Rethinking MMLA: Design Considerations for Multimodal Learning Analytics Systems

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ABSTRACT

Designing MMLA systems is a complex task requiring a wide range of considerations. In this paper, we identify key considerations that are essential for designing MMLA systems. These considerations include data management, human factors, sensors and modalities, learning scenarios, privacy and ethics, interpretation and feedback, and data collection. The implications of these considerations are twofold: 1) The need for flexibility in MMLA systems to adapt to different learning contexts and scales, and 2) The need for a researcher-centered approach to designing MMLA systems. Unfortunately, the sheer number of considerations can lead to a state of "analysis paralysis," where deciding where to begin and how to proceed becomes overwhelming. This synthesis paper asks researchers to rethink the design of MMLA systems and aims to provide guidance for developers and practitioners in the field of MMLA.

CCS CONCEPTS

• Computer systems organization~Embedded and cyber-physical systems~Sensors and actuators • Computer systems organization~Architectures~Parallel architectures~Multiple instruction, multiple data • Information systems~Information systems applications~Decision support systems~Data analyticshere

KEYWORDS

Multimodal Learning Analytics, System Design, Internet of Things, Scalability

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1 INTRODUCTION

Multimodal learning analytics has emerged as a promising approach to support and enhance learning in diverse contexts [1]. MMLA systems collect and analyze data from multiple sources and modalities to provide insights into learners' behavior and performance[2]. However, the dynamic and heterogeneous nature of multimodal data makes it difficult to maintain consistency in data semantics and ensure that the data is accurate and reliable [3]. Designing MMLA systems requires taking into account a wide range of considerations, such as data management, human factors, sensors and modalities, learning scenarios, privacy and ethics, interpretation and feedback, and data collection [4]–[6]. These considerations are interdependent and mutually influencing and impact the system's effectiveness and usability. For example, the choice of sensors and modalities affects the quality and consistency of the data collected, and the way in which the system is designed and implemented can affect the privacy and security of users [7].

This paper identifies key considerations for designing MMLA systems based on an analysis of design practices, literature, and case studies. We argue that these considerations are essential for creating flexible and effective MMLA systems that support learners, teachers, researchers, and policy makers. Furthermore, we highlight that the considerations lead to two implications:

1. The need for flexibility in MMLA systems to adapt to different learning contexts and learners' needs.
2. The need for a researcher-centered approach to designing MMLA systems.

Our analysis contributes to a deeper understanding of the design of MMLA systems and provides guidance for researchers, developers, and practitioners in the field of MMLA.

2 BACKGROUND

Learning analytics is an emerging field that uses data, analytics, and visualization techniques to understand, support, and enhance learning [8]. Traditional learning analytics systems have mainly focused on analyzing data from educational management systems and learning management systems, such as student tracking data, log files, and assessment data [8]. However, these systems have several limitations, including the need for more rich and diverse data sources and modalities, the inability to capture context and multimodal interactions [9]. MMLA (MMLA) is a new field of study that aims to overcome these limitations by collecting and analyzing data from multiple sources and modalities, such as text, speech, video, audio, and sensor data [2]. As a result, MMLA systems can provide a more comprehensive and nuanced understanding of learning and support diverse learning contexts and learners' needs [1]. However, designing MMLA systems is a complex task that requires taking into account a wide range of considerations [1].

Furthermore, MMLA can potentially impact learning and teaching practices, research, and policy making [10]. MMLA systems can provide teachers and educators real-time feedback and insights about learners' performance, engagement, and behavior [11]. Additionally, MMLA can generate new knowledge and insights about learning and support the development of evidence-based policies and practices [12]. Therefore, it is important to consider the needs and perspectives of different stakeholders, such as learners, teachers, researchers, and policymakers in designing MMLA systems.

