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Unveiling the landscape: A systematic review of personalized learning facilitated by learning management system

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Abstract

Personalized learning (PL) initiatives represent a powerful instructional strategy that prioritizes a learner-centered approach, allowing educators to tailor content to meet individual students' characteristics and needs. Various technologies have been developed to support PL, the integration of Learning Management Systems (LMS) has emerged as a particularly effective to deliver adaptive materials and strategies in classroom settings. This study presents a systematic literature review on the application of LMS in facilitating PL, guided by PRISMA protocols to ensure rigorous screening and inclusion of relevant studies. Out of an initial 1,069 publications from 2014 to 2024, a total of 61 studies met the inclusion criteria. Findings highlight promising opportunities to enhance standard LMS features with data-driven tools that support personalized learning. Additionally, this study highlights the need for further research into learner attributes extending knowledge levels and learning styles. It also encourages exploring learning outcomes that transcend cognitive achievements.

Keywords: Personalized learning, Learning management system, Adaptive learning, Instructional technology, Systematic review

Introduction

Each learner entering the learning environment brings a distinct set of unique traits. While some learners are able to grasp learning materials quickly, others may require more time and support. Learners also come with diverse backgrounds and varying capabilities, mandating that educators and instructional designers to recognize and leverage these differences. Grant and Basye (2014) emphasize that learners who receive tailored support for their academic, emotional, and behavioral needs are more likely to succeed. This is in contrast to those who experience uniform instructional approaches. The Personalized

Learning (PL) approach offers a customized learning experience by addressing to the distinct needs, preferences, and performance of learners, thereby enhancing learning outcomes and overall effectiveness. Rooted in a learner-centered paradigm, PL emphasizes the learner in the educational process. This contrasts with the conventional one-size-fits-all educational approach, wherein learners receive uniform instruction, assignments, and assessments, with minimal consideration for individual differences and needs (Li & Wong, 2019).

The U.S. Department of Education defines PL as tailoring learning objectives, content, methods, and pacing to meet learners' needs, preferences, and interest. This approach is focused on aligning instruction with individual learners (Watson & Watson, 2017). Walkington and Bernacki (2020) contend that the implementation of personalized learning can be adjusted to improve learners' affective, motivational, and cognitive processes, which will ultimately improve their overall learning experiences. Notwithstanding the extensively documented advantages of PL in empirical studies, its implementation continues to present significant challenges. A study by Gunawardena et al. (2024) identified challenges encountered by elementary schools' teachers in adopting PL, highlighting that while educators recognize the potential benefits of PL, they struggle to integrate it within the existing school structure. Moreover, it was further observed that a significant challenge to personalized instruction is time constrains. The emphasis on learners' mastering content may conflict with the rigid academic calendar. This could leave some learners without full comprehension by the end of the school year. In addition, the development of personalized activities that address individual learner traits may presents a multifaceted challenge, both pedagogically and technologically (O'Donnell et al., 2015).

Recent technological advancements have enhanced research on PL by addressing some of these challenges within personalized learning environments. Tetzlaff et al. (2021) define personalized education as the data-driven adaption of instructional practices to align with the specific characteristics of individual learners. The PL approach focuses on developing a learner model through assessments and identifying tailored learning objects relevant to each learner model. In this regard, technological advancements and devices may enrich personalized learning experiences (Shemshack et al., 2021). Numerous technology-driven initiatives within PL have been recorded, including intelligent tutoring systems, machine learning algorithms, and artificial intelligence. Nevertheless, the nascent state of adaptive learning technology, coupled with the lack of established standards, presents challenges for educators and institutions in selecting the most suitable tools (Taylor et al., 2021).

In contrast, the adoption of Learning Management Systems (LMS) has been widely adopted for decades (Gharbaoui et al., 2023), positioning LMS as a fundamental platform across various levels of education. LMS platforms are recognized for its user-friendly features that support educators, learners, and administrators in delivering instructional content, managing assessments, and executing educational administration tasks. Ouatik and Ouatik (2021) identified several advantages of LMS, including its ability to host and distribute educational content, along with its functionality to manage and monitor both individual and collective learner progress. Furthermore, Salgado-Chamorro et al. (2023) strongly argues that LMS can proficiently support fully online, blended learning environments, as well as in face-to-face classroom settings.

In terms of integration with personalized and adaptive strategies, Khan et al. (2019) emphasizes that open-source, web-based LMS platforms can be easily augmented with other software solutions to create adaptive learning systems. The incorporation of PL strategies within LMS platforms is feasible and has been examined in numerous studies. This corroborates the findings of Fariani et al. (2023), who similarly examined the PL model within the higher education context, primarily developed in personalized e-learning systems and integrated into existing LMS or e-learning platforms. Nonetheless, this study was unable to find any thorough analyses regarding the PL implications within the LMS platform. Therefore, the study seeks to discover how LMS features and development facilitate PL teaching and learning strategies in educational contexts. In light of this, the study is guided by five research questions, which address the existing gaps in the utilization of LMS within PL environment:

RQ1: How are the study trends of LMS integration in PL environment in studies evolved between 2014-2024?

RQ2: What learner characteristics have been utilized as parameters in PL through the integration of LMS?

RQ3: How are PL initiatives developed and/or implemented in LMS? Which LMS platforms are most frequently used to facilitate the PL environment?

RQ4: What learning aspects are personalized within PL environment through the integration of LMS?

RQ5: What are targeted learning outcomes sought to be achieved through PL facilitated by LMS?

Literature review

Personalized Learning (PL)

The term Personalized Learning (PL) has been widely adopted to promote a learner-centered paradigm (Watson & Watson, 2017). In the classical classroom, teachers are fully authorized to regulate the entire teaching and learning process. In contrast, the PL classroom enabled learners to incorporate their particular traits and control in order to promote greater adaptability in learning. However, there is no consensus on the definition of PL, but various academic disciplines are already researching the specific PL strategy by reflecting on their specialty. Chang et al. (2022) define PL as a learning approach that tailors the learning process based on learners' needs, objectives, and capabilities by providing a variety of learning experiences. Bray and McClaskey (2013) addressed PL as an attempt to strike a balance between learner characteristics and the learning environment. Therefore, PL strategies make the learning process more effective for learners by providing learning experiences that are tailored to their specific characteristics. In addition, Fake and Dabbagh (2023) argued that the best approach to designing PL experiences is to take into account learning theory, learning models, instructional strategies, learning tasks, outcomes, and technology, all of which must be pedagogically aligned.

Shemshack and Spector (2020) revealed that the study of PL research has gained recognition since 2008. However, in the twenty-first century nowadays, the majority of PL research studies currently involve technology-supported adaptive and personalized technologies. Traditionally, learner characteristics have been the primary focus when designing personalized learning experiences, utilizing assessments and manual questionnaires as the predominant methods of data collection. However, current cutting-edge technologies provide the capability to monitor learner behavior, progress, and level of knowledge in real time. By employing appropriate algorithms, personalized learning aspects can be more effectively tailored to enhance the teaching process and enhance implementation success (Alamri et al., 2021).

Learning Management System (LMS)

The Learning Management System (LMS) is a widely recognized web-based platform that supports learners, educators, faculty, and administrators, serving an integral part in the e-learning environment (Sejzi & Aris, 2013). Learning Management Systems (LMS) have been essential in providing modern education through the storage of learning content, delivery of educational materials, and assessment of learner progress. The various menus and functionalities of the LMS may enhance and optimize learning experiences and interactivity, both synchronously and asynchronously. Furthermore, both learners and educators can access all educational materials at any time and from any location, thereby ensuring permanent accessibility of the content (Salgado-Chamorro et al., 2023). Furthermore, Aulianda et al. (2023) propose the implementation of a Learning Management System (LMS) designed to optimize and enhance learning by integrating conventional and online learning formats.

The adoption of LMS is primarily driven by educators and educational institutions in their selection of specific LMS platforms. The excessive number of LMS resulted in a complex procedure for identifying an appropriate option (Cavus & Zabadi, 2014). Mohd Kasim and Khalid (2016) deliberated on selecting the LMS platform according to the institution's requirements, taking into account flexibility, usability, accessibility, and user-friendliness. The study emphasizes that each Learning Management System possesses distinct characteristics, advantages, and drawbacks. Nonetheless, open-source LMS platforms were the most convenient option for institutions, given their affordability, low cost, and minimal effort required to integrate the LMS into a digital learning environment. After evaluating six LMS platforms, including Sakai, ATutor, Blackboard, Moodle, SumTotal, and SuccessFactors, Kasim and Khalid determined that Moodle is the most recommended open-source platform for institutional adoption. Other investigations comparing LMSs, conducted by Cavus and Zabadi (2014), Khan et al. (2019), Salgado-Chamorro et al. (2023), and Sánchez and Hueros (2010), yielded similar conclusions, indicating that Moodle distinguished itself from other LMS platforms. It is a community-owned entity, currently accessible through mobile applications and various electronic platforms worldwide (Reid, 2019). Further LMS examples cited in studies encompass Claroline, Dokeos, dotLRN, Drupal, Paradiso, iLIAS, OLAT, Docebo, Chamilo, Spaghetti Learning, and Canvas.

Related works

Various systematic literature review (SLR) studies pertaining to Personalized Learning have been conducted. This section provides a brief summary of notable SLRs from the past five years. Begin with an extensive study conducted by Xie et al. (2019), which gathered a final total of 70 Social Sciences Citation Index (SSCI) articles from 2007 to 2017. The study aimed to investigate trends and future technology advancements in support of the PL environment. However, Xie et al. (2019) were also able to identify several research issues concerning the actualization of adaptive or personalized learning. The study also revealed the potential for a wide range of PL applications, such as Artificial Intelligence, Virtual Reality, Cloud Computing, and Wearable Devices. Furthermore, the study suggests for future PL research addressing working adults. Li and Wong (2019) also conducted similar investigations into PL trends and technological ventures. The research gathered 203 journal articles from 2001 to 2018. Li and Wong (2019) assert that the practices of Intelligent Learning Systems (ILS) and Learning Analytics can enhance the effectiveness of the PL environment. To discuss its findings, the study used several coding schemes, including research issue, PL strategies, PL devices, PL objectives, and PL success factors. One of the remarkable findings is that the means of achieving PL environments were not limited to technologies alone, but also to flexibility in curriculum and instructional design with an emphasis on individual learner goal setting.

Given the close ties between information technology, computing solutions, and personalized learning, several systematic studies have been conducted to detail particular technologies utilized in PL endeavors. Raj and Renumol (2022) investigated the role of adaptive content recommenders in the Personalized Learning Environment (PLE). The study proposed that the recommender system benefits learners by providing adaptive content recommendations, while also assisting educators with design and content authoring. Raj and Renumol were successful in reviewing 52 publications from 2015 to 2020 and exploring the methodology, attributes, and evaluation measures. Moreover, Khor and Mutthulakshmi (2023) investigated the role of Learning Analytics (LA) in supporting PL and discovered its ability to retrieve learning progress analytics for guiding educator intervention at multiple levels. Raj and Renumol (2022) identified several systems, including machine learning, Intelligent Tutoring System (ITS), knowledge-based, and ontology-based systems, to examine the adaptive recommender system. However unfortunately, Khor and Mutthulakshmi (2023) were not discussed the specific technology engines adopted in the LA environment.

