Computers and Education: Artificial Intelligence 9 (2025) 100429

Contents lists available at ScienceDirect

Computers and Education: Artificial Intelligence

journal homepage: www.sciencedirect.com/journal/computers-and-education-artificial-intelligence

Artificial intelligence-enabled adaptive learning platforms: A review

Le Ying Tan [a], Shiyu Hu [b], Darren J. Yeo [c], Kang Hao Cheong [a,b,*]

[a] College of Computing and Data Science (CCDS), Nanyang Technological University, 50 Nanyang Avenue, S639798, Singapore

[b] School of Physical and Mathematical Sciences, Nanyang Technological University, 21 Nanyang Link, S637371, Singapore

[c] Division of Psychology, School of Social Sciences, Nanyang Technological University, 48 Nanyang Avenue, S639818, Singapore

ARTICLE INFO

Keywords:
Adaptive learning platforms
Educational technology
AI for education
Pedagogy
Recommender system

ABSTRACT

This review provides a comprehensive analysis of adaptive learning platforms (ALPs) in education, focusing on their pedagogical foundations, AI-driven implementations, and the challenges and successes of real-world applications. By collecting and analyzing learner data, ALPs dynamically adjust instructional content and pathways to offer personalized learning experiences, enhancing learning outcomes. The paper explores ALP design frameworks, core algorithms, and evaluation metrics, and assesses their performance across diverse educational contexts through case studies. Lastly, the review highlights key challenges ALPs face, such as privacy concerns and faculty support for implementation, and offers insights into future trends in developing adaptive technologies. This review provides educators and researchers with valuable insights into how ALPs can be effectively applied in various educational settings.

1. Introduction

An adaptive learning platform (ALP) is an e-learning platform that utilizes adaptive technologies to dynamically tailor instructional content to meet individual students' learning needs. Through personalized instruction, each learner receives content suited to their unique profile, maximizing their learning outcomes (Peng et al., 2019).

ALPs personalize the learning experience in multiple ways, such as displaying content in a student's preferred format, recommending specific resources, offering individualized feedback (Liu et al., 2017b), and adjusting the sequence or difficulty level of tasks according to the student's progress (Xie et al., 2019). Consequently, ALPs enable targeted interventions that enhance learning outcomes and student engagement (Özyurt & Özyurt, 2015; Gligorea et al., 2023), expediting knowledge acquisition (Osadcha et al., 2020). These platforms, typically powered by artificial intelligence (AI) (Kardan et al., 2015), continuously analyze learners' data (e.g. prior knowledge, learning preferences (Jando et al., 2017)) to generate learner profiles, adapt resources, and suggest tailored learning paths, allowing each student to advance on a personalized trajectory towards mastery (Kem, 2022).

In contrast, traditional classroom or e-learning methods commonly adopt a "one-size-fits-all" approach (Ennouamani et al., 2020), where teachers provide the same resources to all students. Though limited in addressing individual learning needs, said approach is necessary in classrooms due to large class sizes and restricted time (Sharma et al., 2017). More traditional academic institutions may still rely on non-adaptive e-learning systems due to the lack of buy-in or upfront costs of investing in ALP infrastructure and content customization. However, such uniform instruction delivery may slow down advanced learners while overwhelming those who struggle with the material (Hwang et al., 2020). ALPs can address such limitations, offering a compelling solution to educational psychologist Benjamin Bloom's 2-sigma problem (Bloom, 1984), which demonstrated that one-on-one tutored students performed two standard deviations higher than group-taught peers. By dynamically adjusting to individual learning patterns just like a personal tutor, ALPs strive to bridge this gap, allowing group-taught students to achieve similar learning gains with personalized learning experiences at scale.

Educational institutions employ ALPs through various implementations: by leveraging platforms from external vendors (e.g. Knewton, Smart Sparrow, ALEKS, Realizeit) (Taylor et al., 2021; Alam, 2022) with both pre-made courses and content creation tools; integrating adaptive plugins into Learning Management Systems (e.g. Moodle (Gamage et al., 2022)); or developing in-house solutions. ALPs are deployed in diverse educational contexts, including Massive Open Online Courses (MOOCs) (Rosen et al., 2018), blended learning settings to enrich classroom learning (Liu, 2022), or as dedicated platforms for assign-

* Corresponding author at: College of Computing and Data Science (CCDS) and School of Physical and Mathematical Sciences (SPMS), Nanyang Technological University, 50 Nanyang Avenue, S639798, Singapore.

E-mail address: kanghao.cheong@ntu.edu.sg (K.H. Cheong).

https://doi.org/10.1016/j.caeai.2025.100429
Received 5 December 2024; Received in revised form 2 April 2025; Accepted 26 May 2025
Available online 30 May 2025

ments (Farmer et al., 2020) and pre-class preparations (Kaw et al., 2019).

1.1. The anatomy of ALPs

ALPs generally comprise three core components: the learner model, the domain model, and the adaptation model (Gligorea et al., 2023), as shown in Fig. 1.

The learner model constructs a profile of each learner by employing educational data mining (EDM) techniques (Romero & Ventura, 2020) to capture environmental, demographic, cognitive, behavioral, and emotional attributes (Martin et al., 2020). These attributes may include demographic information (e.g. age, location), responses to assessments, task completion attempts, prior knowledge, cognitive capacities, learning preferences, personality traits, self-efficacy, motivation, internet connectivity, affect and device specifications (Imhof et al., 2020; Fatahi, 2019; Mousavinasab et al., 2021; Gómez et al., 2014; Thalmann, 2014). Data for these attributes can be collected via questionnaires, user interaction tracking (Apoki et al., 2020), or machine learning algorithms (Afini Normadhi et al., 2019). Sensors detecting facial expressions, eye movements, or heart rates may even be integrated to determine concentration and emotional states (Gumbheer et al., 2022). Affective states can also be inferred from recording students' verbal remarks in real-time when they attempt the learning module using speech recognition technology (Grawemeyer et al., 2017). Through such methods, the learner model remains dynamic, constantly updating learner characteristics as he progresses through his learning path (Liu et al., 2017a).

