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Systematic Review on the Application of Multimodal Learning Analytics to Personalize Students' Learning

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ABSTRACT

In personalized learning (PL), learning processes are customized to account for student skills and preferences. However, as PL is generally based on a single data type, it cannot wholly represent students' learning behaviors and progress. Hence, it is crucial to leverage Multimodal Learning Analytics (MMLA) in PL to alleviate these restrictions. A systematic literature review was conducted to explore the use of MMLA in PL and investigate its benefits across several contexts and approaches. The underexplored aspects of MMLA in PL, like the gaps in topics, pedagogies, learning settings and environments, populations, and modalities studied, are addressed, and MMLA's potential to provide real-time tailored feedback and improve engagement is discussed.

Keywords: multimodal learning analytics, multimodal data, personalised learning, systematic review

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Introduction

Students entering formal education have always varied in their cognitive and socio-emotional skills because of differences in their genetic predispositions and environmental factors (Dumont & Ready, 2023). These differences have challenged educational institutions worldwide to

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organize pedagogical methods that ensure equal learning opportunities for each student. While this problem was previously tackled by sorting students according to their academic aptitude, such practices can worsen disparities and cause lower learning outcomes (Dumont & Ready, 2023). Recent technological advancements have drawn attention to Personalized Learning (PL) and student-centered pedagogy. These are approaches that entail customizing teaching methods to fit each student's needs (Dumont & Ready, 2023), abilities, and interests and are growing in importance in modern classrooms (Khor & Mutthulakshmi, 2023). To make this happen, educators need a detailed and holistic understanding of students' learning processes. This is where multimodal learning analytics (MMLA) may play a role in assisting educators to acquire this information by integrating various types of learning data from multiple sources. Equipping educators with knowledge from diverse sources allow them to more accurately identify specific sections of students' learning process to focus on that are most effective to improving their learning experience. By gaining a more holistic view of students' learning landscape, educators may thus better characterize students' learning needs.

Literature Review

Personalized Learning

Rather than a one-size-fits-all approach (Taylor et al., 2021), modern educational systems support students in taking ownership of their education through individualized learning paths instead. Additionally, modern educational systems can identify students' strengths, weaknesses, and learning paces better than existing learning analytics (LA) systems can (Maseleno et al., 2018), thereby enhancing teachers' abilities to provide timely feedback on student performance (Taylor et al., 2021). PL involves monitoring and interpreting user activities, inferring user requirements and preferences, representing these insights in associated models, and dynamically facilitating learning based on available knowledge (Taylor et al., 2021).

Emerging technologies like learning analytics (LA) were initially expected to enhance PL methods by assessing educational data (Taylor et al., 2021). For example, LA tracks learning data patterns, boosting students' self-awareness and thus promoting self-regulation and positive habits, enhancing their learning experiences (Khor & Looi, 2019). However, PL's foundation in constructivist learning theories requires teaching approaches to specifically encourage active student engagement. Learning technologies must identify and support student needs while also preparing students for independent learning (Taylor et al., 2021). While scholars like Alexander et al. (2019) previously expressed concerns about unmet expectations as most pedagogical technologies were still in their infancy, the focus on customizing instruction to meet students' needs has spurred technological innovations, such as MMLA.

Multimodal Learning Analytics

MMLA involves gathering and analyzing data across different modalities or different sources or types of learning information to better inform the understanding of students' learning processes (Blikstein & Worsley, 2016). MMLA promises to observe learning events at the micro level with multimodal data (MMD), which refers to integrated learning data across various modalities, and identify the cognitive, emotional, and psychomotor aspects of individuals, offering a novel framework to improve teaching and learning processes (Maseleno et al., 2018). Its intentions are to enrich the types of learning data collected by expanding the scope beyond those traditionally collected in learning analytics or educational technology research, support the quality of interactions between students and learning systems by expanding the types of interactions available, and provide rich, holistic data that guides learning system developers in maximizing the quality of learning systems (Giannakos et al., 2022).

Research Questions

Since MMLA holds great potential to be integrated into PL, the present study conducted a systematic literature review (SLR) to delve into its application in the field. In this study, the following research questions (RQ) will be addressed:

RQ1: What can MMLA approaches tell us about the nature of the PL landscape?

RQ2: How can MMLA improve PL practices?