3 CONSIDERATIONS

The considerations presented in this paper are the result of a comprehensive synthesis from our three conducted research studies, including a comprehensive literature review (ref anonymous), the design of a theoretical model (ref anonymous), and an in-depth case study (ref anonymous). Our research approach in these studies included a systematic mapping study to review the literature and identify common research types and methodologies as well as trending research themes in the field of MMLA (ref but anonymous). Additionally, we developed a flexible and scalable MMLA system design proposal named MBOX, through prototyping (ref but anonymous). The case study was conducted to explore the development of an activity recognition system using a multi-sensor wristband in an industrial setting (ref but anonymous). Thus, this paper synthesizes the eight key considerations for designing MMLA systems. These considerations are generated through a design science research study that involved a systematic mapping study, a case study, and prototyping of a design proposal.

A comprehensive overview of each consideration, including the relevant references, can be found in Table 1. The table provides a clear and concise summary of the considerations, allowing for easy reference and comparison. Figure 1 illustrates the considerations and how they fit into three main categories: data quality and consistency, learning context, and centered design.

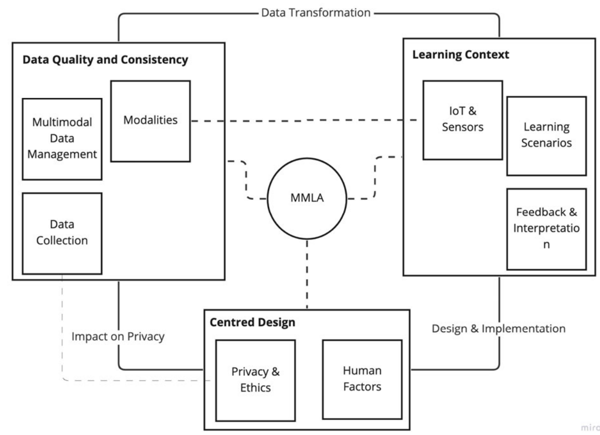

Figure 1: A visual mapping of the different considerations and their connections

Multimodal Data Management

Data management is a crucial in designing MMLA systems. However, the dynamic and heterogeneous nature of multimodal data, including text, audio, video, and sensor data, makes it difficult to maintain consistency in data semantics [4]. This can lead to clarity and accuracy when trying to analyze and interpret the data. Additionally, the lack of well-defined goals in data collection can lead to conflicting initiatives, making it difficult to achieve a cohesive understanding of the data [13].

Human Factors

The human factors involved in MMLA systems are diverse, as they include a variety of stakeholders, such as learners, teachers, researchers, and policy makers [14]. MMLA systems are designed to support and enhance learners' learning experiences, but they can also benefit other stakeholders in different ways. For example, teachers can use MMLA systems to gain insights into the learning process and to inform their teaching practices, while researchers can use the data generated by the system to study learning and develop new theories and models [11]. Policy makers can also use MMLA systems to inform decisions about education policies and practices [12].

Sensors and Modalities

Understanding the types of data that can be collected from different sensors and modalities, and how this data can be used to support learning and analysis, is not easy. Sensors such as cameras and microphones can be used to collect audio and video data, while sensors such as accelerometers and gyroscopes can be used to collect data on movement and physical activity [15]. Each type of data can provide valuable insights into the learning process, but they need to be analyzed and interpreted in different ways. The choice of sensors and modalities also has implications for the design and implementation of the system [2].

Learning Scenarios

When it comes to designing a MMLA system, it is crucial to consider the different contexts in which the system will be used [16]. After all, one size does not fit all in learning. In this consideration, it is crucial to emphasize the balance between customization and generalization in the design of MMLA systems for various learning scenarios. While each learning scenario may present distinct requirements, it is possible to identify commonalities and incorporate them into a more generalized design. For example, a system designed for use in a classroom setting will need to be able to support different types of classroom

