Systematic Literature Review on Artificial Intelligence-Driven Personalized Learning

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***Abstract*—Artificial Intelligence (AI) is widely used in various contexts, including education at different levels, such as K-12 (kindergarten through 12th grade) and higher learning. The impact of AI in education is becoming increasingly significant, making the academic sphere more effective, personalized, global, context-intensive, and asynchronous. Despite the publication of several systematic literature reviews, mapping studies, and reviews on the use of AI in education, there is still a lack of reviews focusing on personalized learning (PL) frameworks, models, and approaches at various levels especially the pre-university level for Science, Technology, Engineering, and Mathematics (STEM) subjects. To address this gap, our work presents a systematic literature review of AI-driven PL models, frameworks, and approaches published over the past ten years from 2013 to 2023, extracted from the Scopus database. This review focuses on the AI techniques used, personalized learning elements, components, attributes, and the possibility of replicating the technique in pre-university level studies, and gaps or prospects that will attract further research. The study reviewed 69 articles, downloaded via the Scopus database, and reported the most used AI techniques, PL components or factors, trends, and prospects for future research. The results show that most existing studies focus on higher learning that requires further research at the pre-university level. In addition, machine learning and deep learning are identified as the most suitable and frequent techniques besides other technologies, knowledge delivery, learners' needs, behavior and interest as the most required components for personalized systems in diverse fields. In terms of publication output by country, the study indicates that Switzerland, USA, UK, and China are leading contributors to PL research. Thus, this study calls for further research on AI-driven personalized learning that thoughtfully integrates educational theories, subject-specific content, and industry needs to enhance outcomes and learner satisfaction.**

Keywords—Personalized learning; model; framework; approach; technique; systematic literature review; personalized learning components; artificial intelligence

I. Introduction

Academic research on artificial intelligence in education (AIED) has made significant progress over the past 30 years toward adopting a more complex learning paradigm that enables successful teaching and learning [1]. Education cannot be discussed today without mentioning the impact of Artificial Intelligence (AI). AI has had a widespread impact on all aspects of education, including its purpose, content, methods, and evaluation systems. Countries worldwide are making AI literacy education mandatory to enhance their understanding of AI. These include methods of using AI devices and services, understanding AI ethics, real-life AI convergence cases, and basic block coding. The curriculum is also being reformed to reflect AI, including its principles and the convergence of courses [2]. AI has the potential to tackle the major challenges faced by the education sector today, leading to innovative teaching and learning practices and ultimately speeding up progress toward achieving Sustainable Development Goals (SDGs). Nevertheless, these fast-paced technological advancements also bring various risks and challenges, surpassing policy debates and regulatory frameworks [3].

Educational technology literature has been exploring ways to incorporate AI into education to make education more personalized. Humans have unique characteristics that require the education sector to focus on individual-specific learning requirements, which is motivated by the desire to move away from the traditional "one size fits all" approach to a more personalized learning (PL) format [4], [5]. The key idea is to prioritize the students by making the system more "student-centered". PL aims to adjust the curriculum and instructions based on students' learning requirements and abilities, and to meet the demand of the modern workforce and address global challenges. Catering to a learner's needs will likely motivate the general student population. It is worth recalling that during the COVID-19 pandemic, educational systems rapidly transitioned to online platforms, prompting many institutions to adopt Content Management Systems (CMS) and Learning Management Systems (LMS) for the duration of the crisis and beyond. However, this rapid adoption has caused issues with productivity, course content, progress analysis, and alignment of learning with industry requirements [6].

PL is defined as "instruction that is paced to learning needs, tailored to learning preferences, and to the specific interests of different learners" [7]. The ongoing evolution of technology, coupled with the rapid advancement of AI, has significantly enhanced teaching and learning processes. AI facilitates a flexible, personalized, and efficient learning environment while also strengthening educational competencies through PL [8]. While there has been much research on learner control, the relationship between learner control and psychological ownership is not well understood [9]. Furthermore, it is still unclear how these concepts manifest in primary and secondary school education [10]. In order to personalize learning content, it is important to start with a classic instructional design model, which means that the learning environment must be designed to achieve a specific learning outcome. The learners will be engaged in the learning process and then assessed for their mastery or achievement of the targeted outcome. In addition, the environment must be adapted based on one or more features of learners to personalize the learning experience. This

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adaptation should be motivated by a desire to achieve educational outcomes. The National Academy of Engineering has identified the development of PL systems as a major challenge in the 21st century. Researchers in various fields have worked on different aspects of this challenge [11]. Personalizing learning involves creating a learning environment that considers the learner's prior knowledge, motivation, goals, beliefs, interests, skills, experience, and culture, among other factors. Instructional experience should be responsive to these features to enhance engagement in a learning task and improve performance. PL presents numerous dimensions and appeals to various disciplines, leading to a diverse body of research on this subject [12].

Learning analytics is vital in personalizing learning, which analyzes data from students and learning environments to support learning at various levels. It is a relatively recent field that has achieved a high level of maturity, particularly in its applications in higher education. However, there is a lack of research on learning analytics that focuses on other educational levels, such as high school [13]. Technology has been deeply integrated into modern society, impacting almost every industry. Basic science subjects are deemed tough and boring for students at K-12 since most of them cannot relate to their applications in the real world. Hence, the technology aspect of Science, Technology, Engineering, and Mathematics (STEM), especially Computer Science (CS), is changing the narrative. CS is trending as its applications and impacts are felt by all and sundry. Skilled workers related to CS are in high demand. In traditional education, students rely on instructors or textbooks for subject knowledge, which can vary. The lack of trained CS teachers at the K-12 (kindergarten through 12th grade) level can result in insufficiently prepared students, owing to the limited number of CS courses offered in high schools [14].

Many college freshmen are hindered from taking CS because of a lack of exposure to the field earlier in their high school time. This is because they have never taken a course on the subject or had limited knowledge of it and are therefore not aware of what it entails. Surveys indicate that 90% of parents believe that CS should be part of their children’s K-12 curriculum, but only 40% of schools offer it. Additionally, most schools that offer CS include it as a high school elective that does not count toward graduation [15].

AI technology is used to establish PL environments by gathering, analyzing, and interpreting data from multiple sources to construct student learning profiles. However, there is limited research on integrating AI into education to improve teaching efficiency in Malaysia. AI technology can predict a student’s learning potential, and this information can be used to create tailored content that aligns with an individual's goals and previous achievements [8]. This is a common issue in most developing and underdeveloped countries. Hence, this systematic literature review (SLR) aims to comprehensively review models of AI and PL in education at various levels, focusing on outcomes and prospects, to further examine the applicability of AI-driven PL at the pre-university level particularly for the CS subject. Subsequently, Section II presents the related work, Section III provides the details on the review process, while Section IV and V report results and discussion respectively, and finally Section VI concludes the study and its future research direction.

II. Related Work

This section deals with the analysis of related works on the broad topic in the form of SLRs, systematic mapping studies (SMS), and other forms of review studies, published in SCOPUS (a large multidisciplinary database of peer-reviewed papers) for the span of ten years, from 2013 to 2023. IT was accessed via the Universiti Teknologi Malaysia (UTM) subscribed databases. The search was recorded as shown in Table I, based on the identified keywords and search terms (ST): systematic literature review”, “systematic mapping study”, “personalized learning”, and “artificial intelligence”.

