The Role of Artificial Intelligence in Multimodal Learning Analytics: A Systematic Literature Review

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Abstract: Multimodal Learning Analytics (MMLA) integrates data from various sources (such as sensors, log files, and physiological signals) to comprehensively understand complex learning processes. Artificial Intelligence (AI) and Machine Learning (ML) technologies play an increasingly important role in the field of MMLA due to their ability to process large-scale, high-dimensional data. This systematic literature review aims to systematically organize and analyze the role, applications, main methods, key findings, challenges, and future directions of AI technologies in MMLA research. We conducted a systematic search of relevant literature from the past decade in the Web of Science (WoS) database and found that the core roles of AI in MMLA include: (1) automating the analysis and prediction of learner states and behaviors; (2) providing personalized learning feedback and interventions; (3) integrating and interpreting complex multimodal data streams; and (4) supporting the development and architectural design of MMLA systems. Commonly used AI methods include supervised learning and deep learning, with application scenarios covering collaborative learning, skill development, online learning, and special education. Key challenges involve model generalizability, data noise, ethical privacy issues (FATE), AI interpretability, and the transition from laboratory research to real-world scenarios.

Keywords: Multimodal Learning Analytics (MMLA), Artificial Intelligence (AI), Machine Learning (ML), Systematic Literature Review, Educational Technology, Learning Analytics

1. Introduction

1.1 Research Background and Significance:

With the proliferation of sensor technology, the Internet of Things (IoT), and wearable devices, the education sector has generated a diverse and vast amount of learning process data [1]. Multimodal Learning Analytics (MMLA) has emerged to capture, integrate, and analyze learning traces from different sources (such as video, audio, physiological signals, eye tracking, interaction logs, etc.) to gain a more comprehensive and in-depth understanding of learning processes occurring in physical or digital spaces [2], [3]. MMLA is no longer limited to traditional log-based learning analytics but strives to reveal the complex aspects of learners' cognition, emotions, behaviors, and social interactions in real learning contexts [4].

Artificial Intelligence (AI), particularly the development of Machine Learning (ML) technologies, provides powerful analytical tools for MMLA. Given the multi-source, heterogeneous, high-dimensional, and temporal characteristics of MMLA data, traditional statistical methods often struggle to handle them effectively [5]. AI/ML algorithms, such as classification, clustering, regression, and deep learning models, can automatically extract features, identify patterns, make predictions, and support personalized feedback and interventions from unprocessed or low-level multimodal data [6], [7]. The application of AI enables MMLA not only to describe learning phenomena but also to predict learning outcomes, diagnose learning difficulties, and even intervene in the learning process in real-time, showcasing tremendous application potential [8].

However, the application of AI in MMLA is still in its developmental stage, with related research presenting diverse methods, application scenarios, and challenges. Although there have been reviews of

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MMLA in the literature (e.g., [9], [10]), there is relatively little research that systematically explores the specific roles of AI in MMLA, the core technologies employed, the practical benefits derived, and the key issues that exist. Therefore, it is necessary to conduct a systematic literature review to comprehensively understand the latest developments, mainstream paradigms, core challenges, and future trends of AI in the field of MMLA, providing references for subsequent research and practice.

1.2 Research Questions:

This review aims to address the following three core questions:

RQ1: What are the main roles and application areas of AI technologies in MMLA research?

RQ2: What key AI methodologies have been adopted in MMLA research? What major findings have emerged from the application of these methodologies?

RQ3: What are the key challenges, limitations, and future research directions regarding the integration of AI in MMLA as discussed in the literature?

1.3 Scope of the Review:

This article is a systematic literature review covering nearly a decade (from 2016 to the present, up to the data export point, including relevant literature until 2025), primarily focusing on research applying AI or ML technologies in MMLA. The disciplinary scope mainly involves interdisciplinary fields such as educational technology, learning sciences, computer science, and human-computer interaction. The types of literature primarily include peer-reviewed journal articles and conference papers. The data source is limited to the Web of Science Core Collection.