Table 1: Summary of the considerations with overview and references

Considerations	Overview	References
Data Management	managing dynamic and heterogeneous multimodal data to maintain consistency in data semantics and avoiding conflicting initiatives.	[13], [24]
Human Factors	involving different stakeholders (learners, teachers, researchers, and policy makers) in the design and implementation of MMLA systems.	[14], [12]
Modalities	choosing appropriate modalities and sensors to suit the learning scenarios and collecting high-quality multimodal data.	[15], [25]
Sensors	using specialized equipment and expertise to collect accurate and reliable sensor-based data sequences.	[26]
Learning Scenarios	designing the system to be suitable for different learning scenarios and providing personalized feedback that is context-sensitive.	[16], [27]
Privacy and Ethics	protecting users' privacy and security by implementing policies procedures for data handling and storage, and being transparent about data collection and usage.	[19], [20], [18]
Interpretation and Feedback	analyzing the data collected to extract meaningful insights and providing real-time or near real-time feedback that is relevant and actionable.	[13]
Data Collection	collecting high-quality multimodal data and overcoming the lack of datasets in the field of MMLA.	[4], [7]

activities, such as lectures, group discussions, and hands-on activities [17].

Privacy and Ethics

The collection, preservation, and analysis of personal data have significant implications regarding the design and implementation of MMLA systems regarding privacy and ethics [18]. It is imperative to establish policies and procedures for the handling and storage of data and implement technical measures to prevent unauthorized access or breaches. Transparency is crucial in building trust with users by providing them with information about the data being collected, the purpose of its usage, and the parties who have access to it [19]. The system must be designed to reduce the collection of redundant or sensitive data, and ensure that the data collected is used for legitimate research or educational purposes [20].

Interpretation and Feedback

The use of sensors creates a complex data landscape that requires advanced techniques for analysis and interpretation. The aim is to uncover patterns and trends in the data that can provide valuable information for learning and decision-making purposes. However, the complexity of the data also means that the insights generated must be communicated effectively, which requires the development of visualizations and reports that stakeholders easily understand. Thus, the development of algorithms and models and effective communication strategies are crucial for the success of MMLA systems in the education context [13]. Additionally, it is important to consider how the system can provide feedback to users in real-time or near real-time, such as providing instant feedback on a student's performance or providing guidance on how to improve. Interpretation and feedback also have implications for the design and implementation of the system [21].

Data Collection

Multimodal data collection is a challenging task, as it involves collecting data from multiple sources and in multiple formats, such as text, audio, video, and sensor data [4]. This can make it challenging to maintain consistency in data semantics and to ensure that the data is accurate and reliable. Additionally, collecting multimodal data often requires specialized equipment and expertise, which can be costly and time-consuming. Furthermore, there is a lack of datasets in the MMLA field, making it difficult to develop and test models and algorithms [13]. This is in contrast to other analytics areas, such as text analytics or web analytics, which have an abundance of data available. This lack of data can make it challenging to validate the results of multimodal analytics, and to ensure that the models and algorithms are robust and reliable.

4 IMPLICATIONS

The considerations outlined in this paper have led to two key implications for the design and development of MMLA systems. The first implication is the need for flexibility to ensure that the system is able to support different types of learning scenarios and instructional approaches. The second implication is the need to focus on researchers as the main potential end users of MMLA systems to ensure that the system is designed and developed with the needs and requirements of these users in mind. This section will explore these two implications in greater detail, highlighting the importance of considering these factors in the design and development of MMLA systems. Additionally, Figure 2 visually illustrates how the considerations are connected to the implications.

The Need for Flexibility

The use of multiple modalities in learning environments presents both opportunities and challenges. On one hand, it allows for more diverse and personalized learning experiences [1]. On the other hand, managing and analyzing this various data can be challenging. The complexity and diversity of modern learning environments and scenarios make it difficult to predict which modalities will be most significant in a given context, which highlights the importance of flexibility in MMLA systems [4]. Flexibility in these systems allows researchers and educators to experiment with different modalities and compare them to identify the most effective ways of tracking student progress and understanding their learning experience. Our studies have shown that flexibility in MMLA systems is essential for capturing a wide range of data and identifying the most significant modalities for a particular learning experience [13].

