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Research trends in multimodal learning analytics: A systematic mapping study

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1. Introduction

The field of data science has become an essential part of our digitalized society’s flow of data, leading to the rise of new statistical and quantitative techniques supported by artificial intelligence (AI) (Woolley et al., 2016). The role of AI importance in education continues to capture attention (Chen et al., 2020). By combining a culture of data-driven techniques that incorporate domain knowledge and AI in the decision-making process, organizations can utilize big data analytics for their strategic planning. The application of data analytics in education has experienced increasing interest in improving the learning process, evaluating efficiency, and enhancing feedback and the learning experience (Luckin & Cukurova, 2019). Learning in a digital environment is becoming more common than before. As with most digital systems, a computer is a primary interface for the learner. Learning analytics (LA) analyzes data in these digital educational environments (Avella et al., 2016). Long and Siemens (Scherer et al., 2012) defined learning analytics as “the measurement, collection, analysis, and reporting of data about learners and their context for understanding and optimizing learning and environments in which it occurs.” Here, the learner can be viewed as a user; therefore, all user-experience best practices can be exploited. For instance, controlled experimentation (e.g., A/B testing) can be applied to improve and personalize the user experience for the learner (Renz et al., 2016). However, a large part of learning in real-world classrooms does not happen in front of the computer.

With computer-mediated learning, LA generally follows a straightforward path when high-quality data and computing tools are available (Mota et al., 2018). As a result, when computers are not used in learning contexts, students’ actions are not automatically captured. Often, learners’ actions that occur in computer-based systems, but cannot be recorded, are ignored. Therefore, students are more likely to be overlooked and express confusion when presented with a problem or yawn during a lecture, which is usually interpreted as boredom or disengagement (DiMitri, Schneider, Specht, & Drachsler, 2018c). In a review by Chen et al. (2020), their findings suggested that scholars “seek the potential of applying AI in physical classroom settings,” indicating the importance of investigating the use of technology in non-virtual space. Applications and tools driven by AI in digital learning are gaining wider attention from educators and learners (X. Chen et al., 2020), and LA is...
the process of analyzing educational data in digital environments (Avella et al., 2016), a field related to AI in education. Specifically, Buckingham Shum and Luckin (2019) emphasized that developing and using analytics and AI in education requires a connected approach to human thinking and cognition.

A subfield of LA (Blikstein & Worsley, 2016), Multimodal Learning Analytics (MMLA),plays a crucial role in addressing educational scenarios in which it is interesting to capture information beyond what is occurring on the computer screen. MMLA collects and integrates data from various sources, enabling a better understanding of the different dimensions of learning and learning processes (Blikstein & Worsley, 2016). To facilitate the advancement of research in this area, a team of researchers organized the 2012 International Conference on Multimodal Interaction (ICMI) to promote discussions about MMLA (Scherer et al., 2012). The ICMI focused on identifying and applying techniques from AI and machine learning (ML). Since then, interest in this area has increased. The LA community has evolved from the observation that learning analytics should reflect the variety of ways in which learners demonstrate their knowledge authentically into a particularly well-established and influential interest group. Furthermore, it was named the first special interest group of the Society of Learning Analytics Research (SoLAR) and has appeared in several journals and conference proceedings (Worsley et al., 2021). Due to its relative newness, MMLA research sometimes seems disjointed, but the field’s relatively inclusive nature has allowed for several significant contributions to be made. Nevertheless, identifying methods and trending themes in MMLA research is vital. These research trending themes will reflect the state of the art in MMLA and serve as a guiding force to maintain the rationale and motivation behind this field as it becomes increasingly prevalent among the learning analytics and education research communities. A discipline like MMLA cannot be viewed as a stand-alone entity, i.e., educators, philosophers, computer scientists, and sociologists should work with economists to discuss possibilities, issues, and normative questions. A more comprehensive solution to the future’s challenges can be found by combining various disciplines (Vanthienen & De Witte, 2017). Despite the value of existing literature reviews concerning MMLA’s promise and challenges, they were not always conducted systematically. Researchers must assess research trends and technologies to support MMLA system development to succeed and proliferate. MMLA research types, methodologies, and trends must be examined in a critical review. This study aims to review trending research themes, practices, and methodological decisions among MMLA researchers and discuss the future development of research. Accordingly, this paper presents a systematic mapping study (SMS) following Petersen et al. (2015) guidelines to examine state of the art in MMLA research, including the research methodologies used and identifying trending research themes.

The rest of the paper is structured as follows. First, we present related work and discuss its importance in Section 2. We then state the research question’s aims and provide methodology details in Section 3. The study’s results are then presented and analyzed in Section 4, in which we answer the research question and conduct the mapping. Finally, we present the trending research themes in Section 5 and conclude the paper in Section 6.

2. Related work

Multimodal data collection, pre-processing, analysis, annotating, and interpretation remain challenging for MMLA (Ochoa, 2022). A methodological challenge also arises with the data’s heterogeneous nature, so it would be worthwhile to investigate how MMLA research can be aware and generalizable contextually in the future. In MMLA research, contextualization and generalizability are critical because of the data-intensive nature and focus on interventions.

Seven literature reviews were identified in the search process out of 276 papers addressing different research questions or contributing to other research areas. Table 1 lays out the seven literature review studies by providing an overview, any limitations in content or methodology, and whether the systematic literature mapping guidelines were followed. Three of the literature reviews were conducted systematically.

