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Technology-Enhanced Multimodal Learning Analytics in Higher Education: A Systematic Literature Review

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ABSTRACT Multimodal learning analytics (MMLA) is an emerging field of learning analytics and promises a more comprehensive analysis of the learning process thanks to advances in technological devices and data science. The purpose of this study was to explore technology-enhanced multimodal learning analytics in higher education systematically. A systematic literature review was performed using the PRISMA guidelines, and 45 studies published between January 2012 and June 2024 were determined. The findings demonstrated that China, the USA, Australia, and Chile were the leading contributors to MMLA research, with a notable surge in publications in 2021. Audio recorders, cameras, webcams, eye trackers, and wristbands were the most used devices. Most studies were conducted in experiment rooms or laboratories, though studies in authentic classroom settings have been growing. Data were primarily collected during activities such as programming, simulation exercises, presentations, discussions, writing, watching videos, reading, or exams, as well as throughout the entire instructional process, predominantly in computer science, health, and engineering courses. The studies were mainly predictive or descriptive whereas quite a few studies were prescriptive. Frequently tracked data types included audio, gaze, log, facial expression, physiological, and behavioral data. Traditional machine learning and basic statistics were the commonly used analytical methods whilst advanced statistics and deep learning were relatively less utilized. Test performance, engagement, emotional state, debugging performance, and learning experience were the popular target variables. The studies also pointed out several implications and future directions, with a significant portion highlighting the development of interventions, frameworks, or adaptive systems using MMLA.

INDEX TERMS Data science, higher education, human-computer interaction, machine learning, multimodal data, multimodal learning analytics, systematic literature review, technology-enhanced learning

I. INTRODUCTION

Traditional methods in learning analytics generally focus on interactions in digital learning platforms such as learning management systems [1]. The biggest reason why traditional methods were preferred was the ease of data collection and extraction [2]. The data used in these studies are mostly obtained by keyboard or mouse and come from a single data source [3], [4]. These studies associated click-based behaviors with learning and yielded important findings about learning, especially until the last decade [5], [6]. However, they do not provide an exploration of the human and process dimensions of learning in detail, thereby giving limited information about learning [7], [8]. This limitation becomes even more apparent in blended [9] and face-to-face learning environments [10], where traditional methods fail to capture critical aspects of student interaction and engagement [11] . In addition, in online learning, findings based solely on digital learning environment data often provide a superficial understanding of learning as it overlooks its comprehensive and social nature [12]. For instance, clickstream data alone cannot fully represent student engagement [13], as engagement is a complex construct that cannot be accurately interpreted using a single data source [14]. Additionally, traditional log data fails to detect students' cognitive and emotional states, such as attentiveness or frustration, which are essential for understanding learning processes [15]. Similarly, traditional learning analytics may not effectively predict learning outcomes [16], as they do not account for deeper cognitive processing or affective factors influencing student performance.

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Advances in technological tracking and monitoring devices have led to improvements in the method of data collection [17]. The development of data science has also made it possible to analyze data from all kinds of sources. These advances offer good opportunities to monitor and evaluate the learning process from a more holistic perspective [18]. As a result, multimodal learning analytics (MMLA) using these devices to improve learning with analytical approaches has attracted the attention of many researchers. MMLA is an interdisciplinary field that brings together many fields such as learning science, data science, and engineering [19]. It encourages researchers from different fields to work collaboratively and obtain more inclusive outcomes to improve learning. Conferences, communities, and special issues of journals contributed to the increase in its popularity [20].

MMLA has many advantages for learning and teaching. First, it produces a more inclusive result regarding the learning process since it allows for obtaining many kinds of data that cannot be obtained with traditional learning analytics [21]. Thanks to MMLA, it is possible to observe and evaluate the students in a natural learning environment or a more complex learning environment [22], [23]. It provides feedback, awareness, and reflection to both students and instructors about their learning or teaching process in a detailed way [24]. In addition, an instructor can design their lecture based on more realistic data. However, there are some important challenges in using MMLA. While some of these challenges are based on the implementation of MMLA-supported environments, others are about what to do after implementation such as measurement and interpretation [25].

Universities are increasingly investing in technology-enhanced classrooms. In an age where data is highly valuable, simply using technology for viewing or recording is no longer enough to unlock the potential of these spaces. Advancing these environments to leverage data through MMLA can greatly enhance their educational value. To achieve this, universities need to carefully plan which devices will be used, what data will be collected, and how that data will be analyzed before setting up these classrooms. This approach could even lead to the creation of smart classrooms, shaping the future of education.

As centers of research, universities are well-positioned to establish technology-enhanced laboratories that support a deeper exploration of learning processes. Such facilities contribute to a research-focused environment that supports MMLA and promotes the university as a high-tech hub, inspiring researchers to focus on innovative learning analytics. Furthermore, universities offer a unique advantage for conducting MMLA studies, as consent can be directly obtained from adult students rather than requiring family approval, as is necessary with younger students.

Although MMLA research in universities is growing, these studies often lack a clear focus on the practical applicability of MMLA in higher education. Additionally, there is currently no comprehensive study that reviews the state of MMLA in higher education as a whole. A systematic review could provide valuable insights and guidance for researchers and educators, highlighting areas for improvement and enabling better application of MMLA practices. Therefore, a thorough review of the field is essential to address these needs.

Considering the gap above, the purpose of this study is to investigate technology-enhanced multimodal learning analytics in higher education in a systematic way. Thus, this study reveals the potential of MMLA with the most recent updates and encourages those who are interested in this field. In addition, the study presents opportunities in higher education that may open new doors for researchers. It demonstrates mostly preferred devices and analysis approaches, which can guide the researchers or educators in MMLA. Moreover, the study can enable us to see what is not yet in this field. As a result, different analytics approaches used in different domains can be adopted or even new devices can be developed to increase the effect of MMLA on university students' learning. The focus of this study is multimodal learning analytics utilizing technological devices since these devices are the primary reason why this field emerged as a sub-field of learning analytics rather than the studies using conventional data collection instruments (such as surveys and interviews) as multimodal data.

The rest of this paper is as follows: the second section presents existing systematic reviews in terms of their strengths and weaknesses. The third section identifies research questions and their rationale. The fourth section presents the research method applied in this study. The fifth section demonstrates the results obtained at the end of the systematic literature review and discusses the findings by making inferences from them. The sixth section concludes with a summary of the study's findings, and the final section explains the limitations of the study.

II. LITERATURE REVIEW

This section examines the strengths and weaknesses of existing systematic reviews for Multimodal Learning Analytics (MMLA). Analyzing these aspects is essential for several reasons. First, it allows researchers to critically assess the current body of knowledge, identifying both the valuable insights provided by past studies and areas where they may have fallen short. This evaluation helps clarify what has been effectively addressed and what gaps remain, creating opportunities for future research to build on or enhance previous work. By recognizing the limitations of past studies, researchers can focus on improving the robustness, relevance, and applicability of new research. Therefore, Table I shows the review studies with their strengths and weaknesses.

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The reviews showcase various strengths, particularly in providing comprehensive insights into multimodal data fusion techniques and predictive analytics that can enhance educational practices effectively [7], [26], [27]. Recent studies highlight the integration of key technologies within multisensory environments [28], [29] and explore how learning theories can be applied to improve MMLA applications. These studies offer practical recommendations and evidence-based approaches for creating smarter learning environments, providing valuable guidance for educators and developers. Additionally, the literature includes in-depth explorations of ethical considerations, trends, and policy implications, which can inform decision-making processes within higher education and educational technology fields [30], [31].

