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A SYSTEMATIC REVIEW: EMPLOYING AI IN ADAPTIVE LEARNING RECOMMENDATION SYSTEM FOR VOCATIONAL EDUCATION

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ABSTRACT

The integration of AI in vocational education, especially in adaptive learning, highlights the importance of automatically detecting individual learning styles. Traditional methods such as questionnaires, though reliable, face limitations like student reluctance and lack of self-awareness. This reveals a research gap in learning style detection, particularly in AI-based adaptive systems, requiring further exploration of effective computational techniques in real-world educational contexts. These challenges are especially relevant to the development of adaptive learning-based recommendation systems for career selection. Accurate learning style detection is essential not only for personalized learning but also for aligning educational content with potential career paths, thereby enhancing both academic and career outcomes according to talent, interests, and major. To address these gaps, this study presents a systematic review of 40 selected articles published between 2014 and 2025. The review examines techniques, approaches, and computational strategies used in automatic learning style detection and their implementation in various vocational educational settings. Findings show that AI, particularly data-driven approaches, significantly supports learning adaptation. The Felder–Silverman model and classification techniques like K-Means and Naive Bayesian are commonly applied due to their adaptability across contexts. Moodle also emerges as a frequently used platform for data collection and experimentation. These insights are fundamental for designing intelligent recommendation systems that adapt to student's learning styles and support personalized career guidance. Integrating such systems can enhance educational relevance, improve learning outcomes, and foster long-term career readiness.

Keywords: *Artificial Intelligence, Career Recommendation, Vocational Education, Adaptive Learning***.**

1. INTRODUCTION

The advent of novel technologies has unlocked new learning opportunities creating a paradigm shift in the education sector [1]. With the progress of technology, the way of education is constantly evolving. Adaptive learning, as a part of educational technology, provides the possibility for personalized teaching and makes learning more efficient and targeted [2]. The expression "adaptive e learning educational system" adjusts the learning knowledge for each student. Each individual has his own characteristics. They show different actions to form convinced set features that led to good grouping [3]. Adaptive education systems aim to enhance learning efficiency and performance and reduce cognitive overload issues by providing an optimal learning path and individualised content based on the knowledge, behaviour and profile of each learner [3], [[4], [5].

With the integration of Artificial Intelligence (AI), adaptive learning has evolved into a data-driven, intelligent framework capable of analyzing vast amounts of learner data to generate personalized recommendations and optimize learning trajectories

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[6]. Notably, AI techniques such as clustering algorithms (e.g., K-Means) and classification models (e.g., Naive Bayes) have been employed to group learners into meaningful profiles and predict suitable career paths in vocational education contexts [7].

According to this research [8], adaptability in education is becoming more and more important in order to boost the effectiveness and efficiency of the teaching and learning process. In 2010, [9] noted that adaptive learning has developed into a trend in modern distant education as well as a significant topic of research. According to the research conducted by [10], adaptive learning integration is growing due to smart devices and smart technologies, which is a trend. Recently, as shown by the study of [11], one of the trends in educational scientific research has been AI-based adaptive learning.

Despite the growing body of research on adaptive learning systems, there remains a significant gap in the application of AI-based adaptive systems specifically within vocational education. Figure 1 illustrates the lack of an adaptive learning recommendation system for career guidance in vocational education, highlighting a critical gap in the dominant logic of adaptive system design framework. The illustration reveals a critical void in current educational technologies: the absence of a comprehensive mechanism that employs artificial intelligence (AI) to bridge adaptive learning and career recommendation in vocational education. While learner data such as academic performance, learning style, and personal interests are often collected, they are rarely harnessed in a unified, intelligent system. As a result, vocational learners are frequently offered static or generic career suggestions that overlook their unique learning trajectories. This gap underscores the urgent need for an AI-driven adaptive recommendation framework that not only responds to how learners engage with content but also anticipates the most fitting career pathways based on their individualized learning profiles.

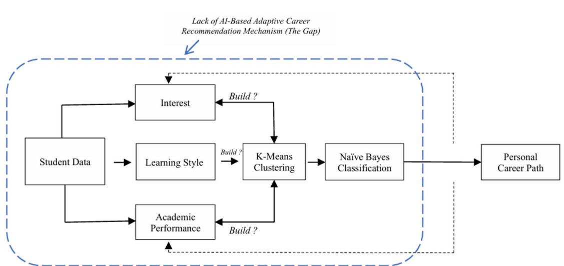

Figure 1. the lack of AI-based adaptive career recommendation mechanisms

Vocational education, which focuses on equipping learners with practical skills for specific trades and careers, presents unique challenges due to its diverse learner demographics, varying skill proficiencies, and industry-specific requirements [12] [13].

While intelligent tutoring systems and adaptive hypermedia have been explored since the 1980s–1990s [14] [15], it was not until the 2000s that AI-based adaptive learning began gaining momentum, driven by advancements in machine learning and data analytics [16]. Today, AI enables the creation of highly personalized learning environments by analyzing real-time learner data and generating tailored content and feedback [17] [18].

Recommender systems—originally developed to combat information overload in commercial domains—have also found relevance in education by filtering and suggesting relevant learning objects (LOs) based on user profiles [19]. However, most existing research focuses on general education or higher education settings, with limited exploration of their applicability in vocational training and career path recommendation.

Moreover, while numerous datasets, methods, and frameworks for adaptive learning systems have been proposed, they often remain fragmented and lack a unified approach, especially when applied to vocational contexts [20] [21]. There is a need for a comprehensive analysis of current trends and methodologies in AI-based adaptive learning systems for vocational education.

This study aims to identify publications in the field of vocational education, particularly those related to the development of adaptive learning recommendation systems based on artificial intelligence (AI), through a literature review. Learning style detection in career recommendation systems—such as mapping students' learning styles and career interests—plays a crucial role in supporting the implementation of personalized learning strategies. Therefore, this study seeks to examine previous research on recommendation system models in the context of AI-driven vocational education. Furthermore, mapping the literature on adaptive recommendation systems based on individual learning characteristics is essential for developing a career recommendation process model that integrates big data analytics, enabling educational institutions to determine the most appropriate learning approaches tailored to each student's needs.

This review uncovers various references to career recommendation systems in vocational education by exploring the current state of adaptive recommendation system development in AI literature, data-driven recommendation models, the application of adaptive system design in learning systems, the use of big data analytics in educational decision support systems, and research areas related to career and learning development in vocational contexts.

The review highlights the novelty of adaptive recommendation system development in vocational education, based on adaptive system design, which has not been previously reviewed. Although several literature reviews have examined AI-based recommendation systems, the mechanism of adaptive career recommendation in vocational education constitutes a primary concern. This mechanism serves as a bridge between learning style information, career potential, and the strategic design of adaptive learning systems. The expected outcome of this review is the identification of various AI-based decision-making mechanisms involved in the development of adaptive recommendation systems to support personalized learning and more accurate, relevant, and contextual career selection.

2. FRAME OF REFERENCE

2.1 Adaptive learning definitions

According to the interpretation "Learning is the relatively permanent change in a person's knowledge or behavior due to experience" [22]. As mentioned in the introduction, "Adaptivity" is one of human beings' intrinsic skills, allowing them to study the intricacies of each circumstance in order to act appropriately [23]. When we combine these two terms, we get adaptive learning, which can be defined based on the previous two definitions as improving a person's knowledge while studying their complexities in order to provide the best possible experience. In [24] adaptive learning is a method of automatically distributing online learning material based on the learner's engagement with previous content. Adaptive learning, according to the US Department of Education's Office of Instructional Technology [25], is more than simply a method; it is educational technology in three different forms: The first is individualization, in which all students have the same learning objectives but can progress through the content at various rates. The second form is differentiation, in which all students' learning objectives are the same, but the teaching style or approach differs based on each student's preferences or what research has discovered works best for students like them. Personalization is the third form, in which the learning objectives and content, as well as the technique and pace, may all be customized. On the other hand, researchers see adaptive learning as an educational approach, which uses several technologies to create a personalized learning experience for students depending on their behavior, interaction, aptitude, learning styles and performance [26] by implementing the "one-size fits all" method [27].

Based on this review, the notion of adaptive learning can be defined as a technology-based approach represented by educational systems and platforms that try to tailor pedagogical content, presentation styles, or learning paths to individual profiles, such as cognitive state, affective status, and knowledge level. We should also mention that, as shown in figure 2.