Recent technological advancements, however, have always included Artificial Intelligence (AI) in their applications, albeit in the PL environment. Bayly-Castaneda et al. (2024) conducted considerable systematic studies to investigate how AI might assist with PL implication in lifelong education settings. The study identified several AI-mediated solutions, including machine learning, content recommendation systems, adaptive learning environments, and virtual or augmented reality. Based on 78 articles reviewed from 2019 to 2024, Bayly-Castaneda et al. pointed out that AI-based PLE has not yet been extensively researched and has been limited in a small number of countries, such as China, the United States, and India, taking into the accessibility gaps and disadvantages of country applicability.

Significantly, comprehensive literature reviews on trends and technologies in Personalized Learning have been undertaken. The reviews indicate promising PL strategies for implementation across various educational levels. Consequently, it is anticipated that this study will contribute to the body of knowledge examining the use of LMS in conjunction with the application of a personalized learning approach.

Method

The systematic literature review entails a comprehensive inquiry into a specific subject. Specifically, this study focuses on Personalized Learning (PL), Learning Management Systems (LMS), and the application of the PL approach within LMS environments. Various systematic literature frameworks exist, including Kitchenham's Framework (Kitchenham & Brereton, 2013), the Cochrane Handbook (Noyes et al., 2013), SPAR-4 SLR (Paul et al., 2021) and the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) (Page et al., 2021). Although PRISMA has been intended mainly for reviewing studies on health interventions, it is also adaptable to other categories of interventions, including social and educational interventions. The comprehensive reports enable assessing of the methods' appropriateness, thus assessing the credibility of the findings (Page et al., 2021). Therefore, this study utilizes the PRISMA strategy to guarantee a transparent screening report.

Data sources and search protocol

The key approach of this study involved accessing an extensive range of scholarly publications by navigating reputable academic databases. Five prominent databases were evaluated, including Science Direct, Scopus, and ERIC. Given the close relationship between PL strategy and technology integration (Fariani et al., 2023), the authors also incorporated IEEE Xplore and ACM Digital Library databases.

Subsequently, the authors enumerated the following significant keywords pertinent to the systematic review: "personalized learning", "adaptive learning", "personalization", "learning management system", "LMS". Additionally, as the study also examines contemporary innovative advancements in LMS technology, the additional keyword "plugin", "tool", and "system" were incorporated. Furthermore, the initial pool was identified using the following three database search strings:

- personaliz* OR adaptive AND learning OR learning management system OR lms OR plugin
- personaliz* OR adaptive AND learning AND plugin or tools or system
- (personaliz* OR adaptive) AND learning AND plugin

Inclusion and exclusion criteria

This systematic review establishes the study's eligibility by applying inclusion and exclusion criteria (see Table 1). All studies included must be published between 2014 and

Table 1 The criteria of inclusion and exclusion of the study

Criteria	Inclusion	Exclusion
Timespan	Published between January 1, 2014 and February 17, 2024	Published outside of January 1, 2014, and February 17, 2024
Language	Must be written in English	Other than English
Population	Setting at Classroom, School, or University	Setting outside of a Classroom, School, or University (e.g., workplace, organization, etc.)
Intervention	• Utilization of LMS environment • Empirical study of PL Integration within LMS environment • Development of adaptive system and/or plugin within LMS environment to support PL strategy	• Does not utilize LMS environment • Design of a PL framework as a future study endeavor
Publication type	Journal article, and conference proceeding	Book chapter, thesis, dissertation, review articles, editorial, and opinion paper
Accessibility	Available in full text under university access	Unavailable in full text

2024, considering that Google Trends analysis indicated a rising interest in PL since 2010 (Zhong, 2022). However, to ensure novelty, we decided to focus on publications from the last decade. Furthermore, the study must be written in English and highlight the PL strategy within the LMS environment as the empirical research design. Not only describe or construct a framework for PL integration, as a future study endeavor. Moreover, all studies pertaining to the theories and literature reviews lacking empirical evidence have been excluded.

Selection process

The systematic review process required the researchers perform rigorous and methodical procedures. The selection process of the study aims to evaluate the study's quality and its relevance to the research questions. Two reviewers independently screened the studies to determine eligibility. Any disagreements that emerged were addressed through discussion to achieve consensus. Furthermore, this study employed Covidence (www.covidence.org), a web-based systematic review management tool. Covidence enhances collaboration by resolving disagreements within the research teams, aiding data extraction, documenting the systematic review process, and generating visual representations of the study outcomes (Kellermeyer et al., 2018). Figure 1 delineates the comprehensive selection process and the quantity of articles at each stage. A total of 1,069 articles were generated from the initial pool utilizing the search strings in the scholarly databases.

The initial filtering process involves eliminating duplicate articles, followed by selection based on title (n=1065), abstract (n=246), and ultimately, full-text accessibility. Following the screening of titles and abstracts, the full-text studies were reviewed by two independent reviewers. If any studies were missing, we attempted to contact the corresponding authors or searched other scientific databases to discover the missing studies. Disagreements over study inclusion were subsequently discussed with two other authors. The final screening of the study comprises a full-text review (n=235) that identifies multiple reasons impeding diverse studies from being included in the final analysis. The primary reason was to eliminate retracted articles to preserve the integrity of scientific literature (k=3) (Chen et al., 2013). The second reason for excluding articles outside the scope of education and information technology, and lack of relevance to the study (k=17). Then, for removing insufficient empirical studies, such as book chapters (k=9), theoretical or reviews (k=22), and not involving the LMS environment (k=21). We also encountered studies where only the title and abstract were in English, while the full article content was in another language (k=11). Additional detailed analysis and screening reasons displayed in Figure 1. Moreover, only articles which also met the criteria outlined in Table 1 were incorporated into the review, resulting in a total of 61 articles included in the analysis.

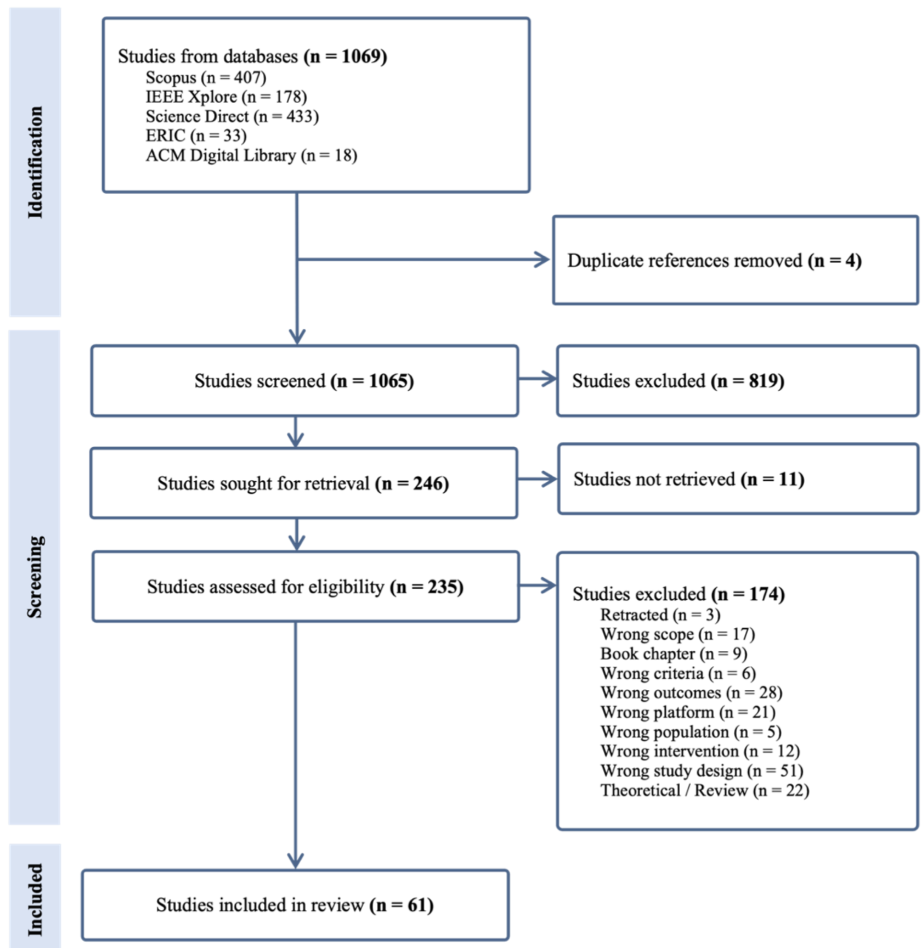

Fig. 1 PRISMA protocol implementation of the study

Data analysis and coding

The selected 61 articles were subsequently extracted into a spreadsheet to address the research questions. This study utilized Cohen's Kappa analysis to evaluate the level of agreement between two reviewers responsible for screening the studies (Cohen, 1960). The quality of the final 61 studies was assessed following the completion of a full-text review (Pérez et al., 2020). Additionally, the Guidelines for Reporting Reliability and Agreement Studies (GRRAS) (Kottner et al., 2011) criteria were employed, to evaluate the quality of the studies, taking the research question into consideration. After the two reviewers provided binary scores for the criteria, the agreement coefficient was calculated to be approximately p_o = 0.70, indicating that the reviewers agreed 70% of the time and disagreed 30% of the time. Notably, the Cohen's Kappa (κ) score was reported as 0.53, which represents a moderate level of agreement according to the scale proposed by Landis and Koch (1977).

Each article was examined and categorized according to the following categorizations: (1) authors; (2) year of publication; (3) type of publication; and (4) level of education. A qualitative synthesis was conducted employing thematic and sub-thematic methodologies to analyze data comprehensively (Surahman & Wang, 2023). The data synthesis process allows the authors to present definitive answers to the research questions (Rana et al., 2022). Subsequently, calculate the data synthesis using quantitative methods to assess the frequency and basic descriptive percentages for each dimension. Eventually, represent the gathered information using data visualization tools, including graphs, tables, and diagrams.

Results

This section presents the outcomes of analysis corresponding to each research question. Basic descriptive analysis and data visualizations are expected to help elucidate the key findings of the study.

RQ1: How are the study trends of LMS integration in PL environment in studies evolved between 2014-2024?

Publication type, year, and geographic distribution

The study extracted a total of 61 articles, consisting of 37 journal articles (61%) and 24 conference papers (39%) from 36 countries. The study indicates that the majority of PL research within the LMS environment has been conducted in Asia (*n*=21, 34%) and Europe (*n*=21, 34%). Subsequently, North America (*n*=8, 13%), the Middle East (*n*=6, 10%), and Africa (*n*=5, 8%). According to the type of publication (refer to Figure 2), there has been a notable increase in journal publications since 2014, while conference publications have exhibited a decline. Nonetheless, the rising number of personalized learning initiatives suggests an increasing interest in personalized instruction to individual learners' needs over the past decade.