<table>
<thead>
<tr>
<th>Paper</th>
<th>Systematic approach</th>
<th>Title</th>
<th>Limitations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shankar et al. (2018)</td>
<td>No</td>
<td>‘A review of multimodal learning analytics architectures’</td>
<td>Not enough details about the search process were provided. No inclusion/exclusion criteria were provided. No details about the data-extraction process were provided.</td>
</tr>
<tr>
<td>Crescenzi-Lanna (2020)</td>
<td>Yes</td>
<td>‘Multimodal Learning Analytics research with young children: A systematic review’</td>
<td>No details about the data-extraction process were provided. No classifications were provided. The focus was narrowed to young children, which leaves out a significant part of MMLA literature. Not enough details about the search process were provided. No inclusion/exclusion criteria were provided. No details about the data-extraction process were provided.</td>
</tr>
<tr>
<td>Worsley (2018)</td>
<td>No</td>
<td>‘Multimodal learning analytics’ past, present, and potential futures’</td>
<td>The focus was narrowed to young children, which leaves out a significant part of MMLA literature. Not enough details about the search process were provided. No inclusion/exclusion criteria were provided. No details about the data-extraction process were provided.</td>
</tr>
<tr>
<td>Blikstein (2013)</td>
<td>No</td>
<td>‘Multimodal learning analytics’</td>
<td>The paper was published in 2013, only one year after the very first international MMLA workshop. The results do not discuss publication frequency, research types, and methodologies.</td>
</tr>
<tr>
<td>Alwahaby et al. (2021)</td>
<td>Yes</td>
<td>‘The evidence of impact and ethical considerations of Multimodal Learning Analytics: A Systematic Literature Review’</td>
<td>The paper provides a proper SLR in terms of methodology, but it does not mention the data-extraction process, and the content is concentrated on multiple data fusions. Methodologically speaking, the paper does not provide a proper SLR. It covers the topic of multiple data integration in LA, which resembles (Mu et al., 2020).</td>
</tr>
<tr>
<td>Mu et al. (2020)</td>
<td>Yes</td>
<td>‘Multimodal data fusion in learning analytics: A systematic review’</td>
<td>The paper provides a proper SLR in terms of methodology, but it does not mention the data-extraction process, and the content is concentrated on multiple data fusions. Methodologically speaking, the paper does not provide a proper SLR. It covers the topic of multiple data integration in LA, which resembles (Mu et al., 2020).</td>
</tr>
<tr>
<td>Samuelesen et al. (2019)</td>
<td>No</td>
<td>‘Integrating multiple data sources for learning analytics—review of the literature’</td>
<td>The paper provides a proper SLR in terms of methodology, but it does not mention the data-extraction process, and the content is concentrated on multiple data fusions. Methodologically speaking, the paper does not provide a proper SLR. It covers the topic of multiple data integration in LA, which resembles (Mu et al., 2020).</td>
</tr>
</tbody>
</table>
while the others were not. For example, two studies by Mu et al. (2020) and Samuelsen et al. (2019) focused on multiple data fusion and integration in learning analytics. Alwahaby et al. (2021) addressed ethical considerations and evidence of MMLA technologies’ impact. In other reviews, specific research topics were highlighted to gain a deeper understanding of this emerging field without using a systematic approach (Blikstein, 2013; Worsley, 2018). Below, we present our analysis of the reviews summarized in Table 1.

Alwahaby et al. (2021) evaluated two aspects of MMLA research through a systematic literature review (SLR). The study’s focus was evidence of MMLA’s impact on real-world learning and its ethical implications. In real-world learning and teaching environments, understanding the challenges associated with MMLA research is very limited. The review’s results indicated that MMLA research rarely addresses ethical issues, and the evidence supporting real-world impacts on learning has been weak. Blikstein (2013) argued that multimodal learning analytics could help us gain insight into students’ learning pathways. Following a non-systematic methodology, he included several examples of how multiple data sources could be applied in the classroom. The paper was published in 2013, only one year after the first international MMLA workshop, i.e., it does not include any research work. To address technical challenges and address the lack of reference architectures for data management in MMLA, Shankar et al. (2018) reviewed architectures in the literature. They also summarized state of the art in MMLA software architectures. The paper states in its abstract that it was conducted systematically but did not include a section with details on its systematic approach, nor did it disclose and explain its inclusion/exclusion criteria, data-extraction process, or classifications.

Crescenzi-Lanna (2020) aimed to identify tools and strategies to help assess learning progress and behavior among children under six years old based on practices described in recent MMLA and LA literature. The paper focused on young children, leaving out a significant part of MMLA literature, but it provides critical insights. The ethics of using multimodal data were discussed, including audio, video, biometric, and quantitative measures of child behavior. Worsley (2018) conducted a review in which MMLA research was assessed by examining key characteristics of empirical papers and non-empirical documents to identify future opportunities. The review needed to be conducted more systematically, and details about the search process, and inclusion/exclusion criteria, were provided. Mu et al. (2020) created a conceptual model of MMLA through an SLR; in terms of methodology, the paper needed to discuss the data extraction process, with the content focusing on multiple data fusion.

Samuelsen et al. (2019) conducted an SLR to determine data integration’s status in higher education based on LA. The paper’s methodological approach methods were more descriptive than systematic, covering the topic of multiple data integration in LA, resembling Mu et al. (2020) approach. Most of these reviews were conducted non-systematically (see Table 1), and those that were systematic had a very narrow scope, examining specific research questions within MMLA that are not relevant to this paper’s focus. Although the above reviews provided valuable insights into MMLA’s promise and challenges, they did not provide detailed information about MMLA’s growth, standard research practices, and themes.

MMLA research trends and research on possible modalities and technologies for enabling the development of systems are essential to the field’s success and proliferation. Through classification schemes and a structure organizing the field of interest, we analyzed the results in terms of the frequency of publications within categories in the scheme and research themes, which can determine the extent to which the research field is covered (Petersen et al., 2008a). Despite this, we are unaware of any work examining research trends in MMLA studies. Thus, a critical review is needed that examines MMLA technologies, modalities, and research trends. In this paper, we attempted to bridge this gap by helping researchers critically review their practices and methodological choices through a mapping study that elicited a classified portfolio of publications on MMLA research, i.e., a map of the literature related to MMLA to guide future research. We provide a visual summary of the status of MMLA research, and a mapping of the various classification categories based on the predefined research question.

3. Method

This study was conducted following the Keele (2007) and Petersen et al. (2015) guidelines for conducting systematic mapping studies (SMS) in software engineering. The goals of SMS (also known as Scoping Studies) are designed to provide a broad overview of a research area. In this section, we describe the design and research process, summarized in the following steps (illustrated in Fig. 1): 1. Planning the mapping; 2. defining the aim and research questions; 3. performing the search and refining the search query; 4. Screening papers; and 5. mapping and data extraction.