Despite these strengths, the literature exhibits notable gaps and limitations, particularly in terms of focus on higher education. Many studies fail to address specific needs and applications within this sector, often concentrating on broader concepts or different educational levels. For instance, some research targets young children, limiting its applicability to higher education [31]. Furthermore, a significant portion of the studies are outdated; with many of the papers published before 2020, there is a lack of recent studies incorporating the latest technological advancements and trends in MMLA [7], [27], [32], [33], [34]. Older studies,

TABLE I
EXISTING SYSTEMATIC REVIEWS

Ref	Year of the latest paper reviewed	Strengths	Weaknesses
[7]	2016	Explores multimodal data fusion techniques that enhance MMLA applications through an in-depth analysis and provides future research directions.	Introduces challenges for practical implementation due to data fusion complexity and offers minimal discussion on real-world applications.
[19]	2020	Identifies trending themes and methodologies in MMLA, guiding future research and practice.	Uses only one database, which may not cover broader themes beyond the identified trends, potentially leaving gaps in the recent literature on advancements in MMLA and failing to address specific needs in the overall findings.
[26]	2021	Provides comprehensive insights into data fusion techniques that enhance MMLA and identifies gaps in research.	Lacks insights specific to higher education and does not incorporate the latest emerging technologies.
[27]	2015	Highlights practical applications of predictive analytics in assessing student performance, which is valuable for educational practitioners.	Focuses primarily on predictive analytics, lacking a deeper exploration of MMLA in higher education.
[28]	2021	Highlights the key technologies and insights related to multisensory environments, providing evidence-based recommendations for integrating learning analytics in educational settings and enhance smart learning environments.	Emphasizes mainly broad concepts, lacking findings specific to higher education.
[29]	2022	Explores how learning theories can enhance MMLA research and applications and provides insights for educational technology developers.	Places extensive emphasis on theoretical concepts, resulting in insufficient attention to the technological dimensions of MMLA.
[30]	2017	Examines the policy implications of MMLA in higher education and offers insights for policymakers to enhance higher education practices.	Analyzes a limited number of studies, which restricts the overall breadth of insights.
[31]	2019	Highlights ethical considerations and tools for assessment and provides insights that can inform educational practices.	Targets young children, which may result in findings that do not readily apply to higher education settings.
[32]	2019	Covers a broad spectrum of educational data mining and learning analytics topics, providing insights into the use of MMLA.	Lacks adherence to systematic guidelines like PRISMA, which may contribute to insufficient depth in certain areas, a broad scope that can dilute specific findings, and reduced focus on practical applications.
[33]	2016	Includes comprehensive overview of studies in higher education and identifies trends and methodologies useful for researchers in higher education.	Lacks emphasis on technical aspects, leading to results that are more aligned with generic learning analytics rather than specific MMLA applications.
[34]	2018	Offers systematic insights into predictive techniques that can inform MMLA applications for student performance.	References potentially outdated predictive models and limits findings to specific educational contexts, which may not generalize to all higher education environments.
[35]	2020	Synthesizes various predictive analytics models relevant to student performance and provides recommendations for future MMLA research.	Focuses narrowly on specific data mining techniques, potentially overlooking broader applications and benefits of MMLA.

such as those from 2015 and 2016, while insightful in predictive analytics, lack a deeper exploration of MMLA-specific applications, and technical details are sometimes insufficient. Limitations in research methodology, such as reliance on single databases or lack of systematic guidelines, contribute to a lack of depth and potential gaps in coverage, reducing the relevance and robustness of findings [19], [32], [35].

In summary, the body of literature on MMLA provides valuable insights into the integration of data fusion, predictive analytics, and emerging technologies within educational contexts. However, there remains a need for more targeted research that specifically addresses the challenges and requirements of higher education. The strengths lie in offering broad, evidence-based recommendations and identifying trends that can guide future research and practice. Still, limitations in scope, methodological rigor, and applicability to higher education highlight areas where future research can make impactful contributions, particularly by focusing on real-world applications and addressing technological advancements more comprehensively. Given the absence of a holistic study addressing the current state of MMLA in higher education, a comprehensive review could serve as a vital resource for guiding future research and application in this field.

III. RESEARCH QUESTIONS

This section presents the research questions and the rationale behind them. In this systematic literature review, there are four research questions to achieve the objectives of this study:

- **RQ1** What are the publication trends (year, publication type, and country) of technology-enhanced MMLA studies in higher education?
- **RQ2** What are the settings (technological devices, research environment, course subject, timing, and number of participants) in which technology-enhanced MMLA studies in higher education have taken place?
- **RQ3** What is the analytical scope (type of analytics, type of data, analytical methods, and target variable) of technology-enhanced MMLA studies in higher education?
- **RQ4** What are the implications and future directions of technology-enhanced MMLA studies in higher education?

Firstly, publication trends describe the evolvement of a particular field [36], and researchers investigate these trends to see the big picture [37], [38], [39]. Nevertheless, no study has shown a holistic view of research on technology-enhanced MMLA in higher education. Therefore, it is essential to examine a general overview of MMLA studies systematically so that the progress and shifts in MMLA studies can be identified thoroughly. To address this need, RQ1 investigates the publication trends in MMLA research, specifically focusing on the year of publication, publication type, and country of origin. Examining the year of publication highlights periods of increased research activity and may indicate influential events or advancements in technology that have spurred growth in the field. Looking at the publication type (e.g., journal articles, conference papers) helps in understanding the preferred avenues for disseminating MMLA research, as well as the rigor and depth of research contributions. Finally, analyzing the country of origin provides insights into geographical patterns, showing which countries are leading in MMLA research and which regions may offer new opportunities for growth and collaboration.

Secondly, researchers face technological, methodological, and practical challenges during MMLA studies [40]. Therefore, they make more effort to design multimodal experiments [41]. However, various factors such as technological devices and the research environment can cause complexity in the studies and the complexity can be different based on the research setting [42]. Therefore, setting up multimodal experiments is a concern for many researchers [43]. In this context, presenting existing research settings helps those who are interested in MMLA to implement it in the right setting. This also allows them to save time and reduce costs. For that reason, RQ2 focuses on the research settings in terms of technological devices, research environment, course subject, timing, and number of participants. Understanding these elements will provide valuable insights into best practices and highlight potential pitfalls, facilitating more successful implementations of MMLA in higher education.

Thirdly, researchers carry out their studies on learning analytics for several purposes. The type of analytics, type of data, algorithms, and outcome determine the analytical scope of these studies. The type of MMLA study can be descriptive, predictive, or prescriptive [44], [45]. The type of data varies according to the used technological device and the context of the research. A variety of algorithms can also be used based on the scope of the study. Studies also examine the effect of these algorithms in relation to their research questions [46], [47]. Depending on the aim of the study, several target variables are investigated with the selected data and algorithms [48]. Determining which data will be captured, which algorithm will be used, which type of analytics, and for what purposes will be adopted is an important issue in MMLA studies [20], [49]. Thus, RQ3 aims to help the researchers define the boundaries of MMLA studies in terms of four main components in learning analytics-oriented studies: type of analytics, type of data, algorithms, and outcome. This well-defined analytical scope makes findings more relevant by helping researchers uncover patterns, predict outcomes, and suggest improvements. Using suitable data and target variables, such as engagement or performance, ensures that MMLA results align with educational goals, offering practical and reliable insights for higher education.