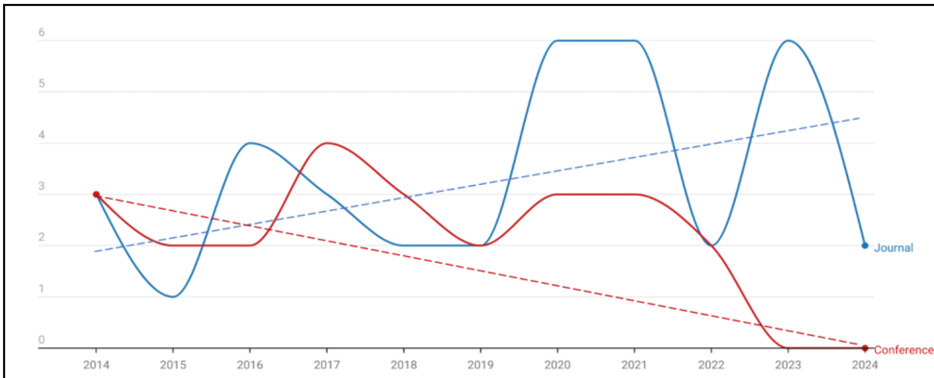

Fig. 2 Publication type and year of the study

Research target level

The study reports that Personalized Learning strategies have been implemented at various educational levels (see Figure 3). Given that there has always been a growing interest in PL implication in higher education, and as evidenced by the findings of this study, the undergraduate level received the highest percentage (70%) of research targets. Nevertheless, the lower educational levels (i.e., elementary, secondary, high school) received minimal interest for investigation. This study found that multilevel research targets (*n*=8, 13%) garnered significant attention. For instance, García-Peñalvo et al. (2014) conducted a study examining the perceptions of learners and teachers regarding Project Management after engaging in a personalized instructional scenario utilizing a Learning Management System (LMS). Other studies also incorporate multiple levels, such as undergraduate and postgraduate cohorts, in their research (El Fouki et al., 2017; Karaoglan Yilmaz & Yilmaz, 2020; Sein-Echaluce et al., 2017).

Academic fields of PL study

During the final study extraction, the authors acknowledged that the literature on PL encompasses multiple academic disciplines. A considerable cohort of scholars is emerging from the domains of Education and Instructional Technology. However, it is not surprising that the study of PL has drawn the attention of several prominent authors and scholars in the fields of computer science and information technology. Bernacki et al. (2021) confirmed that research in PL has resulted from effective collaboration among interdisciplinary researchers. This section attempts to analyze the distribution of academic disciplines that explore personalized learning by coding and examining first author affiliations. There are seven primary categories of academic disciplines who study the Personalized Learning, such as: Computer Science, Computing, Education, Information Technology, Science, Business and Management, and Engineering. Interestingly, this study revealed that researchers in Computer Science (*n*=21; 34%) and Computing (*n*=9; 15%) were more frequently involved in the investigation and development of PL strategies and tools within the LMS environment compared to scholars from the educational field (*n*=9; 15%).

Fig. 3 Target of educational level within 61 studies

Another intriguing finding is that several terms emerged when addressing personalized learning in the included literatures. We identified five frequently used terms: personalized, adaptive, personalised, personalization, and individualized. This significant discussion has arisen and addressed by Shemshack and Spector (2020), the study aims to minimize the gap in the usage of PL terms by identifying a unified and robust term. Since those terms have been known and used interchangeably. Given the circumstances, we attempted to analyze the use of personalized learning terms in our study and investigate the relevance of each term to the authors' academic field. As shown in Figure 4, the majority of terms used were "Personalized" and "Adaptive", with few studies using the term "Individualized". The term "Adaptive" was most commonly used in computer science studies, whereas the term "Personalized" was used in education. Furthermore, limited studies utilized the term in British English writing style by employing the term "personalised". However, the field of Science demonstrated an uncertain use of the term, as studies adopted multiple terms. Table 2 details and samples the studies that used each of the terms, as well as the definition used within each study, in order to assist understandability of the rationale behind the choice of the PL term.

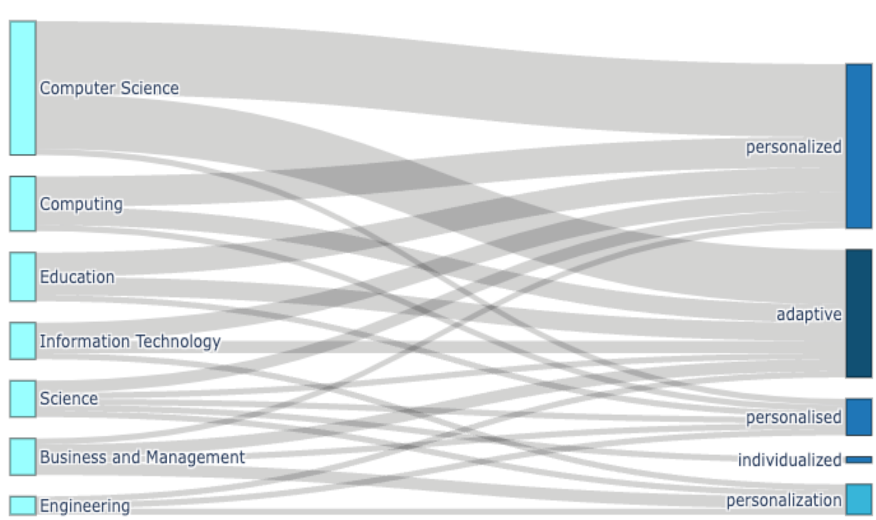

Fig. 4 Relationship between academic fields and personalization terms used

Table 2 Terms in personalized learning used in 61 studies

Term	Author	Academic Field	Definition summary
Adaptive	Chang et al. (2016)	Computer Science	Adaptive learning provides diverse learners the opportunity to pursue personalized learning paths and fulfil their educational needs through adaptive technologies, which include adaptive presentation and adaptive navigation support.
	Bhaskaran & Swaminathan (2014)	Computing	Adaptive learning encompasses intelligent software that must be autonomous and capable of learning within the system architecture of learner agents, classifier agents, and collaborative agents to accurately classify learners.
Personalized	Nguyen et al. (2024)	Education	Personalized learning entails identifying suitable educational resources for every learner based on their specific attributes, such as learning style.
	Jeevamol & Renumol (2021)	Computer Science	Personalized learning entails the development of domain knowledge that includes learner preferences and objectives to recommend suitable learning materials for each learner.
Personalised	Papanikolaou & Boubouka (2020)	Education	Personalized learning addresses the feasibility and effectiveness of tools or features for implementing adaptive courses personalized to individual learner differences.
	Zielinski et al. (2014)	Engineering	Personalised learning seeks to enhance the individual learning experience by defining specific learning objectives and unique learning pathways, facilitated by semantic web educational resources, reasoning frameworks, and formal ontologies.
	Tashiro et al. (2016)	Business and Management	Personalised-inclusive-adaptive refers to a system that evaluates a student's accessibility and preferences, while also enabling students to enroll in the lesson at any time based on their needs.
Personalization	Hinkle (2023)	Science	Personalization of learning entails tailoring content delivery to more targeted teaching methods and improving remediation of specific areas of learners' knowledge deficits.
	Imran et al. (2015)	Information Technology	Personalization of learning assists students by offering recommendations for selecting learning tasks based on their prior achievements, collective grades from the same cohort, individual preferences, and the difficulty level of the tasks.
Individualized	Donevska-Todorova et al. (2022)	Science	Individualized learning enables learners to take greater control over their educational experience, supported by adaptive technologies that provide personalized feedback, tailored sequences of learning activities, and individual pathways.

RQ2: What learner characteristics have been utilized as parameters in PL through the integration of LMS?

This section examined the diverse learner characteristics utilized as parameters or models to tailor the learning experience in the PL strategies (refer to Figure 5). The most commonly referenced attribute was the Learner's Knowledge level (*n*=31; 38%). Over half of the

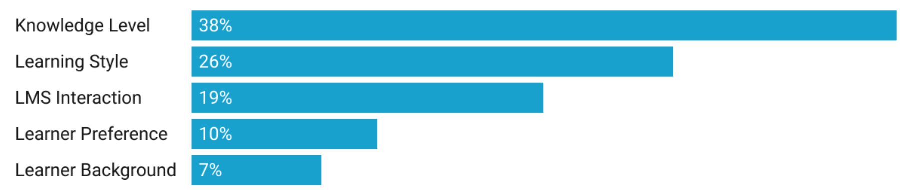

Fig. 5 Learner characteristics used to develop learner model in LMS within the study

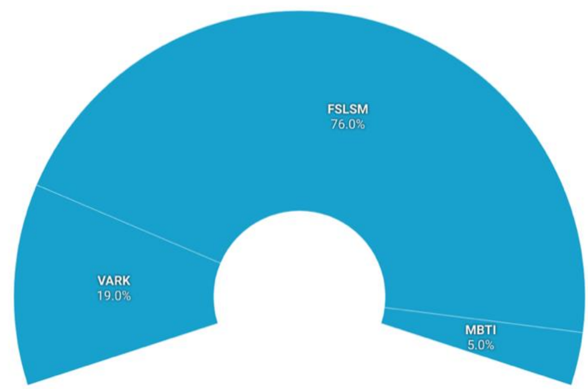

Fig. 6 Learning styles adopted to develop learner model in LMS within the study

studies examined indicated that the academic level of learners may assist the adaptive LMS in delivering customized materials and activities. The determination of knowledge level is often conducted through initial diagnostic tests, a prior knowledge database, and performance monitoring. The second significant characteristic is the incorporation of learning styles (n=21, 26%) in aligning key teaching and learning materials according to the dimensions of the selected learning style. Figure 6 depicted the three most frequently referenced learning styles in the PL research among the reviewed studies, such as: (1) Felder-Silverman Learning Style Dimension (FSLSM); (2) Visual, Auditory, Read/Write, and Kinesthetic (VARK); and (3) Myers-Briggs Type Indicator (MBTI).

The interaction between learners and the LMS platform (19%) was also regarded as a significant input for the PL strategy. The data captures learner behaviors throughout the learning process. This pertains to the frequency and eagerness of learners in engaging with course materials and assessments within the LMS. In addition, it is accessible in nearly all LMS platforms, referred to as data logs. Instructors and administrators may extract these logs to carry out learning analytics and monitor learning progression through the LMS. Learner preference constituted 10% of the studies. This parameter offers learners a certain degree of control over their learning process. The learners may decide on their language and dashboard preferences (Qazdar et al., 2016; Suwawi et al., 2018), or the format of learning materials (Al Abri et al., 2020; Qazdar et al., 2016; Tashiro et al., 2016). Some questionnaires designed to elicit learner preferences can demonstrate learner interest in the personalized aspect that will be provided to them. Further automated methods are also feasible through monitoring via the LMS system. Moreover, a small percentage of studies (7%) utilized learner background characteristics to personalize teaching content.

RQ3: Which LMS platforms are most frequently used to facilitate the PL environment? How are PL initiatives developed and/or implemented in LMS?