This SMS aimed to discover trending research themes and methodologies in MMLA. As part of our research scope, we sought to understand the MMLA research area comprehensively. We assessed the latest literature, identified research gaps, and collected evidence for future research directions. These processes align with SMS goals (Keele, S., 2007; Wohlin et al., 2013). A mapping study classifies publications based on their research area (Petersen et al., 2015). An overview of the existing literature related to a research area or subject of interest that reports its structure visually depicts its status based on predefined research questions. Using the steps outlined (Keele, S., 2007), for the case of a single researcher, the first author conducted the work with the support and input from the other authors.

Based on the findings in our study, we discovered research gaps and trends that determined the next steps in the research process.

3.1. Aims and research questions

Following the guidelines proposed by Keele (2007) and Petersen et al. (2015), this SMS examined the state of the art in MMLA research. Specifically, different research methodologies are used across the themes and research trends and technologies to capture multimodal data in learning experiences. This leads to the following research question:

What research methods, themes, and technologies have been considered in MMLA research?

With this research question, we aimed to provide a general overview of the trending research themes and technologies and research methods employed in the MMLA field.

3.2. Search process and strategy

The search process aimed to designate and select the primary studies relevant to the research question. We achieved this by selecting an unbiased search strategy and developing a research protocol. Our strategy to identify potential primary studies was based on our study’s scope, i.e., MMLA. Therefore, we started by identifying keywords used as search terms to construct the search string.

Google Scholar, a widely used search engine that indexes most academic libraries, was used to conduct the searches. In addition, we participated in regular meetings with other researchers to share our work and get feedback on it. Keywords and search strings were reviewed and discussed with different researchers in the domain during these meetings. For example, we used one search string: “Machine Learning OR ML OR deep learning OR DL AND Multimodal Learning Analytics OR MMLA OR Platform OR System AND Collaboration — About 14 000 results.”

We included the keywords “machine learning” and “deep learning” because they are among the most popular data analytics techniques, and the word “analytics” in MMLA might not be used in some papers. We edited the search string iteratively to match the research question’s logic and improve the search results. The search evaluation comprised a preliminary screening of the search results from Google Scholar by...
viewing the resulting articles’ pertinence and content. The search results and their representativeness based on the research question were the main assessment criteria used to evaluate the search string. The search string’s editing comprised modifying the keywords (e.g., “machine learning,” “ML,” or both), operators (AND, OR …), and their order. This editing process is illustrated in Fig. 2. The assessment comprised screening the first page of the search results. Next, the search was sorted by relevance, i.e., the first listed articles are the most likely to be relevant to our search query. The relevance refers to the search engine’s sorting option (Google Scholar). To ensure that the final search string produced similar results, we evaluated it in Publish and Perish and the Web of Science. (For instance, the top ten papers are the same).

We excluded articles by reviewing titles and abstracts and assessing quality and full-text content. Backward snowball sampling also was used to add studies. We reviewed the titles and abstracts of each paper before choosing which ones to include in the study. The first author performed the initial inclusion and exclusion decisions. The resulting list of included papers was reviewed by two other authors who are viewed as domain experts. We reviewed and discussed the final set of articles to confirm inclusion and exclusion decisions.

3.3. Inclusion and exclusion criteria

Our policy was to conduct a full-text reading when uncertain of a paper’s validity. In keeping with this policy, titles and abstracts were reviewed using the following inclusion criteria.

- Articles that focused on MMLA.
- Papers that proposed and investigated AI/ML/DL in education.
- Articles with MMLA systems or platform proposals.
- Papers addressing the use of edge, fog, cloud computing, IoT, and sensors in education.
A study was excluded from consideration if it met at least one of the following criteria.

- Studies presenting material that has yet to be peer-reviewed.
- Studies written in languages other than English.
- Studies in which full-text access was not available.
- Books and gray literature.

Fig. 2 illustrates the number of articles elicited from each string search.

3.4. Data extraction and classification process

Two options were identified for extracting the data (Petersen et al., 2015): 1. Subject-independent classification (temporal, research type, and research methods), and 2. subject-related classification (research themes). In addition to the first author, two researchers checked the results or extracted all data independently. Several meetings were held to reach a consensus on which papers to include. The second step was to test the criteria’s objectivity. We used a pilot set of articles after they had been extracted. Data extraction determines whether the agreement measure can be applied. Since papers are often grouped into different categories, mapping studies can help evaluate agreement (Petersen et al., 2015). We consulted LA experts to check the data extraction because of the trade-off between the availability of results and classification reliability. This study conducted the classifications first according to general classification schemes and then to topical classification schemes.

3.5. Subject-independent classification

Most mapping studies are supposed to use subject-independent classification to be generally applicable. Comparability can be achieved only by consistently using the same or similar classification schemes. Using requirement elicitation and software product management as examples, we could compare research types conducted within each field and gain insight into their relative maturity levels. It also may help to improve and clarify classifications by using them consistently. By using the same classification scheme in two study settings, Wohlin et al. (2013) identified inconsistencies. Only a few mapping studies used contribution type, so its significance appears to be limited to a few studies. Therefore, research methods and types of research are recommended for consideration. When choosing a publication forum to include or exclude from a study, venue classification also may be helpful. Researchers did not use the same classification, according to Wieringa et al. (2006), as suggested by Wohlin et al. (2013). A decision strategy was provided in Table 2 to classify the papers. We chose this strategy because it contains a comprehensive and sorted set of criteria to decide which research type a study belongs to.

Moreover, we used this strategy to remain consistent with the methodology and other mapping studies. Table 2 was based on Petersen et al. (2015) research types and methods guidelines. We proposed this modified table representation because we found it easier to read and use for decision-making purposes. The classes were based on Peterson et al. (2015) guidelines and proposed by Wieringa et al. (2006). Our classification resulted in three articles categorized as experience papers (Cowling & Birt, 2020; Kasepalu, 2020; Luckin & Cukurova, 2019).