2. Methods

2.1 Search Strategy:

The search strategy for this study is as follows: the research selected the Web of Science (WoS) Core Collection as the database, which has extensive coverage of academic resources and authority, providing rich and high-quality literature sources for this study. The search was conducted using a Topic Search (TS) method, with the search string constructed as: (TS=("Multimodal Learning Analytics") OR TS=("MMLA")) AND (TS=("Artificial Intelligence") OR TS=("AI") OR TS=("machine learning")). This search string aims to accurately capture literature that explicitly mentions MMLA and AI-related terms. Regarding the time frame for the search, although no strict start date was set, the research primarily focuses on literature from the past decade, with actual search results covering publications from 2016 to 2025. This time span ensures the timeliness of the research data while also tracing the development context of the field.

2.2 Inclusion/Exclusion Criteria:

In terms of inclusion criteria, the types of studies were limited to peer-reviewed journal articles or conference papers, ensuring the reliability of the literature quality and academic value, which can provide a rigorous theoretical and practical basis for the research; the language was specified as English to align with international cutting-edge research and to access a broader range of academic resources. Regarding thematic relevance, the research content must clearly involve the use of Artificial Intelligence (AI) or Machine Learning (ML) technologies to process or analyze multimodal learning data (MMLA context), thereby accurately targeting literature closely related to the core topics of this study; the time frame was set to publications after 2016, ensuring the timeliness of the research data and aligning with current trends in the field.

Exclusion criteria are designed to further refine the selection of literature. Non-English documents are excluded due to language limitations and their inconsistency with the linguistic environment of the research setting; non-peer-reviewed literature, such as abstracts, book reviews, editorials, and unpublished works, are excluded due to the lack of a rigorous academic review process, making it difficult to ensure the scientific validity and accuracy of the content; studies that do not apply AI or ML techniques, as well as those that do not use multimodal data or data not derived from learning analytics contexts, are irrelevant to the core content of this research and cannot provide effective support; furthermore, documents that are abbreviated as MMLA but actually refer to other concepts, such as "Multisensor Machine-Learning Approach" and "Multivariate machine learning analysis," are also excluded as they do not align with the concept of multimodal learning analytics defined in this study; duplicate literature can cause data redundancy, affecting the objectivity and validity of the research, and is similarly excluded.

2.3 Study Selection:

The literature selection process follows the basic procedures outlined in the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. It involves four steps: identification, screening, eligibility assessment, and inclusion, ultimately resulting in the inclusion of 87 studies in this systematic literature review (Figure 1).