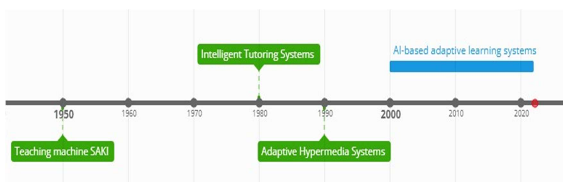

Figure 2 : The timeline of adaptive learning development

The systems or environments designed to implement this approach have undergone a series of developments, innovations, and improvements [28] linked to technological evolution, either in their forms or in their objectives and adaptive capacities provided [29], making a standardized definition difficult to adopt. To begin, there are intelligent tutoring systems (ITSs), which are a specific type of adaptive system that have been developed over the last four decades by researchers from education, psychology, and artificial intelligence (AI). These systems are designed to stimulate the teacher's role in teaching and are based on four models: the Expert Model, the Pedagogic Model, the Learner Model, and the Communication Model [30], [31] [15]. Second, Adaptive Hypermedias (AHs) which refers to the relationships between the elements of any type of media and offers in particular an adaptability of navigation and presentation [15]. Third, the use of web-based technologies in conjunction with the capabilities of AHs and ITS to offer the right content at the right time, to determine current levels of understanding, and to track real-time interactions with the system for students who are physically separated from their teachers [32]. Fourth, there are AI-based adaptive learning systems, which are the focus of our study and are based on machine learning approach. These systems will be described in detail in the following sections [15].

2.2 AI- Career recommendation for vocational

Artificial intelligence (AI) is a branch of computer science that aims to integrate intelligent behavior of humans or animals into computer systems in order to handle complicated problems with little or no human intervention [33], [34]. Over the past three decades, artificial intelligence has established its position in the field of education through its contribution to the development of tools to support and understand the teaching-learning process [35], [36]. The continuous improvement of these AI-based tools has allowed for the development of more efficient learning systems and platforms, providing learners with high quality and specific educational content, adapted to their individual needs and preferences [37] .

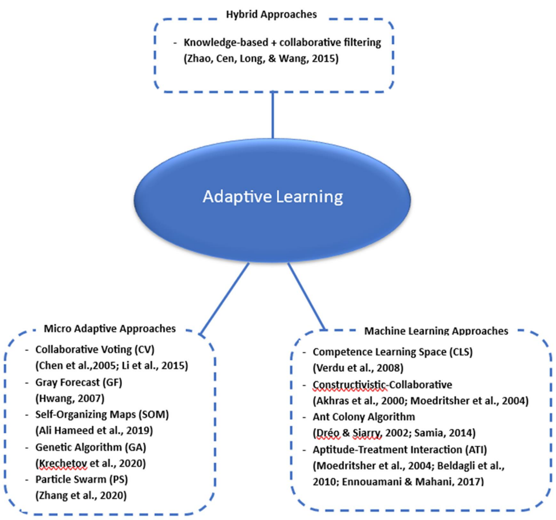

Figure 3: Adaptive Learning Career Recommendation Approaches

As shown in figure 3, there are several adaptive learning approaches, although these AI-based learning systems are built in most cases on one of these approaches supplemented by the machine learning approach, which is a subset of artificial intelligence [38] that attempts to solve data problems in a variety of disciplines using a range of algorithms [39]. Machine learning is at the heart of many adaptive learning systems, which provide better support to the learner, suggest potentially useful material, adapt the instructions to the learner's learning strategies, preferences, and difficulty, generate unique learning paths and provide live feedback [40], [41], [42]. In other words, intelligent tutoring systems, adaptive learning systems, and recommender systems are all included in AI-based learning environments [43]. However, as mentioned in [43] AI, learning analytics and educational data mining are examples of techniques that have accelerated the development of these systems to provide an enhanced learning experience, time flexibility, timely feedback, flexibility in managing student learning experiences and faster student progression [42], [44], [45].

AI-based adaptive learning is not usually a whole system or environment; it may also be a module integrated into a Learning management system (LMS) to improve its functionality by allowing learners to navigate and sequence content more easily to meet their needs. These modules also provide the option of correcting answers with justifications to help students understand how and why things work, as well as taking advantage of the vast number of knowledge resources available online to further their understanding of the subject and using multilingual learning services to present them in the student's preferred language [46], [47]. Some of the most commonly used AI techniques, as identified by [43] include Bayesian networks, neural networks, decision trees, genetic algorithms, K-nearest neighbour, Support vector machines (SVMs) and Bayesian knowledge tracing (BKT). At the end of this part, we note that in recent year AI has played a key role in solving learning and teaching difficulties such as increasing students' learning experiences and outcomes, developing more personalized pedagogical frameworks, and addressing poor motivation and engagement [43]. However, few actual applications have been uncovered, indicating that most AI-based adaptive learning systems have been discussed in the literature but not implemented in real-world situations [48].

2.3 Related work

Identifying the evolution of AI-based recommendation systems in educational contexts over the past decade reveals a significant shift toward more adaptive, context-aware, and ethically grounded frameworks. According to [49], the integration of deep learning and hybrid algorithms—such as Naive Bayes combined with K-Means clustering—has enhanced the precision of learner profiling and content delivery. These systems are increasingly capable of capturing real-time behavioral data, enabling dynamic personalization that aligns with individual learning trajectories. Furthermore, [50] emphasize the emergence of conversational recommender systems powered by generative models like GPT, which facilitate interactive, dialogue-based learning support. This evolution is not solely technical; [51] highlight the growing scholarly attention to ethical dimensions, including algorithmic transparency, fairness, and data privacy. Collectively, these developments underscore the need for a multidimensional evaluation framework that balances algorithmic performance with pedagogical relevance and ethical accountability—thereby reinforcing the urgency and relevance of this systematic literature review.

Moreover, [52] on learning management systems (LMS) with adaptive capabilities have continually been discoursed by scholars. Their work emphasized the importance of personalization and learner modeling in LMS, which has inspired subsequent research on adaptive learning environments and intelligent tutoring systems[53]. The insights and future research directions of [52] research serve as guidelines to underlie the emergence of ai-based recommendation systems, which is the focus of this literature review [54].

Table 1. The insights of AI-based Adaptive Learning Recommendation System evolution article and research agenda

Item Identification	Masciari et al. (2024)	Research Agenda
Objectives	To map the evolution, algorithmic trends, and ethical considerations of AI-based recommendation systems in education.	To explore hybrid algorithm effectiveness, ethical transparency, and learner-centered system design in educational recommendations.
Scope	AI-based Recommender Systems in Education	Adaptive Recommendation Systems using Hybrid AI
Methodology	Bibliometric and systematic literature review covering last three decades of AI recommendation research (1990s–2020s). Mixed-method synthesis.	Systematic Mapping Study with emphasis on algorithm evolution, ethical AI, and adaptive learning alignment.
Results	(1) Shift from basic rule-based to hybrid models (e.g., Naive Bayes + K-Means). (2) Emergence of conversational recommender systems using generative models (e.g., GPT). (3) Strong ethical concerns: transparency, fairness, data privacy. (4) Rise of personalization and learner modeling in recommender design.	1. Apply hybrid AI models in adaptive learning systems for better personalization. 2. Embed ethical considerations into system architecture (e.g., transparency). 3. Explore dialog-based recommendation (e.g., chatbot-GPT). 4. Expand dynamic learner profiling using real-time data.
Future Directions	Theory: Evolution from static to dynamic and dialog-based recommender systems. Context: Personalized education, vocational training, online learning environments. Characteristics: Algorithmic accuracy, ethical fairness, interactivity. Methodology: Hybrid AI integration, user-in-the-loop feedback, real-world deployment.	Design of explainable, transparent, and ethical recommender systems for education; Integration of generative AI for dynamic learner interaction.

Table 1 presents the topic formulation. The research agenda comprises five sections: objective, scope, methodology, results, and subsequent direction. The objective, scope, and methodology were developed based on this study's background, particularly the increasing relevance of ai-driven personalization in educational technologies[49]. Meanwhile, the results and further directions are utilized for formulating the research questions. This research agenda guides this systematic literature study to determine the criteria for the ai-based recommendation systems literature, including the use of hybrid models (e.g., naive bayes and k-means), ethical considerations, and the integration of contextual data to enhance recommendation accuracy[54].

3. RESEARCH METHODOLOGY

The research methodology of review adopts the procedure of the systematic literature review (SLR) introduced by [55] [56]. The three phases of the systematic literature review procedure are planning, conducting, and reporting. The phases are detailed in the eight steps of the review protocol, which follow the systematic literature review process by [57]. Figure 4 shows the methodology of the review, which was developed by combining the methods of [58], [57], and [59]. The planning phase involves formulating the research questions and develop ing the review protocol. In the conducting phase, review planning is executed by searching for literature, screening, quality assessment, data extraction, and data synthesis and analysis. The reporting phase involves documenting the review process, implementation, synthesis, and future research.

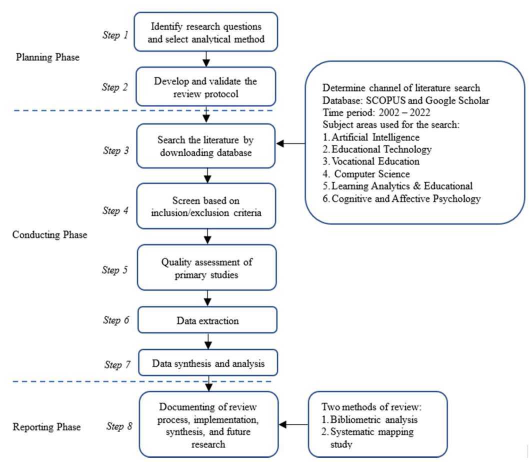

Figure 4. Methodology of review.