Fig. 3 shows how many mapping studies have been identified during the 2014–2020 period. Among the papers included in this mapping study, the first article was published by Chen et al. (2014) and was the only (among the included papers) study in 2014. MMLA studies experienced modest growth in interest in 2017 and 2018, but a significant increase can be observed from 2018 to 2020. It is evident from the rise in research articles that these topics are gaining interest among researchers.

4. Results and analysis

This section presents the mapping study’s results and analysis to answer the research question. First, annual publication frequency illustrated increased interest in MMLA research. Next, we present the research type and method classification results. Later, we provide topic-specific classification results to answer the research question. A descriptive overview is provided for each emerging research theme, including takeaways.

4.1. Annual publication frequency

Fig. 3 shows how many mapping studies have been identified during the 2014–2020 period. Among the papers included in this mapping study, the first article was published by Chen et al. (2014) and was the only (among the included papers) study in 2014. MMLA studies experienced modest growth in interest in 2017 and 2018, but a significant increase can be observed from 2018 to 2020. It is evident from the rise in research articles that these topics are gaining interest among researchers.

4.2. Classification of research type and methods

Research type classification is illustrated in Fig. 4. We conducted the classification following the strategy explained in Subsection 3.4 and summarized in Table 2. Furthermore, we utilized this strategy to remain consistent with our entire methodology and in relation to other mapping studies. Table 2 was adapted from Petersen et al. (2015). We used this table representation modification because we found it easier to read and use for decision-making purposes. The classes were based on Peterson et al. (2015) guidelines and proposed by Wieringa et al. (2006). Our classification resulted in three articles categorized as experience papers (Cowling & Birt, 2020; Kasepalu, 2020; Luckin & Cukurova, 2019).

**Table 2**

<table>
<thead>
<tr>
<th>Research type classification (T = True, F = False, * = irrelevant or not applicable) (Petersen et al., 2015).</th>
</tr>
</thead>
<tbody>
<tr>
<td>Evaluation research</td>
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<tr>
<td>---------------------</td>
</tr>
<tr>
<td>Used in practice</td>
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<tr>
<td>Novel solution</td>
</tr>
<tr>
<td>Empirical evaluation</td>
</tr>
<tr>
<td>Conceptual framework</td>
</tr>
<tr>
<td>Opinion</td>
</tr>
<tr>
<td>Authors’ experience</td>
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</table>

![Fig. 3. Number of publications each year since 2014.](image-url)
and four as opinion papers (Chejara, 2020; Goumopoulos et al., 2019; Shum et al., 2019; Worsley et al., 2016). The what, not the why, is stressed in experience papers. An author summarizes lessons learned from one or more projects, but the experience must be their own (Wieringa et al., 2006). In opinion papers, authors may express their opinions about the desirable course of the research, what the research community should or should not do, or any other preference or value. Experience and opinion papers were the least frequent categories in the classification results. Most of the included articles were empirical evaluation studies and novel solution proposals. Generally, this type of research generates new knowledge about the causal relationship between phenomena or the logical relationship between propositions. However, novel solutions outline a solution technique and argue that it is relevant. The proposal must be new or at least improve existing ones significantly. Many empirical evaluation studies and novel solution proposals can indicate where the research focus is shifting.

Classification of research methods is one of the most common and expected results in mapping studies (Easterbrook et al., 2008). According to two studies (DiMitri, Schneider, Specht, & Drachsler, 2018c; Worsley, 2018), MMLA research is situated at the nexus of different fields, including education science, multimodal data, computer-supported analysis, ML, and social signal processing. However, we chose to follow Petersen et al. (2015) guidelines in the literature. Fig. 5 illustrates the research method classification. Research methods should be selected based on the type of research (evaluation or validation).

It should be noted that research methods may fall under both categories, e.g., experimental research involving students can be classified as validation research. In contrast, experimental research involving practitioners can be classified as evaluation research.

Altogether, 17 of the classified papers were categorized as controlled experiments, six of which had practitioners, i.e., they were validation research. The other 11 were evaluation research and classified as laboratory experiments (Petersen et al., 2015). Controlled experiments involve manipulating independent variables to determine their effects on dependent variables to test a testable hypothesis (Petersen et al., 2008b). Nine papers were classified as case studies, two of which were academic and seven industrial case studies, corresponding to evaluation and validation research, respectively. Case studies can reveal the mechanisms by which cause-effect relationships occur and help explain how and why certain phenomena occur (Petersen et al., 2008b). Altogether, 11 articles were classified as prototyping studies. In the software
development process, prototypes are used to achieve different goals, and different prototypes are available (Easterbrook et al., 2008). Therefore, we can observe that most papers used controlled experimentation or prototyping as a research methodology (regardless of whether validation or evaluation is employed). This can be interpreted using the results from the previous topic-independent classification (see Fig. 4). Considering that most of the studies were proposing novel solutions, it is normal to use prototyping and controlled experiments.

4.3. Validation and evaluation studies

This section discusses some challenges we faced in the data extraction and classification process (Subsection 3.4). First, we noticed that distinguishing between validation and evaluation studies was simple (in our opinion) due to MMLA’s application field, which is education.

“... Validation is not used in practice (i.e., it is done in the lab), while evaluation studies take place in a real-world industrial context ....” (Petersen et al., 2015). This is how evaluation and validation were distinguished in Petersen et al. (2015) guidelines for conducting systematic mapping studies. However, this definition creates confusion when applied to education and learning research. A real-world industrial context in the education field is usually an academic or learning environment (e.g., school, university, students, teachers, etc.). However, when it comes to research types and method classification, we distinguish between evaluation (in real-world and authentic situations) and validation (in the lab and controlled conditions). In practice, validation and evaluation occur in the same environment, e.g., a formal learning space with teachers and students. This makes it difficult to differentiate between the two research types because most of the papers do not explicitly mention research types. Therefore, this needs to be deducted from the details provided in the report’s methodology section. For instance, the following research methods were ambiguous.