Methodology

A systematic literature search was performed using well-known databases and targeted keywords. (TITLE-ABS-KEY ("multimodal learning analytics") OR ("multimodal learning") AND ("personalized learning") OR ("personalized learning environments") AND ("classrooms") OR ("K-12") OR ("education") AND ("students") were the keywords used. 140 articles in Scopus, 38 in Web of Science, and 101 in Semantics Scholar were located. Publications from 2013 onward were chosen because of the enormous advancements that have occurred since. After removing any duplicates, 221 articles in all were reviewed, and 70 were chosen for retrieval. 16 articles could not be retrieved, leaving 54 papers for analysis. Only articles that met the quality criteria, empirical studies, studies published in English, and articles published between 2013 and 2023 were included. Any studies that failed to meet the quality criteria, non-empirical studies, articles which were published in languages other than English, and articles published before 2013 were excluded for lack of relevance. Based on these inclusion and exclusion criteria, three articles were eliminated for methodological relevance, five articles for unclear engagement features, and 16 articles for lacking relevance. Following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) principles, 30 publications were ultimately reviewed (Figure 1).

The following eight criteria were referred to when selecting articles as an assessment of their quality before including them in the study.

a. Are the research objectives visible?

b. Is the research problem clearly addressed?

c. Is the research design relevant to the objectives?

d. Is there an elaborate description of how the research was executed?

e. Does the research study outline the utilised research methods, including information on data collection, participants, research instruments, and data analysis?

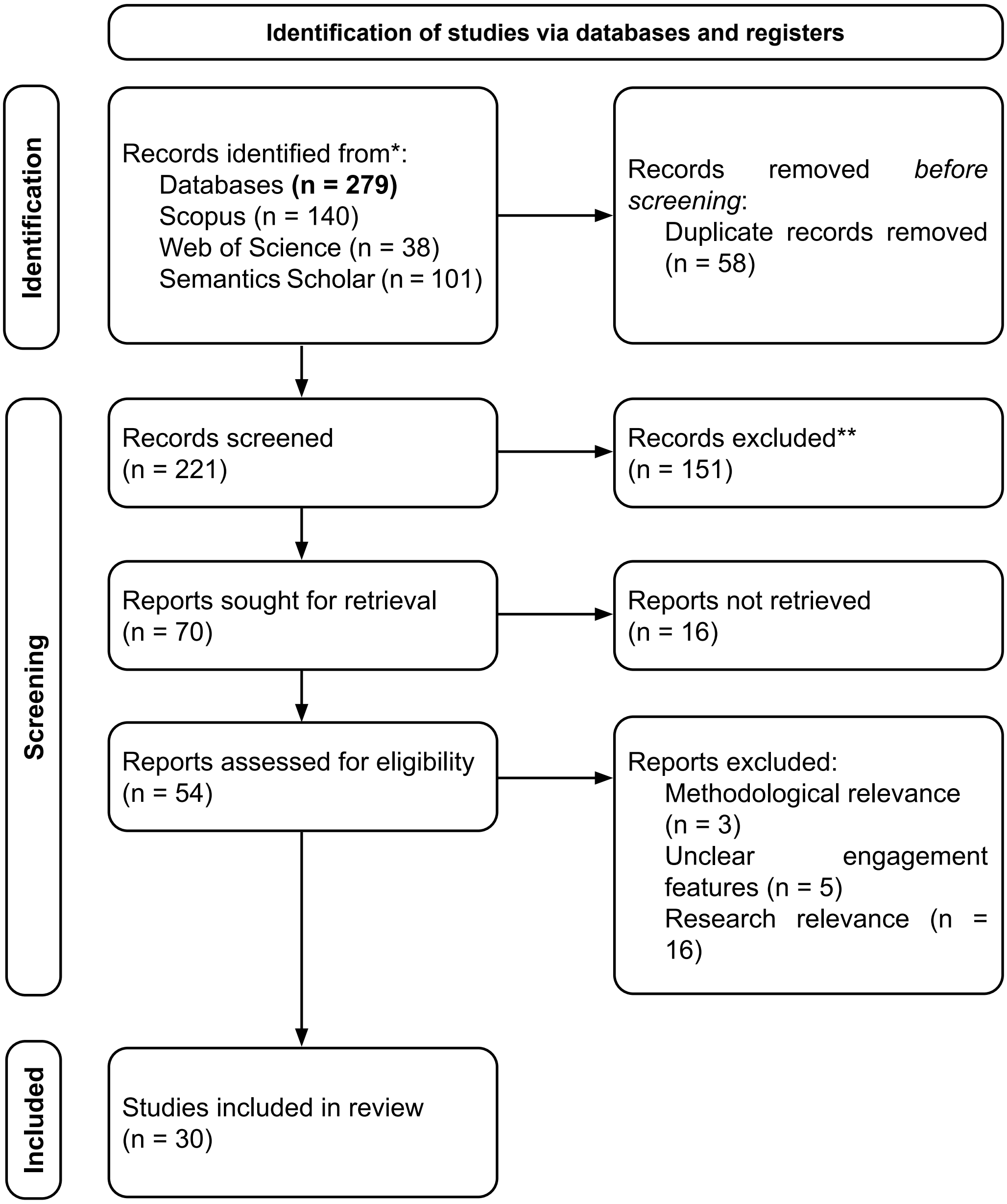
f. Was the process of data analysis conducted diligently and comprehensively?