3.1 Research question

Formulating the appropriate research question can be aided by using a pre-mapping review to identify the subtopics of the research problem [57]. In the pre-mapping review, the researcher searched

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for the initial literature related to the research questions. After obtaining the literature, the researcher began to identify insights related to the research question. The pre- mapping review helps researchers obtain the most out of the topic, or they must be restricted to a particular research question. Table 2 shows the development of the research questions using insight mapping.

Table 2. Research Questions Developed By Insight Mapping

Research Questions	Insights Mapping	Motivation
RQ1:What are the primary research goals of AI adaptive learning studies?	Result in Subsection 4.3 : Derived from theoretical frameworks and general publication trends on AI in education, focusing on personalization, automation, and learner modeling.	To explore the underlying aims that shape the development and evolution of adaptive learning systems using AI.
RQ2: What ways has AI-based adaptive learning addressed research issues and concerns?	Result in Subsection 4.4 : Anchored in studies tackling challenges such as learner disengagement, low content relevancy, and lack of individualized instruction.	To investigate how current research resolves practical challenges in conventional adaptive systems.
RQ3: What design components are needed to build an AI-based adaptive learning recommendation system based on learning style personalization for vocational students?	Result in Subsection 4.5 : Informed by cognitive learning theory and system architecture frameworks tailored to diverse learner profiles.	To identify essential elements that support the development of a system aligning vocational learners' preferences with personalized guidance.
RQ4:What are the popular AI algorithms used to design interventions?	Result in Subsection 4.6 : Based on comparative reviews and systematized analyses of algorithms like Naive Bayes, K-Means, Decision Trees, and hybrid models.	To provide a basis for selecting effective algorithms grounded in prior implementations for educational interventions.
RQ5:How can a hybrid K-Means and Naive Bayes model improve the accuracy of career recommendations compared to single-model approaches	Result in Subsection 4.7 : Derived from hybrid modeling literature that demonstrates superior accuracy and reliability in classification and segmentation tasks.	To justify the proposed hybrid approach by showcasing its potential to outperform standalone models in career guidance systems.
RQ6:What impact will present research have on future AI-based adaptive learning practices?	Result in Subsection 4.8 and 4.9 : Grounded in discussions on scalability, transferability, and future research directions in adaptive AI frameworks.	To highlight the study's contribution in shaping more intelligent, learner-centered systems for vocational education.

3.2 Sampling inclusion-exclusion criteria

Sampling inclusion/exclusion criteria constitute the narrowing-down process to provide a repository corresponding to the research questions [58], [57]. The sampling limitation was carried out in two ways: screening and eligibility. The screening process was article selection based on review criteria. The review criteria consist of period, area, keywords, and language. Eligibility is assessing the full text of the literature based on a review of specific topics.

Table 3. Inclusion-exclusion criteria

Criteria for Inclusion	Criteria for Exclusion
- The study focuses on AI-based adaptive learning. - The study is conducted within educational settings. - The article is peer-reviewed and published in an academic journal. - The publication date is between 2014 and 2025. - The article provides relevant qualitative or quantitative data.	- The article is written in not English. - The document type is an opinion paper, presentation, report, or dissertation. - The article title does not contain the terms adaptive learning, personalized learning, or artificial intelligence. - The full text is not accessible or unavailable. - The study is a duplicate entry.

3.3 Search strategies and Data sources

The rapid proliferation of online scientific literature has made it increasingly difficult for scholars to conduct exhaustive and focused research, even when established criteria are applied.

To ensure methodological rigor, a structured search strategy was implemented following the identification of research objectives and questions.

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This process began with the selection of relevant keywords and the Boolean operators used to construct the search string.

The search focused on three core terms—"adaptive learning," "education," and "artificial intelligence"—along with several synonymous terms such as personalized learning, adaptive learning environment, adaptive learning system, and AI. These terms were logically combined using Boolean operators OR and AND to generate a comprehensive search query. Table 4 shows the keywords search string formulation.

The literature search was systematically conducted across five major academic databases—ScienceDirect, Scopus, ERIC, IEEE Xplore, and Mendeley—which were selected due to their relevance, inclusion of recent publications, and comprehensive coverage of journals at the intersection of AI and education (e.g., Neurocomputing, Computers & Education, Computers in Human Behavior, and the International Journal of Educational Technology in Higher Education). To broaden the scope of the review and capture additional relevant studies, Google Scholar was also utilized as a supplementary search engine.

Table 4: Keywords used in the search string

Search string
adaptive learning AND artificial intelligence
adaptive learning AND artificial intelligence AND Vocational Education
adaptive learning AND AI AND Vocational Education
(personalized learning OR adaptive learning) AND (environment OR system) AND (artificial intelligence OR AI)

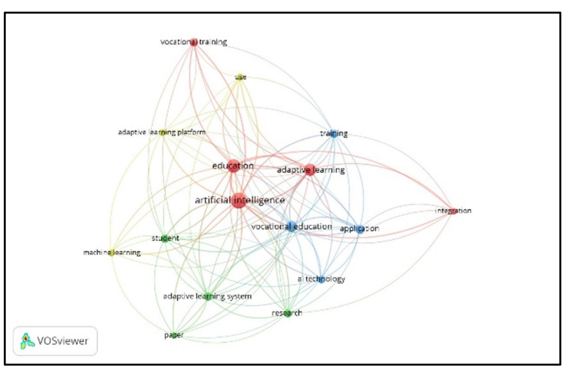

Figure 5. Visualization of co-occurrence and link strength of keywords

3.3.1. Planning phase

The planning phase consists of Steps 1 and 2, including formulating the research problem and developing and validating the review protocol (Xiao & Watson, 2019). Step 1, formulating the research question, was carried out by identifying the insights from previous studies on AI-based recommendation systems research. This research chose the study by [49] to obtain insights into the evolution, techniques, and ethical considerations of AI-based recommendation systems over the last three decades. The background of the chosen study was that it comprehensively presents the current position of AI-based recommendation system studies regarding research areas, algorithmic trends, application domains, influential authors, and future directions. Masciari et al.'s study guided educational technology scholars to select the area that should be investigated. Step 1 also develops a methodology of review that adopts the systematic literature review (SLR) by [57], which emphasizes transparency, replicability, and methodological rigor. Figure 4 describes the review methodology modified from Xiao and Watson's SLR, incorporating stages such as protocol development, inclusion/exclusion criteria, quality appraisal, and synthesis of findings.

Step 2, developing and validating the review protocol, should reflect all the components of the review the following: (a) research question; (b) search strategy; (c) review criteria of primary study selection; (d) assessment of methodological quality; (e) sketching data extraction strategy; and (f) data synthesis and analysis [56].

3.3.2. Conducting Phase

The conducting phase constitutes six steps following the two steps of the planning phase. The conducting phase comprises from Step 3 to 7 of the review methodology. Steps 3 and 4 of the conducting phase were separated into four major sections: automated search, screening, eligibility, and inclusion [56], [57]. In Step 3, the literature database was obtained by an automated search this study was carefully conducted in five databases (i.e. ScienceDirect, Scopus, ERIC, IEEE Xplore, Mendeley), because these databases contain recent and relevant papers as well as a variety of scientific journals linked to AI and education (e.g. Neurocomputing, Computers and Education, Computers in Human Behavior, Computers & Education, International Journal of Educational

Technology in Higher. Figure 4 illustrates the automated search process. The literature database was searched using periods, keyword strings, subject areas, and the English language.

Step 4 and 5 screened the collected results by removing duplicate entries, review articles, publications from non-reputable sources, and those not written in English. Figure 6 illustrates the implementation phase for identifying the primary studies using PRISMA. The eligibility process in Step 4 involved applying inclusion and exclusion criteria based on the title, document type, abstract, and final decision on studies categorized as doubtful.
The initial screening, based on title, document type, and abstract, resulted in 120 articles being retained, 50 articles being excluded, and 43 articles being flagged as doubtful literature. Subsequently, a full-text review was conducted on the 43 doubtful articles to determine their eligibility. As a result, 27 articles were excluded, and 16 were confirmed as meeting the inclusion criteria. Thus, Step 5 yielded a final total of 93 primary studies eligible for in-depth analysis in this research.

Step 6 and 7 Following a thorough study of the chosen articles using the suggested criteria, various data were retrieved. By using the PRISMA program, we were able to retrieve the title, authors, year of publication and reference type of each article. The name of the journal, the abstract and the keywords of the publications were also extracted. After analysing the full text, we extracted the type of intervention used in each research, the solution and the AI algorithms employed, the factors taken into consideration and the objective addressed on step 6.

