Framing the Future of Multimodal Learning Analytics

Marcelo Worsley

Abstract Multimodal Learning Analytics (MMLA) constitutes a broad set of research goals, approaches, and methodologies. Researchers have embarked upon projects that advance theory, improve practice, and offer new forms of interactivity. This plurality has been an important contributor to the growth of MMLA and will undoubtedly continue to propel the field forward. Alongside research in these individual paradigms, this chapter will suggest that one aspect of future MMLA research is integration across paradigms. Furthermore, it highlights opportunities to more thoroughly consider questions of ethics across the different components of the MMLA research pipeline. Finally, the chapter notes some ways that future research in MMLA might contribute to new conceptualizations of learning that hinge on some of the capabilities and affordances of multimodal data and multimodal analytics.

Keywords Multimodal learning analytics · Research paradigms · Theory · Ethics

1 Introduction

Current research in Multimodal Learning Analytics (MMLA) (Blikstein & Worsley, 2016) represents a plurality in perspectives and approaches (Sharma & Giannakos, 2020; Worsley, 2018). This plurality has contributed to advancements in research capabilities and surfaced some important contrasts in ways to conduct MMLA. This chapter will synthesize across different research from within this community and suggest some directions for future research and development within this space. This synthesis will entail three principle components. First, it will touch on different paradigms for MMLA research and development. Second, it will highlight a set of

M. Worsley (✉)
Northwestern University, Evanston, IL, USA
e-mail: marcelo.worsley@northwestern.edu

M. Giannakos et al. (eds.), *The Multimodal Learning Analytics Handbook*,
https://doi.org/10.1007/978-3-031-08076-0_14

commitments that consider how to advance ethics across all aspects of an MMLA research project. Third, it will hypothesize a collection of opportunities that could arguably drive a novel phase in MMLA research and education research more broadly.

2 MMLA Research Paradigms

Researchers embark on a variety of research endeavors under the auspices of MMLA (Sharma & Giannakos, 2020; Worsley et al., 2016). Three common approaches for utilizing MMLA include work for theorizing, for practice, and for interactivity. The sections to follow describe key elements of each of these paradigms and help situate where they differ and where they maintain similarities.

2.1 MMLA for Theorizing

A primary objective of many MMLA projects is to contribute to the fundamental body of research about human learning and cognition (Hammad et al., 2022). Work that uses MMLA for developing theories tends to utilize relatively small datasets and complement the computational analyses with significant human inference (Cukurova et al., 2019; Worsley et al., 2016). Substantively, this MMLA approach provides an increased level of specificity (Kubsch et al., 2022; Giannakos et al., 2022) and nuance in describing the learning processes that participants employ (Abrahamson et al., 2016; Tancredi et al., 2022). This may be accomplished through a small-scale study where researchers compare two or more approaches for differences in multimodal behaviors, or through multimodal analysis of participants using a specific interface (Cukurova et al., 2018; Schneider & Blikstein, 2015; Worsley & Blikstein, 2018) or environment (Malmberg et al., 2022; Vujovic et al., 2022). Within this paradigm the goal is seldom scaling to a large number of participants, or adoption of a specific technology in a given classroom context. Instead, the work aims to inform other researchers about the enactment of a certain learning practice. At the same time, the role of the multimodal technology need not be coupled with the learning objectives of the intervention and are more commonly present for data collection purposes. Furthermore, the use of MMLA in this setting does not necessitate real-time data processing. Researchers will likely return to analyze the data after the conclusion of all data collection.

While currently less common within the MMLA community, researchers might also work towards theory building by conducting large scale randomized trials that compare the efficacy of different interventions and use multimodal data (e.g., electro-dermal activity, heart rate, or verbal engagement) as a mediating, independent, or dependent variables within a quantitative analysis. Within many research communities, this approach represents the ideal approach for demonstrating causality of a given phenomenon. However, as will be described later, this approach is not necessarily the best use of MMLA.

