teachers' existing practices and meet their real needs. At least initially, this will restrict uses of MMLA to specific types of learning environments (open-ended spaces) and to specific types of teachers (those already using formative assessment in their teaching). Even when these conditions are met, care must be taken to ensure that adoption costs are as low as possible. An advantage of human-centered methods, like those used by Martinez-Maldonado in the development of AIAugmentTeam, is that they help keep costs low.

Even after adoption, obstacles to the use of MMLA in higher education remain. Teachers in our interviews expressed concerns about how introducing LA tools into exercise sessions might degrade environments of trust and safety that they had worked hard to cultivate. At least in the context of our study, students were perceived as placing high value on rights to anonymity and privacy, and teachers worried that LA tools would be perceived as violating these rights (Cai et al., 2023). These concerns are likely to be exacerbated by the multiple sources of data collected by MMLA systems. As both Schneider and Martinez-Maldonado explain, care must be taken to ensure that the data collection process is transparent, that students have the option to opt-out of data collection, and that the benefits of these systems are clearly communicated.

Next steps for the project and for the field

Co-designing MMLA tools with teachers and students provides the clearest path to use in classrooms, as it helps break down obstacles to both adoption and use. By tailoring the tools to a specific context and set of needs, adoption costs are lowered and tolerances to those costs are raised. And by building the tools together with stakeholders, fears about malicious uses of data can be defused since the design and implementation is made transparent through the co-design process. This makes co-design ideal for development and small-scale deployment of MMLA tools in higher education.

An important open question is whether co-design methods can be extended to handle medium- and large-scale applications of MMLA for formative assessment, or whether a different approach is needed. When the number of potential users grows into the hundreds, or even thousands, traditional co-design approaches are no longer viable due to the amount of time and care needed. There is a need to identify strategies that bring the same benefits of co-design, otherwise adoption of MMLA for formative assessment will suffer.

Contribution #3: AIAugmentTeam: Multimodal teamwork analytics in immersive healthcare simulation

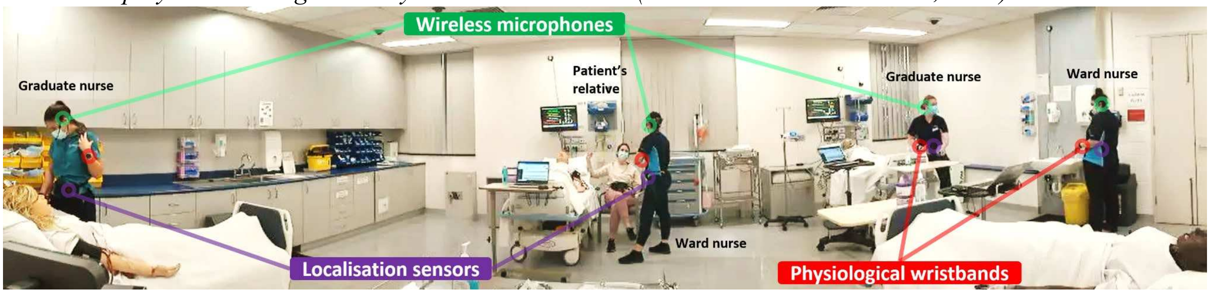
Roberto Martinez-Maldonado

Project description

Advancements in MMLA and Generative AI (GenAI) are revolutionizing how we understand and improve collaborative learning among students. These technologies significantly enhance our ability to support the development of teamwork skills and the reflective practices of both students and teachers, especially in situations where learning is not necessarily mediated by computers. However, currently, only a few MMLA tools offer practical feedback to students and teachers to aid in this reflection (Yan et al., 2022). **AIAugmenTeam** is an MMLA platform designed to give actionable feedback on team interactions. The system includes: (i) *a data capture platform* that works with various sensors (like microphones and position trackers), physiological wristbands, and teacher annotation tools; (ii) *a data analysis system* that turns raw data into meaningful insights, including using GenAI to automate transcription and analyze team dialogues; and (iii) *human-centered interfaces* for teachers to give augmented feedback during team sessions. To date, the tool is currently tailored for immersive team simulations within healthcare settings and has been employed by 620 students and 18 teachers in real-world classrooms from 2021 to 2023. In 2023 alone, five teachers have adopted it as a regular analytics tool. According to the most up-to-date MMLA literature reviews (Yan et al., 2022), our implementation represents the most extensive MMLA study to date that completes the learning analytics loop by offering students and their teachers direct, group-based feedback via MMLA-enabled visual interfaces.