Lastly, researchers are trying to find a way to reveal the potential of MMLA, and accordingly, each study gives important implications to MMLA [50], [51]. These implications can allow the stakeholders to benefit from it at a

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maximum level [52]. However, they have not been explored adequately yet for technology-enhanced MMLA in higher education. Moreover, it takes serious time for researchers to see what other researchers recommend. Nevertheless, existing studies do not present these implications and future directions in a holistic way from MMLA studies in higher education. Therefore, there is a need for the synthesis of future directions of MMLA studies. Such a synthesis helps researchers better understand possible research opportunities and makes it easier for researchers to contribute to this field. With all this in mind, RQ4 highlights the implications and future directions of the studies. Future directions can help integrate advanced technologies such as AI, adaptive systems, and real-time feedback more effectively into MMLA practices. Addressing ethical concerns like data privacy and understanding MMLA's impact on different learning outcomes will create more balanced applications. Collaboration between educators, data scientists, and developers can further enhance and expand MMLA's role in higher education. RQ4 aims to give researchers a foundation for growing MMLA applications, supporting more effective and ethical data-driven strategies.

IV. RESEARCH METHOD

The research method employed in this study is a systematic literature review. The aim of a systematic literature review is to answer the research questions based on the literature by following a systematic guideline. In this study, the PRISMA statement [53] was used as the primary guideline for the systematic review. The details of this review were explained in five main sub-sections: (1) Search String and Databases, (2) Inclusion and Exclusion Criteria, (3) Quality Assessment, (4) Study Selection Process, and (5) Data Extraction and Synthesis.

A. SEARCH STRING AND DATABASES

The systematic literature review was performed using the combination of two key sets, one of which is based on multimodal learning analytics and the other is related to higher education. Based on this, the following search string was determined:

("Multimodal Learning Analytics" OR "Multimodal Data" OR "Multimodal Analytics" OR "MMLA") AND ("Higher Education" OR "University" OR "College" OR "Post-secondary Education" OR "Tertiary Education" OR "Student")*

The search string was applied to seven well-known databases: ScienceDirect, Web of Science, IEEE, Scopus, ERIC, EBSCOhost, and ACM since these databases contain publications related to the focus of this study. Web of Science, and Scopus are recognized for their extensive collections of multidisciplinary research, ensuring access to high-impact journals and conference proceedings. IEEE and ACM are essential for their focus on computer science and engineering, providing technology-driven and analytics-based research within the context of multimodal learning analytics. ERIC and EBSCOhost were included for their strong emphasis on educational research, offering access to relevant studies in teaching and learning contexts. ScienceDirect was also added so as not to miss other scientific papers. Together, these databases offer a well-rounded foundation for identifying relevant studies that align with the focus of this review.

B. INCLUSION AND EXCLUSION CRITERIA

To ensure the selection of the right studies suitable for the purpose of the study, inclusion and exclusion criteria were identified. These criteria are presented in eight titles as seen in Table II: year, document type, language, level, availability, multimodal data, context, and type of study.

TABLE II
INCLUSION AND EXCLUSION CRITERIA

Criteria	Inclusion	Exclusion
Year	Between January 2012 and June 2024	Before 2012
Document Type	Journal article and conference paper	Review, book, book chapter, thesis
Language	English	Non-English
Level	Higher education	Primary school, middle school, high school
Availability	Full-text available	Only abstract available
Multimodal Data	Data from at least one tracking or monitoring device	Data from only traditional multimodal data (survey, interview, etc.)
Context	Learning	Out of learning
Type of Study	Empirical (or studies using dataset of an empirical study)	Non-empirical

The criteria for study inclusion and exclusion were carefully defined to ensure relevance, rigor, and clarity in the analysis. The year criterion was set to start from January 2012, as the 1st International Workshop on Multimodal Learning Analytics [54], held in 2012 as part of the ICMI 14th ACM International Conference on Multimodal Interaction, marked a significant milestone in this research field. Studies up to June 2024 were included, as the review was conducted at the end of June 2024. Only journal articles and conference papers were selected because these types undergo a peer-review process, ensuring quality and reliability.

Studies conducted at the higher education level were the focus of this review to align with the research objectives. Considering the emphasis on technology-enhanced learning analytics, studies were included only if they collected data from at least one tracking or monitoring device, excluding those relying solely on traditional multimodal data sources (such as surveys or interviews).

To support international accessibility and understanding, only studies published in English were considered. Furthermore, only full-text articles were included, as access to

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the complete content is essential for thorough analysis. The context was limited to learning-related settings.

Lastly, only empirical studies or those using datasets from empirical research were included to ensure that the findings were based on observed data, thus excluding non-empirical studies. Empirical studies, which involve data collection and analysis (e.g., through experiments), closely align with the objectives of this systematic literature review, which emphasizes evidence-based insights. In contrast, non-empirical studies, such as purely theoretical papers or conceptual tools, were excluded to maintain the focus on data-driven findings relevant to multimodal learning analytics (MMLA). Additionally, gray literature—including technical reports, and unpublished studies—was excluded to ensure the reliability and credibility of the selected publications.

All these criteria collectively ensure that the review is focused, consistent, and aligned with the study's objectives.

C. QUALITY ASSESSMENT

In addition to inclusion and exclusion criteria, each study in this review was rigorously and systematically evaluated using a set of Generic Criteria and Specific Criteria related to the research questions, as listed in Table III. The first four criteria (QA1-QA4) are generic, while the remaining (QA5-QA15) are specific to research questions. This quality assessment framework is designed to assess the clarity, methodological rigor, and relevance of each study in relation to the objectives of this systematic literature review.

TABLE III
QUALITY ASSESSMENT CRITERIA

Criteria No	Quality Assessment Criteria	Type of Criteria
QA1	Is the purpose of the study clearly defined?	Generic
QA2	Is the study design suitable for addressing the research objectives or questions?	
QA3	Is the methodology clearly described, allowing others to understand and possibly replicate the study?	
QA4	Are the findings presented clearly and logically?	
QA5	Does the study clearly explain the technological devices used and are they suitable for its goals?	Specific to Research Questions
QA6	Is the research environment clearly described, and does it support the study's findings?	
QA7	Is the course subject specified in the study?	
QA8	Is the timing of data collection specified and sufficient for the study's goals?	
QA9	Does the study provide enough information about the participants and sample size?	
QA10	Is the type of analytics extracted clearly from the study?	
QA11	Are the types of data used specified and aligned with the study's goals?	
QA12	Are the analytical methods clearly described and suitable for the data type?	
QA13	Is the target variable clearly defined and relevant?	
QA14	Does the study discuss specific, meaningful implications for higher education?	
QA15	Does the study provide clear recommendations or directions for future MMLA research that are relevant and practical?	

Each study was evaluated against these criteria to determine its overall quality and relevance to the systematic review. Studies that met most or all of these criteria were considered high quality and included as key sources for analysis. This structured assessment approach ensures that only rigorous and relevant studies contribute to the findings of this systematic review, aligning with the research questions and enhancing the validity of the conclusions.

D. STUDY SELECTION PROCESS

After determining the search string, databases, and inclusion and exclusion criteria for this study, the study selection process was performed carefully. Fig. 1 shows the flow of the study selection process: There are four important steps for selecting studies: (1) Identification, (2) Screening, (3) Eligibility, and (4) Included.