- Industrial case study OR academic case study
- A controlled experiment with practitioners OR laboratory experiments
- Action research OR prototyping

Therefore, specifying and classifying the research method was challenging and time-consuming. In our mapping study, we made an extra effort to investigate the details to determine whether the research method was a validation usually performed in a lab. This led us to examine the definition of a lab. According to Bertholf (2016), a laboratory is a facility that provides controlled conditions in which scientific or technological research, experiments, and measurements can be performed. We emphasize the controlled conditions characteristic. In the case of MMLA, a classroom with a teacher and student is an example of a facility where empirical research is conducted. The classroom would be viewed as a lab if used under controlled conditions, which can mean controlling where and when the class will take place, deciding the classroom design and equipment available in the classroom, and recruiting people to simulate the teacher, students, and teaching/learning experience. A real-world scenario would also occur in a classroom with no controlled conditions. It should be a prescheduled class in a pre-booked classroom, leading to a real learning experience scenario. Keep in mind that most people who work in education-related fields (e.g., LA, MMLA, education science, etc.) are academics with research and teaching experience, which might lead to the belief that all their research conducted in this field is classified as action research (Dos Santos & Travassos, 2009). Even with an in-depth look at the papers included in this mapping study, it was still determined whether the research was an evaluation or validation in most cases. When reporting empirical research on learning and education, we sought to make researchers aware of the importance of indicating explicitly whether empirical studies are evaluations or validations.

4.4. Topic-specific classification

An existing classification scheme can be used to categorize topics, or it may emerge from the selected studies. Most mapping studies in software engineering created new classifications (Petersen et al., 2015). If an existing classification is available, this serves as a valuable baseline for supporting comparisons between mapping studies. According to Petersen et al. (2008b), keywording can be a valuable method for creating a classification scheme and counting the number of articles in each category. Each paper’s abstract was used to identify keywords and concepts, and once they were identified, a classification scheme was developed. Portillo-Rodríguez et al. (2012) drew attention to the unclear nature of the keywording process, which has been compared with open coding Glaser and Phd (2016) based on grounded theory. Concepts we encountered in the text are labeled or tagged with keywords, and several open codes must be gathered to create an overall structure. Merging or renaming the codes representing the categories during this process was an important phase in creating a consistent classification scheme, which we did iteratively while evaluating each paper. We then sorted the papers into categories and indicated the number of studies per category after identifying them. Depending on their quality, abstracts may or may not have been subjected to the process.

In some cases, the abstracts needed to be more explicit, in which case the introduction and conclusion sections were examined. Fig. 6 provides the resulting keywords and the number of papers that include them. The keywords were grouped into four categories: learning context; learning process; systems and modalities; and technologies.

5. Trending MMLA research themes

This section aims to provide a broad overview of the trending research topics and topics within each theme. These topics have been addressed in recent MMLA research. In addition to examining the different themes and their connections to teaching and learning, we examine how MMLA was used pedagogically in other studies. By presenting an overview of the discipline, we introduce a common understanding of the field and highlight how far MMLA research differs from what practitioners can expect from it.

We address the main research question in this study through a topic-specific classification: “What emerging research themes and technologies were considered in MMLA research?” Based on our classifications in this mapping study, we identified 14 topics mapped under four themes: learning context; learning process; systems and modalities; and technologies. Throughout this section, we provide descriptions of the themes, the keywords that led to each theme’s emergence, and an analysis of the related literature. To conclude each subsection, we provide a key takeaway from each theme. For example, in conjunction with the systems-and-modalities theme, we found the following keywords: “architecture,” “sensors,” “body-tracking”; “speech-audio”, and “mobile.” For the technology theme, we found the keywords “AI,” “Internet of things (IoT),” and “virtual reality (VR).”

The resulting themes reflect the orientation and subjects addressed in the literature rather than a classification of the keywords themselves. For example, the keyword “sensors” may be classified under either the technologies or systems-and-modalities theme. Essentially, the systems-and-modalities theme focused on using sensors to capture different modalities. However, topics under the technologies theme focused on the use of the technology itself (IoT, AI, etc.) and whether it lies within the MMLA field.

5.1. Learning context

Learning takes place within the learning context, in an environment in which learners are motivated by a task or activity that is engaging and influenced by interactions, studies, practices, and cultures. Various factors—e.g., students, activities, educational material, learning...
strategies, and the environment in which they operate—can be described as learning contexts (Eradze et al., 2020).

Depending on the learning scenario, the context can vary significantly. Considering the increasing combination of hybrid environments and educational practices, collecting data from digital and physical spaces is imperative. Meanwhile, contextual information is crucial to understanding and analyzing machine-aggregated data from technology-enhanced learning environments. Human-labeled observations made in classrooms (multimodal learning data) were suggested as a tool that can compensate for the lack of data. To address learning design challenges in authentic settings, researchers proposed using Contextualizable Learning Analytics Design (Mangaroska & Giannakos, 2019). Technology is viewed as very promising in education’s teaching and learning process (Luckin & Cukurova, 2019). Learning sciences provide theories that can be operationalized and advanced in the design of educational AI technology, driven by interdisciplinary research in learning sciences. Among the topics under the learning-context theme, six papers focused on feedback output, six on classroom environment, and 12 on teaching and monitoring. Feedback and outcomes in MMLA refer to the insights, metrics, or support resulting from the system. Classrooms and contexts refer to considerations concerning the physical space where learning occurs. Both teaching and monitoring are essential parts of education. These terms refer to teaching and monitoring actions and the agent (human or virtual) who acts.

Inter-stakeholder interdisciplinary partnerships allow educators and AI developers to understand each other better, and AI will impact education and training increasingly significantly. Luckin and Cukurova (2019) argued that we could learn greatly about when and how teaching and learning progress positively from data, which is the power behind ML. Therefore, interdisciplinary partnerships are necessary to make AI educationally beneficial. The authors point out that most commercial AI developers are not experts in learning sciences or have limited knowledge and teaching and learning. Thus, inter-stakeholder partnerships (e.g., EDUCATE Educational Technology [EdTech]) among AI developers, educators, and researchers are crucial in ensuring that AI technologies are analyzed and used judiciously to inform learning (Luckin & Cukurova, 2019). Despite its benefits, ubiquitous learning has several orchestration problems: Students need to gain awareness of what they are doing on multiple devices, and face-to-face and blended learning emphasize monitoring for awareness. However, monitoring is usually restricted to specific learning environments (e.g., outdoors). Muñoz-Cristóbal et al. (2018) proposed an adaptive monitoring system that helps people monitor web, augmented-physical, and 3D virtual world environments at an affordable cost.