Fig. 1 shows the number of publications and the percentages resulting from the search terms. Firstly, ST1 “systematic literature review AND artificial intelligence AND personalized learning” yields 92 publications, out of which only 29 (47%) are in the domain of this study and within the range of 2013 to 2023. Secondly, ST2 “systematic mapping study AND artificial intelligence AND personalized learning” only had 6 (10%) publications, and finally ST3 “systematic literature review AND personalized learning AND education” with the highest total of 108 publications, out of which only 54 are related to computer science and only 26 (43%) are in the scope of this study. The publications were further selected to check their findings, key focus, educational level that considered higher learning (HL), K-12 (Primary and secondary levels), as well as the type of review presented (SLR, SMS, and other review protocol).

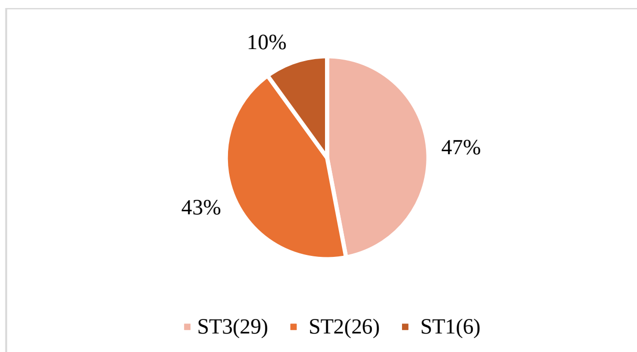

Fig. 1. Results by search terms (ST).

A. Issues and Gaps

Table II provides a brief overview of 20 studies, highlighting their key focus, educational level (HL, K-12), and types of study such as SLR and SMS. It aims to demonstrate that no existing work aligns precisely with the specific focus or title of this research study, indicating an unaddressed gap. This is particularly relevant when considering the pre-university level. Another gap addressed is the identification of major techniques and components that should be used in building personalized models and frameworks.

TABLE I. SEARCH RESULTS ON SLR, SMS, AND CLOSELY RELATED REVIEW PAPERS BASED ON KEYWORDS

Search Terms (ST)	ST1: (systematic literature review) AND (personalized learning) AND (artificial intelligence)					ST2: (systematic mapping study) AND (artificial intelligence) AND (personalized learning)					ST3: (systematic literature review) AND (personalized learning) AND (education)				
Category/ Year	**RV**	**JA**	**CP**	**BK**	**CR**	**RV**	**JA**	**CP**	**BK**	**CR**	**RV**	**JA**	**CP**	**BK**	**CR**
2023	6	4	5	0	0	0	2	0	0	0	3	6	0	1	0
2022	6	0	0	1	0	1	0	0	0	0	5	0	1	0	0
2021	2	1	0	0	0	0	1	0	0	1	1	0	3	0	0
2020	0	0	1	0	0	0	0	0	0	0	1	0	1	0	0
2019	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0
2018	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2017	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
2016	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
2015	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
2014	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2013	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0
Sub Total:	15	6	7	1	0	1	3	0	0	2	10	6	8	2	0
Total:	29					6					26				

Note: RV = Review, JA = Journal Article, CP = Conference Paper, BK = Book Chapter, and CR = Conference Review. The acronyms are derived from nomenclatures on the SCOPUS summary pane on the left side of the window after a successful search display.

In summary, 15 out of the 20 focused on higher learning [5],[16]-[20], [23]-[26], [28][29], [32]-[34]; four [21], [27], [30], [31] considered K-12 level, and only one publication [22] considered both K-12 and higher learning. The limited number of reviews within the selected range shows the pressing need for research in the area. The following section describes 10 elements that can be considered when designing personalized learning models and frameworks.

Teachers, schools, districts, states, and technology developers have attempted to create PL experiences for students. However, there is no consensus on the actual definition of personalized learning, and different designs may include multiple components. This variability can make it difficult to study personalized learning and how it can be designed based on students' characteristics to reliably achieve specific learning outcomes [7].

B. Personalized Learning Elements

Ten learning elements are identified here for designing a befitting PL framework or model extracted from the literature as cited.

1) Learning paths. A learning path refers to customizing an adaptable journey designed to meet the unique needs, preferences, and progress of individual learners. Machine learning can analyze a range of factors, including learners' goals, interests, prior knowledge, and performance, to create a customized curriculum and better learning outcomes. This dynamic approach enables customization of learning experiences, content, and pace, ensuring that each learner receives focused and pertinent educational material. This can enable the system to categorize learners based on different factors and recommend appropriate learning choices and improved outcomes [35]. The system can be powered by innovations, such as data mining, which can extract valuable information from large, unstructured, and random datasets. Adaptive ability of learners with similar characteristics can be identified, classified, and a learning path can be created for future learners [36]. Additionally, pinpointing the strengths and weaknesses of a particular learner can help eliminate learning difficulties.

2) Learner model. Learner models for classifying learners based on defined criteria. For example, learners can be classified based on their knowledge level as Basic or Beginner, Average or Middle, and Advanced or Expert.

3) Learners' metacognitive aspects. This involves designing features, activities, and feedback mechanisms that help students develop and use metacognitive skills like planning, monitoring, and evaluating their learning. This process turns a passive learning environment into a self-regulated, reflective, and adaptive experience [5].

4) Learners' queries. Learners' progress and behavior, including encouraging them to ask questions and addressing their concerns, is essential in creating a personalized and engaged learning environment. Timely responses promote proactive learning [37].

5) Learners' characteristics. This includes learners' profile, personality, and style, in which the system should consider various attributes of learners, such as their preferred learning styles, interests, and socio-cultural background. Adapting teaching strategies to align with these characteristics can enhance engagement and comprehension [16].