This section examines the technological supports that facilitate the personalized learning strategy within LMS. The predominant LMS framework utilized was Moodle (*n*=41, 67%). Figure 7a specifically indicated additional LMS frameworks predominantly utilized following Moodle, including University-based LMS (*n*=5; 8%), Canvas (*n*=3; 5%), and Blackboard (*n*=3; 5%). This study also analyzed a university-based LMS to assess the extent of its utilization in higher education. For instance, Cai (2018) examines the Adaptive Learning (AL) technology within the Web-based Learning Management System at Colorado Technical University (CTU), Huang et al. (2023) examined the use of the iLearning online learning platform at a northern university in Taiwan, while Tashiro et al. (2016) investigated the development of personalized learning at Northern Arizona University, referred to as NAU-PL. The three studies indicated the initial objective of developing the personalized learning management system platform but weren't clear on the framework employed, thus, we classified it as a university-based LMS.

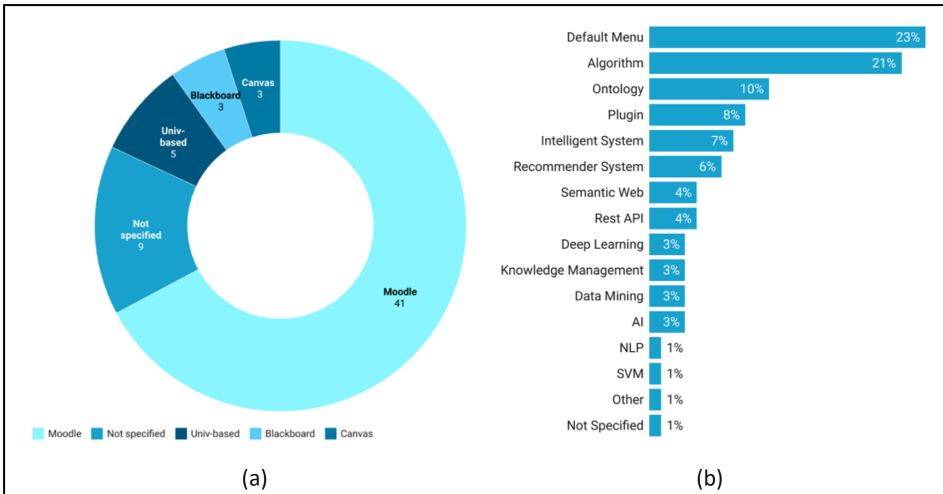

Fig. 7 (a) The distribution of LMS used; (b) Technology initiatives to develop PL environment

Furthermore, Canvas and Blackboard are also popular options for educational institutions to manage their personalized education processes. In addition, this study also indicated that 15% (*n*=9) of the studies did not specify the type of LMS utilized in establishing the PL environment. For example, Bhaskaran and Swaminathan (2014), Nouman et al. (2024), and Al-Chalabi et al. (2021) developed an Intelligent Adaptive System within LMS, yet they did not explicitly state the name of the LMS framework. This suggests that when the study omitted the title of the LMS framework, the researchers developed their own versions of the LMS framework. For instance, Alsobhi and Alyoubi (2019) constructed an innovative adaptive system known as the Dyslexia Adaptive E-learning Management System (DAELMS), without referring any specific existing LMS framework such as Moodle.

Moreover, this study examines the specific technologies utilized to facilitate PL environments, following the identification of the most commonly used LMS platforms (see Figure 7b). The study revealed that default or standard menu of LMS options constitute the most frequently utilized initiative, representing 23% (*n*=16) of the identified technologies. This discovery suggests that numerous researchers were utilizing the built-in menu features of LMS platforms to deliver customized learning experiences. For example, functionalities such as restricting access to educational resources based on individual learners' performance metrics are frequently employed. Subsequently, algorithm-driven initiatives receive significant attention, emphasizing the importance of computational methods in advancing PL. Algorithms utilized encompass fuzzy logic (Bradáč et al., 2016) machine learning, J48 (Maâloul & Bahou, 2021), Bayesian networks (Chang et al., 2022), and k-means clustering (Laksitowening et al., 2020).

In addition, the notable integration of ontology (10%), intelligent systems (7%), and recommender systems (6%) in LMS illustrates the necessity of improving the PL environment by taking into account learners' attributes and providing customized content. In addition, the utilization of plugins (8%) to enhance default LMS functionalities is significant. For instance, Arsovic and Stefanovic (2020) proposed a plugin extension for an adaptation module on Moodle LMS, Limongelli and Sciarrone (2014) developed a plugin in conjunction with adaptive educational hypermedia, and Pagano and Marengo (2021) employed a plugin to provide additional assessments, thereby creating personalized learning paths. The adoption of advanced technologies, including deep learning (DL), artificial intelligence (AI), natural language processing (NLP), and support vector machines (SVM), although representing a minor percentage, indicates an emerging trend towards the integration of innovative technologies into learning management systems (LMS). Pardamean et al. (2021) developed an AI technology designed to enhance the Moodle LMS through collaborative filtering, which yielded satisfied and objective evaluations. This AI technology was capable of creating a logical flow for determining learning styles, forming study groups, managing the learning process, and recommending learning materials. Similarly, Qi et al. (2023) integrated NLP and DL methods to optimize feedback within LMS platforms. The NLP component extracted learners' behaviors and learning portfolios, enabling the delivery of tailored, personalized feedback aligned with each student's progress. These findings emphasize the significant potential of advanced technologies to improve personalization and adaptability in educational settings.

This section presents a Sankey diagram in Figure 8 to elucidate the relationship between the year of publication, the academic disciplines studying personalized learning, and the technological initiatives employed to implement personalized learning. The objective of this effort is to demonstrate trends over time illustrating how various fields have contributed to the advancement of PL through technology. Beginning in 2014, computer science (CS) and information technology (IT) prominently emerged as leading contributors to PL research. Then, commencing in 2018, Education field has been engaged in reporting the development of PL environments, utilizing the default LMS menu and features, along with various additional applied techniques. This highlights practical applications rather than solely technical innovations in fields such as computer science and information technology. Nonetheless, we observed a rising trend of interdisciplinarity in the PL approach, incorporating the academic fields of Computing, Engineering, Science, and Business Management into PL research. Moreover, the introduction of AI and data-driven solutions underscores the potential transition towards interdisciplinary approaches in shaping the LMS to support the PL environment.

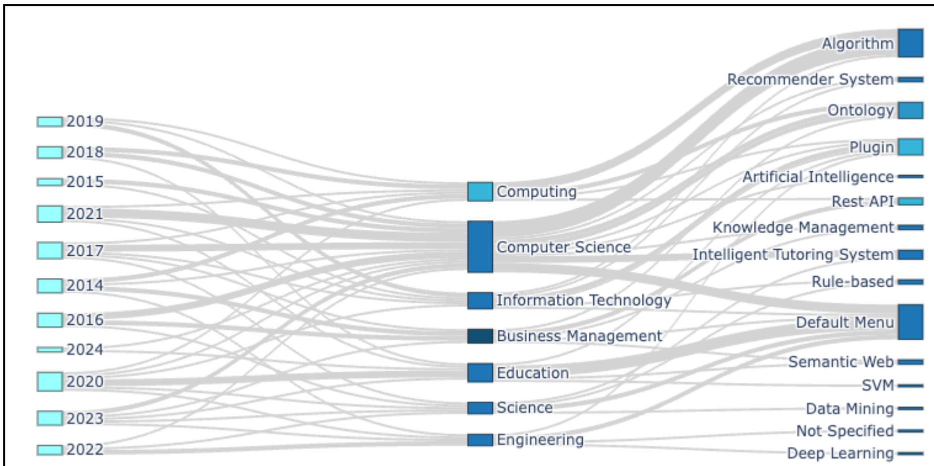

Fig. 8 Relations among year of publication, academic fields, and PL initiatives in LMS

RQ4: What learning aspects are personalized within PL environment through the integration of LMS?

This section emphasizes the predominant aspects of personalized learning within a Learning Management System (LMS) environment. Following the classification of learners according to learners' attributes and requirements, the LMS platform will deliver customized learning aspects designed by instructional designers or educators. Figure 9 demonstrates that personalized learning content constitutes the predominant feature in LMS environments (59%), followed by personalized learning paths (20%), personalized feedback (9%), personalized assessments (7%), customized dashboards and learner profile (3%), and personalized forums at 1%.

Remarkably, the majority of studies (41 out of 61 studies) tailored the learning content in attempt the personalized learning strategy. This study defines learning content as the materials and knowledge to be provided, including reusable learning objects available to learners through the LMS. Ristić et al. (2023) categorized different learning objects, including presentations, video materials, and audio resources, designed for specific learning styles, such as VARK. The alignment of learning objects with distinct learning styles demonstrates the implementation of content personalization. In addition, personalized learning paths have been extensively embraced by researchers in PL. For example, Musumba and Wario (2019) allowed students to modify their learning trajectories based on their preferences, whereas Lagman and Mansul (2017) employed learner achievement metrics to regulate the sequence of educational content, thereby illustrating the adaptability of personalized pathways.

Moreover, personalized feedback and tailored assessments have drawn significant interest. For instance, the study conducted by Qi et al. (2023) which provided feedback based on learners' performance levels, illustrating a considerable effect in contrast to conventional feedback methods. Additional personalized elements, including activity completion notifications (Molins & García, 2023), tailored dashboards (Suwawi et al., 2018), individualized learner profiles (Maâloul & Bahou, 2021), and personalized forums

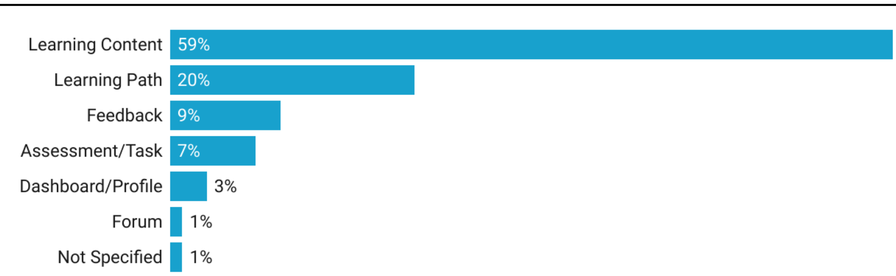

Fig. 9 The distribution of personalized learning aspect in LMS environment

(García-Peñalvo et al., 2014) while constituting a minor percentage of implementations, this illustrates the capacity for expanded personalization beyond educational content, and highlight emerging opportunities for enhancing personalized efforts within LMS platform.

RQ5: What are targeted learning outcomes sought to be achieved through PL facilitated by LMS?

To address this research question, the authors examined the primary objectives of the selected studies that implemented the PL strategies. Although not every research paper explicitly stated their primary rationale, we endeavored to ascertain the reason by examining the end-goal of the proposed PL model in each selected study. Figure 10 provides the specific learning outcomes identified in the selected studies. This study highlights that the incorporation of PL within the LMS environment primarily seeks to improve learners' educational outcomes. A total of 30 analyzed studies concentrating on enhancing performance (Al-Shamali et al., 2020; Holthaus et al., 2018; Maier, 2021), achievement (Alsobhi & Alyoubi, 2019; Lagman & Mansul, 2017; Pardamean et al., 2021), and mastery of course content through the continuous monitoring of learner performance (Al-Chalabi et al., 2021; Hernandez Cardenas et al., 2022; Karaoglan Yilmaz & Yilmaz, 2020). Furthermore, there was a remarkable objective aimed at improving the effectiveness of the learning process (Cai, 2018; Imran et al., 2015; Papanikolaou & Boubouka, 2020), and the overall learning experience (Kaw et al., 2022; Nouman et al., 2024; Zielinski et al., 2014).