The domain model organizes the knowledge and skills relevant to the ALP's subject area (Premlatha & Geetha, 2015). It structures content into discrete learning objects (e.g. lessons, quizzes, exercises) and defines their relationships (Martin et al., 2020) to establish a "hierarchy of instructional resources" that aligns with specific learning outcomes (Ennouamani et al., 2020).

The adaptation model dictates the adaptation process, determining the content delivery based on learner attributes derived from the learner model, such as prior knowledge, cognitive style, resource preference, and motivation level (Nakic et al., 2015). Numerous studies have customized learning content and format based on students' predicted Felder-Silverman learning styles, resulting in learning gains (Truong, 2016). Bauer et al. proposed adjusting content recommendations based on motivation levels, while Hassan et al. tailored gamified elements based on students' tracked collaborative tendencies, such as offering autonomous tasks for self-directed learners or group-based activities for social learners (Bauer et al., 2019; Awais Hassan et al., 2019).

Adaptation models can be further differentiated as having task-loop and/or step-loop adaptivity. Task-loop adaptivity selects resources for learners to interact with (e.g. giving a student questions on topics he has yet to master), whereas step-loop adaptivity refines the learning experience by responding to behaviors within each learning activity (e.g. personalized feedback to students' submissions) (Aleven et al., 2016).

Adaptation in ALPs can be implemented through various methods:

1. **Adaptive content**: This approach customizes educational resources based on identified learner characteristics. For instance, an ALP may prevent a student from advancing to the next module until they have mastered the current content, redirecting them to review unmet objectives (Marienko et al., 2020; Morze et al., 2021). The platform may also offer personalized feedback, hints, or recommend supplementary materials (Aggarwal, 2023). For students with slower progress, additional examples or explanations may be provided for further support (Lim et al., 2022).
2. **Adaptive assessment**: Here, question difficulty is tailored to the student's previous responses, allowing for a personalized progression through assessments (Louhab et al., 2018). For example, the Smart Sparrow platform assigns more challenging questions to high-performing students while simplifying questions for those who answered incorrectly in previous (Marienko et al., 2020).
3. **Adaptive sequencing**: This method adjusts the order of educational content based on learner data, such as answer accuracy and time spent on tasks. By identifying knowledge gaps, the ALP can rearrange content to prompt students to revisit weak areas before progressing to more advanced topics (Morze et al., 2021; Marienko et al., 2020).

1.2. Pedagogical underpinnings of ALPs

Some scholars critique the limited pedagogical grounding in empirical studies on ALPs (or AI in education), advocating for research that prioritizes validating educational theories alongside technological advancements (Bremgartner et al., 2015; Zawacki-Richter et al., 2019; Bartolomé et al., 2018). In response, this review examines the key pedagogical frameworks, philosophies, and theories that underpin typical ALP designs.

The ALP serves as a modern, digitized realization of mastery learning, which is an instructional technique developed by Bloom, the proponent of the aforementioned 2-sigma problem. Mastery learning structures knowledge into smaller units for gradual learning, followed by assessments. Students receive corrective feedback and remediation as needed until they achieve mastery, after which they advance to the next stage (Murray & Pérez, 2015). ALPs incorporate this approach through task- and step-loop adaptivity, using targeted feedback, assessment, and sequencing based on each student's needs.

ALPs also support aptitude-treatment interactions, wherein instructional strategies are tailored to the learner's ability, resulting in optimal learning outcomes. One-size-fits-all strategies do not account for individual learner differences; for instance, novice students benefit from more structured guidance, whereas proficient learners may face cognitive overload from excessive information (Imhof et al., 2020). ALPs mitigate this by adjusting content to align with each learner's progress, providing optimal instructional support tailored to varying aptitudes.

Dynamic scaffolding is another pedagogical principle integrated into ALPs. This approach, based on Vygotsky's Zone of Proximal Development (ZPD), provides incremental support, such as hints or partial solutions, to bridge learning gaps. As students become more capable, these supports are gradually removed. ALPs dynamically adjust scaffolding by continuously analyzing learner data to provide personalized assistance, mirroring the evolving ZPD as the student's knowledge and capabilities increase (Wu et al., 2017).

Revised Bloom's Taxonomy (RBT) also influences the design of adaptive learning activities within ALPs. RBT offers a hierarchical framework for learning objectives across cognitive levels, from Remembering to Creating. For example, an ALP may first guide students through simpler questions (e.g. True/False) and gradually progress to more complex tasks (e.g. essay writing) (Krouska et al., 2019).

Comprehending an ALP's pedagogical foundations is essential for understanding its design and functionality. This foundation establishes the groundwork for further exploration into ALP implementation, which is outlined in the following sections. More specifically, Section 2 will describe the research methods and criteria used for selecting referenced works, Section 3 will review design principles and evaluation metrics, Section 4 will detail algorithms used in learner and adaptation modeling, Section 5 will discuss the effectiveness and challenges of ALP applications, and Section 6 will explore future developments.