TABLE II. FINDINGS OF EXISTING WORKS

Study	Description of Findings	Key Focus	Level	Study Type
[5]	It is a systematic literature review paper investigating issues related to learner diversity, the PL features, the methods used, applications in higher learning, and the impact of implementation.	Learner Diversity	HL	SLR
[16]	The research explores the personalization of vocational education within Indonesia's higher education. It introduces the Personalized Blended Learning model as a solution to the limitations of the "one-size-fits-all" approach. It aims to enhance PL experiences.	Personalizing Vocational Education	HL	S/R
[17]	The paper discusses the challenges and opportunities of blended learning in vocational education, emphasizing the importance of combining face-to-face and online learning to enhance teacher training.	Teacher Training for Blended Learning	HL	DBR
[18]	They examined the use of algorithms in higher education decision-making processes, focusing on their impact on students and educators. It highlights the importance of designing these algorithms with a human-centered approach to ensure fairness, transparency, and ethical considerations.	Algorithms for decision making in higher learning	HL	SLR
[19]	The SLR research focused on learners' psychological and emotional states, along with their abilities and motivations, while also examining the role of personalized instruction in e-learning.	Learners' Psychological and Emotional State	HL	SLR
[20]	The SLR research examined the impact and application of Convolutional Neural Networks (CNNs) in education, particularly in areas such as face detection and student recognition.	CNN and for students' detection	HL	SLR
[21]	The SLR identified Special Educational Needs (SEN) as a form of Personalized Learning for primary and elementary students in the digital era, particularly those with attention challenges who depend on teacher support.	Learners with special educational needs	K-12	SLR
[22]	The SLR explored personalization strategies and gamification techniques in Virtual Reality (VR) to enhance educational outcomes in schools.	Gamification and virtual reality	HL/K-12	SLR
[23]	The scoping review analyzed ChatGPT's impact on higher education for researchers, teachers, and students globally, highlighting its benefits and concerns regarding accuracy, reliability, and academic integrity.	ChatGPT and academic integrity	HL	SSR
[24]	The SLR paper explored the role of AI chatbots as teaching assistants, aiding both educators and students, with a particular focus on their contribution to personalized education in higher learning.	Chatbots as teaching assistance	HL	SLR
[25]	The SLR examined how AI and Data Science integrate sustainable development into education, enhancing personalization, learning prediction, and dropout prevention.	Data Science and Sustainable Development	HL	SLR
[26]	The research explored computer-based methodologies for teaching English, advocating for personalized learning using AI, Text-to-Speech (TTS), and Natural Language Understanding (NLU).	Language Teaching	HL	SLR
[27]	This systematic literature review examines the personalization of e-learning models to adapt to students' learning styles and pace in Indonesian schools.	E-learning models	K-12	SLR
[28]	This SLR explores the essential components for constructing a learner model grounded in learning theories for adaptive e-learning systems.	E-learning systems	HL	SLR
[29]	The SLR assesses research on pedagogical agents using empirical data to enhance personalization in e-learning, emphasizing their flexibility, diversity, simulation capabilities, and overall impact.	Pedagogical agents	HL	SLR
[30]	The research explored the application of AI concepts in science education at the secondary school level.	AI and Science education	K-12	SLR
[31]	The SLR examines the lack of consensus on DPL (Digital Personalized Learning) technology in primary and secondary education by analyzing various empirical studies.	DPL technology	K-12	SLR
[32]	The SLR explored AI methods for identifying learner traits, structuring content, recommending learning paths, and evaluating their benefits and limitations.	AI for learner identification	HL	SLR
[33]	This SMS examined the incomplete implementation of adaptive learning systems and their failure to fully address students' diverse needs, proposing improved AI integration as a solution.	Adaptive learning and students' diversity	HL	SMS
[34]	It highlights the need for more empirical studies to validate adaptive learning models and suggests exploring new adaptive techniques and technologies to enhance personalized learning experiences.	Adaptive learning environment	HL	SMS

Note: SLR (Systematic Literature Review), SMS (Systematic Mapping Studies), SSR (Systematic Scoping Review), S/R (Survey Research), DBR (Design-Based Research), HL (Higher learning, Tertiary education), and K-12 (Primary and Secondary School, Kindergarten 12).

6) Learners' knowledge level. The system should identify and tackle learners' background, prior knowledge, feedback, and current knowledge level that involves adapting educational content and activities to address gaps and challenge the learner based on their understanding and proficiency [38].

7) Flexible pacing. This is achieved by designing the system to allow each learner to move through content at a pace that matches their individual learning needs, prior knowledge, and personal goals. Sturgis and Patrick also emphasized that well-designed systems should enable tracking individual progress and suggest customized learning pathways.

8) Systems and tools. There are available tools that can be incorporated into PL systems for providing learning resources and other supports, like Khan Academy, Knewton, and ALEKS.

9) Smart learning environment. Effective smart learning environments should promote PL by fostering sensitivity, suggestions, self-reflection, assessment, constructive criticism, and enthusiasm. Examples include Intelligent Tutoring Systems, Virtual and Augmented Reality, SNAPP, Minecraft, etc.

10) Learning analytics (LA) and data mining (DM): Data Mining (DM) and Learning Analytics (LA) are powerful tools that support the learning process by collecting and analyzing data. They can help evaluate learning methods, predict the expected performance, and identify areas for improvement [39]. LA is particularly useful for analyzing data from diverse learning environments and can be used to create PL activities tailored to the needs and goals of each learner. As interest in LA continues to grow, it has the potential to transform learning by promoting personalized learning experiences.

Based on these twenty related works in Table II, it is evident that none of them focused primarily on reviewing or examining the existence of PL frameworks or models, and approaches that are subject-specific and focused on the peculiarities of the PU level. Most of the studies focused on advanced levels, and the use of AI in PL is less addressed in the studies. As a result, the next phase of this SLR will extensively review the AI-driven PL models, outcomes, and prospects. Additionally, it will explore further issues and gaps, as well as the components of PL that are appropriate for the pre-university level.

III. Review Process

This review adopts the SLR method outlined by Barbara Kitchenham [40]. These steps are illustrated in Fig. 2 and further explained in the sections ahead. The search process consisted of four stages. The first step was to formulate the research questions, where three research questions were formulated as presented in the sections ahead. The second step was the selection of articles using defined keywords on the identified resources (Scopus-indexed publications only). The search results were then filtered and recorded accordingly.

Fig. 2. Four stages of the review process based on an existing protocol [40].

The articles were then sorted systematically and organized by publication year and type (article, conference, review, conference review, book, or book chapter). The third step is on the inclusion and exclusion criteria: only articles reported in the English language that can be comprehended easily, and adherence to keywords is considered. Moreover, articles that are considered related to PL with AI techniques and centered on either components or factors of PL, model, framework, or approach are also selected. Only 69 articles were considered and selected for the final stage. Finally, the selected articles were used to answer the research questions outlined.

A. Research Questions

In framing the research questions, some requirements or criteria were considered, including population, intervention, comparison or justification, and outcomes, as presented in Table III. These requirements paved the boundaries upon which the direction of search and results were guided.

TABLE III. Criteria for Research Questions

Criteria (Component)	Scope (Coverage)
Population	Articles that propose a framework, model, or approach for PL at any level or consideration
Intervention	model, framework, or approach that addressed the application of AI techniques for PL at any level.
Comparison/ Justification	Strengths, weaknesses, and prospects for each approach.
Outcomes	Problems/issues/gaps addressed on the applicability of AI techniques suitable for PL and the PL components used, and at what level of learning?

Based on the criteria outlined in Table III, the research questions (RQs) were formulated as follows:

1) RQ1. Do the articles discuss the use of AI Techniques in PL, and what are the components of PL involved?

2) RQ2. Are these techniques clearly defined? Can they be replicated in pre-university computer science courses?

3) RQ3. Do the articles present gaps and points of interest attracting future research?

B. Search Process

The main purpose of the search was to obtain existing research on AI applications in the educational domain in the form of PL. Explicitly, PL models, frameworks, and approaches are the center of the review, to see which AI techniques were used and at what level were they applied, and to see the applicability of the techniques at the pre-university level. What are the PL components involved in this process?

1) The search process was carried out using the Scopus database. When papers are not available for download, they are then viewed and downloaded from the publisher's site, ResearchGate, or Google Scholar.

2) Organizing and categorizing articles based on keywords, type of publication, year of publication, and related information.

3) Recording search results according to keywords and publication type.

4) Refining the search involves the search process, and the choice of words is refined to ensure that all relevant papers are obtained.

Table IV presents the list of the seven keywords used in the search process, K1 to K7.

TABLE IV. SEARCH KEYWORDS

Keyword	Representation
K1	Personalized Learning
K2	Approach
K3	Model
K4	Framework
K5	Secondary School
K6	High School
K7	K-12

The search process from the repository considered the content and suitability of the articles by their abstract, publication title, and keywords, derived using the outlined search strings (SS1 to SS7) in Table V, which are partial combinations of the keywords in Table IV.

TABLE V. SEARCH STRINGS

Code	String
SS1	Personalized Learning Approach
SS2	Personalized Learning Framework
SS3	Personalized Learning Model
SS4	Personalized Learning Model OR Personalized Learning Framework
SS5	Personalized Learning Models AND High School OR Secondary School or K-12
SS6	Personalized Learning Approach AND High School OR Secondary School or K-12
SS7	Personalized Learning Framework AND High School OR Secondary School or K-12

Table VI presents the number and its percentage for each search string SS1 to SS7 versus the five document types. The highest found string is for SS5 that is 105 works in the scope of models and high school or secondary school or K-12.