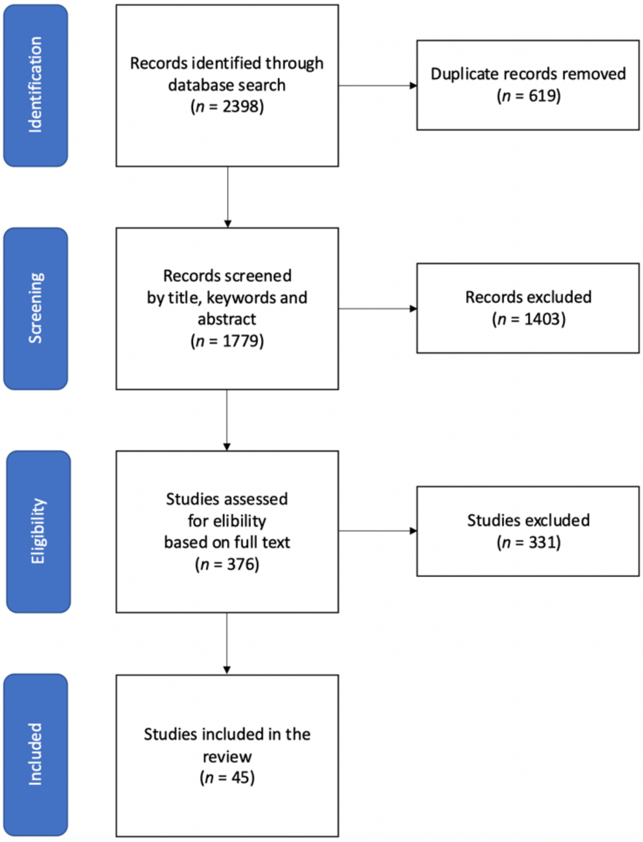

FIGURE 1. PRISMA Flow Chart for Study Selection

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In the identification phase, journal articles and conference papers published between 2012 and 2024 were determined through the database search based on the use of search strings in the title, keywords, and abstract sections. The initial search returned 2398 studies, and 619 duplicate publications were removed from the list. In the screening phase, the remaining 1779 studies were reviewed regarding title, keywords, and abstract. As MMLA firstly aims to improve students' learning, studies whose context is not related to learning were excluded in this phase. In addition, those not written in English and not available in the full text were also removed during screening. As a result, 376 studies were carried to the next step. In the eligibility phase, an in-depth review based on the full text was conducted. Non-empirical studies and those not carried out in higher education were first eliminated during this phase. Since this study focuses on technology-enhanced MMLA, studies using data from at least one tracking or monitoring device were included while studies utilizing data from only traditional multimodal data (survey, interview, etc.) were excluded. Quality assessment of the papers was also performed in the eligibility phase. Moreover, from those sharing the same research setting and analytical scope, only one study with the most information related to the research questions (in case the information in the papers is equal, the highest cited paper) was selected to avoid repetitions in the analysis. Finally, 45 studies were included in this systematic literature review at the end of the PRISMA steps.

E. DATA EXTRACTION AND SYNTHESIS

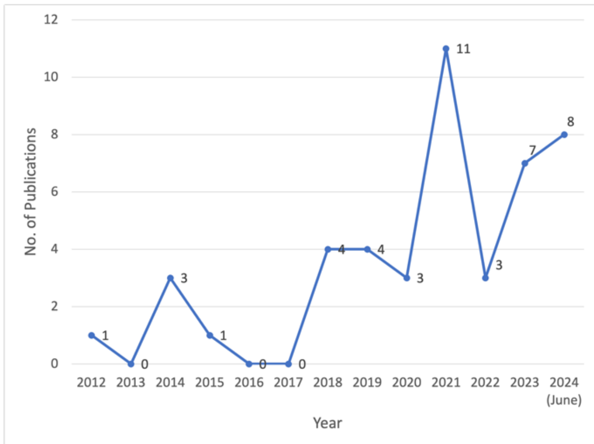
Data from each of the selected 45 studies were extracted based on the research questions. The extracted data were: year of publication, publication type, country for RQ1, technological devices, research environment, course subject, timing, number of participants for RQ2, type of analytics, type of data, analytical methods, target variable for RQ3, and implications and future directions for RQ4. In a spreadsheet, a data extraction form was built to record the studies' data. Then, these data were categorized according to a coding scheme designed based on the analysis of the extracted data. The author was responsible for extracting and coding data from the selected papers, and double-checking was performed during this synthesis by the author. The results were also checked and validated by an independent researcher who has a doctoral degree and many publications. Finally, these coded and tabulated data were used to answer each research question separately.

V. RESULTS AND DISCUSSION

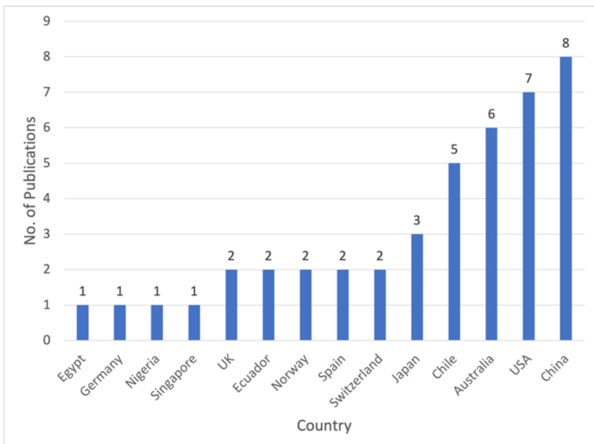
This section comprises four subsections, each dedicated to one research question, where the findings are presented and subsequently discussed in relation to the relevant literature. During this section, the discussions were also supplemented with research opportunities and suggestions where appropriate.

A. WHAT ARE THE PUBLICATION TRENDS OF TECHNOLOGY-ENHANCED MMLA STUDIES IN HIGHER EDUCATION? (RQ1)

A general overview of the studies was explored along with the publication trends. The results showed that most of the studies were published after 2021 (see Fig. 2a). Especially, there was a serious increase in 2021. This result was in line with the other learning analytics studies that focus on either technology or multimodal data [55], [56]. It was also the breakthrough year of artificial intelligence in education [57], which made it possible to perform complex analyses on data obtained from technological devices. Furthermore, in the first half of 2024, 8 studies were already published, highlighting sustained growth in the field and underscoring the relevance of technology-enhanced MMLA in higher education as a timely and up-to-date topic. Looking at the time before 2021, more publications were published in 2014 compared to other years. The most important reason is that there was a grand challenge based on multimodal data in an ACM Workshop held in 2014 [58].



(a) Year



(b) Country

FIGURE 2. Results for Publication Trends.

Publication titles (i.e. journal/conference titles) were also investigated during this study to see the trend in terms of journals and conferences (see Table IV). 30 different journals/conferences, 17 of which are journals and 13 of which are conferences, were identified during the analysis. The British Journal of Educational Technology emerged as the leading journal, with five studies published. Other prominent journals included IEEE Access, IEEE Transactions on Learning Technologies, and Sensors, each contributing three studies on technology-enhanced MMLA. Education and Information Technologies, Journal of Computing in Higher Education, and Journal of Learning Analytics were other notable journals in this field. International Conference on Artificial Intelligence in Education, and ACM Workshop on Multimodal Learning Analytics Workshop and Grand Challenge were the conferences that mostly contributed to technology-enhanced MMLA in higher education.