Another important aspect of flexibility in MMLA systems is scalability. Scalability allows for the monitoring and analysis of student progress at different levels of learning contexts, from the individual level to the classroom level, school level, and even the whole educational system level. This is important because student learning does not occur in isolation; it is affected by a variety of factors, such as the classroom environment, school culture, and educational policies [4]. By being able to monitor and analyze student progress at different levels, researchers and educators can gain a more comprehensive understanding of how these factors influence student learning and identify ways to improve it. Additionally, scalability allows for monitoring and analyzing student progress across different educational systems, which can help identify best practices and improve the overall quality of education [22].

Researcher-Centered Approach

While MMLA systems have the potential to support students and teachers, current design practices for these systems still need to be developed. Most MMLA systems need usability criteria that are tailored to the specific needs of students and teachers, which makes it difficult for them to effectively use and interpret the data generated by these systems [14]. Additionally, the output of these systems often requires interpretation and should be looked at with a critical eye. We suggest that researchers in education science and related fields be involved in the design and development of MMLA systems to ensure that they are usable, accurate, and trustworthy. Furthermore, these researchers have the expertise to interpret and analyze the data generated by these systems, which makes them the primary beneficiaries of MMLA systems.

While most literature suggests that MMLA systems primarily support students and teachers, we noticed that researchers in the field of education science and related fields might be the primary beneficiaries of these systems [14]. This is because researchers in these fields often need tools to observe and analyze learning experiences to better understand the complex factors that influence student learning. MMLA system would significantly support traditional practices by providing a more comprehensive and diverse data set to analyze student's learning process, allowing for more informed decisions about supporting student learning. Flexibility in MMLA systems will enable researchers to capture and analyze a wide variety of data and test and compare different modalities to identify the most significant ones.

5 REASSESSING THE IMPLICATIONS

This section will examine counterarguments to the implications outlined in the previous quarter. Despite the compelling arguments for each of the implications, there may be opposing perspectives that should also be considered in designing MMLA systems.

Flexibility may not be crucial for MMLA systems

While flexibility in MMLA systems can provide a more comprehensive and diverse data set, capturing all modalities of data is not always necessary. In some learning environments and scenarios, data from a single modality may be sufficient to gain a good understanding of student learning [23]. Furthermore, collecting and analyzing data from multiple modalities can be time-consuming and resource-intensive, which can be a disadvantage for some educators and researchers. Additionally, it is also important to consider the ethical and privacy implications of collecting and analyzing data from multiple modalities [18]. The collection and analysis of sensitive data, such as audio and video recordings, can raise privacy concerns and may require additional safeguards to protect the privacy of students and teachers. This highlights the need for careful consideration of the potential benefits and risks of using MMLA systems, rather than assuming that flexibility is always necessary [3].

Researchers May Not Be the Right Target

Focusing exclusively on researchers as the main target for MMLA systems can lead to systems that could be better-suited to the needs of other stakeholders, such as students, teachers, and policy makers [11]. This can create barriers to adoption and use of the systems by different stakeholders, which could ultimately limit the potential impact of the systems on student learning [14]. The assumption that researchers are the end user may also lead to a lack of diversity in the data collected and analyzed by the systems. The systems should be designed to be open for various experts to interpret and analyze the data. This will ensure that all valuable insights are extracted [5].

6 CONCLUSION

The design of MMLA systems is a complex and challenging task, both at small and large scales. With the advent of new technologies and the increasing need for more personalized and effective learning experiences, it is crucial to consider the various aspects of multimodal data management, privacy and security, and user experience when designing MMLA systems. In this paper, we synthesized empirical research based on three studies, a literature review, a model design, and a case study to arrive at eight considerations for designing MMLA systems. These considerations are important in ensuring that MMLA systems are designed to address the dynamic and heterogeneous nature of multimodal data, the need for privacy and security, and the user experience. Furthermore, our considerations led to the two implications of the need for flexibility in MMLA systems and the need to focus on researchers as the main potential end user. Although these implications were met with some counterarguments, we argue that they are still meaningful and worth considering in the design of MMLA systems. We plan to enhance this paper by incorporating empirical evidence that validates and establishes the reliability of the suggested considerations for the MMLA field.