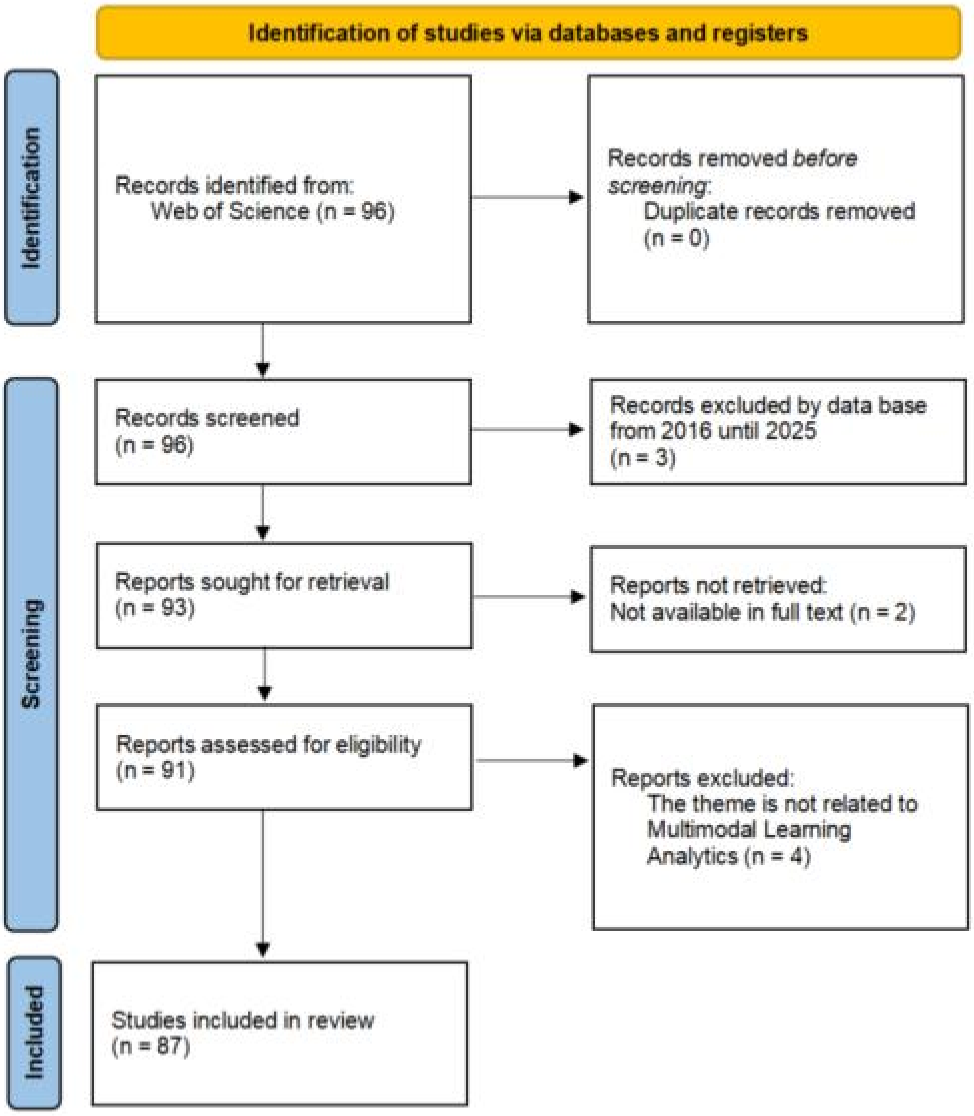

Figure 1: Literature Selection Process

2.4 Data Extraction & Quality Assessment:

Data Extraction: A structured information extraction table was designed to systematically record key information from each included study, including: authors, publication year, source of publication (journal/conference), research objectives/questions, AI/ML methods, types of multimodal data used (such as video, audio, eye-tracking, physiological signals, logs, motion capture, etc.), study subjects (sample size, type), learning contexts/tasks, main findings/conclusions, and reported challenges/limitations.

Quality Assessment: The MMAT (Mixed Methods Appraisal Tool) was referenced as a framework for quality assessment, focusing on the clarity of research design, adequacy of methodology descriptions, completeness of results reporting, and reasonableness of conclusions. Since this review emphasizes outlining the role and trends of AI in MMLA, a strict quantitative scoring of each study was not conducted; however, the assessment results aided in judging the reliability of the research and the weight of the conclusions. The overall impression of the literature quality is that there is a certain degree of heterogeneity in research design and reporting standards.

3 Results

Based on the analysis of the 87 included studies, we present the results from three aspects: basic characteristics of the literature, thematic/paradigmatic classification, and key findings.

3.1 Study Characteristics:

Publication Trends: From the publication years of the included literature (PY 2016-2025), research on AI in MMLA shows a significant growth trend, especially with a noticeable increase in the number of publications in the last five years, which is consistent with the bibliometric analysis results of Pei et al. [9], indicating that the field is in a rapid development phase.

Types of Literature: Most studies are published in international conferences (such as LAK, AIED, ICALT, EC-TEL, ICMI) and journals in related fields (such as JLA, BJET, JCAL, IEEE TLT, Computers & Education, Sensors, IEEE Access). Conference papers typically present newer exploratory work and system prototypes, while journal articles provide more in-depth analysis and validation.

Research Methods: The majority of studies are empirical, including laboratory experiments, quasi-experiments, and "in-the-wild" studies [11]. Many studies involve system development, model construction, and evaluation. A few pieces of literature are reviews or position papers (e.g., [1, 4, 10]).

Research Background and Modalities: The research covers various stages from K-12 to higher education and vocational training (such as nursing). The learning contexts are diverse, including individual learning, collaborative learning [12], [13], project-based learning [14], online learning [15], special education [16], language learning [17]-[19], and STEM education [20]. The modalities of data used are extremely rich, commonly including:

(1)Visual Data: Including videos (facial expressions, postures, gestures), eye-tracking [21], [22];

(2)Auditory Data: Analyzing the content, prosody, and volume of speech [23], [24];

(3)Physiological Signals: Including electroencephalography (EEG) [25], [26], electrodermal activity (EDA/GSR) [27], [28], heart rate (HR/HRV) [16], [29], and body temperature [28].