The study quality assessment can be used to guide the interpretation of the synthesis findings and to define the strength of the elaborated inferences on Step 7. The goal of data synthesis is to aggregate evidence from the selected studies for answering the research questions. A single piece of evidence might have small evidence force, but the aggregation of many of them can make a point stronger. The data extracted in this review include both quantitative data and qualitative data. Different strategies were employed to synthesize the extracted data pertaining to different kinds of research questions. Generally, the narrative synthesis method was used. The data were tabulated in a manner consistent with the questions. Some visualization tools, including bar charts, pie charts, and tables were also used to enhance the presentation of the distribution of software adaptive learning recommendation system methods and their accuracy data

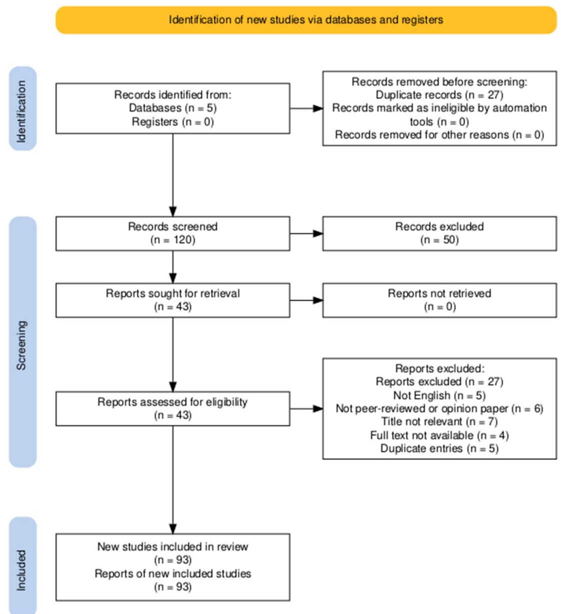

Figure 6. Automated search for searching the primary studies using PRISMA.

3.3.3. Reporting Phase

The reporting phase denotes the final stage of SLR, which encompasses documenting the review process, implementation, synthesis, and future research. Step 8 of the methodology manifests the reporting phase, which employs bibliometric analysis and analysis and structured mapping study (SMS) to document the review process. The reporting phase also provides a discussion of the review results.

4. RESULTS AND DISCUSSIONS

This review is reported through two analytical sections: results and observations from the literature review and discussion of findings.

4.1. Results and Observations from the Literature Review

The purpose of this section is to synthesize and describe the results of the research that served as the basis for the generation of our sample data utilizing descriptive static analysis [56]. This analysis attempts to provide the article overview, of ai techniques, background, systems employed, and research trends related to adaptive learning.

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4.1.1 Bibliometric analysis of research publications on adaptive learning

The graph depicted in figure 7 illustrates the annual distribution of the 93 studies included in this review, covering the period from 2014 to 2025, as retrieved from Google Scholar and Scopus.

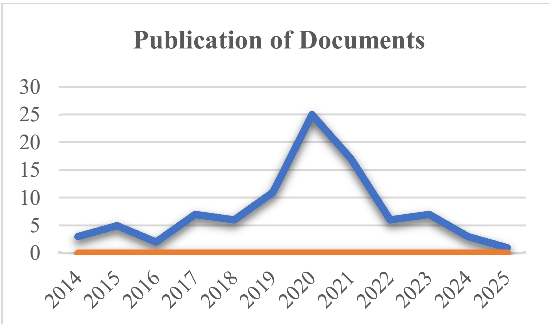

Figure 7. Distribution of Publications Employing AI for Adaptive Learning Systems

As shown, there has been a notable upward trend in publications on AI-enabled adaptive learning. The year 2020 recorded the highest number of publications, with 25 articles, accounting for approximately 26.9% of the total. This was followed by 2021 with 17 publications (18.3%) and 2019 with 11 articles (11.8%). The number of publications also remained steady in 2023 and 2017, each contributing 7 articles (7.5%), while both 2018 and 2022 yielded 6 articles (6.5% each). Earlier contributions include 5 articles in 2015 (5.4%), 3 articles each in 2014 and 2024 (3.2%), and 2 articles in 2016 (2.2%). In 2025, only one study was recorded (1.1%), which likely reflects the recency of the publication year and potential delays in indexing. Taken together, this distribution indicates a sustained and growing academic interest in AI-based adaptive learning, with a marked increase beginning in the period following 2019 with the increasing demand for personalized learning experiences.

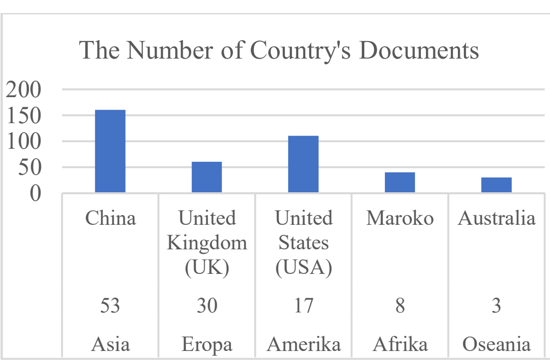

Figure 8. The number of country's documents in AI-based adaptive learning research.

Figure 9. The number of country's citations in AI-based adaptive learning research.

Research on AI-based adaptive learning is being conducted across various regions of the world. As illustrated in figure 8 and Figure 9, Asia is the most prolific continent, contributing 53 publications, with China being the leading country in the region, accounting for 16 articles. Europe follows with 30 publications, including 6 from the United Kingdom. The American continent ranks third with 17 publications, among which the United States is the second-most productive country globally with 11 contributions. Africa comes next with 8 publications, led by Morocco, which contributed 4 articles. Additionally, Australia, representing Oceania, added 3 publications to the growing global literature on AI-enabled adaptive learning. This geographic distribution underscores the international scope and collaborative nature of research in this field.

After identifying the continent (Asia), country (China), and year (2020) with the highest frequency of publication, we now turn to the frequency of journals contributing to AI-based adaptive learning research, as presented in Table 5.

Table 5: Distribution of Publications by Journal in Adaptive Learning Research

Journal	Number of Studies	Percent (%)
Computers & Education	15	17.64
Education and Information Technologies	6	7.05
Computers and Education: Artificial Intelligence	5	5.88
Computers in Human Behavior	4	4.70
International Journal of Educational Technology in Higher Education	3	3.52

International Journal of Emerging Technologies in Learning	2	2.35
Applied Psychological Measurement	2	2.35
Computer Applications in Engineering Education	2	2.35
Others	46	54.11

According to our data, the Computers & Education journal ranks first, publishing 15 articles, which represents 17.64% of the total 93 studies. This journal, widely indexed in abstract and citation databases such as Scopus, is known for advancing knowledge and understanding of how digital technologies can enhance educational processes [60], [61].

In second place is the Education and Information Technologies journal, which contributed 6 publications (7.05%), followed by Computers and Education: Artificial Intelligence, a sister journal of *Computers & Education*, with 5 articles (5.88%). This journal specifically focuses on pedagogical breakthroughs in AI applications for education on a global scale [60].

Other notable contributors include Computers in Human Behavior with 4 articles (4.70%), and the International Journal of Educational Technology in Higher Education with 3 articles (3.52%). Three additional journals—International Journal of Emerging Technologies in Learning, Applied Psychological Measurement, and Computer Applications in Engineering Education—each published 2 articles, contributing 2.35% respectively.

The remaining 46 studies (54.11%) were distributed across various other journals, indicating the interdisciplinary nature and wide-ranging academic interest in AI-enabled adaptive learning. This spread reflects the integration of AI and educational technology within diverse research communities and disciplines.

4.1.2 Frequency of educational contexts

In this part, we will present the educational contexts, namely the levels and subjects mentioned in the reviewed research.

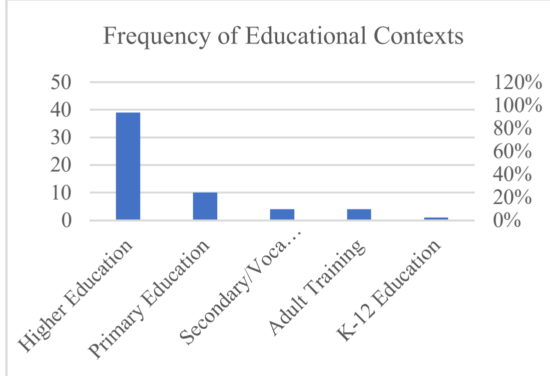

Figure 10: Appearance frequency of educational contexts

In the frequency of educational contexts categorized by educational levels, as shown in figure 10, 67 percent of research focuses on higher education (n = 39), while 17 percent (n = 10) focuses on primary education, 14 percent split equally between secondary education or vocational education (n = 4) and adult training (n = 4), and 2 percent (n = 1) is represented by K-12 education. AI-based adaptive learning is investigated in a variety of fields, including informatics, sciences, languages, healthcare, business, soft skills etc. Computer science, namely programming and data structures, is the subject of the majority of research (n = 19), which is then followed by mathematics (n = 8), languages, and communications (n = 6), physics, chemistry (n = 3), and more in table 6. Not to mention, research that focuses on adapting the learning of various concepts comes in third with a rate of 12% (n = 6).