2. Methods

To address the identified research areas, we conducted a systematic search for empirical studies and theoretical works on ALPs, as depicted

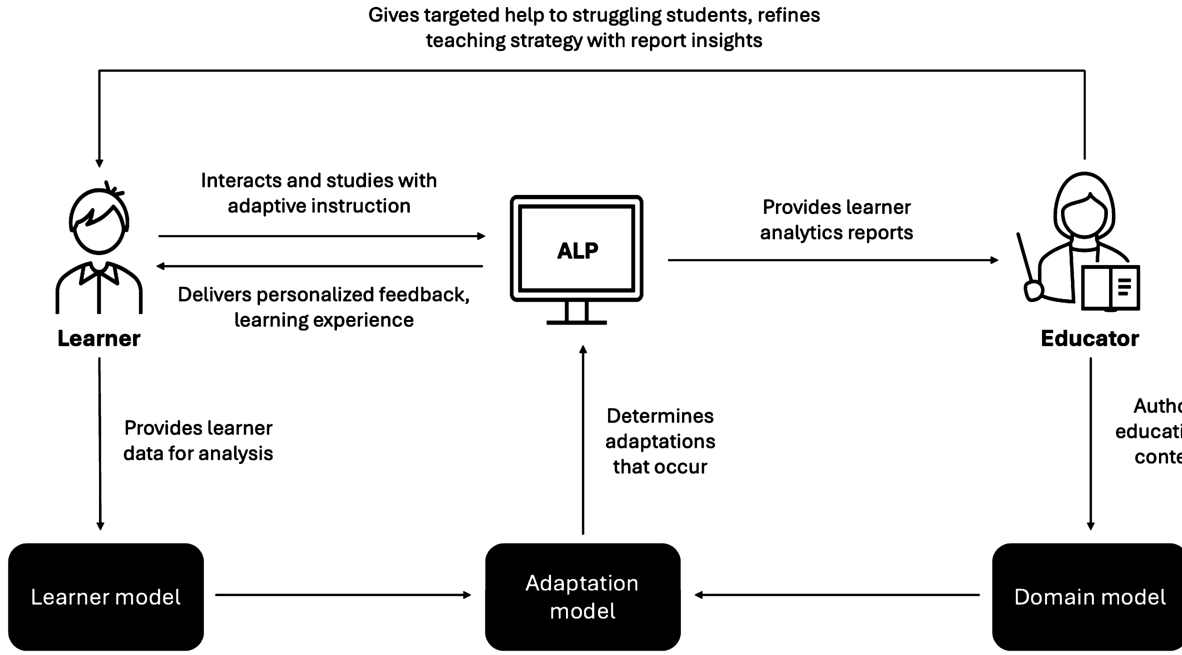

Fig. 1. Schematic diagram representing the overall structure of an ALP.

in the PRISMA flow diagram in Fig. 2. The following criteria guided our search:

Resources were retrieved from the following databases: Google Scholar, IEEE Xplore, Educational Resource Information Center, and Web of Science, resulting in an initial pool of 154 papers. The search focused on publications from 2014 to 2024 to capture recent advancements in the rapidly evolving field of ALPs. We used keywords such as "adaptive learning platforms," "adaptive e-learning," "education research," and "educational pedagogy". Only peer-reviewed papers were included to enhance the validity and credibility of this review.

After the initial screening, 6 duplicate papers were removed. In the subsequent screening, 32 additional papers were excluded following a detailed review of abstracts and introductions. Only studies directly addressing online instruction adaptation (e.g. content, assessment, or sequencing) were included. Studies that did not explicitly address adaptive learning mechanisms or pedagogy relevant to ALPs were excluded. We included empirical research and review papers to maintain a focus on evidence-based sources.

The final selection comprises 127 papers, including 75 empirical studies that detail the development or application of ALPs, and 52 review papers or studies focused on pedagogical research and conceptual frameworks. These works will be analyzed to address the following questions:

1. What frameworks and principles guide the design, implementation, and evaluation of ALPs?
2. What algorithms are employed in the development of ALPs?
3. How are ALPs currently implemented in educational settings, and what are the associated implications?

These questions are critical for understanding how ALPs can be leveraged to improve educational outcomes and meet diverse learner needs.

3. ALP design considerations and evaluation

This section reviews literature on frameworks and principles that inform ALP design (Section 3.1) and identifies metrics commonly used to evaluate ALP implementations (Section 3.2).

3.1. Design frameworks

The following two frameworks offer distinct methodologies for creating personalized learning experiences. Developed by reputable academic institutions or adapted from well-established instructional models, these frameworks are widely cited by other works and serve as foundational resources in ALP design.

3.1.1. University of central Florida's adaptive learning design framework

Instructional designers at the University of Central Florida (UCF) developed the Adaptive Learning Design Framework to support adaptive course design, enabling personalized content and assessments tailored to individual student needs (Cavanagh et al., 2020). This framework consolidates best practices accumulated through years of experience since UCF's initial adoption of adaptive learning in 2014 and is now applied universally across the institution. It comprises five key components, as shown in Fig. 3.

3.1.2. ADDIE instructional design framework

The ADDIE model, a foundational instructional design model, consists of five steps: Analysis, Design, Development, Implementation, and Evaluation. El-Sabagh adapted this model specifically for ALP design (El-Sabagh, 2021) as follows:

- **Analysis**: Identify learning objectives, student characteristics to be analyzed, syllabus to be taught, and more.
- **Design**: Develop personalized learning paths and determine the structure and navigation of course materials by establishing relationships among learning objects (e.g. instructional content, assessments).
- **Development**: Create storyboards, author adaptive content, and develop the technological platforms (e.g. mobile app or website) for accessing the ALP.
- **Implementation**: Validate created course materials (e.g. whether it is consistent with syllabus) and analyze students' engagement with the ALP.
- **Evaluation**: Conduct formative and summative evaluations on instructional quality, interface design, and usability, using feedback to make iterative improvements.