REFERENCES

[1] M. Cukurova, M. Giannakos, and R. Martinez-Maldonado, *The promise and challenges of multimodal*

learning analytics, vol. 51, no. 5. Wiley Online Library, 2020. doi: 10.1111/bjet.13015.

[2] P. Blikstein, X. Ochoa, and P. Blikstein, “Multimodal learning analytics,” *ACM International Conference Proceeding Series*, pp. 102–106, May 2013, doi: 10.1145/2460296.2460316.

[3] X. Ochoa, N. Weibel, M. Worsley, and S. Oviatt, “Multimodal learning analytics data challenges,” *ACM International Conference Proceeding Series*, vol. 25-29-Apri, pp. 498–499, 2016, doi: 10.1145/2883851.2883913.

[4] H. Ouhaichi, D. Spikol, and B. Vogel, “MBOX: Designing a flexible IoT multimodal learning analytics system,” in *Proceedings - IEEE 21st International Conference on Advanced Learning Technologies, ICALT 2021*, 2021, pp. 122–126. doi: 10.1109/ICALT52272.2021.00044.

[5] M. Vujovic, D. Hernández-Leo, S. Tassani, and D. Spikol, “Studying collaborative learning and space design with multimodal learning analytics,” *British Journal of Educational Technology submitted article British Journal of Educational*, 2020.

[6] E. F. Olivares, P. Albert, J. van Helvert, and M. Gardner, “Designing a learning analytics application to improve learner success in interactions based on multimodal dialogue systems,” *Communications in Computer and Information Science*, vol. 621, pp. 171–179, 2016, doi: 10.1007/978-3-319-41769-1_14.

[7] H. Cornide-Reyes *et al.*, “Introducing low-cost sensors into the classroom settings: Improving the assessment in agile practices with multimodal learning analytics,” *Sensors (Switzerland)*, vol. 19, no. 15, 2019, doi: 10.3390/s19153291.

[8] S. K. Banihashem, K. Aliabadi, S. Pourroostaei Ardakani, A. Delaver, and M. Nili Ahmadabadi, “Learning Analytics: A Systematic Literature Review,” *Interdisciplinary Journal of Virtual Learning in Medical Sciences*, 2018, doi: 10.5812/ijvlms.63024.

[9] A. Wilson, C. Watson, T. L. Thompson, V. Drew, and S. Doyle, “Learning analytics: challenges and limitations,” *Teaching in Higher Education*, 2017, doi: 10.1080/13562517.2017.1332026.

[10] M. Worsley, “Multimodal learning analytics’ past, present, and, potential futures,” in *CEUR Workshop Proceedings*, 2018.

[11] M. J. Rodríguez-Triana, L. P. Prieto, A. Martínez-Monés, J. I. Asensio-Pérez, and Y. Dimitriadis, “The teacher in the loop: Customizing multimodal learning analytics for blended learning,” *ACM International Conference Proceeding Series*, pp. 417–426, 2018, doi: 10.1145/3170358.3170364.

[12] I. Celik, E. Gedrimiene, A. Silvola, and H. Muukkonen, “Response of learning analytics to the online education challenges during pandemic: Opportunities and key examples in higher education,” *Policy Futures in Education*, 2022, doi: 10.1177/14782103221078401.

[13] H. Ouhaichi, H. H. H. H. Olsson, and J. Bosch, “Dynamic data management for machine learning in embedded systems: A case study,” in *Lecture Notes in Business Information Processing*, Springer, Cham, Nov. 2019, pp. 145–154. doi: 10.1007/978-3-030-33742-1_12.

[14] S. B. Shum, R. Ferguson, and R. Martinez-Maldonado, “Human-centred learning analytics,” *Journal of Learning Analytics*, 2019, doi: 10.18608/jla.2019.62.1.