TABLE VI. INITIAL SEARCH RESULTS FOR EACH DOCUMENT TYPE VERSUS SEARCH STRING

Type	SS1	SS2	SS3	SS4	SS5	SS6	SS7	Total 100 (%)
Article	10	3	6	23	43	5	13	103 (39.16)
Conference Paper	9	9	13	23	45	3	16	118 (44.87)
Conference Review	0	0	2	2	15	1	5	25 (9.51)
Book Chapter	0	1	3	4	1	2	1	12 (4.56)
Book	1	1	1	1	1	0	0	5 (1.90)
Total	20	14	25	53	105	11	35	263 (100)

Fig. 3 visualizes the percentage of the publication type, with conference papers as the highest in the list with 118 (44.8%) publications, followed by journal articles with 103 (39.16%) publications, 25 (9.51%) conference reviews, 12 (4.56%) book chapters, and five books (1.9%).

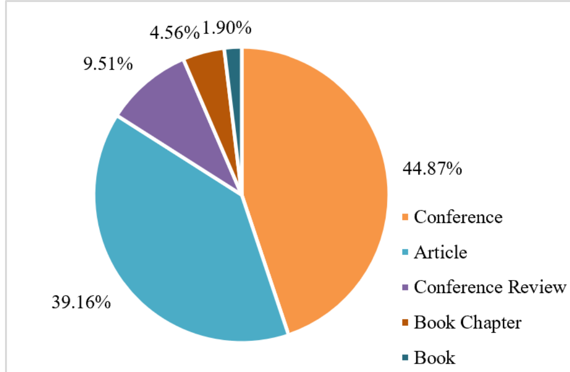

Fig. 3. Percentage of articles by publication type.

C. Inclusion and Exclusion Criteria

At this stage of the SLR, many criteria were considered for inclusion or exclusion. First, the articles were sorted by document type (regardless of the publishers, if the paper is found in the Scopus database), as displayed in Table VI. Second, only articles that were written or reported in English were selected. Third, the selected articles had to be from computer science, information technology, sciences, technology, or topics related to learning, AI, and education. Finally, the selected articles must not negate the search keywords and strings, as enumerated in Tables IV and V, respectively.

Articles that did not meet the inclusion criteria were excluded; articles that did not appear in a relevant field but in conformity with the search criteria were excluded; and articles that did not apply AI techniques in the framework, model, or approach were excluded, except for a few that included other technologies closely related to AI.

D. Quality Evaluation

To ensure the quality and conformity of the relevant articles, Table VII serves as a guide for choosing relevant studies based on the research questions outlined earlier. For each research question, the article should answer yes or no. Those who were neither "Yes" nor "No" were excluded from the study. Those who partially answered were further evaluated for inclusion or exclusion.

TABLE VII. EVALUATION BASED ON RESEARCH QUESTIONS

Research Question (RQ)	Possible Answer
RQ1: Do the articles discuss the use of AI Techniques in personalized learning, and what are the components of PL involved	Yes/No/Partially
RQ2: Are the techniques clearly defined? And can they be replicated at pre-university level computer science courses?	Yes/No/Partially
RQ3: Do the articles discuss gaps and points of interest attracting future research?	Yes/No/Partially

Fig. 4 shows the flow of the evaluation process and how the articles were evaluated to ensure conformance. The classification was adapted to evaluate the articles further, as follows:

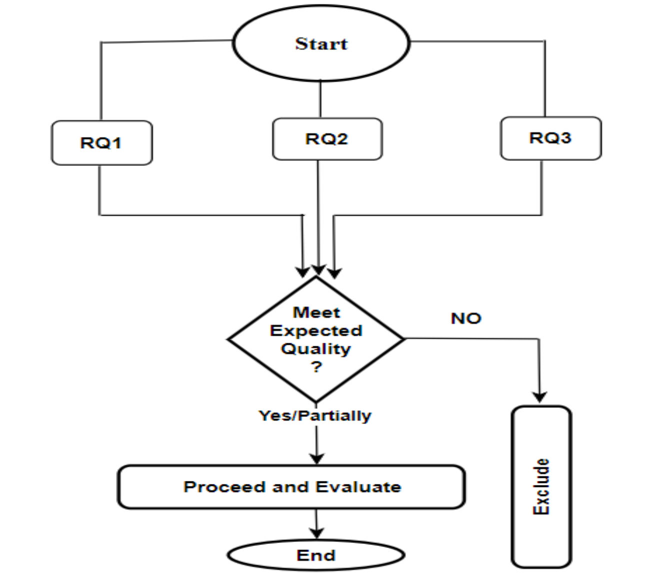

Fig. 4. Evaluation process flow.

1) The article's title or abstract mentioned the framework, model, or approach within a specific field of learning.

2) AI techniques or technology used for personalization were clearly stated.

3) The paper must equally discuss issues and gaps for further research.

IV. Results

The SLR reviews AI techniques and other associated technologies applied in developing PL frameworks, models, and approaches in different educational settings and levels. The SLR considers the frequencies of the techniques and the most considered elements (factors and components) of PL in the models, framework, or approach. In the initial stage of the search process, many results were obtained using the search strings listed in Table V but were narrowed by field and publication dates. For example, the search keyword S5 (personalized learning models AND high school OR secondary school or K-12) yielded 207 documents; only 107 were relevant and further screened to obtain the final selections.

The 69 publications selected are listed in the Appendix, capturing: focus of the article (model, framework, or approach), the PL elements (components, factors, approach) involved, the technique and technology applied, and the educational level (higher learning, K-12, or just general) considered. The results are further discussed in the next section; however, some graphs are presented here.

The articles selected according to the search strings are listed in Table VIII, with S5 (14 out of 69) having the highest number of publications, followed by S3 and S7 with 12 publications respectively, S1 with 10, S4 with 9, S2 with 8, and S6 with at least four publications.

TABLE VIII. Selected Articles by Search Strings

Search String	Selected Articles	Total
S1	[41][42][43][44][45][46][47][48][49][50]	10
S2	[51][52][53][54][55][56][57][58]	8
S3	[59][60][61][62][63][64][65][66][67][68][69][70]	12
S4	[71][72][73][74][75][76][77][78][79]	9
S5	[80][81][82][83][84][85][86][87][88][89][90][91][92][93]	14
S6	[94][95][96][97]	4
S7	[98][99][100][101][102][9][103][104][105][106][107][108]	12
Grand Total		69

Fig. 5 provides a graphical representation of the number of publications selected for the review, along with their respective publication years, 2013 to 2023. In total, 69 publications were included, with 2013 and 2014 having the lowest number of publications, and 2021 having the highest. The curve shows the trend in the number of publications over time.

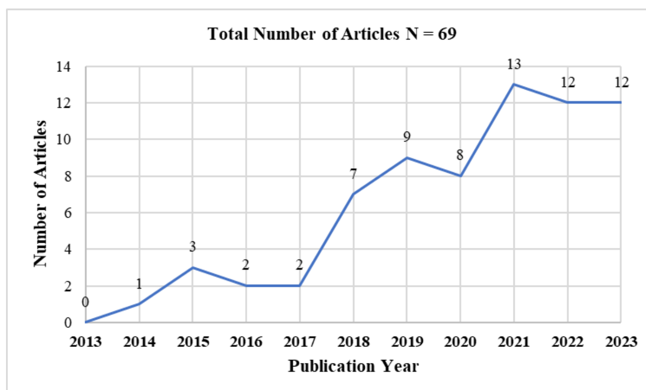

Fig. 5. Number of publications versus year of publication for the 69 studies.