g. Are the findings clear?

h. Does the study contribute towards further research or practice?

Figure 1

PRISMA diagram of the Article Selection Process



Findings and Discussion

RQ1 – What can MMLA approaches tell us about the nature of the PL landscape?

Learning Setting, Environment, and Topic

The research in this field comprised a good mix of case studies (*n* = *12*) and experiments (*n* = *17*), with only one study employing an ethnographic approach. This prevalence of experiments and the incorporation of established frameworks in case studies underscore the preliminary exploratory nature of MMLA research. Sharma et al. (2019) demonstrated how to obtain MMD predictions and employed data collection within a specific case study context. Similarly, Noel et al. (2018) described utilizing MMD to understand user experiences specifically in an engineering course. Most experiments were held in formal learning settings (*n* = *9*), while eight occurred in informal learning environments, such as digital learning platforms (Amarasinghe et al., 20219), or independent study sessions (Di Mitri et al., 2017). This reveals an inclination toward methodological-driven interventions, predominantly within formal educational settings such as classrooms or designated learning environments, as exemplified by Spikol et al. (2018), Worsley and Blikstein (2018). Of the nine formal learning contexts, six were held in universities, where conventional pedagogical practices, which typically draw from established models of instruction featuring instructors taking on a central instructional role while students receive information passively, hold prominence. As the usage of MMLA within informal educational settings remains relatively more uncommon, this finding suggests that there is room for the greater integration of MMLA within informal educational settings.

MMLA contributions covered diverse learning environments (Table 1), mainly focusing on face-to-face classroom instruction (*n* = *13*), simulations (*n* = *5*), laboratory (*n* = *1*), and online systems (*n* = *8*). Online systems include Learning Management Systems (LMS, *n* = *4*), Massive Open Online Course (MOOC, *n* = *1*), Intelligent Tutoring Systems (ITS, *n* = *2*), and Integrated Development Environment (IDE, *n* = *1*). The diversity in learning environments suggests MMLA's potential to successfully support learning across multiple contexts. As MMLA allows for the integration of MMD and is compatible with multiple contexts, it can provide comparisons between learning environments to understand students' individualized learning environment preferences. MMLA approaches can thus inform and describe PL in various environments and settings.

Table 1

Learning Environment

Learning Environments	No. of Studies
Classrooms	13
Simulations	5
Laboratory	1
LMS	4
MOOC	1
ITS	2
IDE	1
Other	3

A significant portion of MMLA investigations (*n* = *11*) centered on Science, Technology, Engineering, and Mathematics (STEM) subjects. Eight studies specifically focused on Computer Science (CS) education. Additionally, some studies delved into more encompassing themes such as teaching (*n* = *5*), gaming (*n* = *3*), healthcare (*n* = *1*), communication (*n* = *1*), and miscellaneous topics (*n* = *1*) (Table 2). This suggests a possible knowledge gap in the literature on exploring MMLA with learners studying topics other than STEM and CS.

Table 2

Subject Topics

Topics	No. of Studies
STEM	11
CS	8
Teaching	5
Gaming	3
Healthcare	1
Communication	1
Others	1

Pedagogical Approach

While the study of PL specifically remains limited in available research, many other educational methodologies have been practiced within the broader PL framework (Table 3). These encompass self-regulated learning (SRL, *n* = *6*), inquiry-based learning (IBL, *n* = *5*), problem-based learning (PBL, *n* = *13*), problem-regulated learning (PRL, *n* = *2*), computer-supported collaborative learning (CSCL, *n* = *2*), and game-based learning (GBL, *n* = *2*).