2.2 MMLA for Practice

In addition to utilizing MMLA to develop new understandings about the inner workings of a given learning environment or context, MMLA research can be applied to supporting practice. Researchers may develop MMLA systems that are designed to support learners or educators in real-time, or post-hoc (Ochoa 2022; Shankar et al., 2022; Worsley et al., 2021a). As an example, researchers may want to help groups as they participate in a collaborative problem-solving task, or an instructor as they think about how best to design a given learning experience (Echeverria et al., 2018; Di Mitri et al., 2020). In both of these scenarios, multimodal sensors can be deployed to gather real-time information about how learners are currently engaging with an activity. Examples might include indoor location tracking, or a microphone array and depth camera. Using these technologies can serve to offload information that participants may find challenging to process or readily utilize without the assistance of computational tools that can aggregate data and visualize it. Unlike the case of theory building or conjecture mapping, much of the utility of practice-oriented systems is to support real-time human inference and insight. This requires that the systems reliably work within ecological settings as opposed to merely working within well-controlled laboratory contexts (Shankar et al., 2022). Moreover, it requires the development of workflows that integrate into the practices of teacher, students, and other stakeholders. However, similar to the instances of theory building, the multimodal sensors are not necessarily integral to the nature of the learning interaction. They are, once again, primarily incorporated for their data collection capabilities.

2.3 MMLA for Interactivity

Finally, researchers commonly explore projects that involve multimodal interactivity. Such systems are characterized by how they use multimodal sensors, and perhaps actuators, as central parts of the participant experience (Di Mitri et al., 2022; Schneider & Blikstein, 2015). These interfaces provide additional ways for learners to engage with a given learning experience. For instance, participants might control an interface using speech, gaze, and gestures. In other instances, they might interact with a sensor-enabled mannequin that provides in the moment, multimodal feedback about how they have approached a given scenario. In these ways, the multimodal technologies and analytics are a central part of the participant experience. These technologies provide novel ways for participants to engage with that learning environment. Frequently, these types of projects are geared towards smaller scale laboratory contexts as scaling up to more ecological settings involves significant financial and practical costs.

MMLA for interactivity also connects to creating opportunities for collaborative learning experiences where participants move away from traditional computer screens and engage in a variety of situated activities with other people. In some instances people might be engaging in a group discussion about a set of mathematics problems or collaboratively designing with a tangible, or gesture-enabled interface. Important to note, however, is that MMLA can be used to support different forms of interactivity with technology and with other people.

2.4 Paradigms Summary

The three paradigms described above represent non-mutually exclusive approaches. Increasingly, researchers are advancing work that bridges across one or more paradigm (Domínguez et al., 2015; Tancredi et al., 2022; Worsley et al., 2021a). For example, a platform designed for multimodal interactivity might also support identification and articulation of new theories. Exploring such cross-paradigm implementations will be an important part of growing MMLA research.

3 Realizing Ethical Practices Across Different Aspects of an MMLA Research Project

Regardless of which specific paradigm(s) a given project explores, researchers should be intentional about adopting equitable, inclusive, and ethical practices throughout the research process. Recent work (Worsley et al., 2021b) posits 12 commitments that can arguably advance the field of MMLA in a way that honors research participants. They organize their commitments around three critical elements of the MMLA research process: data collection, data analysis, and data dissemination. These commitments (see Table 1) represent a first step in thinking about designing the future of MMLA research. Rather than review each of the 12 commitments in details, this chapter will highlight one commitment from each part of the research pipeline.

3.1 Data Collection: Multimodal Data Control/Data Ownership

Multimodal learning analytics often uses very personal data. This is especially true as we endeavor to make algorithms as individualized as possible and minimize

Table 1 Twelve commitments for MMLA researchers to consider in data collection, data analysis, and data dissemination

Data collection	Analysis and inference	Feedback and dissemination
Multimodality: Recognize that learning is a multimodal process.	**Multimodal data and human inference:** Triangulate among different data sources and help inform interpretation of learner actions	**Transparency and benefit:** Ensure that the research process is transparent to participants and that the experiences provide obvious benefits
Expansive learning experiences: Advance opportunities to transcend traditional classroom activities.	**Limitations in prediction from multimodal data**: Predictions should be about learner actions and not about assigning decontextualized and static labels to learners	**Multimodal feedback:** Move beyond dashboards and consider ways to provide multimodal feedback to participants
Make learners' complexity visible: Utilize sensors that can reveal hard to see interactions, actions, and states	**Participatory interpretation of multimodal data**: Include participants within data analysis and inference processes	**Meaningful, usable feedback:** Develop feedback that is both usable and understandable to people outside of the research community
Learning across spaces: People learn in a variety of contexts.	**Representation and multimodal data analysis:** The ways that data are represented and analyzed plays a major role in the inferences that we draw	
Multimodal data control: Learners should have control of their data and how it is used		

bias. In some cases, the algorithms might include log or clickstream data. In other instances, they might include audio/video data, and suggest facial expressions, body poses, or even information about joint attention. Given these challenges, it is essential that researchers carefully reflect on who owns the data within these systems, and the implications this has on participants. Generally speaking, this commitment advocates for student/participant ownership of their data, but recognizes that this introduces additional challenges in terms of data analysis methodology and an additional division between researchers and the data that can be used to support MMLA research.