Fig. 6 presents the chart for learning levels for the selected publications in the form of K-12 (kindergarten or primary and secondary school level), HL (higher learning: colleges, polytechnics, and university levels), and GL (general level with no emphasis on the study level or capacity of the learners).

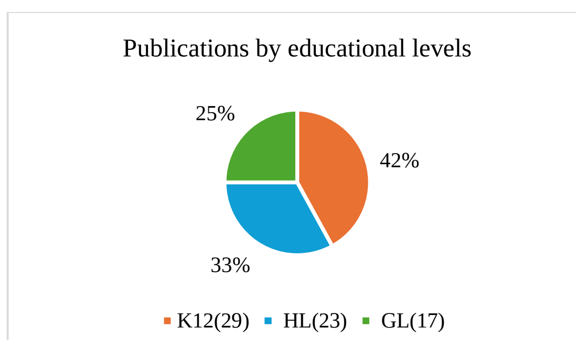

Fig. 6. Number of publications by level of education in the selected studies.

Fig. 7 shows the top five countries based on publisher locations, with Switzerland having 48.40%, the USA (22.60%), and the UK (16.00%), are the leading contributors to research in personalized learning, education, artificial intelligence approaches, models, frameworks, and their applications in education. China and India each have 6.50%, indicating their emerging roles in this scope of study.

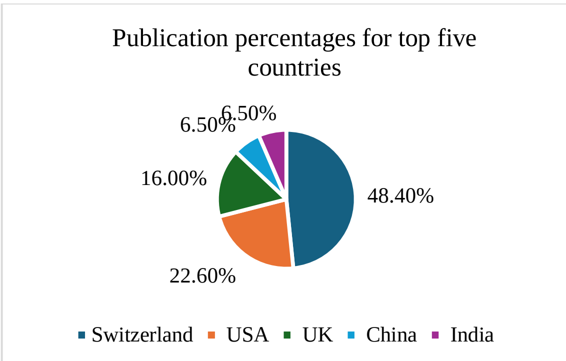

Fig. 7. Top countries with publications on personalized learning education with concepts of artificial intelligence.

This distribution highlights the significant investment and focuses these countries have on advancing educational technologies and AI-driven PL systems, while also underscoring the need for increased research contributions from developing countries to enrich the global research landscape.

Fig. 8 presents the top 10 publishers by the number of publications within the scope and data analyzed. Sustainability (Switzerland) dominates with 11 publications, demonstrating its prominent role and high level of scholarly activity in the area. ACM International Conference Proceedings Series and IEEE Access follow, each contributing 6 publications, indicating their strong engagement in disseminating research in the area. Other publishers like Artificial Intelligence in Medicine and Applied Sciences (Switzerland) have each possessed four publications, while several others, including Technology, Knowledge and Learning, Computers and Education, and Computers in Education: Artificial Intelligence, each have around 3 publications.

Finally, Computers in Biology and Medicine rounds off the list with two publications. This distribution highlights the significant role of multidisciplinary and technology-focused journals and proceedings in advancing PL and AI technology, with Swiss publishers particularly standing out in their contribution.

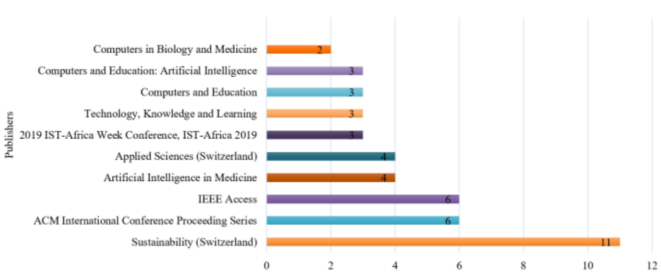

Fig. 8. Top 10 publishers by number of publications (two and above).

V. Discussion

As outlined in the earlier sections, the selected articles were intended to answer the three research questions guiding the SLR's findings. The percentages of articles concerning each research question are RQ1 (39%), RQ2 (42%), and RQ3 (19%), as shown in Table IX.

TABLE IX. Total Number of Articles Answering each Research Question

Research Question	Total	%
RQ1: Do the articles discuss the use of AI techniques in PL, and what components of PL are involved?	27	39
RQ2: Are the techniques clearly defined? And can they be replicated at pre-university level computer science courses?	29	42
RQ3: Do the articles discuss gaps and points of interest attracting future research?	13	19

A. Research Question 1 (RQ1)

RQ1 is stated as: “Do the articles discuss the use of AI techniques in PL, and what components of PL are involved?”

To answer this question, the Appendix presents all the articles in this review, the techniques, and elements of PL involved in the framework, model, or proposed approach. Fig. 9 is a graphical representation of the AI techniques and related technologies used in developing PL frameworks and models captured in the publications selected for this study.

The ten most frequent techniques were considered, in which machine learning tends to be the highest, followed by deep learning. Although other technologies (OT) are seen to be at the peak of the curve, it is a collection of various technologies, including big data, smart technology, digital, and mobile technology, as used in the context of the selected articles, which we deemed are not solely AI techniques, but contains elements of AI and its approach.

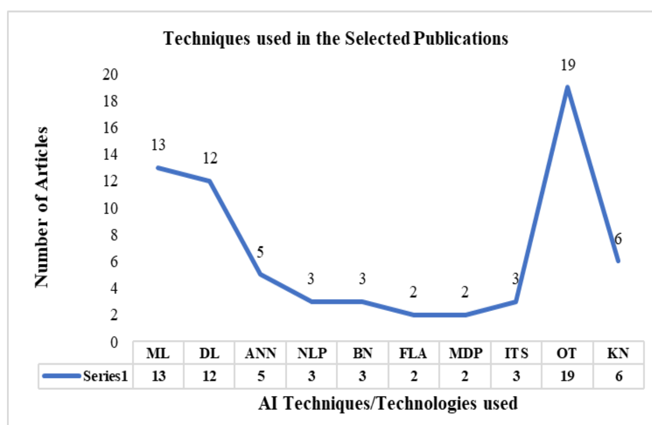

Fig. 9. AI techniques and other related technologies for building PL models and frameworks.

Key: ML (Machine Learning), DL (Deep Learning), ANN (Analytical Neural Network), NLP (Natural Language Processing), BN (Bayesian Network), FLA (Fuzzy Logic/Agent), MDP (Markov Decision Process), ITS (Intelligent Tutoring System), OT (Other Technologies), and KN (Knowledge Representation).

Although technology serves as the primary element in enabling and enhancing PL, there is a lack of consensus regarding the essential components of a dynamic PL approach. Furthermore, technology enables customization of learning experiences, but still no consensus on the essential elements required to create a distinct and effective learning experience tailored to individual learners [46].

Fig. 10 shows the PL components and their frequencies. The existing study [56] presented an additional ten attributes and components of PL as noted under the figure.