Figure 2

Sensors Deployed in the High-Fidelity Medical Simulation (Martinez-Maldonado et al., 2023).



Lessons learned

We synthesized a set of lessons learned from a large human-centered MMLA study conducted in-the-wild (i.e., a deployment that is as naturalistic as possible) in the context of nursing education (e.g., see Figure 2). This study took place over three years, with three key phases. The first focused on data collection only, the second on using an MMLA dashboard for classroom reflection, and the third on enhancing teachers' reflection and leadership with a co-designed orchestration/analytics tool. Our lessons learned have been detailed elsewhere (Martinez-Maldonado et al., 2023) and are summarized as following: 1. *Human-Centered Design, Teaching and Learning*: Teachers partnering with researchers in the design process of MMLA systems leads to better alignment with teaching practices and learning goals. 2. *Human-Centered MMLA and Research Innovation*: Involving teachers and students in the design process helps validate MMLA interfaces and improves the logistics of MMLA research studies. 3. *Consenting and Participation Strategies*: Explaining complex MMLA studies to students in person rather than providing excessive technical details about sensors and analytics helps in gaining informed consent. 4. *Data Privacy and Sharing*: Students are willing to share their multimodal data for learning purposes if their privacy is ensured. Some see the benefit in making their data available for others' learning or for teachers to improve learning tasks. 5. *Technological Sustainability*: A lightweight microservices-based architecture that allows for easy attachment and detachment of various sensors can enhance long-term technical sustainability. 6. *MMLA Appropriation in the Classroo*m: Embedding sensing capabilities in the classroom, empowering users, training teachers in system usage and data interpretation, and minimizing the need for technical support can maximize the adoption and effective use of MMLA technology.

Suggestions for the field

Based on our first-hand experiences in deploying MMLA in-the-wild, we have synthesized the following suggestions for researchers and practitioners. *1. Collaborative Design with Teachers and Students:* Effective use of sensor data in education requires close collaboration between teachers, students, and technology developers. This collaboration can ensure that the data and technology align with educational goals and teaching methods. Involving teachers and students in designing these systems helps address practical challenges and makes the data more meaningful and useful in real classroom settings. 2. *Acknowledging Data Limitations and Empowering Teachers*: Data from sensors can be imperfect or incomplete. MMLA systems should avoid making automatic decisions based on this data. Teachers need control over these systems and should be informed about the reliability of the data. This also highlights the importance of training teachers to understand and use this technology effectively. 3. *Prioritizing Safety and Privacy*: Introducing advanced technology in classrooms raises privacy and surveillance concerns. Teachers and students should be aware of how their data might be used and have control over it. Guidelines for data privacy and user consent are crucial, especially for sensitive information. Systems should be designed to allow users to manage their own data, including the option to delete it after educational use.

Contribution #4: Multimodal learning analytics in embodied learning environments

Gautam Biswas

Project description

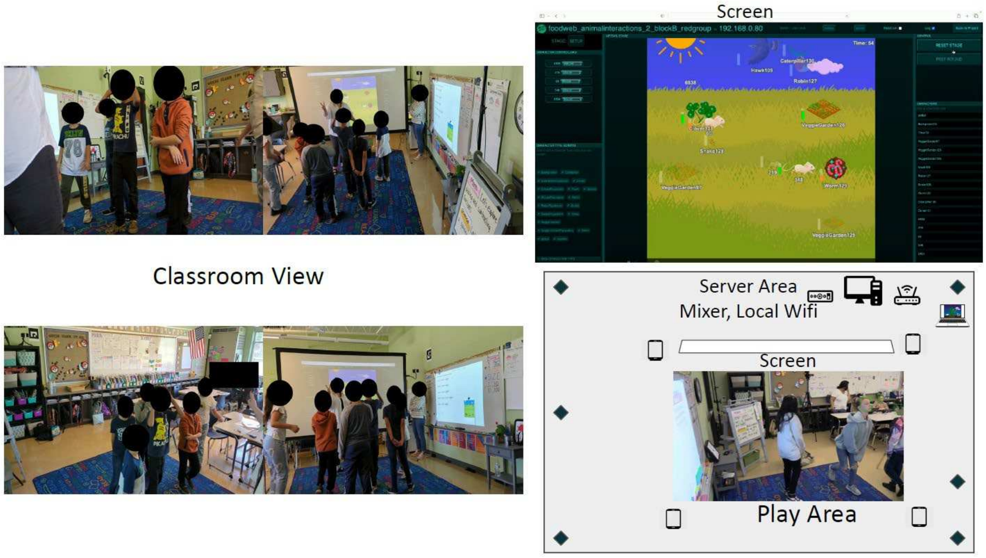
Embodied Learning builds on the demonstrated value of play or game-based learning in supporting the learning of domain knowledge and collaboration processes. In embodied learning, students are immersed in a mixed-reality environment, and this allows them to playfully explore science phenomena, such as the rules of particle behavior in solid, liquid and gas and the photosynthesis process through collective embodied activity (Tu, et al, 2019). Frameworks for analyzing embodied cognition, such as the Learning in Embodied Activity Framework (LEAF) framework have developed methods that account for collective activity without erasing and replacing the individual's role as part of the collective. LEAF supports the synthesis across individual and sociocultural theories of embodiment and thus provides a more robust account of how the body can play a role in both individual and collective cognition and learning (Danish, et al, 2020).