[15] J. Schneider, D. Börner, P. van Rosmalen, and M. Specht, “Augmenting the senses: A review on sensor-based learning support,” *Sensors (Switzerland)*, 2015, doi: 10.3390/s150204097.

[16] M. Eradze, M. J. Rodríguez Triana, and M. Laanpere, “Context-aware multimodal learning analytics taxonomy,” *CEUR Workshop Proc*, vol. 2610, pp. 1–6, 2020, [Online]. Available: http://ceur-ws.org/Vol-2610/paper1.pdf

[17] M. C. E. Chan, X. Ochoa, and D. Clarke, “Multimodal learning analytics in a laboratory classroom,” *Intelligent Systems Reference Library*, vol. 158, pp. 131–156, 2020, doi: 10.1007/978-3-030-13743-4_8.

[18] H. Alwahaby, M. Cukurova, Z. Papamitsiou, and M. Giannakos, “The evidence of impact and ethical considerations of Multimodal Learning Analytics: A Systematic Literature Review,” in *The Multimodal Learning Analytics Handbooks*, EdArXiv, 2021, pp. 1–34. doi: 10.35542/OSF.IO/SD23Y.

[19] A. Pardo and G. Siemens, “Ethical and privacy principles for learning analytics,” *British Journal of Educational Technology*, 2014, doi: 10.1111/bjet.12152.

[20] J. Zhao, R. Mortier, J. Crowcroft, and L. Wang, “Privacy-Preserving Machine Learning Based Data Analytics on Edge Devices,” in *AIES 2018 - Proceedings of the 2018 AAAI/ACM Conference on AI, Ethics, and Society*, 2018, pp. 341–346. doi: 10.1145/3278721.3278778.

[21] J. Wagner, F. Lingenfelser, T. Baur, I. Damian, F. Kistler, and E. André, “The social signal interpretation (SSI) framework: Multimodal signal processing and recognition in real-time,” in *MM 2013 - Proceedings of the 2013 ACM Multimedia Conference*, 2013. doi: 10.1145/2502081.2502223.

[22] A. H. Celdrán, J. A. Ruipérez-Valiente, F. J. G. Clemente, M. J. Rodríguez-Triana, S. K. Shankar, and G. M. Pérez, “A scalable architecture for the dynamic deployment of multimodal learning analytics applications in smart classrooms,” *Sensors (Switzerland)*, vol. 20, no. 10, 2020, doi: 10.3390/s20102923.

[23] Ouhaichi Hamza, Daniel Spikol, and Bahtijar Vogel, “Towards designing a flexible multimodal learning analytics system,” Malmö university, Malmö, 2022. doi: 10.24834/ISBN.9789178772988.

[24] M. N. Giannakos, K. Sharma, I. O. Pappas, V. Kostakos, and E. Velloso, “Multimodal data as a means to understand the learning experience,” *Int J Inf Manage*, 2019, doi: 10.1016/j.ijinfomgt.2019.02.003.

[25] M. Worsley, R. Martinez-Maldonado, and C. D’angelo, “A New Era in Multimodal Learning Analytics: Twelve Core Commitments to Ground and Grow MMLA,” *Journal of*

Learning Analytics, vol. 8, no. 3, pp. 10–27, Nov. 2021, doi: 10.18608/jla.2021.7361.

[26] T. B. Ahn and J. Harley, "Exploring emotions and multimodal learning analytics: Eye-tracking and facial recognition," *British Journal of Educational Technology*, 2020.

[27] F. Riquelme, R. Munoz, R. mac Lean, R. Villarroel, T. S. Barcelos, and V. H. C. de Albuquerque, "Using multimodal learning analytics to study collaboration on discussion groups: A social network approach," *Univers Access Inf Soc*, vol. 18, no. 3, pp. 633–643, Aug. 2019, doi: 10.1007/s10209-019-00683-w.