TABLE IV
THE JOURNAL/CONFERENCE TITLES OF THE SELECTED PUBLICATIONS

Type *	Journal/Conference Title	Publication	No. of Publications
J	British Journal of Educational Technology	[48], [59], [60], [61], [62]	5
J	IEEE Access	[15], [63], [64]	3
J	IEEE Transactions on Learning Technologies	[65], [66], [67]	3
J	Sensors	[68], [69], [70]	3
J	Education and Information Technologies	[71], [72]	2
J	Journal of Computing in Higher Education	[46], [73]	2
J	Journal of Learning Analytics	[52], [74]	2
C	ACM Workshop on Multimodal Learning Analytics Workshop and Grand Challenge	[75], [76]	2
C	International Conference on Artificial Intelligence in Education	[77], [78]	2
J	Computers and Electrical Engineering	[50]	1
J	Data Technologies and Applications	[79]	1
J	Distance Education	[51]	1
J	Journal of Computer Assisted Learning	[47]	1
J	Journal of Educational Data Mining	[80]	1
J	IEEE Transactions on Affective Computing	[81]	1
J	Journal of Universal Computer Science	[82]	1
J	International Journal of Human–Computer Interaction	[83]	1
J	International Journal of Educational Technology in Higher Education	[84]	1
J	Universal Access in the Information Society	[23]	1
C	IEEE Frontiers in Education Conference	[85]	1
C	IEEE Global Engineering Education Conference	[86]	1
C	IEEE International Conference on Engineering, Technology and Education	[87]	1
C	International Conference of the Learning Sciences	[88]	1
C	International Conference on Advanced Learning Technologies	[89]	1
C	International Conference of Educational Innovation Through Technology	[90]	1
C	International Conference on Educational Data Mining	[91]	1
C	International Conference on Electrical, Computer and Energy Technologies	[92]	1
C	International Conference on Learning Analytics & Knowledge	[93]	1
C	International Joint Conference on Information, Media and Engineering	[94]	1
C	International Workshop on Learning Technology for Education Challenges	[95]	1

*J = Journal Article, C = Conference Paper

B. WHAT ARE THE SETTINGS IN WHICH TECHNOLOGY-ENHANCED MMLA STUDIES IN HIGHER EDUCATION HAVE TAKEN PLACE? (RQ2)

Technological devices are essential for enabling technology-enhanced MMLA, as demonstrated by the diverse array of tools employed in studies (see Fig. 3a). The most frequently used devices were microphones/audio recorders (20 studies) and cameras (18 studies), highlighting their importance in capturing verbal and visual data. Microphones or audio recorders were used both internally and externally to collect audio data. Cameras, typically positioned for top-down views, allowed simultaneous recording of multiple participants' behaviors, whereas webcams (11 studies), set up for frontal views, focused on specific behaviors, such as facial expressions, of individual participants. Wristbands, used in 11 studies, were commonly employed to track physiological responses through devices like skin conductance bracelets and smartwatches. Eye trackers, featured in 10 studies, provided valuable insights into participants' gaze patterns and focus. EEG devices, recorded brainwave activity, offering data on cognitive and emotional states. Other devices, such as Kinect (5 studies), positioning sensors (3 studies), and tabletops (2 studies), were used less frequently but added diversity to data collection in MMLA research.

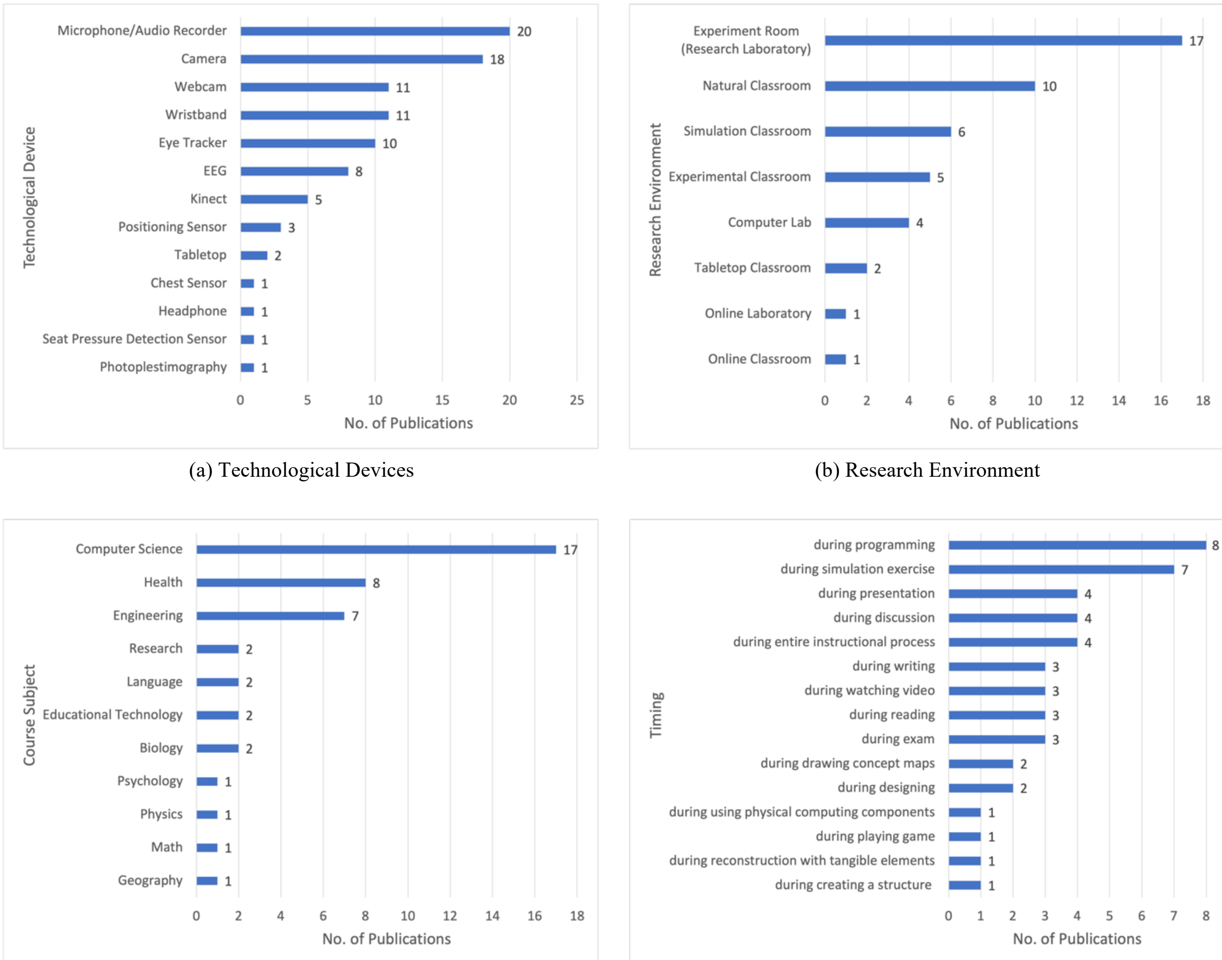
Additional tools, including photoplethysmography sensors, seat pressure sensors, headphones, and chest sensors, each appeared in one study, indicating specialized applications. These are important indicators of what is needed for data-driven and technology-enhanced classes or laboratories in higher education. While some of them were sensor-based wearable devices that need each participant individually to interact with [18], others were found to be more straightforward digital devices such as cameras and audio recorders. The use of devices such as EEG, eye trackers, and Kinect also shows that MMLA has also been affected by the field of human-computer interaction [25]. The use of straightforward devices shows that MMLA studies can also be conducted in technology-enhanced classes established already to support hybrid education [96]. This enables the advancement of existing technology-enhanced classrooms even further and encourages the creation of such new classes. As stated in the literature, human-human interaction can also be tracked thanks to these devices [97]. To sum up, a variety of devices, or even new devices from different fields, such as health, can be utilized to obtain multimodal data in the context of learning.

The research environment, where the technological devices are installed, and data are collected, may affect a study, depending on whether it is a natural environment or not [42]. The study results indicate that MMLA studies have been conducted across various settings (see Fig. 3b), with most commonly conducted in experiment rooms or research laboratories (17 studies). These fully controlled settings, equipped with devices such as eye trackers, webcams, and EEGs, allow for precise data collection by minimizing external variables, thereby facilitating an organized approach to MMLA and enabling structured observations of participant behaviors.