The nurturant learning effects beside cognitive academic performance have also garnered considerable interest. This study indicates that PL strategies can enhance satisfaction (Bhaskaran & Swaminathan, 2014; Kouis et al., 2020; Lee et al., 2018), motivation (Huang et al., 2023; Qi et al., 2023), self-regulated learning (SRL) (Manickavasagam & Surwade, 2017; Molins & García, 2023), and self-directed learning (SDL) (Donevska-Todorova et al., 2022). Additionally, an equivalent proportion of studies (4%) focused on improving

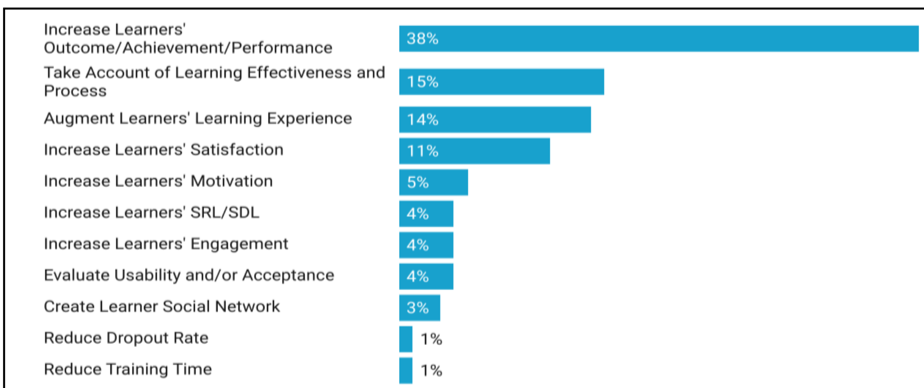

Fig. 10 Targeted learning outcomes within the selected studies

learner engagement (Huang et al., 2023; Pagano & Marengo, 2021; Sweta & Lal, 2017), assessing the acceptance (Apoki, 2021; Louhab et al., 2020), and usability of LMS tools (Chang et al., 2016) that facilitate personalized learning. A minor portion of the studies (3%) investigated the establishment of learner social networks through the development of LMS plugins, thereby allowing learners to maintain personal pages featuring posts and widgets (Suwawi et al., 2018), as well as through the delineation of learner social profiles to categorize learners according to their interests (Maâloul and Bahou, 2021). Furthermore, a mere 1% of studies concentrated on mitigating dropout rates (Sein-Echaluce et al., 2017) and training time (Pagano & Marengo, 2021).

Discussion

This paper provides a review of the literature concerning personalized learning initiatives utilizing learning management systems over the past ten years. Over 61 studies indicate that the investigation of PL practices within classroom settings has become increasingly prevalent, particularly in Asia and Europe. This study reveals that the implementation of Learning Management Systems (LMS) in achieving personalized learning (PL) is primarily observed in higher education contexts, particularly at the undergraduate level. Nonetheless, this finding corroborates prior systematic literature reviews in PL, which indicated that the primary focus of PL implementation was mainly on higher education level (Bernacki et al., 2021; Li & Wong, 2019). Moreover, there was also an increase in interest in the employment of multi-level learner as research subject, which were followed by lower education levels. For instance, a study conducted by Al-Chalabi et al. (2021) involved 60 learners aged 18 to 30 years in Python programming courses to assess their knowledge levels in relation to their personalized strategies.

This study argues that the practice of PL should not be confined to higher education. For instance, The US Department of Education has established PL regulations for elementary schools since 2015 through the "Every Student Succeeds Act" (ESSA) (Zhang, 2020). Similar policies have been implemented by the Australian Curriculum, Assessment, and Reporting since 2010 (Zhang & Stephens, 2013), Japan's GIGA initiatives (Yu & Anezaki, 2024), and the United Arab Emirates' Mohammed bin Rashid Smart Learning Program (MBRSLP), which proposes digital tools for adaptive learning technologies (Alnaqbi & Sarah, 2022). This presents a research opportunity to examine the implications of Learning Management Systems (LMS) and Personalized Learning (PL) within lower education levels, taking into account the capabilities of young children, specifically elementary and secondary learners, in utilizing the LMS platform.

In addition to discussing our findings, this study highlights the persistent inconsistency in the use of the term "personalization" within learning research. Despite the significant contributions from leading scholars in fields such as Computer Science, Computing, and

Education, this inconsistency mirrors previous research observations. Notably, we uncovered intriguing variations in how different academic disciplines define and employ the concept of personalized learning. Studies led by scholars in Computer Science, Computing, and Engineering predominantly used the term “adaptive” learning, while those from the Education field and other disciplines tended to employ the broader term “personalized” learning in their research. This inconsistency in terminology has been previously examined by Shemshack and Spector (2020), who concluded that a unified consensus on the adoption of either “adaptive” or “personalized” learning is necessary, particularly as these terms may evolve due to advances in human-machine interaction. Furthermore, our study identified only one instance of the term “individualized” learning, which originated from research within the Science discipline. To address these discrepancies, this study attempts to define and clarify the terms “personalized,” “adaptive,” and “individualized” in Table 3, providing a framework for adoption in future research.

The second research question examined which learner characteristics are most frequently incorporated into modelling adaptive learning plans LMS. Findings from this study indicate that learners’ knowledge levels and learning styles are of primary interest in adaptive learning design. These characteristics are integral to building a learner model, serving as indicators that assist PL systems in understanding learners’ perceptions and recommending suitable learning resources (Ulfa et al., 2019). According to Fariani et al. (2023), the learner model involves categorizing learners based on distinct components, forming a foundation for tailored recommendations. Al-Chalabi et al. (2021) further emphasized that learners’ knowledge levels significantly influence the overall learning experience. Based on knowledge level classification, a personalized LMS platform can suggest tailored learning materials, promoting differentiated learning paths for each learner according to their progress and achievements. A related study by Apoki (2021) demonstrated the value of tracking learners’ progression through details such as knowledge level, grades, and completed competencies. These elements contribute to the learning state, which establishes associations with domain-specific knowledge and supports semantic reasoning.

Another notable finding is the importance of learning style as a critical variable in adaptive learning, with the Felder-Silverman Learning Style Model (FSLSM) becoming widely used. The FSLSM categorizes learners into four dimensions: active/reflective, visual/verbal, sensing/intuitive, and sequential/global, allowing for a more nuanced approach to personalized learning. In contrast, this study contradicts the categorization of learners based on learning styles, corroborating the concerns of Nancekivell et al. (2020), Newton and Miah (2017), and Riener and Willingham (2010), who contend that learning styles are predominantly a “myth.” This assertion is bolstered by the absence of substantial evidence indicating that distinct learning styles (i.e., auditory, visual, kinesthetic, or sensory) necessitate customized educational resources for optimal results. Riener and Willingham (2010), for instance, asserted that tailoring media exclusively to various learning styles, such as offering videos solely for visual learners or podcasts exclusively for auditory learners, is typically unwarranted and lacks empirical support. Shemshack et al. (2021) addressed the prevalent method of utilizing self-reported questionnaires for gathering learning style data. Such methods frequently permit learners to select their preferred style, which may not produce optimal educational outcomes, as learners often find it challenging to discern the most effective style for their requirements. In their conclusion, Newton and Miah (2017) assert that, due to the debates regarding learning styles, educators may more effectively enhance their classrooms by prioritizing empirically validated instructional strategies instead of accommodating assumed learning style preferences. For example, Sumarlin et al. (2024) developed Mobile Adaptive Educational Hypermedia (AEH) tailored to the learning styles of specific engineering students, resulting in improved learning outcomes empirically.

This study indicates that Moodle is the most extensively utilized LMS for enhancing personalization in the classroom. Reid (2019) asserts that Moodle is the preferred Learning Management System employed by numerous universities worldwide for managing educational activities, owing to its cost-effectiveness. Moodle possesses a comprehensive array of features, and its open-source nature renders it especially conducive to developing customized strategies. Furthermore, Moodle's default menu encompasses a broad variety of features to support personalized learning, including access restrictions, activity completion functionality, conditioned activities, and an alert system (Molins & García, 2023). Consequently, it involves the potential for customizing course learning materials (Alsadoon, 2020; Lim et al., 2019; Pardamean et al., 2021), and learning paths (Donevska-Todorova et al., 2022). Although these default features may not seem cutting-edge, they are systematically designed to be adaptive based on learner-centric approaches. In addition, frequently associated with more sophisticated strategies such as monitoring learner progress and tailoring feedback. Furthermore, this finding underscores the significance of synchronizing instructional strategies with Moodle's tools, as demonstrated by Donevska-Todorova et al. (2022) and Hernandez Cardenas et al. (2022). Cevikbas and Kaiser (2022) also contributed to the body of knowledge regarding the potential integration of flipped classroom and personalized learning initiatives.

The enhancement of learning performance emerged as one of the primary instructional objectives within PL initiatives facilitated by LMS in our study. Despite the potential challenges associated with digital learning strategies, particularly in monitoring and evaluating progress due to the vast and complex data generated (Surur et al., 2024). LMS platforms mitigate these difficulties through built-in grading and tracking features. These tools enable instructors to closely monitor individual learners' progress, identify areas of strength and areas needing support, thereby subsequently provide personalized recommendations. Such functionality aligns with the overarching goal of PL to promote mastery learning by tailoring instruction to each learner' unique needs. Interestingly, our study also highlights a potential emerging trend in exploring nurturant effects within LMS-supported PL environments. Nurturant effects refer to the significant, often implicit, impact that instructional models have on learners' emotional and social development, alongside cognitive outcomes (Joyce et al., 2016). In the context of PL, these broader effects encompass learner satisfaction, motivation, Self-Regulated Learning (SRL), Self-Directed Learning (SDL), engagement, and perceived usability of the learning platform. In addition, the increasing focus on outcomes beyond cognitive gains has garnered significant attention within educational research. Various technology initiatives have been investigated for their potential to boost learner engagement, especially within online learning contexts (Fatawi et al., 2020). Furthermore, heightened levels of SRL and SDL have demonstrated positive impacts on learners, facilitating autonomy and responsibility in the learning process (Lasfeto & Ulfa, 2023). Such findings underscore the potential of PL strategies to cultivate enriching and positive learning experiences, thereby contributing to improved achievement, persistence, and overall educational satisfaction.

In summary, this study has explored the trends and advantages of integrating personalized learning through the use of LMS over the past decade. It is noteworthy that this research makes a significant contribution to the body of personalized learning theory. According to Watson and Watson (2017), personalized learning is deeply rooted in constructivist frameworks, including Self-Regulated Learning (SRL), Self-Determination, Goal-Orientation, and Flow Theories. Additionally, this study suggests that personalized learning environments supported by LMS can be conceptualized through Bandura's Social Learning Theory (SLT) (Bandura, 1977), which emphasizes that learning occurs through observation, imitation, and reinforcement within social interaction contexts. A key feature of LMS is its ability to extend the classroom and foster meaningful interactions among users (i.e., teachers, learners, and peers) irrespective of time and location (Sejzi & Aris, 2013). Moreover, the accessibility of diverse learning materials enables learners to engage with content prior to applying it in real classroom settings. Features such as discussion forums, feedback mechanisms, and public learning progress tracking further encourage learners to reinforce positive learning behaviors. The alignment between personalized learning via LMS and SLT lies in the enhancement of both individual and social learning experiences, creating a more holistic educational process.