(4)Behavioral Data: Interaction logs [30], keyboard and mouse operations, physical sensors (accelerometers, location tracking) [31], [32], handwriting data [22], [33].

3.2 Thematic or Paradigm Classification (Thematic/Synthesis):

Based on the research objectives and the application of AI, the included literature can be categorized into the following main themes (addressing RQ1 and RQ2):

Theme 1: Automation Analysis and Prediction of Learner Status and Behavior Based on AI.

This is the most widespread application of AI in MMLA, mainly including the analysis and prediction of the following aspects:

Cognitive states: predicting cognitive load [22], [28], attention [34], [35], flow state, comprehension level, confusion state [36], etc.

Affective and motivational states: identifying emotions [37], [38], engagement/involvement [39]-[41], stress/arousal levels [29], [42], motivation [26], boredom [36], drowsiness [43], etc.

Behavioral patterns: assessing collaboration quality and its dimensions [44]-[48], identifying help-seeking behavior [49], predicting self-regulated learning (SRL) strategies [50], quantifying specific teaching practices [51], body movements and interaction patterns [52].

Learning outcome prediction: using multimodal features to predict academic performance, task success rates, learning gains, etc. [14], [30], [53], [54].

In terms of AI algorithms, supervised learning algorithms are widely used, such as Support Vector Machines (SVM), Random Forests (RF), Decision Trees (DT), Naive Bayes, and AdaBoost [12]. Deep learning methods are also increasingly common, especially for processing time-series data and complex feature extraction, such as Long Short-Term Memory networks (LSTM) [55], Recurrent Neural Networks (RNN), Convolutional Neural Networks (CNN) (commonly used for image/video analysis), and Transformer-based models. Reinforcement Learning (RL) is also beginning to be explored for personalized education [8].

Theme 2: AI-based personalized feedback and interventions

Using AI to analyze MMLA data, driving adaptive learning systems, intelligent tutoring systems, or providing decision support for teachers to achieve personalized instruction.

Personalized recommendations/adaptations: adjusting learning content, difficulty, or pace based on learner status [8].

Real-time/near-real-time feedback: providing feedback to learners or teachers regarding engagement, collaboration, emotions, etc. [25], [35], [52], [56].

Agent Interaction: Developing Embodied Conversational Agents (ECAs) or social robots that utilize MMLA to understand and respond to learners, facilitating interaction and learning [57], [58].

In the application of AI technologies in this area, in addition to predictive models, natural language processing (NLP) techniques are involved to analyze text/audio interactions and generate feedback [7], [59], and reinforcement learning is used to optimize intervention strategies [8].

Theme 3: AI-Driven Multimodal Data Fusion and Feature Engineering

AI technologies are used to process and integrate heterogeneous data from different sensors and extract meaningful high-level features.

Data Fusion Strategies: Exploring early fusion (feature-level fusion), late fusion (decision-level fusion), or hybrid fusion methods [36], [60].

Feature Extraction/Selection: Automatically extracting features using deep learning or selecting key multimodal features related to learning using ML techniques (such as Principal Component Analysis (PCA), feature importance ranking) [14].

Theme 4: AI-Supported MMLA System and Framework Development

The research focuses on designing and implementing MMLA platforms, architectures, or toolkits that integrate AI functionalities.

Reference Architecture: Proposing a logical architecture for MMLA systems, clarifying modules for data collection, processing, analysis, and presentation [61], [62].

Toolkits/Platforms: Developing user-friendly MMLA tools to lower the barriers for research and application [37], [52].

Design Framework: Proposing methodologies or models for MMLA system design [18], [19].