It is worth noting that there is a pronounced emphasis on learning in face-to-face classroom contexts and active learning, indicating efforts to extract MMD from non-digital educational contexts. This is exemplified in Worsley and Blikstein (2018), who employed IBL for engineering analysis, Junokas et al. (2018) and Mangaroska et al. (2019) in their investigations of gesture recognition and coding, and Spikol et al. (2016) and Martinez-Maldonado et al. (2018) in their examinations of healthcare and programming contexts.

Table 3

Pedagogical Approaches

Pedagogical Approaches	No. of Studies
SRL	6
IBL	5
PBL	13
PRL	2
CSCL	2
GBL	2

Population, Sample Size, and Methodology

The most studied population was undergraduates, followed by high school students (Table 4), suggesting that the understanding of MMLA and its uses for PL may revolve around learners with moderate expertise. This leaves room for further exploration of MMLA and its uses in PL for simpler topics or beginners such as elementary school students or advanced learners such as postgraduate students..

Table 4

Types of Participants in MMLA Studies

Type of Participants	No. of Studies*
Elementary Students	6
High school Students	9
Undergraduate Students	13
Postgraduate Students	2
Teachers	2

**2 studies had multiple groups of participants.*

Three studies employed fewer than 10 participants, while two studies had over 200 participants. Four studies' participant numbers ranged between 10 to 20 individuals, while nine studies had over 20 to 40 individuals, three studies had over 40 to 60 individuals, and one study included a range of 60 to 80 participants. Two studies' participant groups ranged from 80 to 100 individuals, and another two studies featured participant groups exceeding 100 individuals. Four studies did not disclose their participant numbers.

As for the number of modalities employed, most studies used one (*n* = *6*), two (*n* = *8*), three (*n* = *7*), or four (*n* = *5*) modalities, with only two studies using five modalities and two using six modalities. However, the average number of modalities employed hardly differed across studies with varying sample sizes (Table 5). Studies with complex data collection methodologies such as eye-tracking (Mangaroska et al., 2018), electroencephalogram (EEG) (Giannakos et al., 2019; Sharma et al., 2019), electrodermal activity (EDA) sensors (Worsley & Blikstein, 2018), and the incorporation of Kinect technology (Kosmas et al., 2018; Martinez-Maldonado et al., 2017), were present in studies with small sample size. Interestingly, studies employing over 40 participants mostly used MMD like audio, logs, video, and surveys. This synergy between various modalities is the source of MMLA's value. By combining insights from diverse modalities, MMLA reveals a holistic understanding of students' interactions and learning strategies (Alwahaby et al., 2022). The surveyed studies demonstrated that students' learning-task performance can be predicted by tracking their gaze, movement, and positions. Thus, by exploring multiple modalities of learning data (e.g., facial expression, learner positioning, affective state), researchers can obtain a multifaceted view of PL dynamics.

Table 5

Average Number of Modalities Per Sample Size

Sample Size	Average No. of Modalities
<10	3.33
10-20	3.5
20-40	2.67
40-60	2.67
60-80	2
80-100	2.5
100-200	3.5
>200	1.5

The most popular forms of analysis were quantitative methods (*n* = 21), followed by mixed methods (*n* = 6) and qualitative methods (*n* = 3). A variety of data modalities were used to understand specific aspects of students' learning experiences. Video data was used to assess presenter attributes, dialogue characteristics, and facial dynamics (Prieto et al., 2016, 2018; Worsley & Blikstein, 2018), while students' attention and visual behavior were measured using eye-tracking technology (Mangaroska et al., 2018; Prieto et al., 2018). Skin sensing techniques, like galvanic skin response and temperature and heart rate measurements, allowed researchers to study students' cognitive load and arousal (Giannakos et al., 2019; Prieto et al., 2016; & Sharma et al., 2019). Deep cognitive processes like cognitive workload, long and short-term memory load were explored using EEG and physiological data (Giannakos et al., 2019; Prieto et al., 2016; Sharma et al., 2019). Emotions like happiness, boredom, engagement, and sadness were studied using facial expressions (Florian-Gaviria et al., 2013; Ochoa et al., 2018). Finally, location sensing technology kept track of students' positions, movements, and collaboration in physical environments (Sharma et al., 2019).

Diverse techniques were employed for data collection (Table 6). Frequently used methods included logs (*n = 14*), audio recordings (*n = 14*), video recordings (*n = 12*), motion tracking data (*n = 6*), and surveys (*n = 6*).