Natural classrooms were the second most common setting, with 10 studies conducted in these authentic learning environments. Here, participants are not required to interact directly with the equipment, allowing for a more realistic representation of learning processes. In these classrooms, top-down cameras and audio recorders are frequently used to unobtrusively capture audio and visual data, providing valuable insights into real-world educational settings. Simulation classrooms, used in 6 studies, offer semi-controlled environments that replicate real-world conditions, balancing control with realism. Some studies also utilized classrooms specifically augmented for experiments or existing computer labs within the university's infrastructure. Experimental classrooms (5 studies) and computer labs (4 studies) can be considered semi-natural environments as they are familiar spaces used by students prior to the experiment, but are equipped with additional devices, such as webcams or screen-recording software, during the experiment. This setup allows for data collection in a setting that combines elements of both natural and controlled environments, balancing authenticity with the precision needed for research. Apart from these environments, a few MMLA studies were also conducted in tabletop classrooms (2 studies) and online environments (1 study each in online classrooms and online laboratories). These findings suggest that MMLA studies can be conducted in diverse environments, which can be classified as natural, semi-natural, or controlled. Observing students in natural classrooms provides the most realistic insights into their learning processes, as these environments lack complex equipment that could disrupt typical interactions. The use of natural classroom settings in MMLA research has increased recently, likely due to their availability in higher education institutions. However, natural settings can be adapted to semi-natural by incorporating additional devices, or fully controlled environments can be established within experimental rooms. For studies conducted in semi-natural or controlled environments, researchers should carefully consider and mitigate the potential impact of additional devices in the studies since they may be interrupting students' learning process in a learning environment [98]. In other words, these studies should focus on ecological validity, one of the limitations of current studies [99]. In summary, the findings indicate that MMLA research is adaptable to any learning environment, provided that the appropriate devices are thoughtfully implemented.

The study findings showed that MMLA studies were mostly performed in courses related to computer science, with 17 studies focusing on this subject (see Fig. 3c). The research has also been done in health (8 studies) and engineering (7 studies) courses even though not as intensely as computer science courses. Additionally, a small number of studies were conducted in research, language, educational technology, and biology courses (2 studies each). On the other hand, psychology, physics, mathematics, and geography courses were in only one study each. The high number of studies in computer science and engineering courses may be attributed to the strong technological focus and the researchers' expertise in these fields. Health courses, on the other hand, may benefit from MMLA due to the growing use of technology in medical and health education, particularly for simulations, clinical training, and collaborative learning. This highlights both the adaptability of MMLA across disciplines and the opportunity to expand its application to other less-explored areas of study.

In a research setting, when the data is collected is also highly crucial. In this context, data collection times in an MMLA study were also investigated. The findings related to timing have yielded a significant number of situations where data can be obtained from learners (Fig. 3d). Programming (8 studies) was the most frequently analyzed activity, followed by simulation exercises (7 studies), highlighting their



(a) Technological Devices
(b) Research Environment
(c) Course Subject
(d) Timing

FIGURE 3. Results for Settings.

prominence in MMLA studies. Other significant contexts included writing (3 studies), reading (3 studies), and watching videos (3 studies) where learners' actions were studied to extract meaningful insights. Additionally, experiments were conducted during presentations (4 studies), discussions (4 studies), entire instructional sessions (4 studies), exams (3 studies), drawing concept maps (2 studies), and designing solutions (2 studies), demonstrating the diversity of contexts in which data can be collected. Less frequently, MMLA studies captured data while learners were using physical computing components (1 study), playing games (1 study), engaging in reconstruction activities with tangible elements (1 study) or creating a structure (1 study). These results yield that each learner action can result in a source of multimodal data and thus can be a suitable timing for conducting MMLA research. Based on the nature of a course, one of these timings can be preferred to collect data.

In addition to these findings, the number of participants in the studies was also examined. The results revealed that only 7 studies (15.6%) involved more than 100 participants, while the majority, 38 studies (84.4%), were conducted with fewer than 100 participants. This shows that a small sample is an important limitation of the studies [87]. The number of studies with more participants should be increased to obtain more generalizable results.

The diversity of research settings highlights that the practical effects of Multimodal Learning Analytics (MMLA) can be observed in real-world applications across different disciplines. In computer science education, MMLA has been utilized to analyze students' debugging performance. One study [74] used wristbands, eye trackers, webcams, and IDE log data to capture gaze patterns, facial expressions, physiological signals, and interaction logs in the Eclipse IDE, providing deeper insights into students' cognitive and affective states. These multimodal data sources helped researchers explain students' debugging performance and refine instructional strategies to support adaptive learning. In engineering education, frontal and top-down cameras (including Kinect) integrated with microphones have been used to capture facial expressions, gestures, audio interactions, and log data from Arduino IDE to analyze how students collaborate and predict their group performance in project-based learning with physical computing components [47]. This insight allows educators to offer timely and meaningful support, helping students navigate challenges and improve their teamwork and problem-solving skills. Similarly, in health education [61], an MMLA system incorporating indoor positioning sensors, biometric wearables, and voice analysis was used to monitor teamwork, communication, and stress levels in a high-fidelity healthcare simulation, allowing for automated feedback and performance assessment. Additionally, in oral communication training, an MMLA-based system used Kinect, a smartwatch (wristband), and EEG sensors to capture physiological signals, facial expressions, EEG activity, and gaze patterns during student presentations [82]. The system analyzed body posture and non-verbal behaviors, providing data-driven feedback to help students refine their public speaking skills and presentation techniques. These diverse research settings demonstrate how MMLA applications can enhance learning experiences, provide real-time feedback, and support data-driven instructional improvements across disciplines.

C. WHAT IS THE ANALYTICAL SCOPE OF TECHNOLOGY-ENHANCED MMLA STUDIES IN HIGHER EDUCATION? (RQ3)

The existing MMLA studies were categorized into three main types of learning analytics: (1) Descriptive, (2) Predictive, and (3) Prescriptive. The findings revealed that most studies focused on either predictive analytics (23 studies) or descriptive analytics (20 studies), while prescriptive analytics accounted for only 4 studies (see Fig. 4a). The most important reason for fewer prescriptive studies is that they are the most sophisticated type of learning analytics, as in other fields, such as business analytics [100]. It is one step further than predictive analytics, which naturally needs more effort and investigation [101]. On the other hand, the popularity and development of prediction methods have made predictive analytics the most preferred type of analytics in MMLA studies [102].

In MMLA studies, different types of data were tracked and used in the analysis thanks to a variety of technological devices (see Fig. 4b). Audio data was the most frequently used, collected in 20 studies, often through microphones integrated into cameras or external voice recorders. Audio data provided insights into pronunciation, language use, and vocal characteristics, which are valuable for learning analytics [75]. Gaze data and log data, each used in 16 studies, were also prominent. Gaze data was captured not only via traditional eye trackers but also through webcams, demonstrating its accessibility. Log data, obtained from educational systems, offered a reliable source of information about student activity and engagement. Facial expression data appeared in 13 studies and was primarily captured through webcams, including front cameras on smartphones. The frequent use of gaze and facial expression data, especially for technology-enhanced MMLA, highlights their significant potential. As demonstrated in various studies [103], [104], [105], these data types have had a considerable influence on MMLA research within higher education institutions, providing unique insights into learner attention, emotional engagement, and interaction patterns. Physiological data (12 studies), such as heart rate and blood pressure, was collected using wearable devices like wristbands, underscoring its feasibility for learning analytics [106]. Action or behavior data (11 studies), often captured through top-down cameras, enabled researchers to code behaviors related to learning and engagement [73]. Body posture data (10 studies) was another key modality, used to assess physical engagement and attention during learning activities. Less frequently, EEG data (8 studies), gesture data (5 studies), head pose data (4 studies), and location data (3 studies) were also employed. These data types, while less common, provided unique insights into brain activity, movement patterns, and spatial interactions. Although the type and capture of data may vary depending on the technologies used [107], utilizing more than one of these types of data increases the impact of educational research since multimodal data are complementary to each other and provide different dimensions of a learning variable [108].