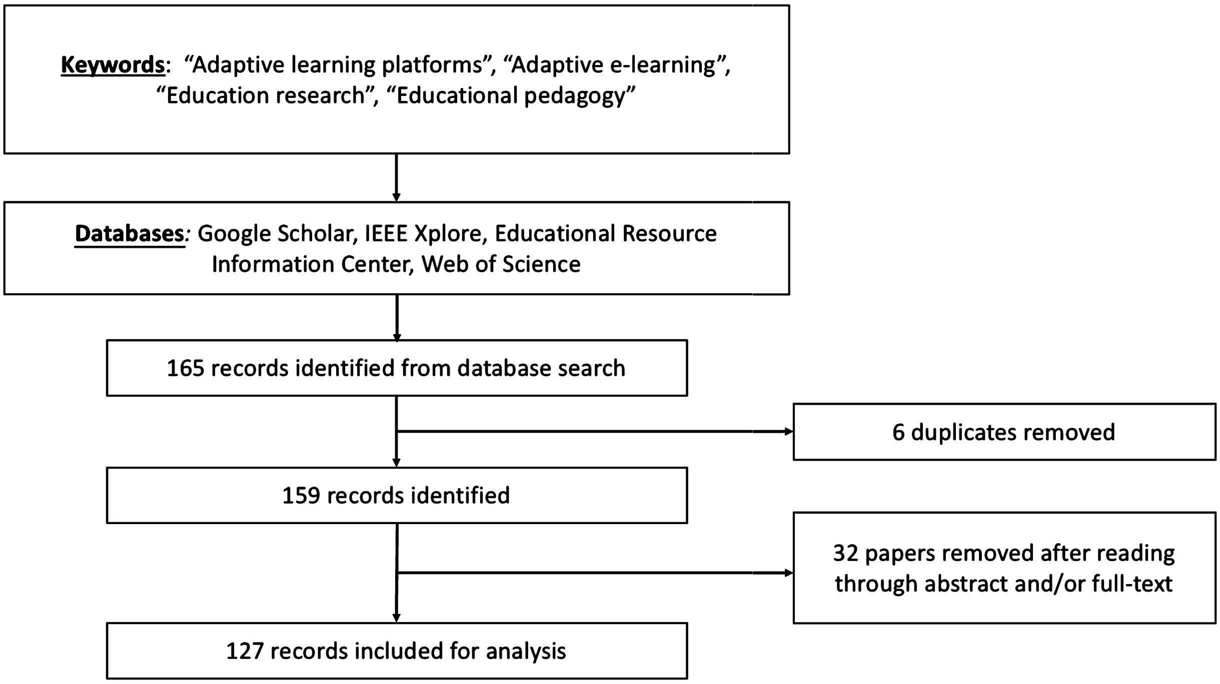

Fig. 2. PRISMA flow diagram for selecting papers to include in this review.

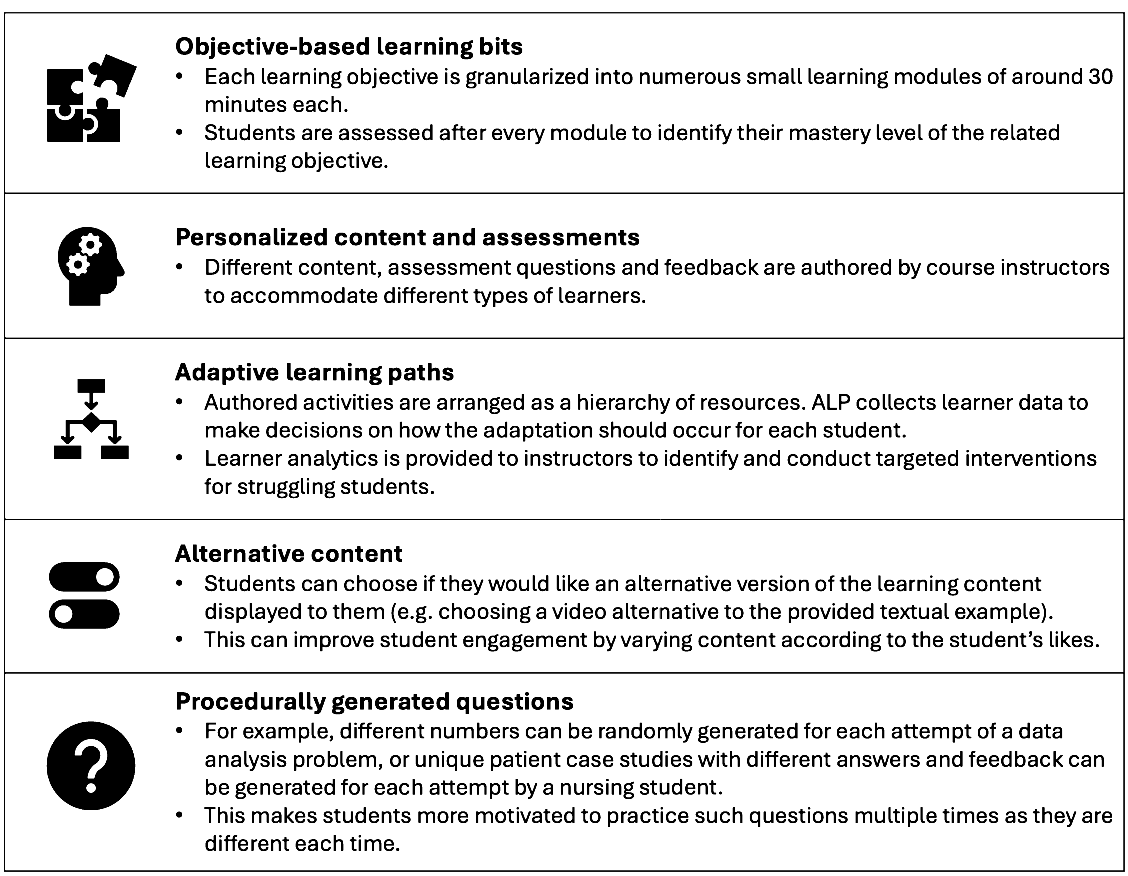

Fig. 3. Framework on designing an ALP proposed by (Cavanagh et al., 2020).