3.3 Key Findings:

In the field of Multimodal Learning Analytics (MMLA), AI/ML models demonstrate powerful data analysis capabilities, with their core advantages first reflected in the effective identification and prediction of learning-related states and behaviors. The accuracy of such models is often significantly better than random guessing, and they even show extremely high precision in specific tasks; for example, the prediction accuracy of behavior change reached 98% in literature [16]. Furthermore, integrating multimodal data often yields more accurate and robust predictive results than single-modal data [60,50,43,63], thanks to the complementarity of different modal data: physiological signals can reflect the internal states of learners, while behavioral data presents external performances, and the combination of both can construct a more complete learning profile. Specifically, certain modalities are often highly correlated with specific psychological or behavioral constructs: speech features are closely linked to collaborative communication skills [24], eye-tracking data can reveal attention distribution and cognitive load states [22], and physiological signals (such as Electrodermal Activity (EDA) and Heart Rate (HR)) can effectively represent emotional arousal, stress levels, and cognitive load [27]-[29]. In terms of technical pathways, although deep learning models show unique potential in handling high-dimensional time-series data such as video and EEG [55], traditional ML methods are still favored by researchers in scenarios requiring transparent analysis due to their stronger interpretability [5], [14]. It is noteworthy that the current application of AI in MMLA is shifting from laboratory environments to real classroom settings; however, this process faces many challenges—the generalizability of models is significantly influenced by contextual factors such as task types, disciplinary differences, cultural backgrounds, and population characteristics [5], [13], [16], [45]. Meanwhile, as the application of technology deepens, ethical concerns continue to rise, particularly regarding data privacy protection, algorithm fairness, transparency, and accountability mechanisms (FATE: Fairness, Accountability, Transparency, Ethics), which have become important dimensions that cannot be ignored in research and practice in this field [61], [64], [65].

4. Discussion

4.1 Significance of Main Findings: (Answering RQ1 and RQ2)

The results of this review clearly indicate that AI is not merely a tool for MMLA, but is profoundly shaping its development direction and capability boundaries. AI technology enables researchers to:

(1)Go beyond surface phenomena: By analyzing multidimensional data such as physiological and behavioral data, AI can reveal internal learning states (such as cognitive load and emotional fluctuations) that traditional methods struggle to capture, as well as their complex relationships with overt behaviors and learning outcomes.

(2)Achieve large-scale, automated analysis: The ability of AI to process massive MMLA data makes it possible to conduct fine-grained analyses of large learning populations and automate processes that previously required extensive manual coding (such as behavior annotation and collaboration quality assessment).

(3)Empower personalization and adaptability:

Based on AI predictions and analyses, more intelligent and adaptive learning environments and interventions can be constructed, truly achieving tailored education, such as providing timely scaffolding through agents [57] or adjusting learning paths [8].

(4)Facilitate the integration of theory and practice: AI models can be used to test learning theories (such as cognitive load theory and self-regulated learning theory) in real multimodal data and provide data-driven insights and tools for educational practices (e.g., [56] using AI to reveal effective teaching practices).

The role of AI is shifting from retrospective analysis to real-time monitoring and proactive intervention, marking a development towards a more practically impactful direction in the field of MMLA.

4.2 Comparison with Previous Reviews:

The findings of this study present both consistencies and supplements compared to previous MMLA reviews. Firstly, consistent with the bibliometric analysis conducted by Pei et al. [9], this study also confirms the rapid development trend in this field and the central role of AI/ML within it, further validating previous research's judgments on industry trends. In contrast to the review by Giannakos and Cukurova [10], which focuses on theoretical applications, this review emphasizes the role and methods of AI technology itself; however, the exploration process also indirectly reflects that many current studies still tend to lean towards the technical implementation aspect, lacking in-depth theoretical integration, a finding that supports their viewpoint that theoretical applications need further strengthening [66]. Meanwhile, this review aligns closely with the review by Prinsloo et al. [1], which emphasizes ethical and privacy issues, also finding that ethical considerations, especially topics related to FATE (Fairness, Accountability, Transparency, Ethics), have become hot and challenging issues in current research [64]. Compared to the review by Shankar et al. [61] on early MMLA frameworks, this study reveals continuous progress in system architecture, data models, and tool development [37], [62], with an increasingly in-depth integration of AI components. It is worth emphasizing that the uniqueness of this review lies in its systematic focus on the specific roles, methodological classifications of AI in MMLA, and the key findings and challenges it brings, thus providing a comprehensive and detailed picture of the development in this interdisciplinary field over the past decade.

4.3 Gaps & Future Research: (Answering RQ3)

Despite significant progress, the application of AI in MMLA still faces numerous challenges, pointing to future research directions:

(1)Enhancing model generalizability: This is one of the most prominent challenges. Most models perform well in specific contexts, but their performance drops sharply when applied across tasks, populations, cultures, and environments [5], [13]. Future research needs to adopt more robust feature engineering, domain adaptation techniques, and multi-task learning, and validate in a more diverse range of real-world scenarios.