Table 6: Distribution of discussed Academic Discipline in Adaptive Learning

Disciplinary Area	Number of Studies	Percent (%)
Computer science	19	38.77
Mathematics	8	16.32
Multiple concepts	6	12.24
Languages and communication	6	12.24
Physics and chemistry	3	6.12
Nursing, medicine and pharmacy	3	6.12
Economy and business	1	2.04
Biology	1	2.04
Learning skills	1	2.04
Scientific subjects	1	2.04

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4.1.3 Frequency of AI-based adaptive learning interventions

The frequency of AI-based adaptive learning interventions, as categorized in the study by [62], served as a foundation for refining our research sample. Through an iterative process of coding and collaborative discussion among the authors, the interventions identified in the selected studies were classified into ten distinct groups—namely System, Model, Approach, Game, Framework, and others, as illustrated in figure 11. This categorization provides a structured overview of the various implementation strategies employed in the application of adaptive learning techniques using AI, offering insights into the methodological diversity present within the field.

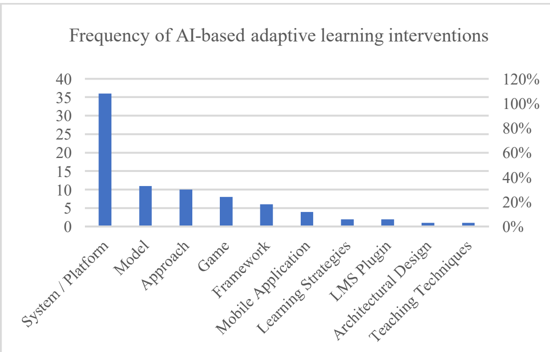

Figure 11: Appearance frequency of AI-based adaptive learning interventions

In frequency of AI-based learning interventions, we can confirm that researchers are very interested in the design, development, and testing of adaptive learning systems and platforms, as shown in figure 8, of which 36 publications are in this direction (44%). On the other side, 11 highlight AI models supporting adaptive learning (14%). To put it simply, a model is generally a description of a pattern that aids in visualizing something that cannot be seen directly [63]. Particularly, an AI model is a collection of complex algorithms that analyzes a variety of inputs to recognize specific patterns. This analogy enables one to predict, categorize, or draw a conclusion [64]. 10 articles address the various theories, perspectives and methodologies used to approach the problem of adaptability in the learning process (12%), while 8 are interested in adaptive serious games and the ludic dimension in the service of learning adaptation (10%). Wide-ranging advantages of this intervention refers to games that are used in a range of educational settings to improve learning by helping students to acquire knowledge and skills [Kaimara et al., 2020]. Following that, 6 research focuses on developing a Framework that allows for the adaptation of the educational process which represents 7% of the total, 4 studies on learning using mobile devices (smart phone, tablet) (5%), and 4 divided between the learning strategies and the plugin integrated into the LMS. The plugins suggested as solutions in our sample are a combination of libraries and algorithms that empower a learning management system (LMS) with adaptive capabilities. In order to better understand other ideas, let us define a framework as a structure that solves issues by inserting a general design that offers the required functionality [65]. In our context, it is utilized to make sane decisions about adaptive learning design and to create a roadmap outlining actions, models, and artificial intelligence technologies that are beneficial for achieving a highly successful adaptive learning result [66]. Learning strategies describe a group of procedures, tools and plans that can make it easier to gather, store and implement data in the interest of adaptive learning [67]. Finally, we discover that only one contribution for each, architectural design and teaching techniques are the AI-based adaptive learning interventions that receive the least attention in this literature.

Table 7: Distribution of AI-Based Adaptive Learning Interventions Identified in the Literature

Intervention Type	Number of Studies	Percentage (%)
System / Platform	36	44%
Model	11	14%
Approach	10	12%
Game	8	10%
Framework	6	7%
Mobile Application	4	5%
Learning Strategies	2	2%
LMS Plugin	2	2%
Architectural Design	1	1%
Teaching Techniques	1	1%
Total	81	100%

4.1.4 Frequency of AI- career recommendation for vocational applications

In frequency of AI-based technologies offer a wide range of potential benefits for education, particularly in their capacity to personalize the learning experience for individual learners. Within

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the scope of our research sample, we identified and categorized various types of AI-based applications that have been implemented to support and enhance adaptive learning processes. As shown in the figure 12, 38 applications (48%) are interested in web-based platforms, seven are related to recommendation systems (9%), 12 are divided between intelligent tutoring systems and educational games (15%), and 4 contributions are interested in prediction systems (5%). For the remaining applications, we find, six publications related to Mobile applications and E-learning plugins representing 8% for each, whereas chatbots, offline learning environments and expert systems each was mentioned in two searches. As for the least used systems, the following are found: educational hypermedias, semantic bliki systems, intelligent control systems, hybrid environments, dashboard systems and adaptive instructional systems.

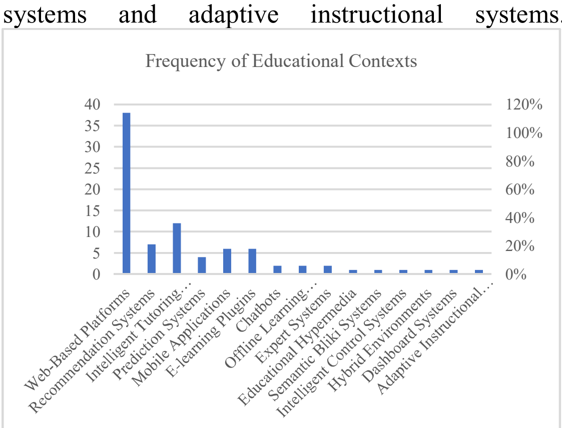

Figure 12: Appearance frequency of AI- career recommendation for vocational applications

Adaptive learning systems have emerged as a leading educational innovation due to their significant advantages in convenience, flexibility, and the ability to deliver diverse course materials. Empirical evidence underscores their effectiveness; for instance, a study conducted in Taiwan involving 76 students demonstrated that such platforms enhance the learning process, facilitate the identification of learning barriers, and provide meaningful feedback to both learners and educators[68]. Supporting this, research by [69] involving three cohorts of college freshmen indicated that the integration of adaptive web-based learning environments positively influences students' motivation to learn. Furthermore, adaptive platforms offer real-time data analytics capabilities that enable instructors to monitor student performance and progress. As noted by [70], these systems support the construction of personalized learning pathways, allowing educators to track learning trajectories and make data-informed instructional decisions. Distribution of discussed Academic Discipline in Adaptive Learning.

Table 8: Distribution of AI- career recommendation for vocational applications

Application Type	Number of Studies	Percentage (%)
Web-Based Platforms	38	48%
Recommendation Systems	7	9%
Intelligent Tutoring Systems & Educational Games	12	15%
Prediction Systems	4	5%
Mobile Applications	6	8%
E-learning Plugins	6	8%
Chatbots	2	3%
Offline Learning Environments	2	3%
Expert Systems	2	3%
Educational Hypermedia	1	1%
Semantic Bliki Systems	1	1%
Intelligent Control Systems	1	1%
Hybrid Environments	1	1%
Dashboard Systems	1	1%
Adaptive Instructional Systems	1	1%

Recommendation systems, which rank as the second most prominent AI-based intervention in adaptive learning, typically operate based on a variety of factors such as the learner's past behavior, preferences, and demographic information (as in K-Means clustering to group learners with similar profiles), or by utilizing the behavior and interaction patterns of other learners (as in Naive Bayes classification predicts suitable outcomes based on probabilistic associations). These systems are designed to enhance the learning experience by providing personalized guidance, optimizing learning pathways, and increasing engagement and efficiency. By combining these approaches, a hybrid model can capture both individual characteristics and collective trends, offering greater accuracy and contextual relevance in adaptive educational environments. These systems aim to improve the learning experience by offering personalized recommendations, increase learning efficiency by analyzing a large amount of information, providing real-time recommendations; optimizing navigation time and helping the learner find the most appropriate learning content [71]. A recommendation system called X5Learn optimizes learning paths based on the interests of the student and offers a clear interface for choosing educational materials. As said in this study [72], the usability applications of these systems have demonstrated that they helped students better engage with the content by facilitating their ability to navigate it. A study on the implementation and evaluation of a recommendation-based hybrid adaptive learning system showed that recommending learning content appropriate to the needs of each learner contributes to improving the learning effects. In particular, this research investigated how to use content-based and collaborative-filtering based hybrid recommendation technology in an adaptive learning system through a field experiment with 30 selected students from the undergraduate computer science program [73].