Table 1
Methods to evaluate the effectiveness of ALPs.

Evaluation Metric	Evaluation Instrument
Learning gains	The instructional effectiveness of an ALP can be quantitatively assessed by analyzing improvements in student performance using a pre- and post-test methodology. Students take a pre-test to establish baseline knowledge, and after interacting with the ALP, a post-test measures learning gains (Mohammad & Alshammari, 2019).
Learner satisfaction	Learner satisfaction reflects students' perceptions of their experience with the ALP. Lim et al. used the Learner Satisfaction Questionnaire for e-learning tools to evaluate factors like user-friendliness and content relevance among Singaporean part-time learners (Lim et al., 2022). Liu et al. surveyed pharmacy students on usage experience (e.g. navigation ease) and learning experience (e.g. effectiveness of tasks and feedback), and held focus groups to collect feedback (Liu et al., 2017b).
Student engagement	An ALP's effectiveness can also be evaluated by student engagement, defined as the learner's behavioral, cognitive, emotional, and motivational involvement in the learning process. High engagement levels are associated with better performance (Ifenthaler et al., 2018). El-Sabagh adapted the Dixson scale to assess engagement, providing students with a 5-point scale to rate skills, participation, emotion (e.g. interest), and performance (El-Sabagh, 2021).
Learner motivation	Motivation, which drives goal-directed behavior, is another key evaluation metric (Bauer et al., 2019). Motivation levels can be measured through self-reported questionnaires like the Motivated Strategies for Learning Questionnaire (Farmer et al., 2020), analysis of learner interactions with the ALP, or sensors tracking facial expressions, posture, and heart rate (Aleven et al., 2016).

The ADDIE model provides a structured, sequential approach to instructional design, ensuring that the ALP addresses learner needs comprehensively. In contrast, the UCF framework specifies essential features for ALPs without a strict sequence, offering a checklist of elements to include. Together, these models form a comprehensive guide for ALP development, with ADDIE detailing a step-by-step process and UCF focusing on key content and functional requirements.

In addition to technical and pedagogical considerations, practical factors like scalability, cost-effectiveness, open learner models for transparency, adaptability for non-STEM fields, and integration with enterprise systems, as highlighted by Essa (Essa, 2016), are essential. By incorporating these elements, designers can create ALPs that are pedagogically sound and sustainable in real-world educational settings.

3.2. Evaluation

As we transition from theory to practice, it becomes essential to examine how these platforms perform in real-world educational settings. Table 1 draws from relevant empirical works to discuss the metrics and instruments employed to evaluate ALPs.

4. Algorithms powering ALPs

To analyze learner data and adapt educational content delivery in real-time, ALP backends typically employ AI techniques ranging from basic rule-based systems to advanced machine learning algorithms (Mirata et al., 2020). This section focuses on the AI methods used in the learner model (Section 4.1) and adaptation model (Section 4.2).

4.1. Learner model

Learner modeling algorithms are computational techniques used to create a representation of the learner characteristics upon which adaptations are based. As displayed in Fig. 4, a student's performance (i.e. competence, ability) was found to be the most frequently used learner characteristic in ALPs, appearing in 78% of 75 empirical studies. This is followed by learning styles, which were used in 16% of the analyzed systems. Characteristics like social behavior and student engagement were also incorporated into ALPs, though to a lesser extent. To adequately capture such variety of learner characteristics, various AI approaches were employed.

For example, the Fuzzy C-Means algorithm clusters user data (e.g. time spent on learning objects) according to the Felder-Silverman Learning Style Model, helping to identify students' learning styles (Azzi et al., 2020). Alternatively, Martin and Maria used the Random Forest algorithm to classify learners into VARK learning styles based on user interactions with the ALP (Martin & Maria, 2019).

Deep Knowledge Tracing, employing Recurrent Neural Networks, can dynamically represent a student's knowledge state on specific skills by taking inputs such as skill level and responses to problems (Sein Minn, 2022). Maravanyika et al. applied Item Response Theory, using mathematical functions to model latent traits like ability, with adaptive assessment responses and item characteristics (e.g. difficulty, guess-ability). Probabilistic Graphical Models, such as Bayesian Networks, then use this data to infer readiness for new topics based on assessed student proficiency (Maravanyika et al., 2017). Matrix Factorization can predict scores and completion times for learning objects, which inform sequence adjustments, such as advancing to the next learning object or revisiting unmastered content (Nabizadeh et al., 2020). Wu et al. applied the YOLOR model in computer vision to detect students' hand actions (e.g. typing on computer to complete project, assembling Raspberry Pi components) in recordings to measure engagement in class (Wu et al., 2023). These learner characteristics then guide decisions in the adaptation model.

4.2. Adaptation model

The adaptation model utilizes data from the learner model to customize each student's learning process. Recommender systems drive this model by delivering learning activities "at the right time, in the right context, and in the right way" (Maravanyika et al., 2017). Based on learner model insights, these systems recommend resources from the domain model tailored to each student's needs, such as simpler or more complex questions aligned with the student's knowledge level, or selecting video versus text instructions based on learning style. Recommender systems continuously make decisions about the next learning steps using real-time information (Chen et al., 2018). Table 2 outlines various approaches for constructing recommender systems within ALPs.