Currently, research teams use a combination of interaction analysis and qualitative coding of teacher and student interactions to examine patterns in the learning processes during the embodied play activities (Davis, et al, 2019). To support our embodied learning research team, we have now deployed our multimodal learning analytics (MMLA) pipeline to facilitate data collection from multiple cameras and microphones, posyx data for tracking student movements, and simulation log data that maps student movements and actions into the evolving science simulation (Davalos Anaya, et al, in press). In addition, we are combining state-of-the-art deep learning methods and human-in-the-loop learning to perform some of the interaction analyses online and capture events of interest as students enact a scenario, and then provide this information back to teachers and students to enhance classroom teaching and learning experiences. Currently, we have developed and applied methods for motion and gaze tracking for groups of 3-4 students enacting a scenario, the teacher, and other students in the classroom environment who support the group in their enactments. We are also developing face tracking algorithms that capture students' affective states, with the goal of extending the socio-cognitive framework in LEAF to a socio-cognitive-affective framework for embodied and collaborative learning.

Challenges and lessons learned

In this work supported by the NSF AI Institute on Engaged Learning, we have faced a number of computational, logistic, and IRB-related challenges in deploying our MMLA pipeline called Chimera Py in a constrained and noisy classroom environment (Figure 3). ChimeraPy is a minimal setup distributed streaming platform, is optimized for high throughput multimodal data transfer. Its architecture is designed to handle multiple challenges, such as time-aligned data collection and scalable multimodal analysis that overcomes the computational complexity of running multiple deep learning algorithms online by developing a reconfigurable distributed computing architecture. Besides, we have had to deal with additional issues, such as coherent treatment of signals from heterogeneous sensors, and the requirements for fusing large volumes of multimodal data. To address privacy issues, it advocates for in-network de-identification of sensitive data like video or GPS before internet transmission. Furthermore, in classroom environments space is constrained, configurations differ from classroom to classroom, and setup and takedown of the equipment has to happen quickly so as not to disrupt class scheduling and day to day classroom activities.

Figure 3.
Classroom Setup for Data Collection and Analysis.



Additional challenges that we are working on include human in the loop training of deep learning algorithms to study gaze cohesion and shifting from video that includes multiple actors (Zhou, et al, in review), the diarization of speech and the use of LLMs to summarize student conversations, and link the movements, gaze events, and utterances to generate a comprehensive summary of students' enactments in a scenario.

Suggestions for the field

Collecting, aligning, and analyzing multimodal data itself is a challenge, and it becomes an even greater challenge when the data has to be processed online to support feedback to learners as well as provide actionable insights to teachers to support their debriefing activities. Two key suggestions in this regard are: (1) the need for close collaboration between learning science and AI researchers to ensure that the analyses and inferences made from the data can be linked to educational theories; and (2) the emphasis on active learning that includes human in the loop few-shot approaches and in-context learning in training and fine tuning the deep learning models for multimodal analysis. Other suggestions include the development of robust infrastructure pipelines to support data collection and analyses in classroom environment, and building in ethical considerations into

Contribution #5: Collaboration analytics in K-12 and higher education space

Marcelo Worsley

Project description

Over the past decade, learning analytics researchers have developed a host of dashboards, toolkits, and algorithms that can help researchers and educators leverage video and audio data. However, we very seldom consider ways that learners might want to leverage this data to support self-regulated learning, metacognition, or reflection. The Building Literacy in N-Person Collaboration (BLINC) project (Worsley, Anderson, Melo & Jang, 2021) addresses this opportunity by providing a platform whose capabilities align with the ways that students want to learn about their collaboration practices. The BLINC architecture allows participants to use web-enabled devices with a microphone and, optionally, a camera to collect collaboration analytics in near real-time. The platform provides metrics about: distribution of speech, question annotation, sentiment analysis, topic annotation and keyword detection. Most metrics provided through BLINC are customizable to the user's needs. Additionally, the BLINC platform provides user anonymity by representing data at the group level.