Table 6

Types of Modalities Employed

Modality	No. of studies^
Logs	14
Audio	14
Videos	12
Motion-based	6
Survey	6
Gesture	5
Physiological	5
Eye-tracking	5
Gaze	5
Facial expressions	5
EEG	3
Interviews	2
Human Observations	2
Posture	1

^Most studies employed multiple modalities.

While the current MMLA literature largely focuses on specific data modalities, namely logs, audio, and video recordings, the surveyed studies reveal several other unique methods employed, like EEG and eye-tracking. The diversity of data collected by MMLA approaches has facilitated a deeper understanding of variables which are known to influence the learning processes yet are difficult to measure objectively. These variables include emotions (Florian-Gaviria et al., 2013; Ochoa et al., 2018), cognitive load (Giannakos et al., 2019; Prieto et al., 2016; Sharma et al., 2019), and attention (Mangaroska et al., 2018; Prieto et al., 2018). Researchers can make use of these precise, targeted insights to further personalize learning strategies. These unique yet underexplored data modalities can thus provide innovative perspectives on PL and its unseen effects.

RQ2 – How can MMLA improve PL practices?

Adaptation and Feedback

While much research focuses on modifying feedback messages, particularly by using empathy to boost student motivation, MMLA approaches instead tailor the type of feedback, instructional or reflective prompts, based on real-time assessment of students' interaction and performance (Grawemeyer et al., 2017). This process unfolds in two phases. Firstly, MMLA capabilities facilitate comprehensive investigation into student-centered learning, learner behavior, and interactions at a granular level (D'Mello & Graesser, 2012). Junokas et al. (2018) showcased the potential of gesture-based educational simulations using MMLA to create personalized interfaces, and Ezen-Can et al. (2015) contributed to understanding students' utterances by integrating language-based MMD processing features into PL environments. Kaklauskas et al. (2015) introduced an innovative organization incorporating a student's preferred learning style to deliver suitable learning adaptations.

Next, facilitated by post-assessment and formative feedback, researchers can use MMLA techniques to streamline the evaluation process (D'Mello & Graesser, 2012). This empowers researchers to devise better PL support systems, pedagogical methodologies, and learning materials (D'Mello & Graesser, 2012). Ochoa et al. (2018) found significant concordance between system and human feedback, where students have identified MMD-based feedback (i.e., audio, voice, and hand-annotated data) as significantly more beneficial to oral presentation skills. Santos et al. (2014) employed physiological and log data to highlight how students' emotional dispositions should be considered when designing effective and well-received recommendation systems. Moreover, the implementation of personalized feedback has identified opportune moments during students' interactions with educational technology. Such knowledge was used to customize real-time formation of groups and scaffolding within classroom environments (Amarasinghe et al., 2019) and to forecast students' ongoing learning states, facilitating the timely provision of scaffolding (Di Mitri et al., 2017).

Increased Student Engagement

Engagement patterns with MMLA offer valuable insights into student engagement levels. Nguyen et al. (2018) observed that while all students spent substantial time learning, high-performing students allocated more time to proactive studying, like preparatory activities, whereas low-performing students were more involved in catching-up activities. Chan et al. (2020) noted that student talk, gaze direction, and teacher talk efficiently predicted students' engagement levels. These studies suggest a potential for linking PL with MMLA-based insights to enhance student engagement. MMLA could be utilized to highlight pertinent events to students (Pardo et al., 2017) or offer upfront scaffolding and support for pedagogy materials to address disengagement factors (Nguyen et al., 2018). Nevertheless, further exploration is essential, as the current focus on engagement scores primarily captures behavioral engagement. Additional evidence sources and interpretive analyses may be required to assess cognitive engagement (Nguyen et al., 2018; Pardo et al., 2017; Chan et al., 2020).

Implications

Actionable Insights for Teachers

While understanding student learning is undoubtedly essential, adopting a complementary teacher-oriented perspective is equally imperative. As a sub-field within LA, 'teaching analytics' specifically concentrates on the creation, advancement, and assessment of visual analytics methods and tools to understand the mechanisms behind learning processes and intervention assessment (Prieto et al., 2016). Incorporating student-centered and teacher-centered viewpoints can enhance existing PL approaches to foster effective teaching and learning strategies (Prieto et al., 2016). For instance, Prieto et al. (2016) found that eye-tracking data (and other MMD describing emotional and cognitive load factors) ascertained how various teaching activities at distinct social planes can elicit different levels of cognitive load. Chan et al. (2020) found that visualizing student attention, teacher position, and engagement scores offered valuable feedback that enabled teachers to experiment with teaching strategies and assess student attention capture. The integrated data also identified which students collaborated better in pairs or groups, facilitating the evaluation of the effectiveness of group work.