3.2 Data Analysis: Limitations in Prediction from Multimodal Data/Commitment to Fair and Ethical Language When Talking About Research Participants

Another commitment concerns how we talk about the individuals that participate in research. This is particularly important for marginalized communities whose values, practices, and identities may often be treated as inferior. This commitment suggests that MMLA research avoid classifying or labeling individuals based on their performance within a given learning environment. For instance, learners who receive low grades should not be labelled, or defined, as low achievers. Doing so reiterates many of the approaches that educational institutions have used to exclude and oppress marginalized groups. It also fails to acknowledge the contextual nature of the data and belies the understanding that people can learn and improve. A commitment to inclusive language also translates into the terms that we use to refer to different minoritized groups. Different groups have different preferences, and, we, as researchers and practitioners, that aim to engage with these different groups, must be sufficiently committed and invested to learn how different individuals wish to be referred to.

3.3 Data Dissemination: Transparency and Benefit/Moving Away from Research as an Extractive Process

This third commitment is about ensuring that the research can provide meaningful benefits to the participants. Furthermore, it advocates for processes and practices that are transparent and interpretable for the participants. While learning analytics research does not tend to produce noticeable physical or medical harm to participants, the MMLA community needs to move beyond avoiding harm, and actively consider how the research practices can provide substantive benefits to research participants in ways that extend beyond monetary compensation. We must commit to sharing findings with participants in ways that they can reasonably interpret. This has implications for research participants, but also serves to drive the research forward. At very least, it means that researchers must distill their findings into representations that can be interpreted by people outside of their discipline. It also increases the need for researchers to gather reflections and corroborate interpretations of data from participants, something that scarcely happens within current MMLA research projects.

3.4 Commitments Summary

The commitments outlined above bring new challenges for the field of MMLA. However, overcoming these challenges could prove to be essential for ensuring the longevity of this approach, and perhaps result in better integration between learning technologies and the various contexts where learning takes place. The following section will outline some potential opportunities related to driving the future of MMLA, and how taking an MMLA perspective can help reframe how the field thinks about and studies learning.

4 Re-conceptualizing Learning Through an MMLA Perspective

Thus far, this chapter has looked at existing paradigms within MMLA and some suggested considerations for how to conduct ethical research across different parts of a project. This chapter will now turn to discussing future visions for MMLA and how MMLA tools and techniques could have a substantive impact on the future of learning and education research.

4.1 Methods for Data Analysis with Increased Data Privacy and Control

If we as a field are to embrace privacy and ethics to their fullest extent, we must take seriously the need to allow participants to own and control their data. This means allowing them to determine when their data is being collecting and which aspects of their data will be shared. This, however, can introduce a significant challenge for many of our current analytic approaches. Notably, this would mean that the data being received is probably not a representative sample of the participant(s). The data will likely include significant gaps and may include an inconsistent set of modalities at different time points. Hence, analyzing this data in meaningful ways will require new techniques and innovations, as many existing algorithms experience significant difficulty under any of the three conditions listed above.

4.2 Developing New Standards for Non-traditional Metrics

Significant prior research in education has privileged certain forms of knowledge. This commonly amounts to knowledge that is provided in written form, and that relates to what may traditionally have been described as cognition. However, recent developments in education research have begun to highlight the various socio-cultural aspects of cognition, for example. Hence, we are moving away from a conceptualization of education that views cognition, or thinking, in isolation from the rest of the body. Importantly, MMLA can provide useful tools in realizing and surfacing a complementary set of metrics related to emotions and self-regulation for example. An important next step for MMLA research will be to further demonstrate the salience and interconnectedness of these different factors, while also establishing unbiased metrics and analytic processes for inferring them from different multimodal sensors.

4.3 Thinking About These Standards over Different Time Scales, Levels of Granularity, and Contexts

Alongside discussions about new metrics and standards, the field can also think about measuring learning across different time scales and contexts. At present, significant education research is concerned with learning from a single context and, frequently, over relatively fixed time scales. With the tools of MMLA and the ability to look at a wide range of learning-related metrics of different grain sizes, and in different contexts, the field can potentially ask new questions about how student learning is unfolding. Put differently, many of our existing metrics for success reflect a student's performance within a narrow context. In the case of standardized tests, that context is restricted to a small timescale and exists through a relatively unimodal task. As more tools are developed that support multimodal learning across spaces, we can start to reframe the dominant narratives around learning and elevate learning across contexts and across varying timescales.