Challenges

Developing this platform is requiring us to overcome a number of ongoing challenges. One of our early challenges was to think about a hardware infrastructure that would allow for reliable use across different contexts, and that could scale quickly. To address this challenge, we employ a *bring your own device* capability where participants use their own smartphones, computers, or tablets to utilize the platform. This eliminates the need for specialized hardware that can be hard for organizations to acquire and deploy. At the same time, the bring your own device capability, together with some backend decisions gives learners more ownership over when and how their data is collected. Students exercise control over when their data is being recorded.

Another significant challenge is student concerns about privacy and anonymity. As noted previously, we represent data at the group level, and avoid labeling any of the data with names. However, surveys among college students suggested that many of them would be concerned about having a video recording device used within the BLINC platform. We address this concern in a number of ways. First, participants can decide if they want to enable the video component of the platform at the start of each collaboration session. Secondly, we have integrated a cartoonification of the video data to obfuscate participant identities. We are currently in the process of testing if this approach will sufficiently assuage concerns around the use of video. While video is an optional feature, the addition of video information can help document contextual information about the collaboration, and support the extraction of additional relevant features (e.g., attention, facial expressions, head pose, gestures).

An additional set of challenges that we will briefly mention is with regard to the constantly changing landscape of artificial intelligence. Research teams around the world are constantly creating new innovations, and pushing the boundaries on what we can extract from various modalities. From a platform development perspective, we want to ensure that our tool is doing the best that it can to accurately represent student engagement and participation, but also want to maintain a stable and reliable platform.

Lessons learned

One of the main lessons learned within this work is the importance of building around the needs and desires of the stakeholders. In particular, we have centered the needs of students and made significant effort to ensure that the data, data representations, and interface aligns with their goals. At the same time, we have observed the importance of understanding the technological constraints/pain points of participants. While many technologies can work well in the context of small scale laboratory spaces, the challenge of scaling to large numbers of users in ecological settings can add significant constraints. For the BLINC project, we found success in using students' smartphones, as opposed to trying to deploy specialized microphone arrays. This constraint did result in some shifts in the quality of data that we could collect, and required us to find some additional approaches for giving people the data that they wanted to see without utilizing state of the art technology. The other major lesson that we have learned along the way has been the importance of not forgetting about the contextual nature of data and how it is interpreted. Our research participants have done a great job of reminding us that the shifts in context can result in the same piece of data being seen in a completely different light. Hence, part of our job is to provide participants with the pertinent data, and not be too quick to draw decontextualized inferences about what that data might be suggesting about the nature of the collaboration.

Suggestions for the field

Engaging participants in the process has been integral to our design process. This has meant thinking broadly about how the platform might be used, as well as connecting with participants that might have some very specific use cases. Part of being able to follow a user-centered design process is having a technical architecture that features flexibility, with components that can be quickly customized or swapped out. For BLINC this involves having a web-based API and a collection of services that we can connect to.

An additional suggestion is to acknowledge that perfection is infeasible, while also acknowledging where your tool might have gaps. There is no artificial intelligence tool on the market that works perfectly. The MMLA tools that we employ will not be an exception to that trend. In our case, we avoid making specific recommendations about how people should collaborate because of known shortcomings in our ability to effectively capture and represent the context. Instead, we invite learners to practice careful reflection and metacognition with regard to their data.

Discussion

The five contributions of this symposium highlight key challenges in the use of MMLA in real-world settings. Beyond technical obstacles (implementation, data collection, storage, data fusion, analysis, data-driven interventions), one of the foremost challenges is the sensitive nature of data privacy. MMLA researchers must navigate the complex landscape of ethical considerations, ensuring the protection of student information while leveraging data to enhance learning experiences. As suggested above, adopting a user-centered approach that involves educators, students, and stakeholders in the design process, can foster analytics tools that not only inform but also empower users. This requires analytics platforms to be intuitively understandable and seamlessly integrated within the existing pedagogical frameworks, ensuring that insights are directly translated into practical strategies for enhancing teaching effectiveness and student learning outcomes. This symposium and its panelists will explore these questions in depth, in collaboration with the ISLS community.

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