Despite the extensive body of knowledge on personalized learning, concerns have emerged regarding its practical application in real-world educational settings. These concerns are driven by the complex challenges educators face, such as managing increasingly heterogenous classrooms, and adapting to new digital learning media (Mötteli et al., 2023). Consequently, the integration of personalized learning systems and technologies prompts educational stakeholders to formalize the adoption of advanced teaching and learning solutions that extend conventional learning environments. For instance, the enactment of LMS in educational institutions can alleviate instructors' loads to identify individual learner characteristics and deliver customized learning experiences. Bernacki et al. (2021) argue that educational stakeholders designing PL strategies must align their teaching materials with these changes, thereby allowing decision-makers to determine and adopt PL strategies that complement and enhance prior one-size-fits-all learning approach. In sum, this study suggests that the establishment of policy briefs and comprehensive guidelines on personalized learning would benefit educational stakeholders by bridging the gap between PL theory and its application in authentic learning environments.

Conclusion

This study has performed a comprehensive analysis of Personalized Learning (PL) strategies executed through Learning Management System (LMS) platforms. In the last ten years, there has been a notable increase in publications examining the construction of PL strategies, indicating growing scholarly interest, especially within computer science and education disciplines. The varied functionalities of LMS platforms have allowed instructors, scholars, and learners to gain significant educational advantages by employing the multitude of tools and features available within LMS, thereby improving the effectiveness of the educational process. This study concludes that the knowledge levels and learning styles of learners are the primary attributes utilized in developing learner models to inform personalized strategies within LMS. Furthermore, it was noted that the personalization of learning materials, learning paths, and feedback were the most commonly tailored components enabled by LMS platforms. Moreover, the main learning outcomes aimed at by these PL learning initiatives were the improvement of learning performance and learning effectiveness. Nevertheless, the overall objectives beyond cognitive improvements, including enhanced motivation, satisfaction, engagement, self-regulated learning (SRL), and self-directed learning (SDL), exhibited promising interest. These findings indicate that LMS platforms can facilitate the development of favorable nurturant learning outcomes, promoting an engaging and supportive educational atmosphere.

Notwithstanding the contributions of this study, several limitations must be recognized. Some important findings might have been unintentionally overlooked due to the lengthy literature review process and the enormous number of included studies. Future investigations into personalized and adaptive learning within Learning Management Systems are highly advisable to rectify current gaps. Significantly, since the majority of personalized learning studies concentrate on higher education, there is a necessity for additional empirical research investigating the effects of personalized learning in lower educational contexts. Secondly, empirical evidence concerning the efficacy of learning styles, especially within frameworks beyond FSLSM and VARK, would contribute significantly to the existing knowledge on PL. Finally, augmented research on data-driven technologies is crucial to improve personalized instructional strategies, allowing LMS to provide customized learning experiences that cater to each learner's pace, preferences, and distinct attributes. These advancements will guarantee that LMS platforms persist in evolving as dynamic instruments for promoting effective, learner-centered education across diverse educational levels and contexts.

Abbreviations

AEH: Adaptive Educational Hypermedia; AI: Artificial Intelligence; AL: Adaptive Learning; CS: Computer Science; DAELMS: Dyslexia Adaptive E-learning Management System; DL: Deep Learning; FSLSM: Felder-Silverman Learning Style Model; GRRAS: Guidelines for Reporting Reliability and Agreement Studies; ILS: Intelligent Learning Systems; IT: Information Technology; ITS: Intelligent Tutoring System; LA: Learning Analytics; LMS: Learning Management System; MBTI: Myers-Briggs Type Indicator; NLP: Natural Language Processing; PL: Personalized Learning; PLE: Personalized Learning Environment; PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses; SDL: Self-directed Learning; SLT: Social Learning Theory; SRL: Self-regulated Learning; SSCI: Social Sciences Citation Index; SVM: Support Vector Machines; VARK: Visual, Auditory, Read/Write, and Kinesthetic.

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Authors' contributions

Conceptualization, Writing Original Draft, Visualization: MSRB; Methodology, Validation, and Supervision: PS; Supervision and Review: DK; Methodology, Conceptualization, and Software: SU.

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Availability of data and materials

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Declarations

Competing interests

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References

Al Abri, A., Jamoussi, Y., AlKhanjari, Z., & Kraiem, N. (2020). Perlcol: A framework for personalized e-learning with social collaboration support. *International Journal of Computing and Digital Systems*, *9*(3), 483–493. https://doi.org/10.12785/IJCDS/090312

Alamri, H. A., Watson, S., & Watson, W. (2021). Learning technology models that support personalization within blended learning environments in higher education. *TechTrends*, *65*(1), 62–78. https://doi.org/10.1007/s11528-020-00530-3

Al-Chalabi, H. K. M., Hussein, A. M. A., & Apoki, U. C. (2021, July 1). An adaptive learning system based on learner's knowledge level. In *Proceedings of the 13th International Conference on Electronics, Computers and Artificial Intelligence* (pp. 1–4). IEEE. https://doi.org/10.1109/ECAI52376.2021.9515158

Alnaqbi, S. S. O., & Sarah, O. S. (2022). A review of the smart educational system and students' performance through teachers' efficiency in the United Arab Emirate. *Journal of Positive School Psychology*, *6*(3), 43807–44816. https://journalppw.com/index.php/jpsp/article/view/2681

Alsadoon, E. (2020). The impact of an adaptive e-course on students' achievements based on the students' prior knowledge. *Education and Information Technologies*, *25*(5), 3541–3551. https://doi.org/10.1007/s10639-020-10125-3

Al-Shamali, F., Yan, H., Graf, S., & Lin, F. (2020). Educational data mining and personalized support in online introductory physics courses. In A. N. Rafferty, J. Whitehill, C. Romero, V. Cavalli-Sforza (Eds.), *Proceedings of the 13th International Conference on Educational Data Mining* (pp. 561–564). International Educational Data Mining Society.

Alsobhi, A. Y., & Alyoubi, K. H. (2019). Adaptation algorithms for selecting personalised learning experience based on learning style and dyslexia type. *Data Technologies and Applications*, *53*(2), 189–200. https://doi.org/10.1108/DTA-10-2018-0092

Apoki, U. C. (2021). The design of WASPEC: A fully personalised Moodle system using semantic web technologies. *Computers*, *10*(5), 59. https://doi.org/10.3390/computers10050059

Arsovic, B., & Stefanovic, N. (2020). E-learning based on the adaptive learning model: Case study in Serbia. *Sādhanā*, *45*(1), 266. https://doi.org/10.1007/s12046-020-01499-8

Aulianda, N., Wijayati, P. H., Ebner, M., & Schön, S. (2023). Analysis of learning management system towards students' cognitive learning outcome. *International Journal of Emerging Technologies in Learning*, *18*(23), 4–26. https://doi.org/10.3991/ijet.v18i23.36443

Bandura, A. (1977). *Social learning theory*. General Learning Press.

Bayly-Castaneda, K., Ramirez-Montoya, M.-S., & Morita-Alexander, A. (2024). Crafting personalized learning paths with AI for lifelong learning: A systematic literature review. *Frontiers in Education*, *9*. https://doi.org/10.3389/feduc.2024.1424386

Bernacki, M. L., Greene, M. J., & Lobczowski, N. G. (2021). A systematic review of research on personalized learning: Personalized by whom, to what, how, and for what purpose(s)? *Educational Psychology Review*, *33*(4), 1675–1715. https://doi.org/10.1007/s10648-021-09615-8

Bhaskaran, S., & Swaminathan, P. (2014). Intelligent adaptive e-learning model for learning management system. *Research Journal of Applied Sciences, Engineering and Technology*, *7*(16), 3298–3303. https://doi.org/10.19026/rjaset.7.674

Bradáč, V., Smolka, P., & Klimeš, C. (2016). Personalization of foreign language education in the LMS Moodle environment. In G. Vincenti, A. Bucciero & C. Vaz de Carvalho (Eds.), *E-Learning, E-Education, and Online Training. eLEOT 2015. Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering, vol 160* (pp. 27–34). Springer, Cham. https://doi.org/10.1007/978-3-319-28883-3_4

Bray, B., & McClaskey, K. (2013). Personalize learning. *Learning & Leading with Technology*, *5191*(May), 12–19.

Cai, R. (2018). Adaptive learning practice for online learning and assessment. In *Proceedings of the 2018 International Conference on Distance Education and Learning* (pp. 103–108). ACM. https://doi.org/10.1145/3231848.3231868

Cavus, N., & Zabadi, T. (2014). A comparison of open source learning management systems. *Procedia - Social and Behavioral Sciences*, *143*, 521–526. https://doi.org/10.1016/j.sbspro.2014.07.430

Cevikbas, M., & Kaiser, G. (2022). Promoting personalized learning in flipped classrooms: A systematic review study. *Sustainability*, *14*(18), 11393. https://doi.org/10.3390/su141811393

Chang, Y. C., Li, J. W., & Huang, D. Y. (2022). A personalized learning service compatible with Moodle e-learning management system. *Applied Sciences*, *12*(7), 3562. https://doi.org/10.3390/app12073562

Chang, Y.-H., Chen, Y.-Y., Chen, N.-S., Lu, Y.-T., & Fang, R.-J. (2016). Yet another adaptive learning management system based on Felder and Silverman's learning styles and Mashup. *Eurasia Journal of Mathematics, Science and Technology Education*, *12*(5), 1273–1285. https://doi.org/10.12973/eurasia.2016.1512a

Chen, C., Hu, Z., Milbank, J., & Schultz, T. (2013). A visual analytic study of retracted articles in scientific literature. *Journal of the American Society for Information Science and Technology*, *64*(2), 234–253. https://doi.org/10.1002/asi.22755

Cohen, J. (1960). A coefficient of agreement for nominal scales. *Educational and Psychological Measurement*, *20*(1), 37–46. https://doi.org/10.1177/001316446002000104

Donevska-Todorova, A., Dziergwa, K., & Simbeck, K. (2022). Individualizing learning pathways with adaptive learning strategies: Design, implementation and scale. In M. Cukurova, N. Rummel, D. Gillet, B. McLaren & J. Uhomoibhi (Eds.), *Proceedings of the 14th International Conference on Computer Supported Education - Volume 2* (pp. 575–585). SCITEPRESS Digital Library. https://doi.org/10.5220/0010995100003182

El Fouki, M., Aknin, N., & El Kadiri, K. E. (2017, November 14). Intelligent adapted e-learning system based on deep reinforcement learning. In J. Zbitou, S. Larbi & E. El Mokhtar (Eds.), *Proceedings of the 2nd International Conference on Computing and Wireless Communication Systems* (pp. 1–6). ACM. https://doi.org/10.1145/3167486.316757

Fake, H., & Dabbagh, N. (2023). *Designing personalized learning experiences*. Routledge. https://doi.org/10.4324/9781003121008

Fariani, R. I., Junus, K., & Santoso, H. B. (2023). A systematic literature review on personalised learning in the higher education context. *Technology, Knowledge and Learning*, *28*, 449–476. https://doi.org/10.1007/s10758-022-09628-4

Fatawi, I., Degeng, I. N. S., Setyosari, P., Ulfa, S., & Hirashima, T. (2020). Effect of online-based concept map on student engagement and learning outcome. *International Journal of Distance Education Technologies*, *18*(3), 42–56. https://doi.org/10.4018/IJDET.2020070103

García-Peñalvo, F. J., Conde, M. Á., Alier, M., & Colomo-Palacios, R. (2014). A case study for measuring informal learning in PLEs. *International Journal of Emerging Technologies in Learning*, *9*(7), 47–55. https://doi.org/10.3991/ijet.v9i7.3734

Gharbaoui, H., Mansouri, K., & Poirier, F. (2023). Towards a social learning analysis using learning management system and learning experience to predict learners' success. In C. Frasson, P. Mylonas & C. Troussas (Eds.), *Augmented Intelligence and Intelligent Tutoring Systems. ITS 2023. Lecture Notes in Computer Science, vol 13891* (pp. 364–370). Springer, Cham. https://doi.org/10.1007/978-3-031-32883-1_33

Grant, P., & Basye, D. (2014). *Personalized learning: A guide for engaging students with technology* (K. Hamman, Ed.). International Society for Technology in Education.