4.4 Moving Beyond Randomized Control Trials as the Gold Standard

MMLA approaches could have a measurable impact on the school-based assessment landscape, but could also change how researchers approach generalizing research. Traditionally, randomized controlled trials have been the gold standard for demonstrating causality. Despite their experimental rigor, they tend to offer a limited window into the overall participant experience, and require highly regimented and narrow learning interventions. It is possible that MMLA can support more expansive ways to study the impact of different learning interventions and interfaces. Realizing such a methodological advancement would be a major stride in enabling different forms of education research.

4.5 *Embracing Deep, Nuanced, and Potentially Divergent Pictures of the Learner*

Finally, MMLA has the potential to advance a practice that pushes researchers, practitioners, and learners to examine and interrogate more of the nuances associated with learning. Consequently, much of the existing work in MMLA aims to support triangulation among different modalities. The assumption is that all of the modalities should seemingly point to the same insight or inference. However, we may find considerable value in exploring apparent divergence within the multimodal data that we collect. Doing so would move away from a model where we expect to see a single correct or more accurate behavior or response. It would instead ask us to think about how these differences might live alongside and respectfully inform one another. As envisioned, this process necessarily pushes towards acknowledging the nuance of these learning situations, while also noting the uncertainty and noise embedded in many multimodal data sources and their associated analytic techniques.

5 Conclusion

Current and prior work in MMLA has demonstrated that the techniques and technologies associated with MMLA hold apparent promise for advancing theory, practice, and interactivity. Moreover, a future where MMLA bridges across these three different paradigms will likely result in even richer and more fulfilling research. These future research initiatives, however, must carefully consider how to be intentional about adopting ethical, equitable, and inclusive practices across data collection, data analysis and data dissemination. While the research community may currently view these as nice-to-haves, it is likely that participant expectations for what constitutes ethical research will become more stringent. Moreover, MMLA research should endeavor to empower participants alongside researchers, as this may be essential to helping the field grow in impact and adoption. Most importantly, the future of MMLA has the potential to include several innovative new techniques and technologies that push the broader education community to reframe how they think about learning. This reframing encompasses the aspects of learning we attend to and the spaces where we study learning. It also opens doors to conversations around how learning is evidenced across different modalities and provides a space to nuance apparent divergences and synergies among different multimodal data.

References

Abrahamson, D., Shayan, S., Bakker, A., & Van Der Schaaf, M. (2016). Eye-tracking Piaget: Capturing the emergence of attentional anchors in the coordination of proportional motor action. *Human Development*. https://doi.org/10.1159/000443153

Kubsch, M., Caballero, D., & Uribe, P. (2022). Once more with feeling-emotions in multimodal learning analytics. In M. Giannakos, D. Spikol, D. DiMitri, K. Sharma, X. Ochoa, & R. Hammad (Eds.), *The multimodal learning analytics handbook*. Springer.

Blikstein, P., & Worsley, M. (2016). Multimodal learning analytics and education data mining: Using computational technologies to measure complex learning tasks. *Journal of Learning Analytics, 3*(2), 220–238. https://doi.org/10.18608/jla.2016.32.11

Cukurova, M., Luckin, R., Millán, E., & Mavrikis, M. (2018). The NISPI framework: Analysing collaborative problem-solving from students' physical interactions. *Computers & Education, 116*, 93–109. https://doi.org/10.1016/j.compedu.2017.08.007

Cukurova, M., Kent, C., & Luckin, R. (2019). Artificial intelligence and multimodal data in the service of human decision-making: A case study in debate tutoring. *British Journal of Educational Technology, 50*(6), 3032–3046.

Di Mitri, D., Schneider, J., Trebing, K., Sopka, S., Specht, M., & Drachsler, H. (2020). Real-time multimodal feedback with the CPR tutor. In *Artificial intelligence in education* (pp. 141–152). Springer.

Di Mitri, D., Schneider, J., Limbu, B., Mat Sanusi, K. A., & Klemke, R. (2022). Multimodal learning experience for deliberate practice. In M. Giannakos, D. Spikol, D. DiMitri, K. Sharma, X. Ochoa, & R. Hammad (Eds.), *The multimodal learning analytics handbook*. Springer.