Limited research has been conducted on visualizing and supporting multimodal data sensemaking for teaching and learning. Visualizing data streams alone will not help teachers and learners make sense of them. Organizing multimodal data into layers that explain critical insights to students and teachers is an approach that Martinez-Maldonado et al. (2020) introduced. Two studies by Corride-Reyes et al. (2019) and Eradze et al. (2020) on educators and students revealed concerns regarding accountability and automated insight discovery. Students can have unique insights into collaborative, project-based learning through MMLA. The MMLA platform collected data from multiple streams, processed it, and extracted multimodal interaction data. Collaborative problem-solving (CPS) scores were regressed using ML to determine MMLA characteristics that help predict collaboration when working on open-ended problems. The studies aimed to identify collaboration aspects in project-based learning automatically.

5.1.1. Key takeaway

The learning context is where learning occurs. In a learning environment, learners are motivated by an engaging task or activity that is influenced and changed due to interactions, studies, practices, and cultures. Students, activities, educational content, learning strategies, and the environment in which they operate can be described as learning contexts (Eradze et al., 2020). In our classification, the learning-context theme includes three keywords: “feedback output” (six papers), “classroom-environment” (six papers), and “teaching and monitoring” (12 papers). In MMLA, feedback and output refer to the insights, metrics, or support resulting from the system. Classroom and context refer to the considerations concerning the physical space where the learning is happening. Teaching and monitoring are viewed as part of the learning context because they are a common and essential part of education. They refer not only to teaching and tracking actions but mainly to the acting agent (human or virtual).

5.2. Learning process

As a learning process, CPS is gaining attention in MMLA research. Providing real-time visuals of group work and supporting the teacher’s awareness and ability to supervise multiple workgroups can benefit the classroom. Considering that CPS often involves group discussions and is generally combined with video data, the data for such a process usually comprises speech or voice data.

This classification recognizes face-to-face (f2f) collaboration, online collaboration, and self-regulated learning (SRL). Researchers have developed a framework for defining awareness information that...
facilitates the design of cooperative systems involving implicit and explicit interactions (Gallardo et al., 2018). A conceptual description-specification process and an application process comprise the framework. These systems may have multimodal user interfaces if implicit and explicit interactions are considered. Furthermore, the framework contains widgets and devices designed to support awareness. Correlation studies’ authors contend that their work can provide insights into engineers’ behavior and how they improve their approach. The learning-process theme comprised five papers on self-regulated learning, nine on computer-supported collaborative learning, and 14 on face-to-face collaboration. When students work in groups, paying attention to individual engagement becomes more challenging. A study by Anderson et al. (2019) described a system for supporting group collaboration by providing instructors with an easy-to-navigate dashboard connected to multiple pods distributed throughout a classroom or lab. Students use words specified by the instructor and participate in the discussion proportionally, based on their speech acts. Using a framework that highlights the main process features, steps, and actions can help identify “meaningful” LA data from CPS significantly.

Cukurova et al. (2016) created an analytical framework to identify critical components of CPS in practice-based learning activities. The authors argued that effective analytical frameworks are crucial for practice-based learning activities. While teachers need more information about collaborative learning, they still must plan, monitor, support, consolidate, and reflect on student interactions. How can a teacher provide support without full knowledge of students’ progress and situation? Kasepalu (2020) conducted a design science study that examined MMLA’s efficacy in supporting collaborative learning efforts. Participants expressed interest in getting an overview of the group activities and helped with assessment after design-based research cycles. If collaboration analytics can ensure a certain level of accuracy, then teachers would be ready to use it. However, more research is needed to support teachers using MMLA.

Information technologies can facilitate large-scale data storage, intelligent data analysis, and complex performance measurements that support MMLA. For example, Riquelme et al. (2019a) modeled a collaborative discussion network based on influence graphs. The immediate visualization of relationships between subjects enables complex decision-making, and it enhances data analysis with social network analysis. Using ReSpeaker devices (a quad-microphone expansion board designed for AI and voice applications), the proposed computational environment analyzes voice interventions exclusively, making it challenging to perform outdoors or in noisy environments.

Furthermore, the obtained data did not consider student profiles, prior knowledge, and nonverbal communication. Video recordings and surveys to profile the study groups would enhance the studies. The model of discussion groups as social networks opens various research possibilities.

5.2.1. Key takeaway

The keywords “SRL” (five papers), “Online collaboration” (nine papers), and “F2F collaboration” (14 papers) were categorized under the learning-process theme. Self-regulated learners monitor, direct, and evaluate their actions to acquire information, expand their expertise, and improve themselves (Okada et al., 2020). Computer-supported collaborative learning is a pedagogical approach to learning via social interaction and computer technology. This approach is used as the primary communication method or as a shared resource in this kind of learning (Martiner-Maldonado et al., 2019).

5.3. Systems and modalities

Most MMLA research is designed for a specific learning scenario, implying that the architecture specification is usually not flexible for different environments. Nevertheless, MMLA techniques appear as a promising alternative for developing and evaluating core skills, e.g., students in a software engineering course learning Scrum using Lego bricks during an exploratory study (Cornide-Reyes et al., 2019).

Recently, education research has been paying considerable attention to the effect on learning through targeted interventions that adjust to changes in students’ emotional states based on accurate predictions of affective states. Unfortunately, many studies into affective states rely on stationary lab equipment that is not well-suited for classroom use. Using signals from low-cost mobile bio-sensors, a pipeline was presented to predict users’ affective states as they solve math problems using their tablets. Because of the increasing use of tablets in the classroom and increased digitization of classrooms, stylus data might be a viable alternative to bio-sensors in predicting affective states.