The third major system in our study sample is the intelligent tutoring systems, which stand for an effective self-learning tool that makes choices depending on the learner's affective and cognitive state, as well as provide a customized learning environment by tailoring the learning process and content to each unique learner [74], [75]. This astounding usage rate is a result of the numerous benefits that these kinds of systems provide, including customized lessons, quick responses, increased engagement, and improved learning outcomes, as demonstrated by the studies that follow. This study [76] examines the effects of OSCAR, an intelligent tutoring system that converses in natural language to identify the learner's preferred learning style and utilize it to dynamically tailor tutoring sessions. Another study suggested a fresh method for developing intelligent tutoring systems that relies on serious games and adaptable processes. With the use of these innovative summative assessment techniques, teachers may now motivate and inspire their students to learn [77]. This method leads us to the fourth system type, adaptive educational games, which is comparable to the latter in term of study percentage. These AI-based solutions, which primarily aim to adjust a portion or all of the learning process, also boost learner motivation and engagement, enhance social and collaborative abilities, and incorporate multi-sensory learning. An adaptive gamified learning system that combines classification, gamification, and adaptation approaches was created to improve the efficacy of online learning. A data structure course was taught to 73 students using three different teaching approaches to evaluate this solution: classical, gamification, and adaptive gamification. The findings indicated that, when compared to alternative approaches, the adaptive gamification method improved student engagement and academic achievement [78]. Additionally, other crucial applications that are significantly influential on the learning process include:

1. Prediction systems that analyze learner data to predict several key elements of the adaptation mechanism (performance, learning style etc.) [79].
2. Mobile applications that provide easy access to learning materials, convenience and flexibility so that students can learn at their own pace and according to their own interests [80]
3. Plug-ins that adds new, non-existent adaptation functionality to an LMS [81].
4. Chatbots, which are a solution characterized by availability, immediate feedback, efficient information dissemination etc [82].
5. Dashboard that allows teachers and administrators to view and analyze instructional data in real time to improve their decisions and allow them to adapt their teaching [83].
6. Educational hypermedia that provides a high level of information organization enables students to investigate complex concepts etc [84].

4.1.5 Frequency of AI techniques and algorithm typologies

Frequency of AI techniques and algorithm typologies based on the mapping of collected studies we revealed a wide number of AI algorithms used to deal with problems related to learning adaptation. In this regard, we have chosen to classify these algorithms into four groups, those related to symbolic AI, machine learning, neural networks, Natural language processing (NLP), and Deep learning. The figure 13, below shows the frequency of these AI algorithm typologies used in the collected studies.

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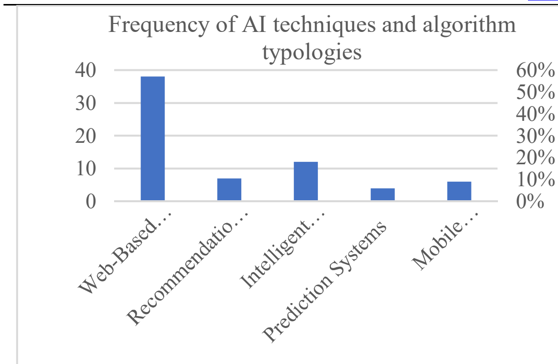

Figure 13:Distribution Frequency of AI Algorithm Typologies in Extracted Studies

The diverse categories of artificial intelligence techniques employed in adaptive learning research. The most common category was Machine learning algorithms (e.g. Decision Tree algorithm, Support Vector Machine algorithm, K-means clustering algorithm), which were referenced in 62 of the identified studies. Deep learning algorithms (e.g. Convolutional Neural Networks, multi-layer feed-forward neural network) are the second most frequently stated types (n = 11). Seven studies used algorithms falling into the category of symbolic AI (e.g. Rule-based algorithm, Fuzzy rules algorithm), followed by six adopted neural networks algorithms (e.g. Radial Basis Function Neural Networks, Gravitational Search-based Back Propagation Neural Network). The remaining ones are classified as NLP (n = 2).

Table 9: Distribution of AI techniques and algorithm typologies

AI Algorithm Category	Number of Studies	Percentage (%)
Machine Learning	62	70.5%
Deep Learning	11	12.5%
Symbolic AI	7	8.0%
Neural Networks	6	6.8%
Natural Language Processing	2	2.2%

Several studies have demonstrated the use of various AI algorithms in adaptive learning environments, with a particular emphasis on machine learning approaches for prediction and classification tasks. In a study conducted by [85], the J48 decision tree algorithm was employed to categorize learners based on their learning styles, which were then applied to personalize the interface and course materials in an adaptive virtual learning environment. Similarly, [73] utilized the K-Means clustering algorithm to group users in a hybrid recommender system, enabling the computation of user similarity based on collected information. Another approach implemented by [86] involved the use of Support Vector Machines (SVM) in an ensemble classification framework to automatically detect learning styles within a mobile adaptive learning environment, leading to improved learner outcomes through preference-based content delivery.

In addition to traditional machine learning methods, deep learning algorithms have also been applied in adaptive systems. For instance, Convolutional Neural Networks (CNNs) were used by [87] to infer emotional states from facial expressions and gaze estimation, thereby enabling classification of learners with intellectual disabilities. In a separate study, Multilayer Feedforward Neural Networks (MLFFNs) were used to identify learners' cognitive styles and adaptively recommend content, benefiting from the model's capacity to manage uncertainty and continuously integrate new data [69].

Symbolic AI techniques, such as fuzzy rule-based systems and rule-based reasoning, have also been explored. Developed a fuzzy rule-based reinforcement model to map cognitive skills to learning objects based on learner feedback, facilitating differentiated learning paths. In language learning, rule-based reasoning was applied by [88] using a NAO robot, which interpreted vocal responses through conditional logic (IF–THEN–ELSE) to extract keywords. This interaction fostered improved retention and engagement among learners.

Furthermore, neural network algorithms were adopted by [89] to predict on-time graduation among students with learning difficulties, enabling the development of tailored remediation strategies. In parallel, Natural Language Processing (NLP) techniques have been used to support content personalization. [82] introduced an NLP-driven chatbot that identifies keywords to index and recommend multimedia learning resources aligned with student needs.

Given the widespread application of machine learning algorithms, particularly for prediction and classification tasks in adaptive learning, it is essential to distinguish this category as a core typology, as illustrated in figure 14.

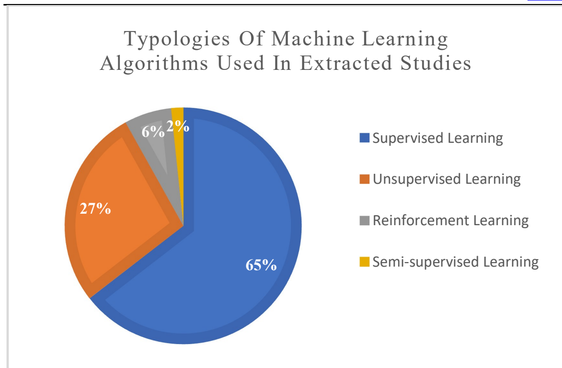

Figure 14: Typologies of Machine learning Algorithms used in Extracted Studies

The distribution of studies employing machine learning (ML) algorithms in adaptive learning environments is illustrated in figure 14. The most frequently cited category comprises supervised learning algorithms, which were applied or discussed in 40 studies. These algorithms are predominantly used to solve classification (e.g., classification based on learning behaviors [90] and prediction problems (e.g., predicting learning styles [76]). Supervised approaches are widely favored due to their ability to learn from labeled data and provide accurate, targeted interventions in adaptive systems.

The second most represented category is unsupervised learning, referenced in 17 studies, which is primarily employed to reduce data dimensionality and group data points into clusters. A common application involves clustering learner behavior data to identify learning style categories [79], as well as recommending personalized content based on grouped user profiles [73], [91].

Reinforcement learning algorithms were identified in four studies, where they are utilized for constructing intelligent tutoring systems and adaptive educational games [40], [92]. These algorithms operate on the principle of rewarding desirable learner behaviors and have also been employed in the development of recommendation systems that adapt content delivery based on iterative feedback loops [93], [94], [95].

Finally, semi-supervised learning represents the least frequently mentioned category, with only one study incorporating this approach. Semi-supervised methods are particularly useful in scenarios involving limited labeled data, allowing models to leverage both labeled and unlabeled datasets to perform classification tasks effectively [96].

4.1.6 Frequency of research objectives

The distribution of research objectives identified in the reviewed studies is illustrated in figure 15.

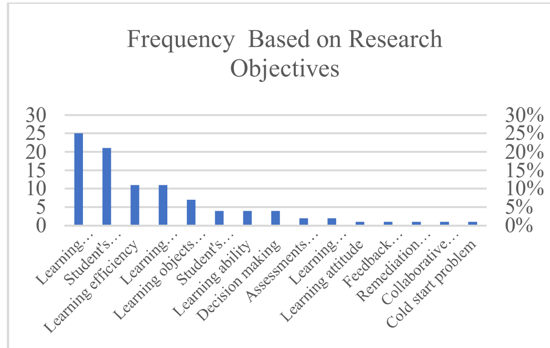

Figure 15: Appearance frequency based on research objectives

In the frequency of research objectives, a total of 25 studies (26%) focused on improving learning performance, defined as the learner's ability to apply acquired knowledge to real-life contexts [97]. The second most commonly addressed objective, found in 21 studies (22%), was enhancing learner motivation, typically measured by levels of engagement and participation [87], [98]. An additional 11 studies aimed to enhance learning efficiency, referring to the effectiveness and speed with which learners assimilate knowledge [94] while another 11 studies targeted learning achievement, often used as a benchmark to assess learners' success in achieving educational goals [99], [100]

Furthermore, 7 studies addressed the objective of personalizing course content or learning resources to better accommodate individual learner needs and preferences [101]. Other notable objectives include enhancing student satisfaction [102] and improving learning ability—such as reducing cognitive load [103] each reported in 4 studies. An additional 4 studies aimed to support decision-making processes, ultimately contributing to improvements in teaching quality [104]. As shown in Table 10, the studies included in this review address a range of research objectives with varying frequencies.