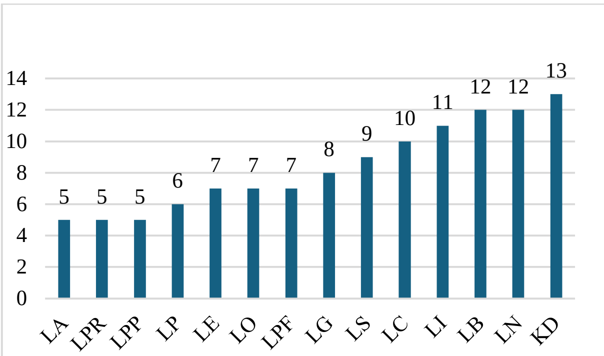

Fig. 10. Frequencies of PL components extracted from the selected studies.

Note: LPP (Learning Pace/Pacing), LP (Learning Path), LB (Learner/Learning Behavior), LS (Learning Style), LC (Learning Content), LPF (Learner Profile), LI (Learning Interest), LPR (Learning/Learners Preference), LN (Learners Need), LG (Learning/Learners Goal), LE (Learner/Learning Experience), KD (Knowledge Delivery), LO (Learning Outcome), LA (Learners/Learning Attitude).

Culture, emotional or mental state, socialization, motivation, learning preferences, prior knowledge, educational background, learning and cognitive style, navigation, and learning goals. Table X presents a brief description of fourteen of the components alongside reference articles for each. These components adapt dynamically based on the needs and preferences of the target user, educational level, and other considerations. They can be selected at random to suit the issues and purpose of development (framework, model, or approach for a particular educational level). The terms and names vary from one author to the other (since research on AIED is still new and dynamic). Knowledge delivery had the highest frequency, then learners' behavior, and needs towards learning, learners' interest, until LA, LPR, and LPP, which had the lowest frequencies, see Fig. 10.

Table X and Fig. 10 indicate that nearly all reviewed publications highlight a specific component related to personalized learning. The study concludes that knowledge delivery, learner behavior, and learner needs are the most emphasized aspects, whereas learning pace, attitude, path, and preferences receive less attention. This suggests that prioritizing the former may inadvertently diminish the significance of the latter.

B. Research Question 2 (RQ2)

RQ2 is stated as "Are the techniques clearly defined? Can they be replicated in pre-university level Computer Science courses?" The answer is "yes". Some of the articles clearly defined the techniques and justified them in the context of why such techniques were used in their work and specifically mentioned the level of study considered. However, some works have stated it as general, without targeting any educational level. Although in Fig. 6, K-12 level (primary, secondary, or pre-university), possesses the largest sector of the three, not all articles centered around AI techniques for PL, as they also consider other technologies.

Furthermore, the studies only point to the need for research on the K-12 educational level as a gap left unfilled; most of the publications are more about the feasibility of AI at that level, considering their peculiarities. Some of the works include the BPRMF model based on deep learning, neural networks, and data mining, proposed by Peng [93] to be applied to the problem of recommendation for the Civics and Political Science course, while another work proposes a system by hybridizing Visual/Aural/Read, Write/Kinesthetic (VARK) presentation or gamification and exercises difficulty scaffolding through skipping or hiding, or reattempting using Deep Q-Network Reinforcement Learning (DQN-RL) [81]. Another study proposed a novel approach for evaluating the co-learning performance of human intelligence (HI) and machine intelligence (MI) using a Knowledge Graph-based genetic fuzzy agent technique and a genetic algorithm [60].

Maddalora [77] introduced a PL model that recommends the Shortest Learning Sequence (SLS) to remediate students with learning difficulties, using Item Response Theory (IRT). On the other hand, a study provides an in-depth analysis of English course recommendation techniques through a combination of the bee colony algorithm and neural network algorithm, a deep learning model combined with collaborative filtering, to recommend suitable courses for users [88]. Other studies have used deep learning [62], [93], [43], [42], [72], neural networks [65], [105], [88], intelligent tutoring systems [46], [44], [92], natural language processing [53], [92], [87], knowledge representation [43], [89], [91], [66], and other techniques that are captured in Fig. 9.

TABLE X. DESCRIPTION OF FACTORS USED IN THE SELECTED STUDIES

Comp.	Description	Related Works
LPP	The speed at which a learner progresses through the materials is based on their capabilities and understanding.	[73][46][101] [108] [41]
LP	A strategically designed sequence of courses or modules aimed at guiding learners through a specific subject or program, ensuring a structured and progressive learning experience.	[44][73][46][65] [64] [47]
LB	Actions and responses demonstrated by a learner in a learning environment aim to cultivate positive and productive engagement.	[91][61][44][67] [65][42][86][85] [50][92] [47][81]
LS	An individual's preferred approach to acquiring and processing information is often categorized as visual, auditory, or kinesthetic.	[52][95][102][105][66][81][48] [56][47]

Comp.	Description	Related Works
LC	The material or resources that are used for educational purposes, including text, multimedia, and interactive elements.	[78][75][87][84][27][68][70][79][49][81]
LPF	Learner's characteristics, preferences, strengths, and weaknesses serve as a foundation for personalizing instruction.	[95][70][61][94][46] [64][56]
LI	Specific topics or subjects that capture a learner's curiosity and engagement influence PL experiences.	[97][43][76][46][90][45][58][85][50][47] [48]
LPR	Individual choices and inclinations of a learner in terms of instructional methods, content formats, and assessment styles.	[44][41][93][50][56]
LN	The individual needs and requirements of a learner, focusing on bridging gaps in understanding and skill development.	[43][95][79][46][90][41][103][67][86][50][47][107]
LG	The desired outcomes or achievements that a learner aims to attain through the learning process.	[61][9][44][46][41] [96][85][56]
LE	The overall encounter a learner has during the educational journey encompasses interactions, challenges, and outcomes.	[78][84][43][27][95] [70][83]
KD	The strategies and tools employed to deliver information and enhance learning experiences, according to individual preferences.	[78][87][52][27][70][83][61][9][76][49][94][54][55]
LO	It refers to quantifiable outcomes and accomplishments that reflect a learner's proficiency in specific knowledge or skills.	[78][87][52][84][68] [95][70]
LA	Addresses learners' mindset, approach, and attitude toward the learning process, which significantly impact engagement and success.	[95][61][44][46][86]

Note: Comp stands for components (see also the note below Fig. 10)

C. Research Question 3 (RQ3)

Addressing RQ3, which is “Do the articles discuss gaps and points of interest attracting future research?”, the answer is “yes”. The selected publications identified existing research gaps, highlighted their contributions, and proposed future directions for further studies, as outlined in the abstract, conclusion, and future research sections. Table XI summarizes ten publications, detailing their contributions and recommended areas for future research.

Additionally, other studies have presented varied perspectives on the methods and requirements for personalizing education at the K-12 level. An existing study suggests gamification of learning content to drive better outcomes [81], while another study suggests further research to examine the implementation and impact of PL strategies in different areas and educational levels, as they only focused on higher learning in Saudi Arabia [41].

Xia and Cheng [70] highlighted four issues: lack of holistic learning data, lack of an acceptable learning profile, equipping educational robots is a big challenge, and there is no function for choosing proper strategies. In addition, some studies have suggested the need to explore key technologies, such as big data, data mining, and recommendation algorithms, for supporting PL [67], and the need for researchers to explore the learning outcomes of PL models based on specific practices and strategies [78].

VI. Conclusion and Future Direction

PL involves tailoring teaching approaches at both macro and micro levels to align with the unique needs of individual learners and is a focal point in global educational policy initiatives. Despite its widespread adoption, the methods of personalization vary, accommodating diverse priorities and influencing transformations at both individual and societal scales. The underlying philosophy emphasizes placing the learner at the core of the education system. However, upon closer examination, it becomes apparent that while these policies aim to diminish educational disparities, they occasionally contribute inadvertently to their exacerbation. This calls for a deeper understanding of what PL entails, its components, factors, target level (learners’ level and need), policies, mission, vision, and goals of a particular country in terms of education, economy, and industrialization.