The programmatic implementations discussed above vary in complexity and technical sophistication, but all aims to connect pedagogical components with adaptation criteria to enable real-time customization of educational resources, addressing learner variability (Talaghzi et al., 2020). This adaptive approach enhances learning outcomes and reduces information overload for students (Khanal et al., 2020). To understand the evolution of adaptive learning technologies, we conducted a temporal analysis of AI techniques used in ALPs between 2014 and 2024. As illustrated in Fig. 5, rule-based methods were dominant during 2014–2019 (27.9%), whereas recent years (2020–2024) witnessed a notable increase in deep learning techniques (from 4.7% to 9.4%) and the emergence of generative AI (12.5%). This shift reflects a broader trend toward more context-aware and personalized adaptation approaches. Not all studies disclosed the algorithms used, especially those involving commercial platforms or proprietary systems.

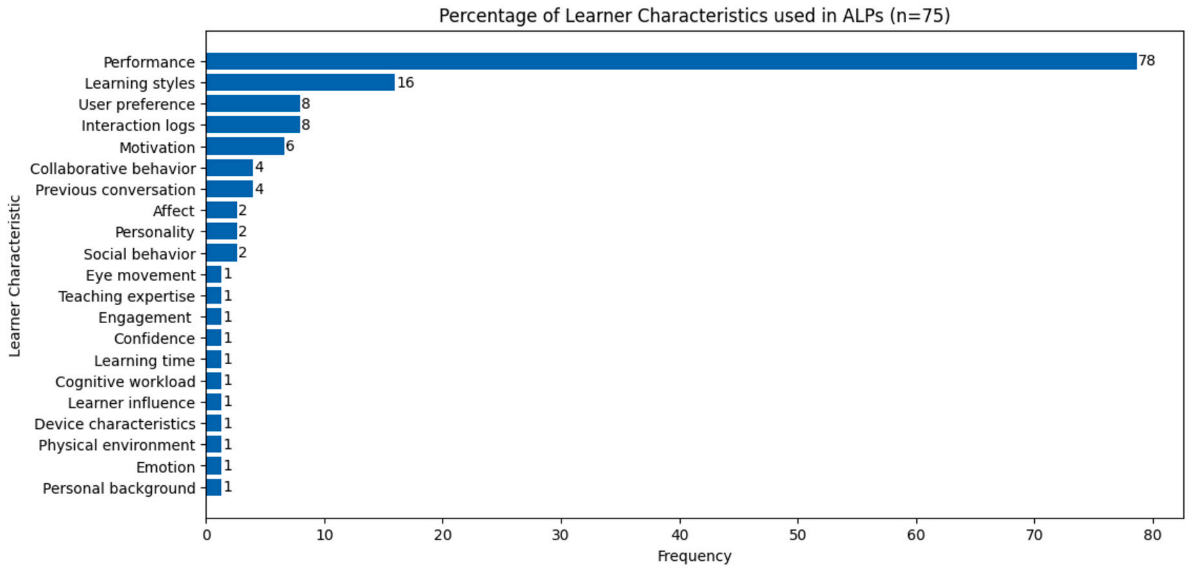

Fig. 4. Chart visualizing the distribution of learner characteristics involved in ALP empirical studies (n = 75).

Table 2
Implementation approaches of recommender systems in ALPs.

Technique	Implementation Details
Fuzzy logic, Rule-based (Troussas et al., 2021)	The ALP uses fuzzy logic and Revised Bloom's Taxonomy (RBT) to assign students to one of seven learning levels (Novice to Expert). This enables tailored learning activity recommendations; advanced students receive fewer, more complex tasks at higher RBT levels, such as solution creation or essay writing.
Rule-based (Said, 2019)	Content formats (e.g. video, text) are scored based on user preferences, battery level, and connectivity. The format with the highest cumulative score is displayed to the learner.
Reinforcement learning (Shawky & Badawi, 2019; Sayed et al., 2023)	Reinforcement learning selects actions (e.g. recommending materials) based on the student's current state (e.g. knowledge level), following an ϵ-greedy policy. Actions are rewarded based on student feedback and academic improvement, creating a personalized learning path.
Neural network (Pardos et al., 2017)	Long Short-Term Memory (LSTM) networks use students' click-stream events to predict and recommend the next page in an adaptive MOOC, enhancing navigation efficiency.
Self-organizing map, Neural network (Idris et al., 2017)	This hybrid approach leverages both unsupervised and supervised learning. First, a Self-Organizing Map clusters and labels learning materials. Then, a Multi-Layer Perceptron classifies and selects content based on student knowledge levels.
Genetic algorithm, Ant colony optimization (Birjali et al., 2018)	A MapReduce-based Genetic Algorithm determines a student's remaining educational objectives based on pre-requisite knowledge. Ant Colony Optimization then generates a personalized learning path, with material volume adjusted based on student motivation and social productivity inferred from social media data.
Collaborative filtering (Madani et al., 2020)	Social collaborative filtering uses learners' social media data to identify similar users, recommending content previously completed by similar peers through K-Nearest Neighbor and cosine similarity.
Collaborative filtering, Neural network (Saito & Watanobe, 2020)	A student's ability chart is updated to identify similar learners through k-means clustering. An LSTM network then predicts and recommends the next best problem based on competence level and history.
Fuzzy logic, Clustering, Sequential pattern mining (Wan & Niu, 2020)	Learners are grouped into cliques using a Learner Influence Model optimized by intuitionistic fuzzy logic. Sequential pattern mining then assigns a learning path to each clique.
Large Language Models (Generative AI) (Abolnejadian et al., 2024)	OpenAI's gpt-3.5-turbo model is prompted to adopt the persona of a programming teacher and recommend adaptive explanations to each student, given personal information such as their age, grades and prior coding experience. As such, the model generates explanations with more detail and examples for less proficient students, while giving proficient learners more concise answers and advanced examples.

The insights in this section reflect the current state of adaptive learning technology, offering a foundation for developers and educators to evaluate and build upon for specific applications.