Domínguez, F., Echeverría, V., Chiluiza, K., & Ochoa, X. (2015). Multimodal selfies: Designing a multimodal recording device for students in traditional classrooms. In *Proceedings of the 2015 ACM on international conference on multimodal interaction* (pp. 567–574). https://doi.org/10.1145/2818346.2830606

Echeverria, V., Martinez-Maldonado, R., Power, T., Hayes, C., & Shum, S. B. (2018). *Where is the nurse? Towards automatically visualising meaningful team movement in healthcare education*. Springer.

Giannakos, M., Cukurova, M., & Papavlasopoulou, S. (2022). Sensor-based analytics in education: Lessons learned from research in multimodal learning analytics. In M. Giannakos, D. Spikol, D. DiMitri, K. Sharma, X. Ochoa, & R. Hammad (Eds.), *The multimodal learning analytics handbook*. Springer.

Hammad, R., Bahja, M., & Kuhail, M. A. S. (2022). Bridging the gap between informal learning pedagogy and multimodal learning analytics. In M. Giannakos, D. Spikol, D. DiMitri, K. Sharma, X. Ochoa, & R. Hammad (Eds.), *The multimodal learning analytics handbook*. Springer.

Malmberg, J., Saqr, M., Järvenoja, H., Haataja, E., Pijeira-Díaz, H. J., & Järvelä, S. (2022). Modeling the complex interplay between monitoring events for regulated learning with psychological networks. In M. Giannakos, D. Spikol, D. DiMitri, K. Sharma, X. Ochoa, & R. Hammad (Eds.), *The multimodal learning analytics handbook*. Springer.

Ochoa, X. (2022). Multimodal systems for automated oral presentation feedback: A comparative analysis. In M. Giannakos, D. Spikol, D. DiMitri, K. Sharma, X. Ochoa, & R. Hammad (Eds.), *The multimodal learning analytics handbook*. Springer.

Schneider, B., & Blikstein, P. (2015). Unraveling students' interaction around a tangible interface using multimodal learning analytics. *Journal of Educational Data Mining, 7*(3), 89–116. https://doi.org/Retrieved from https://jedm.educationaldatamining.org/index.php/JEDM/article/view/JEDM102

Shankar, S. K., Rodríguez-Triana, M. J., Prieto, L. P., Calleja, A. R., & Chejara, P. (2022). CDM4MMLA: Contextualized data model for multimodal learning analytics. In M. Giannakos, D. Spikol, D. DiMitri, K. Sharma, X. Ochoa, & R. Hammad (Eds.), *The multimodal learning analytics handbook*. Springer.

Sharma, K., & Giannakos, M. (2020). Multimodal data capabilities for learning: What can multimodal data tell us about learning? *British Journal of Educational Technology*, e13280.

Tancredi, T., Abdu, R., Balasubramaniam, R., & Abrahamson, D. (2022). Intermodality in multimodal learning analytics for cognitive theory development: A case from embodied design for mathematics learning. Multimodal learning analytics and the design of learnings paces.

In M. Giannakos, D. Spikol, D. DiMitri, K. Sharma, X. Ochoa, & R. Hammad (Eds.), *The multimodal learning analytics handbook*. Springer.

Vujovic, M., Hernandez-Leo, D., Martinez-Maldonado, R., Cukurova, M., & Spikol, D. (2022). Multimodal learning analytics and the design of learnings paces. In M. Giannakos, D. Spikol, D. DiMitri, K. Sharma, X. Ochoa, & R. Hammad (Eds.), *The multimodal learning analytics handbook*. Springer.

Worsley, M. (2018). Multimodal learning analytics' past, present, and, potential futures. In *Companion proceedings of the 8th international conference on learning analytics & knowledge*.

Worsley, M., & Blikstein, P. (2018). A multimodal analysis of making. *International Journal of Artificial Intelligence in Education, 28*(3), 385–419. https://doi.org/10.1007/s40593-017-0160-1

Worsley, M., Abrahamson, D., Blikstein, P., Grover, S., Schneider, B., & Tissenbaum, M. (2016). Situating multimodal learning analytics. In *International conference for the learning sciences* (Vol. 2, pp. 1346–1349).

Worsley, M., Anderson, K., Melo, N., & Jang, J. (2021a). Designing analytics for collaboration literacy and student empowerment. *Journal of Learning Analytics*.

Worsley, M., Martinez-Maldonado, R., & D'Angelo, C. (2021b). A new era in multimodal learning analytics: Twelve core commitments to ground and grow MMLA. *Journal of Learning Analytics*, 1–18. https://doi.org/10.18608/jla.2021.7361