(2)Enhancing AI explainability (Explainability, XAI): "Black box" models are difficult for educators and learners to understand their decision-making basis, limiting trust and application [41]. There is a need to develop and apply explainable AI technologies that provide pedagogically understandable insights and feedback.

(3)Deepening ethical considerations (Ethics & FATE): How to enhance learning using MMLA data while protecting student privacy, ensuring algorithmic fairness, avoiding biases (such as gender and racial biases [34]), and clarifying data ownership and usage rights are urgent issues that need to be addressed [64], [65]. Clear ethical guidelines and technical solutions need to be established.

(4)Addressing data quality and noise: Data collected from real-world scenarios ("in-the-wild") often contains noise, missing values, and synchronization issues [11], [12]. More effective signal processing, data cleaning, and noise-resistant AI algorithms are needed.

(5)Strengthening theoretical guidance and integration: The construction of AI models and the interpretation of results should be more closely aligned with learning science theories, avoiding a technology-driven approach that neglects the essence of education [10], [66].

(6)Promoting the translation of research into practice: Bridging the gap between laboratory research and large-scale classroom applications, developing tools and systems that are friendly to teachers and students and easy to integrate into existing teaching processes [11], [37].

(7)Exploring more advanced AI technologies: for example, exploring the application of Generative AI (GenAI) in MMLA data augmentation, personalized feedback generation, and data storytelling presentation

[49], [67].

4.4 Implications for Practice/Policy:

Practical Level: AI-driven MMLA can provide teachers with richer perspectives on student understanding and classroom management tools (such as automated collaborative monitoring dashboards [35, 52]). Personalized learning systems can be developed to offer targeted learning support and feedback [8]. It can be used for student reflection tools to help them understand their learning processes [64].

Policy Level: Educational institutions and policymakers need to establish ethical guidelines and privacy protection policies regarding the collection and use of MMLA data and the application of AI algorithms. Support should be provided for the development of standardized data formats and interfaces to promote system interoperability. Consideration should be given to providing relevant training for teachers to equip them with the ability to understand and effectively utilize AI-driven MMLA tools [56].

5. Limitations

This systematic literature review has limitations in several aspects. First, the database usage was relatively singular, only retrieving literature from the Web of Science database, which may have led to the omission of relevant literature indexed in other databases such as Scopus, PubMed, and ACM Digital Library. Second, the search terms used may not have covered all relevant studies, especially those that did not use standard terminology but are substantively related to the field. Additionally, there is a clear bias in language, as the review only included English literature, neglecting significant research findings in other languages, which limits the comprehensive analysis of related research globally. Furthermore, in the quality assessment phase, no strict quantitative quality scoring was conducted; the judgment of literature quality was based solely on the researchers' overall assessment, lacking more precise and quantitative standards. Moreover, there is subjectivity in the thematic summarization process, as the categorization of themes and extraction of key findings inevitably carry the researchers' subjective interpretations, which may affect the objectivity of the conclusions. Finally, this study did not include gray literature, such as theses and technical reports, which were not analyzed, resulting in a lack of completeness in the types of literature considered.

6. Conclusion

This systematic literature review systematically reviewed the research on Artificial Intelligence (AI) in the field of Multimodal Learning Analytics (MMLA) over the past decade. The results indicate that AI has become the core technological engine of MMLA, primarily functioning in automating the analysis and prediction of complex states and behaviors in learning processes, achieving personalized feedback and interventions, facilitating the integration and interpretation of multimodal data, and supporting the design and development of related systems. Supervised learning and deep learning are the main AI methodologies employed, which have made significant progress in understanding collaborative learning, emotional states, cognitive load, and more.

However, the application of AI in MMLA also faces severe challenges, particularly regarding the generalizability of models, the interpretability issues arising from the "black box" nature of AI algorithms, and the increasingly prominent ethical and privacy (FATE) risks. Future research needs to focus on enhancing the robustness of technology while paying more attention to the construction of ethical norms, the exploration of explainable AI, the deep integration of theory and technology, and the effective translation of research findings into real educational practices.

Looking ahead, with the continuous advancement of AI technology (such as the integration of generative AI) and deeper research, AI-enabled MMLA is expected to provide strong support for creating more effective, equitable, and personalized learning experiences, provided that its development and application are advanced in a responsible, ethical, and human-centered manner.

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