Analytical methods form the basis of studies on learning analytics. Four main categories were determined for analytical methods: (1) Basic Statistics, (2) Advanced Statistics, (3) Traditional Machine Learning, and (4) Deep Learning. Basic statistics include central tendency (e.g., mean), t-test, and ANOVA whereas advanced statistics contain linear mixed models, hidden Markov models, and social network analysis. Traditional machine learning consists of more traditional algorithms such as support vector machines, logistic regression, and random forests. On the other hand, deep learning focuses on neural networks including multilayer perceptron and convolutional deep neural networks.

The findings yielded that traditional machine learning (19 studies) and basic statistics (17 studies) were the two commonly used analytical methods in the studies (see Fig. 4c). Basic statistics are mainly applied in descriptive analytics to summarize data in a meaningful way [109] whereas traditional machine learning algorithms are preferred for small data sizes [110] and thus are applicable to the current studies, most of which include a small number of participants or limited multimodal data. On the contrary, advanced statistics (12 studies) and deep learning (7 studies) were relatively less utilized techniques in the MMLA literature. Even so, deep learning has the potential for large volumes of data obtained from especially sensors [111]. Therefore, the increase in technology-enhanced learning environments is likely to raise the use of deep learning in MMLA studies soon. Similarly, as multimodal data become larger, the need for advanced statistics inevitably will grow in the near future [112].

All MMLA studies have a purpose focusing on at least one target variable. The findings indicate that test performance, including exam and quiz scores, is the most frequently studied variable in MMLA research, appearing in 12 studies (see Fig.

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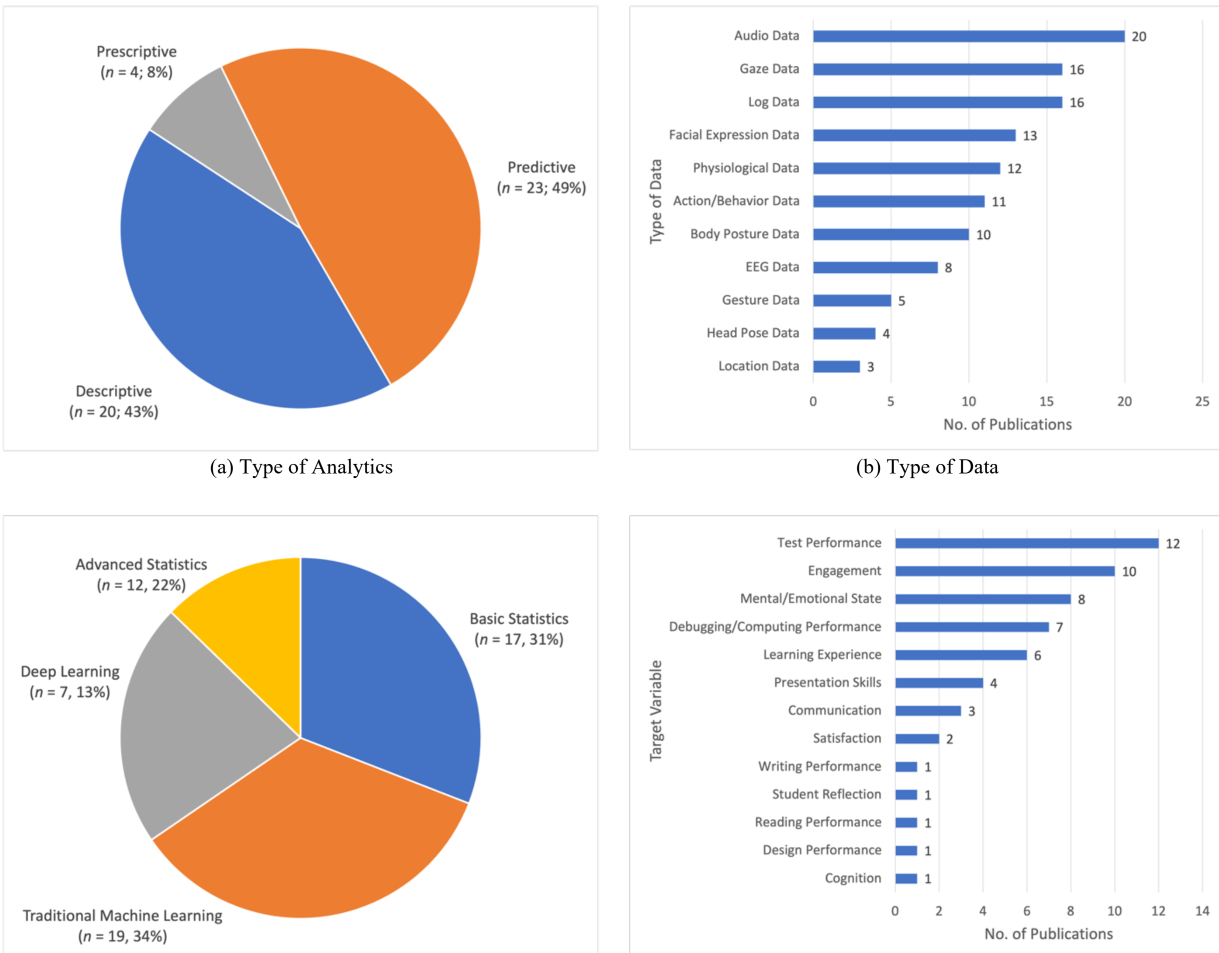
4d). Engagement is the second most common focus, with 10 studies exploring students' involvement in learning activities. Mental and emotional states, analyzed in 8 studies, highlight the growing influence of affective computing in MMLA [113], [114]. Debugging or computing performance, addressed in 7 studies, emphasizes the importance of evaluating students' programming-related activities. Learning experience appears in 6 studies, reflecting the effort to understand students' overall perceptions of their educational environment. Presentation skills and communication were less frequently targeted, appearing in 4 and 3 studies, respectively, focusing on specific competencies in learning contexts. Relatively little research has explored satisfaction (2 studies), writing performance, student reflection, reading performance, design performance, and cognition (each appearing in 1 study). This distribution reveals a strong focus on performance and engagement in MMLA while highlighting the potential for expanding research into these less-studied areas.