This study focused on the PL elements (components, factors, and technologies) involved in building frameworks and models at various educational levels. This study also presents the most frequent techniques and components used in 69 studies. It is evident that most studies concentrate on higher learning and proposals for different approaches to PL, regardless of educational policies, goals, and targets of stakeholders, but on mere assumptions. There is a lack of research that considers industrial demand, marketability of courses, tolerance in competitiveness, and employment chances upon one decision in choosing what to study or what to personalize. Personalization enhances one's technical skills, and hence, high chances of employability and adaptability, promoting learning autonomy and readiness for the workforce. Overall, PL promotes greater academic gain by narrowing learners' tasks to a specific target and promoting expertise. The scope of the study used mainly the Scopus database and other supporting primary research in the area to avoid voluminous and duplicate information from other sources, since Scopus has larger coverage. It can then be one of the limitations of this study as other databases may contain additional information regarding the area, and other researchers can explore further.

Advancements in AI are scaring nontechnical minds about job displacement, as many employees forecast that machines built on AI technology may render many people jobless. In contrast, AI has been proven to promote economic growth, boost productivity, enhance skills, and create new jobs. Today, information and communication technology and ICT-related industries have the highest prospects in Computer Science-related fields and subfields, especially those specializing in AI, Software Engineering, web development, and data analytics. Unfortunately, from the 69 selected studies, almost none focused on Computer Science and related fields for preparing students at the pre-university level to study Computer Science when they enter the tertiary level.

Our future work will focus on designing a framework for PL at the pre-university level, to prepare students for various fields of Computer Science that the world needs today. The framework will prioritize and expose students to various opportunities and industrial needs, awaiting those who have studied Computer Science and have catalyzed solving issues using computer-based technologies.

TABLE XI. TEN SELECTED STUDIES: PROBLEM, CONTRIBUTION, TECHNIQUE, AND PROSPECT

Ref.	Identified problem	Paper Contribution	Applied Technique	Potential gap and prospects
[9]	The absence of psychological ownership of learning content among students and teachers.	Perception and assessment framework for the I-Learn portal.	Non-AI (Educational Technologies and Conjecture Mapping)	The necessity of creating tools for assessing and validating psychological ownership.
[43]	Standardized teaching approaches and ineffective skill development strategies in colleges and universities.	Proposed a personalized learning model utilizing IoT and deep learning algorithms.	AI-IoT integration with clustering algorithms, hierarchical clustering, collaborative filtering, and AI-based recommendations	The need for a flexible database for recommendations and content adjustments, enabling the integration of diverse materials.
[55]	The absence of study ownership and the impact of PL implementation in universities.	Proposed a framework on students' study ownership and learning outcomes.	Knowledge management through thematic analysis.	A necessity for research on the impact of personalization within authentic educational environments.
[57]	The ineffectiveness of traditional systems in tracking student needs during emergency remote education.	Proposed a framework for tertiary learning during and beyond the pandemic era.	Computer Technology	The necessity for research to validate the framework through longitudinal studies, utilizing technology for PL across all disciplines.
[62]	The absence of collaborative learning and limited facilitator-learner engagement in addressing students' needs.	Proposed a model centered on learner foundations, resources, community involvement, and diverse learning approaches.	Deep learning algorithms and learning analytics.	Future research should employ an alternative classifier to assess and validate the proposed approaches.
[73]	The absence of customized experiences that enhance students' learning journeys.	The research proposes a Personalized model to standardize entry-level requirements for health schools, emphasizing.	Knowledge Management.	Future research should incorporate evaluation and assessment components into the model and explore design enhancements to improve learning
[80]	Traditional one-size-fits-all systems are characterized by inefficient scheduling methods and a lack of individualized learning approaches.	An adaptive large neighborhood metaheuristic search integrated with an integer linear programming model.	Integer linear programming approach and Metaheuristic approach	Future research should explore modifications in school structure and staffing, along with extensions to accommodate longer timeframes.
[88]	Current research is insufficient for practical implementation, lacking sensitivity and collaborative strategies.	The research article introduces a novel recommendation technique that integrates bee colony optimization with neural network algorithms.	Bee colony, deep learning algorithm, and neural network techniques.	Future research should investigate user behavior analysis components, content evaluation mechanisms, and the integration of NLP for semantic analysis.
[106]	Lack of preparedness and absence of effective strategies for technology-enhanced learning.	A framework for Digital Learning Implementation.	Delphi Method	Future researchers should explore the practical applications of the proposed framework while prioritizing learners' needs.
[109]	Highlights the lack of learner data tracking, the dynamic nature of learners, and the insufficient development of computational thinking skills in existing studies.	A model that is supported by human-computer cooperation.	Big data technology and Machine Intelligence.	Future studies should expand on the proposed work to address the diverse learning needs of students in rural areas, both during pandemics and in post-pandemic settings.

ACKNOWLEDGMENT

This study is partly supported by the Centre for Advancement in Rural Education Information (iCARE) UTM-KEJORA Cost Centre No. 4B905 and its matching grant from UTM, Cost Centre No. 05M01.

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APPENDIX: SELECTED PUBLICATIONS BASED ON SEARCH STRINGS

Research Paper	Search Strings	Approach/ Strategy for PL	Framework	Model	Component, Attribute, and other Consideration for Effective Implementations of PL Framework, Model, Approach, and System	Technique/Technology Applied	Learning Level		
							HL	K-12	GL
[41]	SS1	✓			Flexible pacing, adaptive assessment, learner agency, feedback, and student-centered learning.	Knowledge-based	✓		
[42]	SS1	✓	✓	✓	Data privacy, distribution, behavior, time, and location.	Deep Learning, Blockchain, IoT	✓		
[43]	SS1	✓		✓	Previous knowledge, Learning: interest, effectiveness, data, content, and satisfaction	Deep learning, IoT	✓		
[44]	SS1	✓			Feedback, autonomy, learning: path, pace, behavior, suggestions, and goal.	Machine Learning-Self regulated approach		✓	
[45]	SS1	✓		✓	Learning interest, previous knowledge, skills, and pedagogy.	Knowledge Management	✓		
[46]	SS1	✓		✓	Learners: profile, interest, goal, experience, knowledge and belief, attitude, and paths/pace.	Intelligent Tutoring System, Learning Analytics, Machine Learning, Data mining			✓
[47]	SS1	✓		✓	Students: interest, domain, skills, behavior, Learning: style, outcome, satisfaction, recommendation.	Analytical Neural Network, Fuzzy Logic			✓
[48]	SS1	✓			Learning: style, approach, interest, preferences. Profile, content, recommendation, pedagogy.	Data-driven (Bayesian Network)			✓
[49]	SS1	✓			Learner's needs, motivation, feedback, paths, data content, and tracking.	Machine Learning, Data Analytics	✓		
[50]	SS1	✓			Learning: speed, preference, needs, interest, experience, choices, behavior, skills.	Markov Decision Process, Data Mining			✓
[51]	SS2			✓	Encoding alignment, variational approximation algorithm, Meta-learning.	Deep generative model, ML algorithm			✓
[52]	SS2		✓		Learning content, technology, skills, methods, and outcomes.	Machine learning, learning analytics	✓		
[53]	SS2		✓		Learning skills, habits, and awareness.	Natural language processing, Deep Learning	✓		
[54]	SS2	✓	✓		Learning approach, task, and tools.	Theory of cognitive fit, Deep learning	✓		
[55]	SS2		✓		Flexible content, learning environment, and support.	Thematic Analysis, Data-driven Decision making	✓		
[56]	SS2		✓		Learner profile, style, behavior, pedagogy, and previous knowledge.	Intelligent Tutoring System	✓		
[57]	SS2		✓		Learning capability, competency level, skills, and passion.	Intelligent tutoring system, Technology-supported system.	✓		
[58]	SS2		✓		Individual data, level, uniqueness, sharing and feedback.	Machine learning	✓		
[59]	SS3		✓		Learning outcomes, contents, and students' growth.	Neural Network, Machine learning	✓		
[60]	SS3	✓		✓	Learner profile, knowledge domain, content, and outcome.	Genetic Algorithm, Fuzzy Agent	✓		
[61]	SS3	✓	✓	✓	Learning progress, profile, attitudes, skills, and target goals.	Exp3 algorithm, Q-Matrix approach			✓
[62]	SS3		✓	✓	Learner foundation, facilities, community engagement, learning approach.	Deep learning algorithm		✓	
[63]	SS3	✓	✓	✓	Personality, Knowledge, Behavior, interest, preferences.	Datamining, Bayesian Network			✓
[64]	SS3			✓	Learning: strength, support, path, flexibility, measurement, achievement.	Strength-Based learning		✓	
[65]	SS3			✓	Attention mechanism, learning paths, learning: awareness, supervision, cognition, behavior, and outcome.	Bigdata Technology, Recurrent Neural Network	✓	✓	
[66]	SS3			✓	Learning methods, style, ability, stages, prediction, and achievements.	Knowledge Visualization	✓		
[67]	SS3			✓	Learner information, behavior, learning resources, and matching degree	Support Vector Machine, Collaborative Filtering			✓
[68]	SS3			✓	Learning speed, performance, and pedagogical strategies	Formative Assessment	✓		