5. Current ALP usage

ALPs have been implemented in educational settings across a plethora of disciplines and age groups. Figs. 6 and 7 demonstrate the distribution of these systems across various subject domains and education levels in the dataset of 75 empirical studies. As shown, while most ALPs developed typically focus on STEM-related subjects such as Computer Science and Math, other fields like Psychology and Music are represented as well. Over half of all ALPs were designed for tertiary education, though a substantial percentage also caters to primary and secondary school students. To dive deeper into the diverse applications of ALP, this section will present their implementations in the contemporary educational landscape (Section 5.1), discuss their reception and implications (Section 5.2 and Section 5.3), as well as the challenges pertaining to their implementation (Section 5.4).

5.1. Implementation across educational levels and disciplines

YiXue's Squirrel AI Learning is a mathematics ALP for Chinese middle school students, adapting content based on student abilities. Fast

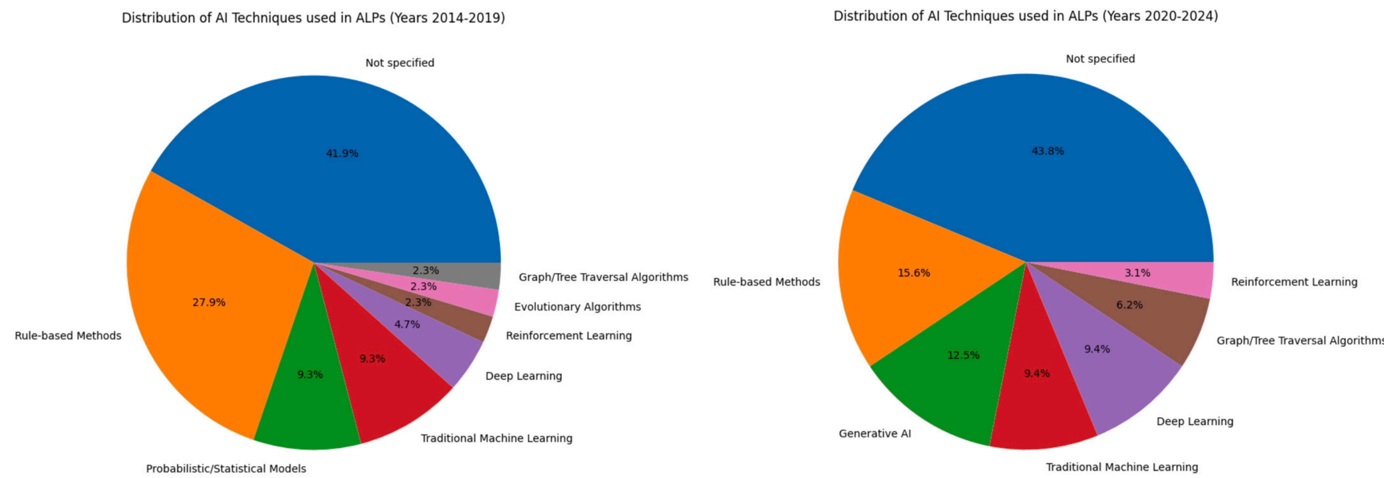

Fig. 5. Evolution of AI techniques used in ALPs from 2014-2024.

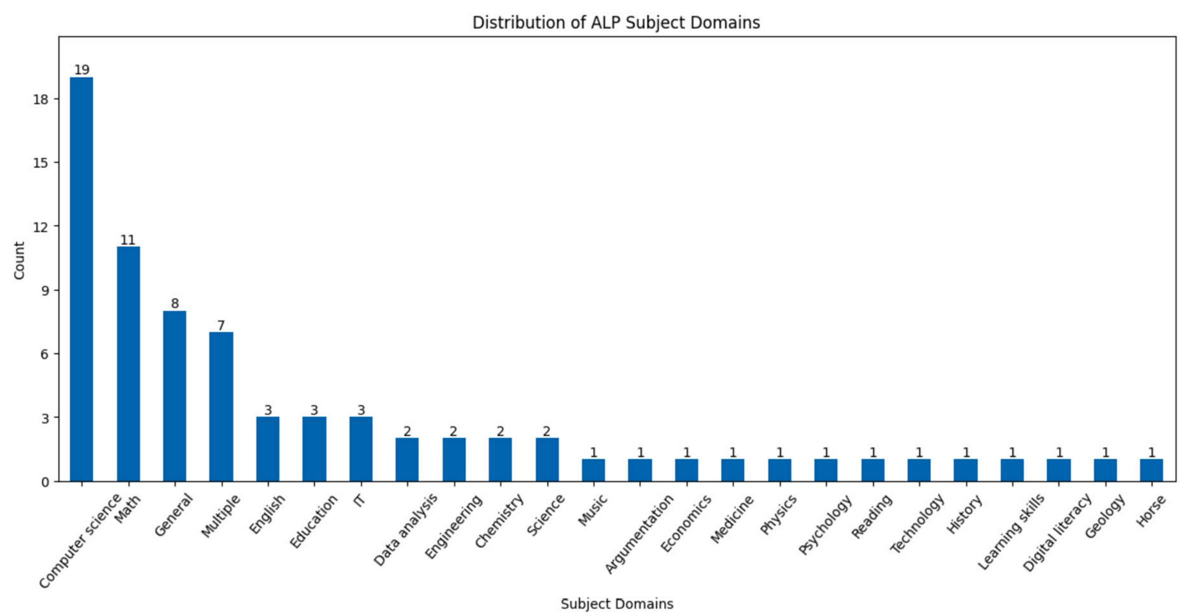

Fig. 6. Chart visualizing the distribution of subject domains of ALP empirical studies (n = 75).

learners are presented with more complex problems, while those struggling receive tutorials and resources for review (Li et al., 2018). In two experiments comparing ALP and teacher-led instruction, Wang et al. found that 75.5% of ALP-using students in small classes and 64.4% in large classes scored above the mean of teacher-led groups, indicating that ALPs may be effective across different class sizes and even outperform traditional teaching in some cases (Wang et al., 2023). However, teachers remain integral to the learning process; YiXue can be used as a blended tool, allowing teachers more time to provide targeted assistance and encourage classroom discussions (Li et al., 2018).