Furthermore, MMLA positively influences prediction performance and can enhance teachers' abilities to interpret learning data and respond accordingly, as shown by Rodríguez-Triana et al. (2018). MMLA solutions could also relieve teachers' workload and reduce the time and effort needed to manage learning designs by simplifying the data gathering and integration processes, supporting them to efficiently facilitate PL environments (Rodríguez-Triana et al., 2018). Additionally, MMLA's analytical foundation for teaching categorization models can reveal how classroom decisions are made (Cukurova et al., 2018), which could be used to inform teachers' efforts in identifying and customizing support for weaker students. At-risk students could also grow through practicing self-reflection using PL techniques (Cukurova et al., 2018). MMLA research in education has notably centered on simpler modalities (e.g., video, audio, and motion) easily implemented within an educational context. These studies suggest that MMD holds significant implications for individualized teaching design and produces useful insights about teaching processes over time due to its ability to extract nonobvious or cognitively demanding information (e.g., posture, gestures, collaboration level).

Conclusion

The present study reaffirms the value of MMLA in improving students' learning experience. The reviewed studies supported its ability to gain insights into various unseen, internal, aspects of students' learning experiences, such as the emotional and cognitive domains, through the wide variety of data modalities collected and analyzed. This information may then be used to precisely predict changes in students' learning performance or behavior, which can guide the customization of learning interfaces or contexts to suit their needs and boost student engagement in the process. This study's data reveals recognizable patterns in STEM and CS, namely, extensive scholarly inquiry, clearly defined problem formulations, and established problem-solving methodologies. Though the underlying reasons for these trends remain uncertain, they may reflect the advantages of university-based research and the prevalence of action-oriented learning approaches, especially in STEM disciplines. However, there still remains room for further exploration in integrating MMLA into non-STEM disciplines or informal educational environments. Out of the learning settings investigated, face-to-face classroom settings and Intelligent Tutoring Systems (ITS) appear to be most conducive to multimodal data (MMD) collection as they are most compatible with physiological sensors, in comparison to other common learning settings such as MOOC or LMS. In a physical setting, it is most convenient to set up physiological sensors as one can interact with students directly to measure their physiological reactions. Amongst the online learning settings, it is easiest to integrate eye trackers and webcams into ITS, and it comes with the advantage of utilizing system timestamps for synchronization purposes.

The present study also identified an issue where modalities that cannot inform researchers of students' learning outcomes, processes, and behavior (eg; logs, audio, video, and gestures) are more commonly used when collecting MMD. This is due to their cost-effectiveness, ease of setting up, and non-intrusiveness. On the other hand, MMD offering more profound insights into students' affect, attention, and cognition are rarely explored. Obstacles challenging EEG data integration in

MMLA include a low signal-to-noise ratio thus requiring extensive preprocessing, higher data collection costs, and concerns about ecological validity. Fortunately, recent EEG technological advancements featuring less invasive devices capable of approximating deeper cognitive states are now available. Researchers can now consider employing a wider variety of modalities to improve the depth of their obtained findings.

Another noteworthy discovery is the narrow scope of learning scenarios in the MMLA literature, which is dominated by studies on scripted group work and controlled face-to-face contexts. This emphasizes the exploratory nature of MMLA research, wherein many studies are tailored to specific learning contexts. Based on these works, this SLR will shed light on MMD's potential for informing PL. Furthermore, it can empower researchers when selecting MMD based on specific goals and learning scenarios.

This paper thus brings teachers and other education stakeholders up to speed with the concepts of PL, MMLA, and common applications of MMLA in the PL environment. The benefits of incorporating various data sources and contextual information into PL to better understand students' demands are also discussed. At the same time, it is important to keep in mind that these findings may not reflect the most current trends and technology used in the MMLA and PL landscape, due to the ever-changing nature and rapid development of such technologies. Nevertheless, the findings presented still cover most of the developments in this field, and may still be used to gain a broad understanding of MMLA and its benefits when integrated in PL.

■ ■ ■

Statements and Declarations

1. **Funding details.** None

2. **Disclosure statement.** The authors declare that they have no conflict of interest.

3. **Ethical approval.** According to the Nanyang Technological University Institutional Review Board, ethics approval was not required for this study.

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