Gunawardena, M., Bishop, P., & Aviruppola, K. (2024). Personalized learning: The simple, the complicated, the complex and the chaotic. *Teaching and Teacher Education*, *139*, 104429. https://doi.org/10.1016/j.tate.2023.104429

Lim, E. H., Sangodiah, A., Muniandy, M., Isawasan, P., Yuen, P. K., & Nallusamy, S. a. (2019). Integration of teaching taxonomy into personalized learning management system using Felder-Silverman model. In *Proceedings of 2019 IEEE Conference on Sustainable Utilization and Development in Engineering and Technologies* (pp. 29–33). IEEE. https://doi.org/10.1109/CSUDET47057.2019.9214765

Hernandez Cardenas, L. S., Castano, L., Cruz Guzman, C., & Nigenda Alvarez, J. P. (2022). Personalised learning model for academic leveling and improvement in higher education. *Australasian Journal of Educational Technology*, *38*(2), 70–82. https://doi.org/10.14742/ajet.7084

Hinkle, J. F. (2023). Personalization and learning outcome in a nursing pathophysiology and pharmacology course: Canvas© Mastery Adoption Pilot Study. *SAGE Open Nursing*, *9*. https://doi.org/10.1177/23779608231186030

Holthaus, M., Hirt, F., & Bergamin, P. (2018). Simple and effective: An adaptive instructional design for mathematics implemented in a standard learning management system. *CHIRA 2018 - Proceedings of the 2nd International Conference on Computer-Human Interaction Research and Applications* (pp. 116–126). SciTePress. https://doi.org/10.5220/0006927601160126

Huang, A. Y. Q., Lu, O. H. T., & Yang, S. J. H. (2023). Effects of artificial Intelligence–Enabled personalized recommendations on learners' learning engagement, motivation, and outcomes in a flipped classroom. *Computers and Education*, *194*, 104684. https://doi.org/10.1016/j.compedu.2022.104684

Imran, H., Belghis-Zadeh, M., Chang, T.-W., Kinshuk, & Graf, S. (2015). In G. Chen, V. Kumar, Kinshuk, R. Huang & S. C. Kong (Eds.), *Emerging Issues in Smart Learning. Lecture Notes in Educational Technology* (pp. 337–344). Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-662-44188-6_47

Jeevamol, J., & Renumol, V. G. (2021). An ontology-based hybrid e-learning content recommender system for alleviating the cold-start problem. *Education and Information Technologies*, *26*(4), 4993–5022. https://doi.org/10.1007/s10639-021-10508-0

Joyce, B., Weil, M., & Calhoun, E. (2016). *Models of Teaching Model-Model Pengajaran (Edisi Sembilan)* (9th ed.). Pearson.

Karaoglan Yilmaz, F. G., & Yilmaz, R. (2020). Student opinions about personalized recommendation and feedback based on learning analytics. *Technology, Knowledge and Learning*, *25*(4), 753–768. https://doi.org/10.1007/s10758-020-09460-8

Kaw, A., Yalcin, A., Braga Gomes, R., Serrano, L., Lou, Y., Scott, A., & Clark, R. (2022). Development, implementation, refining and revising of adaptive platform lessons for an engineering course. In *Proceedings of 2022 ASEE Annual Conference & Exposition*. American Society for Engineering Education. https://doi.org/10.18260/1-2--40477

Kellermeyer, L., Harnke, B., & Knight, S. (2018). Covidence and Rayyan. *Journal of the Medical Library Association*, *106*(4). https://doi.org/10.5195/jmla.2018.513

Khan, F. A., Shahzad, F., & Altaf, M. (2019). Fuzzy based approach for adaptivity evaluation of web based open source Learning Management Systems. *Cluster Computing*, *22*(S3), 7099–7109. https://doi.org/10.1007/s10586-017-1036-8

Khor, E. T., & Mutthulakshmi, K. (2023). A systematic review of the role of learning analytics in supporting personalized learning. *Education Sciences*, *14*(1), 51. https://doi.org/10.3390/educsci14010051

Kitchenham, B., & Brereton, P. (2013). A systematic review of systematic review process research in software engineering. *Information and Software Technology*, *55*(12), 2049–2075. https://doi.org/10.1016/j.infsof.2013.07.010

Kottner, J., Audige, L., Brorson, S., Donner, A., Gajewski, B. J., Hróbjartsson, A., Roberts, C., Shoukri, M., & Streiner, D. L. (2011). Guidelines for Reporting Reliability and Agreement Studies (GRRAS) were proposed. *International Journal of Nursing Studies*, *48*(6), 661–671. https://doi.org/10.1016/j.ijnurstu.2011.01.016

Kouis, D., Kyprianos, K., Ermidou, P., Kaimakis, P., & Koulouris, A. (2020). A framework for assessing LMSs e-courses content type compatibility with learning styles dimensions. *Journal of E-Learning and Knowledge Society*, *16*(2), 73–86. https://doi.org/10.20368/1971-8829/1135204

Lagman, A. C., & Mansul, D. M. (2017). Extracting personalized learning path in adaptive e-learning environment using rule based assessment. In *Proceedings of the 2017 International Conference on Information Technology* (pp. 335–340). ACM. https://doi.org/10.1145/3176653.3176679

Laksitowening, K. A., Hasibuan, Z. A., & Santoso, H. B. (2020). Ontology-based approach for dynamic e-Learning personalization. In *Proceedings of 2020 Fifth International Conference on Informatics and Computing* (pp. 1–5). IEEE. https://doi.org/10.1109/ICIC50835.2020.9288570

Landis, J. R., & Koch, G. G. (1977). The measurement of observer agreement for categorical data. *Biometrics*, *33*(1), 159. https://doi.org/10.2307/2529310

Lasfeto, D. B., & Ulfa, S. (2023). Modeling of online learning strategies based on fuzzy expert systems and self-directed learning readiness: The effect on learning outcomes. *Journal of Educational Computing Research*, *60*(8), 2081–2104. https://doi.org/10.1177/07356331221094249

Lee, D. H., Hong Cho, S., & Kim, Y. (2018). A design and development of the learning contents management based on the personalized online learning. *International Journal on Advanced Science, Engineering and Information Technology*, *8*(4), 1321. https://doi.org/10.18517/ijaseit.8.4.5724

Li, K. C., & Wong, B. T.-M. (2019). How learning has been personalised: A review of literature from 2009 to 2018. In S. Cheung, L. K. Lee, I. Simonova, T. Kozel & L. F. Kwok (Eds.), *Blended Learning: Educational Innovation for Personalized Learning. ICBL 2019. Lecture Notes in Computer Science, vol 11546* (pp. 72–81). Springer, Cham. https://doi.org/10.1007/978-3-030-21562-0_6

Limongelli, C., & Sciarrone, F. (2014). Fuzzy student modeling for personalization of e-learning courses. In P. Zaphiris & A. Ioannou (Eds.), *Learning and Collaboration Technologies. Designing and Developing Novel Learning Experiences. LCT 2014. Lecture Notes in Computer Science, vol 8523* (pp. 292–301). Springer, Cham. https://doi.org/10.1007/978-3-319-07482-5_28

Louhab, F. E., Bahnasse, A., Bensalah, F., Khiat, A., Khiat, Y., & Talea, M. (2020). Novel approach for adaptive flipped classroom based on learning management system. *Education and Information Technologies*, *25*(2), 755–773. https://doi.org/10.1007/s10639-019-09994-0

Maâloul, M. H., & Bahou, Y. (2021). Learning management system based on machine learning: The case study of Ha'il University - KSA. *International Journal of Advanced Computer Science and Applications*, *12*(1), 2021. https://doi.org/10.14569/IJACSA.2021.0120127

Maier, U. (2021). Self-referenced vs. reward-based feedback messages in online courses with formative mastery assessments: A randomized controlled trial in secondary classrooms. *Computers & Education*, *174*, 104306. https://doi.org/10.1016/j.compedu.2021.104306

Manickavasagam, P., & Surwade, S. S. (2017). Cognitive, affective and conative model for analysing higher education students. *Asian Journal of Pharmaceutical and Clinical Research*, *10*, 133–136. https://doi.org/10.22159/ajpcr.2017.v10s1.19592

Mohd Kasim, N. N., & Khalid, F. (2016). Choosing the right Learning Management System (LMS) for the higher education institution context: A systematic review. *International Journal of Emerging Technologies in Learning*, *11*(6), 55–61. https://doi.org/10.3991/ijet.v11i06.5644

Molins, L. L., & García, E. C. (2023). How to embed SRL in online learning settings? Design through learning analytics and personalized learning design in Moodle. *Journal of New Approaches in Educational Research*, *12*(1), 120–138. https://doi.org/10.7821/naer.2023.1.1127

Mötteli, C., Grob, U., Pauli, C., Reusser, K., & Stebler, R. (2023). The influence of personalized learning on the development of learning enjoyment. *International Journal of Educational Research Open*, *5*, 100271. https://doi.org/10.1016/j.ijedro.2023.100271

Musumba, G., & Wario, R. (2019). Towards a personalized adaptive remedial e-learning model. In *Proceedings of 2019 IST-Africa Week Conference (IST-Africa)* (pp. 1–11). IEEE. https://doi.org/10.23919/ISTAFRICA.2019.8764848

Nancekivell, S. E., Shah, P., & Gelman, S. A. (2020). Maybe they're born with it, or maybe it's experience: Toward a deeper understanding of the learning style myth. *Journal of Educational Psychology*, *112*(2), 221–235. https://doi.org/10.1037/edu0000366

Newton, P. M., & Miah, M. (2017). Evidence-based higher education – Is the learning styles 'myth' important? *Frontiers in Psychology*, *8*. https://doi.org/10.3389/fpsyg.2017.00444

Nguyen, H. H., Do Trung, K., Duc, L. N., Hoang, L. D., Ba, P. T., & Nguyen, V. A. (2024). A model to create a personalized online course based on the student's learning styles. *Education and Information Technologies*, *29*(1), 571–593. https://doi.org/10.1007/s10639-023-12287-2

Nouman, N., Shaikh, Z. A., & Wasi, S. (2024). A novel personalized learning framework with interactive e-mentoring. *IEEE Access*, *12*, 10428–10458. https://doi.org/10.1109/ACCESS.2024.3354167

Noyes, J., Hannes, K., Booth, A., Harris, J., Harden, A., Popay, J., Pearson, A., Cargo, M., & Pantoja, T. (2013). *Chapter QQ: Qualitative and Implementation Evidence and Cochrane Reviews*. Cochrane Qualitative and Implementation Methods Group.