A multimodal learning hub (MLH) combines multimodal data from customizable configurations of ubiquitous data providers for ubiquitous learning. An MLH enriches ubiquitous learning scenarios using multimodal data. A paper by Schneider et al. (2016) described MLH and presented results from tests examining its reliability in integrating multimodal data. Ubiquitous computing and AI offer many possibilities to develop new solutions across virtually every domain in modern life. The goals of Schneider et al. (2016) were to use such technologies to enhance learning practices and promote positive attitudes toward science and engineering by using pedagogical principles and fostering collaboration between relevant stakeholders. Modern educational scenarios include online gaming, reflections, and problem-solving forums. In a study by Goumopoulos et al. (2019), conceptual models were outlined to define stakeholder requirements, develop digital services, integrate software tools, and support data management.

5.3.1. Key takeaway

The systems-and-modalities theme emerged out of the following keywords: “architecture” (three papers); “sensors” (seven papers); “body-tracking” (16 papers); “speech-audio” (six papers); and “mobile” (five papers). Human communication is multimodal by nature and well-aligned with multimodal approaches. Di Mitri and colleagues (2018c) state that behavioral modalities can be either motoric or physiological. The human body uses multiple modalities to convey intentions and emotions—e.g., facial expressions, voice intonation, and body movement—and this information creates overlap across multiple modalities, which is convenient when analyzing incomplete data sets, particularly those with missing data in which their overall meaning can be preserved (Riquelme et al., 2019b).

5.4. Technologies

Designing MMLA artifacts that utilize AI technology to enhance or enable human cognition can result in personalized support for learners. Within the technologies theme, we found the keywords “IoT” and “VR” that appeared in four papers each, while “AI” appeared in 19, indicating more interest in AI for MMLA. The papers mentioned some systems that could be described as IoT, but they did not use the keyword “IoT,” so it is more a question of terminology.

Several studies examined the use of virtual technologies in MMLA. Virtual environments’ immersive nature makes them an excellent platform for tracking learners’ body movements and behaviors. A study by Petukhova et al. (2017) proposed a coaching system for training young politicians to effectively use multimodal rhetorical devices in debates. The study developed methodologies and models for assessing debate performance and interacting with a virtual debate coach (VDC) application. The language largely determines an argument’s efficacy, how well it is structured, and how well it is delivered by collecting and analyzing multimodal data. It also determines how trainee debate behavior differs from professional debate behavior. Observation, correlation, and ML were used to identify and link multimodal correlates of convincing debate performance with expert assessments. In most mixed-reality environments, interactions are never recorded or analyzed, resulting in crucial insights being lost to learning.
stakeholders, particularly when navigating, interacting, and communica-
ting within mixed-reality learning environments. Furthermore, 
learners in mixed-reality environments need synchronous communica-
tion, and multimodal data recording is becoming increasingly 
important.

In the shift toward a multi-disciplinary stakeholder team model in 
education, it will be increasingly important to enable biometric, spatial, 
and reflective multimodal analytics, which humans and AI can evaluate 
(Cowling & Birt, 2020). As a result of this multimodal data recording, 
privacy, security, and unfair bias in ML issues will arise by examining 
current MMLA methods and applications within mixed-reality learning 
applications. The contributions of immersive technologies and 
mixed-reality innovation in education were reported in a chapter that 
reflected the challenges associated with data security, privacy, and ML. 
In another chapter, Gorham et al. (2019, pp. 101–116), using the 
Kingspry Graffiti Simulator on the Oculus Rift VR system, had partici-
pants in the experimental group learned how to write Japanese kanji 
characters within the VR graffiti simulator. An MMLA approach was 
used to compare the experimental group to the control group in an 
embodied cognition study. The participants’ body movements were 
recorded with a 3D motion tracker and clustered with a 
machine-learning algorithm. Posttests and follow-up surveys also were 
used to compare the groups.

AI can also help teachers monitor and comprehend students’ prog-
ress. SAGLET augments existing tools to support learners’ group 
collaboration to bring a teacher into the loop and support long-term 
collaborations (Segal et al., 2017). With diverse classroom settings 
possible, the teacher’s role becomes more flexible and multifaceted. 
Teachers need to be alerted to critical interactional moments in 
real-time, and in real classrooms, SAGLET can help teachers detect these 
moments that require intervention, leading to further participation. 
SASGLET’s core system is based on a random forest ML algorithm 
trained on group communication data. The system was evaluated in two 
classrooms using teachers’ subjective experiences in real classrooms to 
analyze the logs.

The key results pertain to computer-based operation span (OSPM) 
and baseline measurements (Larmuseau et al., 2020). The OSPM 
findings suggest that heart rate and heart rate variability are sensitive to 
high cognitive load and the learner’s associated psychological states (e.
, stress). Considering that high cognitive loads cause stress, it is not 
always clear what is measured when medical data are analyzed. As a 
result, a study by Larmuseau et al. (2020) suggested that future studies 
need to integrate self-reports of mental states with physiological data. 
Sharma et al. (2019) presented a generalized methodology for gener-
cally building ML pipelines for multimodal educational data, aiming to 
explain each step in the process, predict learners’ effortful engagement 
and performance in adaptive learning settings, and bridge existing gaps 
in such literature. A series of sophisticated AI techniques were simplified to 
shed light on a “black box” of ML for educationally meaningful out-
comes. This first study explicitly determined the steps in the 
pipeline-building process and grounded the selection of multimodal 
features in the relevant literature.

5.4.1. Key takeaway

The keywords “AI,” “IoT” and “VR” are classified under the tech-
nologies theme. Three papers included the keyword “IoT.” We noticed 
that some of the systems discussed in the papers could be categorized as 
IoT, but the papers did not use that keyword, so it is a matter of ter-
minality. The use of virtual technologies was addressed in several 
studies to investigate their potential in MMLA (Birt et al., 2019; Cowling 

Virtual environments are also immersive, making them ideal spaces to 
track learners’ behavior and body movements. However, a more 
important question arises: Is VR a perfect space for learning? We believe 
that one of MMLA’s main enablers (among others) is the IoT. Like 
intelligent cities and smart homes, IoT can capture different modalities 

in a learning context (e.g., bringing up IoT as part of the results). Thus, 
more research on MMLA systems’ architecture should be conducted.