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Table 10. Distribution of based on research objectives

Research Objective	Number of Studies	Percentage (%)
Learning performance	25	26%
Student's motivation	21	22%
Learning efficiency	11	12%
Learning achievement	11	12%
Learning objects personalization	7	7%
Student's satisfaction	4	4%
Learning ability	4	4%
Decision making	4	4%
Assessments personalization	2	2%
Learning methods personalization	2	2%
Learning attitude	1	1%
Feedback personalization	1	1%
Remediation personalization	1	1%
Collaborative learning	1	1%
Cold start problem	1	1%

4.1.7 Frequency of adaptive factors

In analyzing the distribution of adaptive factors, this section aims to identify and synthesize the various elements considered throughout the learning adaptation process. These factors are typically connected to the learner model, which describes learner qualities, knowledge and skill, behavior, preferences, and individual differences that are utilized to customize the material [105].

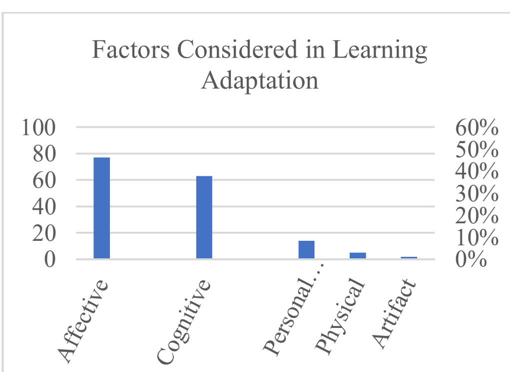

Figure 16: Appearance frequency of adaptive factors

The distribution of adaptive factors considered in AI-based adaptive learning systems is presented in the figure 16. The most prominent category comprises affective factors, which were cited in 77 studies (48%). This category is further divided into several key dimensions: learning styles (32%), learner preferences (13%), learning behaviors (12%), and learner motivation (5%). In addition to these primary indicators, a wide array of affective sub-factors—accounting for 38% of the total—were also identified, including personality traits, prior experience, emotional states, persistence, time management, learner feedback, interest levels, click patterns, viewing time, imperfect help-seeking behaviors, willingness to learn, patience, and concentration.

The second most frequently considered category consists of cognitive factors, cited in 63 publications (39%). This category encompasses a range of learner mental abilities and learning-related metrics. Notably, domain knowledge accounts for 29%, followed by academic performance (13%), learning outcomes and success (20%), study level (8%), problem-solving or submitted solutions (6%), time spent (5%), and learning progress (3%). The remaining 16% of cognitive dimensions are distributed among learner proficiency, cognitive deficits, learning needs, and vulnerability.

In addition to affective and cognitive considerations, several studies also accounted for other dimensions. These include personal data (e.g., demographic information) found in 14 studies (9%), physical conditions (e.g., disabilities or environmental context) in 5 studies (3%), and artifacts both digital and physical representations of learner interactionwith a minimal representation in 2 studies (1%). Table 11 presents the distribution of various factors considered in the implementation of adaptive learning, highlighting the key learner characteristics used to personalize the vocational education process.

Table 11. Distribution of Factors Considered in Learning Adaptation

Category	Number of Studies	Percentage (%)
Affective	77	48%
Cognitive	63	39%
Personal Data	14	9%
Physical	5	3%
Artifact	2	1%

4.2. Discussion of Findings

This section presents and discusses the results obtained in relation to the proposed research questions. As illustrated in figure 7, the concept of adaptive learning—whether approached as a method, solution, or pedagogical strategy—has shown a marked increase in scholarly publications over recent years. This upward trend indicates a growing academic interest and recognition of its relevance. Supported by findings from numerous studies, as summarized in Table 12, the data suggest that adaptive learning represents an emerging research focus in the educational technology domain. This development can be attributed, in part, to the considerable promise adaptive learning holds for enhancing personalized instruction, learner engagement, and overall educational effectiveness.

Table 12 : Summary of research identifying adaptive learning as a recent focus

Ref.	Research Presentation	Citation and Affirmation
Bozkurt et al. (2021)	Systematic literature review of 276 AI-in-education studies (1976–2019), identifying adaptive learning as a key thematic cluster.	Adaptive learning and personalization of education through AI-based practices are among the most researched themes.
Zhang & Aslan (2021)	Review of 40 empirical studies on AI in education (1993–2020), focusing on intelligent tutoring and personalized systems.	A lot of research focused on intelligent tutors or personalized learning systems/environments.
Ref.	**Research Presentation**	**Citation and Affirmation**
Martin et al. (2020)	Systematic review of adaptive learning research designs and strategies (2009–2018).	Learning style was the most observed learner characteristic; adaptive feedback and navigation were the most investigated targets.
El-Sabagh (2021)	Experimental study on adaptive e-learning based on learning styles and its impact on student engagement.	The adaptive group showed significantly higher engagement and performance than the control group.
Gligorea et al. (2023)	Literature review on AI/ML in adaptive e-learning systems.	AI/ML algorithms optimize learning paths, enhance engagement, and improve academic performance.
Chiu et al. (2023)	Systematic review of 92 AIEd articles published between 2012 and 2021.	Delivering adaptive teaching methodologies and enhancing adaptability and interactivity in digital settings are two of the major educational domains.
Jing et al. (2023)	Bibliometric analysis of 644 adaptive learning articles (2000–2022) using CiteSpace and VOSviewer.	Identified four major clusters: deep learning in education, adaptive models, intelligent tutoring systems, and knowledge tracing.
Ezzaim et al. (2023)	Survey of 400 research calls (thesis projects and CFPs) from 2019–2021 to analyze AI research themes.	Artificial intelligence and especially the sphere of adaptive learning is one of the most requested categories by researchers.
Canan Güngören et al. (2024)	Bibliometric study of adaptive learning trends in *IJERE*, analyzing publication networks, citations, and keyword evolution.	Adaptive learning has become a trending topic with increasing citation centrality in educational technology research.
Sajja et al. (2025)	Development and evaluation of an AI-powered educational tool for vocational certification in floodplain management.	The tool demonstrated 91.03% and 95.52% accuracy in answering open-ended and multiple-choice questions, respectively, confirming its effectiveness in adaptive vocational training

To establish a clear basis for the subsequent analysis, it was first necessary to define the contemporary understanding of adaptive learning. Conceptually, adaptive learning refers to an instructional approach that dynamically adjusts the learning process—such as content, pace, sequence, and method—based on individual learner characteristics, including cognitive abilities, affective traits, learning preferences, and prior knowledge. This personalization is designed to enhance learner engagement and optimize educational outcomes.

Over the past decades, adaptive learning has evolved significantly through various technological stages, including Intelligent Tutoring Systems (ITSs), Adaptive Hypermedia Systems (AHs), and adaptive e-learning platforms. In its current and most advanced form, adaptive learning is increasingly powered by artificial intelligence, particularly machine learning algorithms. These technologies facilitate more accurate learner modeling, real-time decision-making, and predictive personalization. As supported by the findings in this study—illustrated in figure 17 and detailed in Table

13—supervised learning algorithms are the most frequently employed, owing to their effectiveness in solving classification and prediction problems within adaptive learning environments.