O'Donnell, E., Lawless, S., Sharp, M., & Wade, V. P. (2015). A review of personalised e-learning. *International Journal of Distance Education Technologies*, *13*(1), 22–47. https://doi.org/10.4018/ijdet.2015010102

Ouatik, F., & Ouatik, F. (2021). Learning management system comparison: New approach using multi-criteria decision making. In M. Fakir, M. Baslam & R. El Ayachi (Eds.), *Business Intelligence. CBI 2021. Lecture Notes in Business Information Processing, vol 416* (pp. 239–248). Springer, Cham. https://doi.org/10.1007/978-3-030-76508-8_17

Pagano, A., & Marengo, A. (2021). Training time optimization through adaptive learning strategy. In *Proceedings of 2021 International Conference on Innovation and Intelligence for Informatics, Computing, and Technologies* (pp. 563–567). IEEE. https://doi.org/10.1109/3ICT53449.2021.9582096

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ*, *71*, 372. https://doi.org/10.1136/bmj.n71

Papanikolaou, K., & Boubouka, M. (2020). Personalised learning design in Moodle. In *Proceedings of IEEE 20th International Conference on Advanced Learning Technologies* (pp. 57–61). IEEE. https://doi.org/10.1109/ICALT49669.2020.00024

Pardamean, B., Suparyanto, T., Cenggoro, T. W., Sudigyo, D., Anugrahana, A., & Anugraheni, I. (2021). Model of learning management system based on artificial intelligence in team-based learning framework. In *Proceedings of 2021 International Conference on Information Management and Technology* (pp. 37–42). IEEE. https://doi.org/10.1109/ICIMTech53080.2021.9535088

Paul, J., Lim, W. M., O'Cass, A., Hao, A. W., & Bresciani, S. (2021). Scientific procedures and rationales for systematic literature reviews (SPAR-4-SLR). *International Journal of Consumer Studies*, *45*(4). https://doi.org/10.1111/ijcs.12695

Pérez, J., Díaz, J., Garcia-Martin, J., & Tabuenca, B. (2020). Systematic literature reviews in software engineering—enhancement of the study selection process using Cohen's Kappa statistic. *Journal of Systems and Software*, *168*, 110657. https://doi.org/10.1016/j.jss.2020.110657

Qazdar, A., Er-Raha, B., Cherkaoui, C., Bakki, A., & Mammass, D. (2016). A proposed framework to support adaptivity in online learning environment: Use case in LMS. *Journal of Theoretical and Applied Information Technology*, *29*(3). http://www.jatit.org/volumes/Vol84No3/10Vol84No3.pdf

Qi, X., Sun, G., & Yue, L. (2023). Applying self-optimised feedback to a learning management system for facilitating personalised learning activities on massive open online courses. *Sustainability*, *15*(16), 12562. https://doi.org/10.3390/su151612562

Raj, N. S., & Renumol, V. G. (2022). A systematic literature review on adaptive content recommenders in personalized learning environments from 2015 to 2020. *Journal of Computers in Education*, *9*(1), 113–148. https://doi.org/10.1007/s40692-021-00199-4

Rana, M. S., Nobi, M. N., Murali, B., & Sung, A. H. (2022). Deepfake detection: A systematic literature review. *IEEE Access*, *10*, 25494–25513. https://doi.org/10.1109/ACCESS.2022.3154404

Reid, L. (2019). Learning management systems: The game changer for traditional teaching and learning at adult and higher education institutions. *Global Journal of Human-Social Science*, *19*(6), 1–14. https://globaljournals.org/GJHSS_Volume19/1-Learning-Management-Systems.pdf

Riener, C., & Willingham, D. (2010). The myth of learning styles. *Change: The Magazine of Higher Learning*, *42*(5), 32–35. https://doi.org/10.1080/00091383.2010.503139

Ristić, I., Runić-Ristić, M., Savić Tot, T., Tot, V., & Bajac, M. (2023). The effects and effectiveness of an adaptive e-learning system on the learning process and performance of students. *International Journal of Cognitive Research in Science, Engineering and Education*, *11*(1), 77–92. https://doi.org/10.23947/2334-8496-2023-11-1-77-92

Salgado-Chamorro, D. L., Noble-Ramos, V. M., & Gómez-Jaramillo, S. (2023). Adoption of learning management systems in face-to-face learning: A systematic literature review of variables, relationships, and models. *International Journal of Learning, Teaching and Educational Research*, *22*(12), 326–350. https://doi.org/10.26803/ijlter.22.12.16

Sánchez, R. A., & Hueros, A. D. (2010). Motivational factors that influence the acceptance of Moodle using TAM. *Computers in Human Behavior*, *26*(6), 1632–1640. https://doi.org/10.1016/j.chb.2010.06.011

Sein-Echaluce, M. L., Fidalgo-Blanco, Á., & García-Peñalvo, F. J. (2017). Adaptive and cooperative model of knowledge management in MOOCs. In P. Zaphiris & A. Ioannou (Eds.), *Learning and Collaboration Technologies. Novel Learning Ecosystems. LCT 2017. Lecture Notes in Computer Science, vol 10295* (pp. 273–284). Springer, Cham. https://doi.org/10.1007/978-3-319-58509-3_22

Sejzi, A. A., & Aris, B. (2013). Learning Management System (LMS) and Learning Content Management System (LCMS) at virtual university. *2nd International Seminar on Quality and Affordable Education (ISQAE 2013)*. https://humanities.utm.my/education/wp-content/uploads/sites/6/2013/11/301.pdf

Shemshack, A., & Spector, J. M. (2020). A systematic literature review of personalized learning terms. *Smart Learning Environments*, *7*(1), 33. https://doi.org/10.1186/s40561-020-00140-9

Shemshack, A., Kinshuk, & Spector, J. M. (2021). A comprehensive analysis of personalized learning components. *Journal of Computers in Education*, *8*(4), 485–503. https://doi.org/10.1007/s40692-021-00188-7

Sumarlin, S., Setyosari, P., Ulfa, S., & Degeng, M. D. K. (2024). Improvement of engineering student's learning outcomes in high schools using adaptive educational hypermedia system. *International Journal of Evaluation and Research in Education*, *13*(5), 2925. https://doi.org/10.11591/ijere.v13i5.28381

Surahman, E., & Wang, T.-H. (2023). In-service STEM teachers professional development programmes: A systematic literature review 2018–2022. *Teaching and Teacher Education*, *135*, 104326. https://doi.org/10.1016/j.tate.2023.104326

Surur, A. M., Ulfa, S., Soepriyanto, Y., & Mohamed, H. B. (2024). Personalized learning in a digital environment. *Indonesian Journal of Multidisciplinary Educational Research*, *2*(1), 79–99. https://doi.org/10.30762/ijomer.v2i1.2737

Suwawi, D. D. J., Laksitowening, K. A., & Putri, I. (2018). Enhancing online classroom towards personalized learning environment. In *Proceedings of 6th International Conference on Information and Communication Technology* (pp. 476–480). IEEE. https://doi.org/10.1109/ICoICT.2018.8528728

Sweta, S., & Lal, K. (2017). Personalized adaptive learner model in e-learning system using FCM and fuzzy inference system. *International Journal of Fuzzy Systems*, *19*(4), 1249–1260. https://doi.org/10.1007/s40815-017-0309-y

Tashiro, J. S., Hung, P. C. K., Vargas Martin, M., Brown, A. L., & Hurst, F. M. (2016). Personalised-adaptive learning-an operational framework for developing competency-based curricula in computer information technology. *International Journal of Innovation and Learning*, *19*(4), 412–430. https://doi.org/10.1504/IJIL.2016.076793

Taylor, D. L., Yeung, M., & Bashet, A. Z. (2021). Personalized and adaptive learning. In J. Ryoo & K. Winkelmann (Eds.), *Innovative Learning Environments in STEM Higher Education. SpringerBriefs in Statistics* (pp. 17–34). Springer, Cham. https://doi.org/10.1007/978-3-030-58948-6_2

Tetzlaff, L., Schmiedek, F., & Brod, G. (2021). Developing personalized education: A dynamic framework. *Educational Psychology Review*, *33*(3), 863–882. https://doi.org/10.1007/s10648-020-09570-w

Ulfa, S., Lasfeto, D. B., & Kurniawan, C. (2019). Modeling the learner model based ontology in adaptive learning environment. *Journal of Disruptive Learning Innovation*, *1*(1). https://journal2.um.ac.id/index.php/jodli/article/view/10191

Walkington, C., & Bernacki, M. L. (2020). Appraising research on personalized learning: Definitions, theoretical alignment, advancements, and future directions. *Journal of Research on Technology in Education*, *52*(3), 235–252. https://doi.org/10.1080/15391523.2020.1747757

Watson, W. R., & Watson, S. L. (2017). Principles for personalized instruction. In C. M. Reigeluth, B. J. Beatty & R. D. Myers (Eds.), *Instructional-Design Theories and Models, Volume IV The Learner-Centered Paradigm of Education*. Routledge.

Xie, H., Chu, H.-C., Hwang, G.-J., & Wang, C.-C. (2019). Trends and development in technology-enhanced adaptive/personalized learning: A systematic review of journal publications from 2007 to 2017. *Computers & Education*, *140*, 103599. https://doi.org/10.1016/j.compedu.2019.103599

Yu, P., & Anezaki, K. (2024). "Suspending Classes Without Stopping Learning": An initiative to ensure learning in Japan during the pandemic. *ECNU Review of Education*, *7*(1), 195–206. https://doi.org/10.1177/20965311231210310

Zhang, L. (2020). Personalized learning and ESSA: What we know and where we go. *Journal of Research on Technology in Education*, *52*(3), 253–274. https://doi.org/10.1080/15391523.2020.1728448

Zhang, Q., & Stephens, M. (2013). Personalized education and the teaching and learning of mathematics: An Australian perspective. *Journal of Mathematics Education*, *6*(2), 48–57.

Zhong, L. (2022). A systematic review of personalized learning in higher education: Learning content structure, learning materials sequence, and learning readiness support. *Interactive Learning Environments*, *31*(10), 7053–7073. https://doi.org/10.1080/10494820.2022.2061006

Zielinski, A., Bock, J., Heberle, F., Henning, P. A., Bock, J., & Kohen-Vacs, D. R. (2014). Enhanced e-learning experience by pushing the limits of semantic web technologies. In I. Celino, O. Corcho, D. Dell'Aglio, E. Della Valle & M. Krötzsch (Eds.), *3rd International Workshop on Ordering and Reasoning* (pp. 23–34). CEUR-WS.org.

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