6. Conclusion

This paper investigated and reported on emerging research themes 
and technologies in MMLA. For MMLA to succeed and proliferate, it is 
necessary to assess the research trends and approaches used to support 
the development of beneficial and useable systems for learners, teachers, 
and other stakeholders. This study presented an SMS following Petersen 
et al. (2015) guidelines to examine the state-of-the-art in MMLA 
research, discuss the research types and methodologies used, and 
identify trending research themes. We identified two classifications 
(research type and methodology; see Subsection 4.2). Experience and 
opinion papers were the least commonly used categories in the first 
classification, with most included papers describing novel solutions. 
Furthermore, many studies employed controlled experiments and pro-
typting as a methodology (regardless of whether they were validating 
or evaluating). An essential key is that all solution proposals (except 
two) were classified as evaluation research (see Fig. 5), which was not 
applied in real-world settings.

To address the trending research themes within the MMLA field, we 
conducted a topic-specific classification, through which we identified 14 
topics that we mapped under four themes.

- Learning context: In MMLA, feedback and outputs refer to the insights, 
metrics, or support delivered by the system. Classroom and environ-
ment refer to the physical characteristics of where learning is 
starting. Since teaching and monitoring are integral to 
education, they are viewed as part of the learning context.

- Learning process: Self-regulated learners monitor, direct, and regulate 
their actions to gain knowledge, broaden their expertise, and 

- Systems and modalities: Communication is multimodal by nature, 
aligning well with multimodal approaches. In addition to facial 
expressions, voice intonation, and body movement, the human body 
conveys intentions and emotions. Multiple modalities facilitate the 
analysis of incomplete data sets, particularly those with missing data, 
so that the data’s overall meaning can be preserved (Riquelme et al., 
2019b).

- Technologies: AI is the most exploited/exploited technology in 
MMLA. The special attention to AI is not unique in MMLA, but it is a 
common trend across different field. For example, VR is an ideal 
place to capture learners’ behavior and body movement. However, it 
is doubtful whether VR is an ideal space for actual learning. Along 
with “AI,” “IoT” received wide attention from the research commu-
nity. In essence, IoT collects data from the physical world, while AI is 
the means for making sense of that data.

Rather than classifying keywords, the resulting themes reflected the 
orientation and topics of the literature. For example, “sensors” could be 
classified under the technologies theme. However, it was classified 
under the systems-and-modalities theme because it focused on capturing 
several modalities via sensors.

Section 5 (“Trending MMLA Research Themes”) included an answer 
to the third research question in both the systems, the modalities, and 
the technologies themes. The systems-and-modalities theme comprised 
the keywords “architecture,” “sensors,” “body-tracking,” “speech-
audio,” and “mobile,” and the technologies theme incorporated the 
keywords “AI,” “IoT” and “VR” MMLA systems have minimal real-world 
evidence regarding their impact on educational outcomes (Alwahaby 
et al., 2021).

This SMS illustrates the growing interdisciplinary field of MMLA 
research, which leans heavily toward technological development. It 
argues that MMLA needs to overcome technological challenges and
focus more on learning’s social aspects.

This study’s overall contributions are related to identifying emerging themes and the most frequently used research methodologies in the MMLA field. Researchers can use the results further to advance MMLA research, development, and evaluation. These themes can contribute to the development and integration of MMLA tools by clarifying different aspects of the learning context and process, systems and modalities, and technologies, as well as providing guidance on which research approaches can be used to evaluate MMLA tools. Furthermore, this study illustrates emerging themes that can help researchers further develop and validate new research by breaking down the presented themes.

6.1. Limitations and future research

This report is the first mapping study to discuss research types, and methodologies and present emerging research themes and methods related to the development of MMLA systems. The study took a systematic approach, using a search database (Google Scholar) and following the guidelines suggested by Keele (2007) and Petersen et al. (2015). These types of systematic mapping studies have limitations that include methodological decisions (i.e., the chosen databases and query) that can introduce bias into the results. Another potential bias lies in the quality check and study selection. Additionally, since this study has been conducted as scoping study primarily by the first author, the results identify critical areas for a future systematic mapping study. Finally, we acknowledge that the search might have overlooked some examples of systems that support multimodality but are situated in areas that only primarily emphasize learning and analytics. However, the present paper aims to examine and report on relevant literature arising only from MMLA systems and not from other, broader research communities (e.g., human-computer interaction or social signal processing), in which the term multimodality may be interpreted differently, and the focus is not on MMLA itself.

This study’s sample selection also lacked papers that addressed ethical considerations in MMLA, coupled with studies implemented in authentic settings. However, these gaps offer opportunities for future studies that can investigate real-world evidence and ethical implications, e.g., the datafication of children and the education system (Alwahaby et al., 2021; Lupton & Williamson, 2017).

We acknowledge that the analysis and coding of the data were primarily conducted by the main author, rather than being independently reviewed and coded by multiple raters. While using multiple independent raters is a recommended practice in research, we believe that the study results are still meaningful and relevant despite this limitation. We also took great care to ensure the accuracy and thoroughness of the coding process and conducted a thorough literature review. The limitations of the study should be considered when interpreting and applying the results, but we also believe that the results contribute valuable insights to the field.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

We want to thank the authors and researchers whose work we reviewed and analyzed as part of this literature review. Without their contributions, this research would not have been possible. We would also like to thank the organizations that provided access to data and resources for this research. We are grateful for their commitment to open data and their willingness to share their data with us.

Finally, we thank our colleagues and peers for their feedback and support throughout the research process. Their insights and guidance have been invaluable to this work. We also want to disclose any conflicts of interest that may have influenced this research. Again, we have no conflicts of interest to report.

We also want to emphasize that this research was conducted following ethical principles, including respect for the autonomy, confidentiality, and privacy of the authors and researchers whose work we reviewed. Furthermore, all data were collected and analyzed by relevant laws and regulations.

Acronyms

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<th>Description</th>
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<td>AI</td>
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<td>Self-Regulated Learning</td>
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<td>VR</td>
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References


Di Mitri, D., Schneider, J., Specht, M., & Drachslar, H. (2018c). From signals to emerging themes that can help researchers further develop and validate new research by breaking down the presented themes.

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