A closer look at the analytical scope of Multimodal Learning Analytics (MMLA) studies shows that predictive analytics is at the forefront, with traditional machine learning models such as Random Forest, Support Vector Machine, Decision Tree, Logistic Regression, and Gradient Boosting being widely used. Among these, Random Forest stands out as both the most frequently applied (9 studies) and the best-performing model (5 studies), with accuracy ranging from 63% to 95.6%. In cases where multimodal data requires comprehensive analysis [47], [79], deep learning (DL) models like Deep Neural Networks (DNN) and Fast-Slow Neural Networks have been explored, with Fast-Slow Neural Networks achieving 97.5% accuracy in engagement classification, highlighting their potential for capturing complex learning behaviors. One of the most significant findings in predictive MMLA research is that combining multiple data sources improves predictive accuracy, particularly in areas such as affective computing, behavioral modeling, and learning analytics. Studies that integrate eye-tracking, physiological signals (e.g., EEG, heart rate), facial expressions, and speech data consistently outperform those relying on a single data source. For instance, a study [94] on reading difficulties that incorporated EEG, facial cues, and eye movement data achieved an F-measure of 0.78, while a mental



(a) Type of Analytics

(b) Type of Data

(c) Analytical Methods

(d) Target Variable

FIGURE 4. Results for Analytical Scope.

state recognition model [64] that combined heart rate and acoustic features reached an AUC of 0.842. Similarly, a blended learning performance prediction model [46], integrating clickstream data, facial recognition, and physiological indicators, recorded 87.47% accuracy and an AUC of 0.942, demonstrating the advantages of multimodal fusion. In evaluating these models, accuracy and AUC are the most commonly reported metrics, followed by F1-score, precision, recall, and RMSE, depending on the predictive task. While traditional ML models are often preferred for structured multimodal datasets, DL models are primarily applied in speech and text analytics. However, some challenges remain. For example, one study [80] reported 100% accuracy, which is likely due to a small sample size (N=38) and a simplified binary classification task, raising concerns about overfitting and generalizability. This highlights the need for larger datasets and external validation to ensure reliable findings. Looking ahead, MMLA research is evolving rapidly, with multimodal data fusion and deep learning techniques playing an increasingly important role. As learning environments integrate more sensor-based technologies, the use of deep learning and advanced statistical methods is expected to expand, further refining the accuracy and applicability of predictive models in higher education.

D. WHAT ARE THE IMPLICATIONS AND FUTURE DIRECTIONS OF TECHNOLOGY-ENHANCED MMLA STUDIES IN HIGHER EDUCATION? (RQ4)

The implications and future directions were determined based on the Conclusion and Future Study sections of the studies using a content analysis strategy. Firstly, categories were determined for all of them, and these categories were merged to determine implication themes. As a result, five implications and future directions were extracted with the data analysis. Table V shows these implications:

TABLE V
IMPLICATIONS AND FUTURE DIRECTIONS

Implication and Future Direction	No. of Publications
To develop intervention, framework or adaptive systems based on MMLA	20
To improve accuracy of prediction with MMLA	14
To determine group/classroom dynamics and interactions based on MMLA	14
To provide report or feedback based on MMLA	11
To provide guidance/solution for implementation of MMLA	8

Nearly half of the studies point out there is a research opportunity for the development of the intervention, framework, or adaptive systems using MMLA, and thus, researchers should mostly focus on adaptive technology-enhanced learning environments. Those studies highlight that multimodal data may be helpful for real-time adaptive systems [92]. Especially, affect-aware technologies with automated interventions based on students' affective states can be designed to support students' learning [91], [81]. Those interventions aim to accelerate students' learning progress [52] and contribute to self-regulated learning [86]. However, designing real-time adaptive systems is complex, as it requires advanced algorithms that seamlessly integrate multimodal data while maintaining scalability across diverse learning environments. Furthermore, interventions need to undergo rigorous testing and validation in real-world educational settings, which can be resource-intensive and time-consuming.

Existing studies also emphasize that MMLA has huge potential to improve the prediction of different variables such as performance and affective state [15] and more research is also needed to perform more accurate results with multimodal data. This is crucial for identifying students who may drop out or fail the course [46]. Even estimation tools can be developed based on them [75]. However, improving prediction accuracy is challenging due to issues like noisy or incomplete multimodal data. Developing algorithms that work well across different populations and settings is also difficult. Additionally, educators and researchers may find it hard to turn predictive results into practical, meaningful actions.

The other implication is related to group or classroom dynamics and interactions. MMLA can be used to determine collaborative patterns in a classroom. Even though existing studies reveal important findings based on especially collaborative learning, group dynamics can be investigated more deeply with the help of technology-enhanced MMLA. The identification of patterns or behaviors, as highlighted in previous research [88], provides valuable insights for teachers to effectively support students' collaborative learning, enabling them to design tailored learning scenarios based on these identified patterns or behaviors [90]. Despite these opportunities, capturing the subtleties of group dynamics through multimodal data remains challenging. Additionally, teachers may find themselves overwhelmed with the amount of information generated, making it difficult to extract actionable insights. Group dynamics also vary widely depending on cultural and contextual factors, which can limit the generalizability of findings.

The literature also highlights that comprehensive reports or feedback can be generated based on MMLA. These reports can be used for both designing teaching activities [73] and increasing self-awareness [66]. Therefore, researchers should be better to focus on obtaining suitable reports from multimodal data. The reports prepared for the students also reduce the burden on the instructors [75]. Nonetheless, generating such reports faces challenges, such as ensuring they are personalized and tailored to the needs of individual students and teachers. Providing timely feedback that is actionable in real-time requires highly efficient data processing capabilities. Moreover, the usability of these reports must be prioritized to ensure they are user-friendly and easily interpretable by educators and students alike.

Moreover, studies tried to provide solutions to the implementation issues related to MMLA [64], especially for guiding researchers on how to collect and analyze multimodal data in learning settings [51]. Nevertheless, researchers do not have enough information about how to implement MMLA in their studies. Therefore, there is a need for comprehensive roadmaps for the implementation of technology-enhanced MMLA in higher education. Despite these efforts, implementation remains challenging due to a lack of technical expertise among researchers and educators. The absence of widely accepted frameworks or roadmaps for MMLA adoption further complicates the process. Moreover, the high cost and resource requirements for implementing MMLA systems make it inaccessible to many institutions.

VI. CONCLUSION

This study provides a comprehensive analysis of publication trends, settings, analytical scope, implications, and future directions of technology-enhanced multimodal learning analytics (MMLA) in higher education, elucidating the clear potential and applicability of MMLA. Through a systematic literature review spanning the period from 2012 to 2024, 45 publications that met the predefined inclusion and exclusion criteria, and passed quality assessment were identified and subjected to detailed investigation. The findings have significant implications for students, instructors, higher education institutions, and researchers alike. Higher education institutions can leverage these findings to establish data-driven and technology-enhanced classrooms and laboratories, while researchers can conduct MMLA studies in these settings, employing appropriate analyses to enhance learning and teaching practices. The analytical results derived from these studies offer valuable insights for both teachers and students, enabling teachers to refine their lectures and empowering students to optimize their learning experience. Moreover, this study presents research gaps and noteworthy recommendations based on the review of MMLA, which can inform future research endeavors. In conclusion, the findings of this study serve as a foundational reference for further exploration of MMLA, while also providing remarkable suggestions for educational stakeholders in designing and implementing MMLA-oriented learning environments and conducting related studies.

VII. LIMITATIONS

This study is limited to the constructed search string and the selected databases. To mitigate this limitation, an inclusive search string was utilized to ensure that no relevant articles were overlooked. The most extensive databases suitable for this study's objectives were selected, including ScienceDirect, Web of Science, IEEE, Scopus, ERIC, EBSCOhost, and ACM. However, it is possible that there are studies in the field that do not employ the identified core and comprehensive terms or are outside the scope of these databases. Nevertheless, the selected publications underwent a rigorous elimination process, which included applying strict inclusion and exclusion criteria and conducting a thorough quality assessment. This ensured that they are representative of the field, and thus, the findings of this study can be generalized to the higher education context. Additionally, since Technology-Enhanced MMLA is particularly relevant to fields such as STEM (Science, Technology, Engineering, and Mathematics), a considerable number of STEM studies were also among the selected papers. However, this does not affect the applicability of the findings, as the principles and methodologies of Technology-Enhanced MMLA in this study extend beyond STEM and can be adapted to various disciplines. Although MMLA is a relatively new field and the focus of this study (technology-enhanced MMLA in higher education) is even more specific, an adequate number of studies with substantial data have been obtained to answer the research questions thanks to the systematic investigation.

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