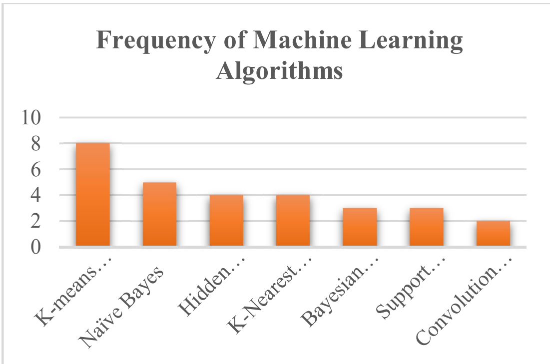

Figure 17. Distribution of Machine Learning Approaches Used in AI-Based Adaptive Learning Systems

Table 13. Typology of Machine Learning Algorithms Employed in AI-Based Adaptive Learning Systems

AI Algorithm	Number of Studies
K-means clustering	8
Naïve Bayes	5
Hidden Markov	4
K-Nearest Neighbor	4
Bayesian Network	3
Support Vector Machine	3
Convolutional Neural Network	2

Meanwhile, the review synthesis constitutes a means to seek the convergence of all findings to answer six research questions (RQ1, RQ2, RQ3, RQ4, RQ5, and RQ6). This review provided four insights from the bibliometric analysis and six from the systematic mapping study (SMS) analysis. Subsequently, all insights were synthesized into convergent answers to the research questions. The synthesis of the findings provides the following answers:

4.2.1 Q1 addresses the primary research goals of AI adaptive learning studies.

Across the literature, these goals consistently include enhancing learner performance, motivation, personalization, and academic achievement through intelligent adaptation mechanisms2. The primary goals observed across the literature center on enhancing learner performance, motivation, learning efficiency, and academic achievement, underscoring the significant influence of adaptive learning technologies on the quality of educational outcomes. In addition to these commonly pursued objectives, several less frequently explored yet equally important issues have also emerged. These include the integration of K-Means clustering as a segmentation technique to group learners by behavioral or cognitive similarities, the enhancement of help-seeking behavior, and the development of mechanisms for real-time learner adaptation, which enable systems to dynamically adjust recommendations even in the absence of extensive historical data. Such findings demonstrate the broad applicability and transformative potential of adaptive learning systems in addressing both instructional and technological challenges within contemporary educational environments.

4.2.2 RQ2 explores how AI-based adaptive learning addresses research issues and concerns.

Studies show that AI systems mitigate challenges such as rigid instruction, low engagement, and lack of scalability by enabling real-time personalization, predictive analytics, and dynamic content delivery [106]. Adaptive learning systems particularly web-based platforms emerge as the most widely implemented solutions, as highlighted in the results section and illustrated in figure 13 of this study. Their extensive adoption is attributed to their flexibility, accessibility across various devices, and applicability in diverse learning environments. Recommender systems follow closely, having gained considerable attention in recent years for their effectiveness in analyzing learner behavior and suggesting appropriate learning resources through machine learning and other AI-driven techniques [71], [107]

Moreover, intelligent tutoring systems (ITS) have demonstrated strong pedagogical benefits, offering personalization, real-time feedback, and enhanced learner engagement—making them one of the most impactful applications of adaptive learning [74], [75]. Adaptive educational games are also evolving, offering immersive and playful learning scenarios that incorporate adaptive mechanisms based on user engagement and problem-solving strategies, enabling the implicit detection of learner preferences.

As previously established, adaptive learning typically revolves around the learner's

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characteristics, which are broadly categorized into affective and cognitive dimensions. Affective factors include learning styles, preferences, and motivational states, often identified through psychological assessments or advanced machine learning techniques. Cognitive factors, by contrast, focus on prior domain knowledge, learner responses, and performance, commonly evaluated through pre-tests and interactive assessments.

In direct response to the second research question (RQ2), this review reveals that objectives such as improving learning outcomes are predominantly addressed through online adaptive systems and recommender systems. These systems operate by aligning instructional strategies with learners' dominant learning styles, current performance, and knowledge levels—identified through system interactions and processed via supervised machine learning algorithms, as detailed in Table 14.

Table 14: Primary adaptive aspects addressed in the analyzed studies

Adaptive factors	Number of studies
Learning styles	25
Domain knowledge	18
Preferences	10
Learning behaviour	9
Learner's performance	8

4.2.3 RQ3 investigates the design components required to build an AI-based adaptive learning recommendation system based on learning style personalization for vocational students.

Literature emphasizes the importance of integrating learning style detection algorithms, clustering techniques (e.g., K-Means), and real-time feedback mechanisms to support personalized learning pathways.

4.2.4 RQ4 focuses on popular AI algorithms used to design interventions.

Reviews highlight the frequent use of Naive Bayes, K-Means, Decision Trees, Neural Networks, and hybrid models, each contributing to improved classification, clustering, and learner modeling accuracy [108].

4.2.5 RQ5 examines how a hybrid K-Means and Naive Bayes model can improve the accuracy of career recommendations compared to single-model approaches.

Evidence suggests that hybrid models outperform single algorithms by combining unsupervised segmentation with probabilistic classification, leading to more context-aware and personalized recommendations3.

4.2.6 RQ6 considers the impact of present research on future AI-based adaptive learning practices.

The reviewed studies project that adaptive learning systems will continue to evolve toward greater personalization, ethical transparency, and integration with vocational and lifelong learning frameworks—especially when supported by scalable, data-driven architectures [109].

According to the synthesis of the review, our findings and mapping have helped us obtain a better knowledge of this educational technology, while providing an opportunity for future researchers to better select the AI-based adaptive learning solutions for each application. In this respect, we can estimate the impact of current research on future adaptive learning techniques as well as the target of our future research. In addition, the following are the broad conclusions on which we have relied. Firstly, the attention paid by researchers to this area is evidenced by the increasing amount of research related to adaptive learning. Second, the positive influence of this technology on a variety of characteristics, including learner performance, engagement, and results, as well as the high level of adaptability given by these systems, are significant advantages that stimulate additional research in this field. Finally, the limits of prior studies are another motivation to seek other, more effective solutions to issues such as:

1. The lack of learning at secondary education levels (especially vocational education) compared to higher and basic education levels. This indicates a significant gap in the adoption and development of adaptive learning approaches.
2. Evaluation of adaptive learning systems is often conducted based on a single factor, limiting the comprehensiveness of the analysis and its applicability in diverse learning contexts.

3. Static survey instruments are commonly used to identify students' learning styles, despite their inability to capture dynamic and evolving learner needs.
4. Insufficient adaptation of assessment strategies, even though assessment is an essential component of the learning process that should align with personalized learning pathways.
5. Underutilization of modern pedagogical models, such as flipped classrooms, blended learning, and other learner-centered approaches, within adaptive learning environments.
6. Scarcity of significant research contributions from African countries, indicating a geographical gap that affects the global inclusivity of adaptive learning innovations.

The goal of our future studies is to address the need for scientific research in this highly promising field. To this end, we intend to conduct experiments in the context of secondary education, particularly vocational education. This initiative is aligned with the Indonesian Education Roadmap, which is part of the country's long-term development plan, where the government actively prioritizes the integration of modern educational technologies [110]. Furthermore, through a Presidential Regulation of the Republic of Indonesia, the government is promoting the revitalization of vocational education and training (TVET), shifting from a supply driven to a demand driven model that is more aligned with labor market needs [111].

These national initiatives, combined with the government's recognition of artificial intelligence as a strategic driver for education and workforce development, provide a strong policy foundation for conducting AI-based adaptive learning research in vocational education settings

These experiments will be grounded in the identified research gap concerning the automatic detection of learning styles in vocational education. Initially, existing AI-based adaptive learning systems will be utilized to evaluate their capabilities, particularly in identifying individual learning preferences. Building upon these insights, we intend to develop a tailored adaptive learning environment that allows for the strategic selection of machine learning algorithms, such as K-Means or Naive Bayes, which have shown high adaptability across educational contexts. This environment will enable fine-tuned manipulation of adaptation factors, particularly those aligned with students' cognitive and affective traits, to ensure more accurate personalization of both educational content and career pathway recommendations. By doing so, the experiments aim to strengthen the connection between learning style detection and personalized vocational guidance, thereby improving both academic engagement and long-term career readiness in line with national educational priorities.

5. CONCLUSION

This systematic literature review of 93 peer-reviewed studies published between 2014 and 2024 provides robust evidence that AI-based adaptive learning systems are rapidly becoming a transformative force in modern education. The findings confirm that the integration of AI, especially through machine learning algorithms such as K-Means clustering and Naive Bayes classification, has significantly enhanced personalization, learner engagement, and learning outcomes across diverse educational contexts. The most dominant implementations leverage web-based platforms and supervised learning models to dynamically tailor learning experiences according to learners' affective and cognitive characteristics.

The review also highlights notable gaps and research priorities. Vocational and secondary education remain underrepresented compared to the strong focus on higher education. Furthermore, current adaptive systems often rely on limited learner dimensions and static learning style assessments, leaving room for improved responsiveness and contextual adaptation. This reinforces the relevance of developing hybrid models that combine clustering and probabilistic inference with real-time learner modeling.

The synthesis of research questions reveals six convergent areas of inquiry, from understanding foundational goals of AI-based adaptive learning to evaluating the long-term impact on educational innovation. Notably, bibliometric and mapping analyses confirm the global distribution of scholarly interest, with Asia leading in publication volume and Computers & Education emerging as the most influential journal.

Despite the study's limitations, such as the constrained keyword scope and database selection, this work establishes a solid foundation for future empirical research. Specifically, it calls for experimentation in Indonesian vocational settings, aligned with national priorities under the Education Roadmap and Presidential Regulation of the

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Republic of Indonesia. The authors propose to explore adaptive systems capable of detecting learning styles automatically and guiding career pathways through intelligent, scalable frameworks. By addressing both policy and pedagogical needs, this research paves the way toward more inclusive, personalized, and effective learning environments.

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