Research Paper	Search Strings	Approach/ Strategy for PL	Framework	Model	Component, Attribute, and other Consideration for Effective Implementations of PL Framework, Model, Approach, and System	Technique/Technology Applied	Learning Level		
							HL	K-12	GL
[69]	SS3			✓	Learners' participation, technology reliability, learners' autonomy, feedback and assessment, experience, methods, and beliefs.	Bigdata, AI Technology	✓		
[70]	SS3	✓		✓	Learning strategies, learners' profile, pedagogy, and Mistake diagnosis.	Bigdata, Datamining			✓
[71]	SS4			✓	Learning dynamics, teaching ideas, evaluation, and learner support.	Big Data, Machine Learning		✓	
[72]	SS4		✓		Learning process and relevant knowledge.	Deep learning, content filtering	✓		
[73]	SS4			✓	Mastery level, knowledge level, requirement, performance, learning flexibility, and student autonomy	Knowledge leveling	✓		
[74]	SS4			✓	Competency and pedagogical experience.	AXMA Story Maker, Interactive Novels		✓	
[75]	SS4			✓	Test learning effectiveness, economic requirements in mathematics.	Digital Technologies AXMA Story Maker		✓	
[76]	SS4			✓	Learning evaluation, curriculum, resources, cooperative, and independent.	Datamining, Deep Mining		✓	
[77]	SS4			✓	Lerner's ability, learning process, and diversity.	Item Response Theory	✓		
[78]	SS4		✓	✓	Learner Profile, Mastery level, learning path, and flexible environment.	Technology enabled		✓	
[79]	SS4			✓	Assessment, academic achievement, efficacy, and student wellbeing.	Technology enabled		✓	
[80]	SS5	✓			Course module, course planning, feasible instruction, and self-regulation.	Integer linear programming, Metaheuristic Algorithm		✓	
[81]	SS5	✓			Cognitive level, learning style, reinforcement, and gamification.	Deep Q-Network Reinforcement Learning		✓	
[82]	SS5	✓			Learning style and learner profile	Generative AI (Chat GPT)		✓	
[83]	SS5			✓	User behavior, interest, teaching strategy, notification, recommender component, and learning process tracking.	Intelligent Technology, Recommendation Algorithm			✓
[84]	SS5			✓	Oral English evaluation, tracking, recording, and evaluation	Data Mining, Machine Learning		✓	
[85]	SS5		✓		Feedback, progress, learning goals, and emotional state.	AI-Machine learning			✓
[86]	SS5			✓	Learner profile, characteristics, needs, and attitude.	Data mining			✓
[87]	SS5		✓		Learner's attitude, curriculum design, and feedback.	Machine learning, NLP		✓	
[88]	SS5			✓	Learning resources, data, and recommendations, learner characteristics.	Deep learning algorithm, Bee colony, Neural Network		✓	
[89]	SS5	✓			Learning content, curriculum, and learners' characteristics.	AI-Knowledge management			✓
[90]	SS5		✓		Learning flexibility, assessment, style, and learners' needs.	M-Learning Technology			✓
[91]	SS5			✓	Cognitive level, collaboration, and path recommendation	Bigdata Technology	✓		
[92]	SS5			✓	Learner recognition and exercise generation, learner behavior.	Natural Language Processing		✓	
[93]	SS5			✓	Interpretability of recommendation results and learning preferences.	Deep learning		✓	
[94]	SS6				Cognitive perception, personality, and student profile.	AI Systems, Bayesian Knowledge Tracing		✓	✓
[95]	SS6			✓	Learning style, needs, and attitude.	Technology Driven		✓	
[96]	SS6	✓			Planning, learning, record keeping, and assessment.	Technology Driven		✓	
[97]	SS6	✓			Prior Knowledge, motivation, and achievement.	Smart Technology		✓	

Research Paper	Search Strings	Approach/ Strategy for PL	Framework	Model	Component, Attribute, and other Consideration for Effective Implementations of PL Framework, Model, Approach, and System	Technique/Technology Applied	Learning Level		
							HL	K-12	GL
[98]	SS7	✓			Motivation, interest profile, and level.	Technology Driven			✓
[99]	SS7	✓			Interest, self-regulation, and learning speed.	Markov Decision Process		✓	
[100]	SS7		✓		Skill, flexibility, interface, choice, and feedback.	Delphi Technique			✓
[101]	SS7	✓	✓		Learning pace, goal, method, and flexibility.	Hyper-heuristic		✓	
[102]	SS7	✓	✓		Learning style, content, and behavior.	Mobile Technology		✓	
[9]	SS7	✓			Learner motivation and ownership.	Technology Driven		✓	
[103]	SS7		✓		Course plan, selection, assessment, ability, and achievement.	Information Technology	✓		
[104]	SS7		✓		Learning content, goals, a flexible environment, and a learner profile.	Datamining		✓	
[105]	SS7		✓		Text summarizer, gamification, video lessons, learner profile, learning path, style, and experience.	Machine learning (Deep Neural Network)		✓	
[106]	SS7		✓		Evaluation and assessment, school capacity, and digital learning.	Delphi Method		✓	
[107]	SS7		✓		Learners' needs, interests, behavior, and learning evaluation.	Hour of Code		✓	
[108]	SS7		✓		Learning ability, profile, level, and pace.	Technology enriched		✓	

Note: HL is Higher Learning, K-12 is Kindergarten 12 (Primary to Secondary School/Pre-university Level), SS (Search Strings 1 to 7)