Another example, TECH8, adapts learning content based on students' Technology and Science knowledge levels, offering additional materials and explanations for less proficient learners. In a study with 117 Slovenian secondary school students, those using TECH8 outperformed peers in a control group by over 10% on a summative assessment (Dolenc & Aberšek, 2015). Chen designed an ALP for physics, which adjusts scaffolding based on students' cognitive and motivational levels. Taiwanese students who used the ALP achieved higher grades and motivation scores than those in the control group (Chen, 2014). Ristić's ALP adapts content by matching learning objects to students' learning styles, such as audio to auditory learners and flowcharts to visual learners. A study found that IT students who used the ALP outperformed those in the standard course both immediately and one month after course completion, indicating that the ALP improved knowledge retention over time (Ristić et al., 2023).

Positive outcomes have also been observed in younger learners. Villesseche et al. developed an ALP for French primary school students that adapts reading comprehension exercises according to performance. Results showed that extended ALP use led to better outcomes, with less proficient students (especially girls) and older pupils making the most progress (Villesseche et al., 2019).

ALP usage is also prevalent in higher education. Undergraduates using Realizeit in a General Psychology course reported high satisfaction, finding the ALP effective for engagement and knowledge assessment. 78% indicated they would take another Realizeit-based course (Dziuban et al., 2016). Arizona State University's cybersecurity students used ThoTh Lab, an ALP for virtual lab sessions that adapt content according to learning styles, enhancing engagement and improving grades for 65% of students (Deng et al., 2018). Brinton et al. designed an adaptive MOOC alternative, the Mobile Integrated and Individualized Course, which personalizes learning sequences and scaffolding. Student engagement was 72% higher in this ALP than in traditional one-size-fits-all

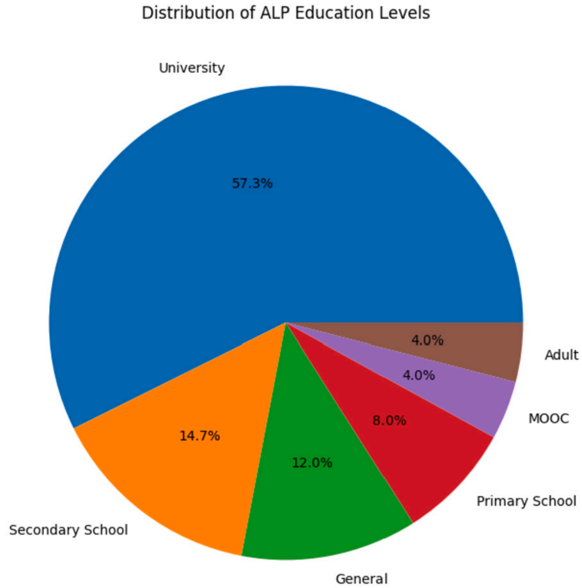

Fig. 7. Chart visualizing the distribution of education levels of ALP empirical studies (n = 75).

courses, potentially reducing dropout rates (Brinton et al., 2015). These positive results extend to adult learners, including in-service teachers who used an ALP to enhance their TPACK skills in integrating technology into their teaching. The participants who received adaptive content tailored to their teaching fields and performance outperformed the control group using a conventional system with mean scores of 230.67 and 191.97 respectively (Elmaadaway & Abouelenein, 2023).

ALPs are even effective in creative disciplines. Yuksel et al. introduced BACh, an adaptive brain-computer interface that adjusts task difficulty based on cognitive workload during musical training, resulting in fewer errors and missed notes (Yuksel et al., 2016). Other positive outcomes have been observed across diverse fields, including programming courses in Morocco (Ennouamani et al., 2020), IT courses in Serbia (Arsovic & Stefanovic, 2020), medical education in Barbados (Gupta et al., 2020), primary school education in Czech Republic (Hubalovsky et al., 2019), educational design courses (Li & Li, 2024) and English pronunciation training for Chinese undergraduates (Hengbin Yan & Liu, 2018).

Educators' perspectives on ALPs are also valuable. Delgado et al. studied My English Lab, an ALP by Pearson that provides instant feedback for English learners. Teachers reported increased student motivation, higher grades, and greater commitment, noting that the ALP's learner analytics help tailor subsequent lessons to address student weaknesses (Orsi Koch Delgado et al., 2020).

5.2. Factors undermining effectiveness of ALPs

It is noteworthy that although less common, some studies have reported less favorable outcomes. Said's experiment with an ALP that adapted content display based on device connectivity and student preferences showed no significant difference in post-test scores between ALP and non-ALP groups of Grade 11 students in Cairo, potentially due to the brief experiment duration (1 week) (Said, 2019).

Selecting inappropriate or overly simplistic learner characteristics for adaptation can also yield unsatisfactory results. Scheiter et al. designed an ALP that adapted content based solely on students' eye movements, zooming out materials if students showed brief fixation, encouraging re-reading. In two experiments with German university students, this approach did not benefit all learners. Results showed that students with less prior knowledge "suffered" from these adaptations, while those with more prior knowledge benefited, and user satisfaction was similar across adaptive and non-adaptive groups. This outcome suggests that eye movements alone may not accurately capture learning behaviors, as longer fixation could indicate slow or incorrect processing rather than engagement. These findings emphasize the importance of choosing meaningful and multi-dimensional learner characteristics for effective adaptation (Scheiter et al., 2019).

White's study explored an ALP that adjusted question difficulty based on students' performance and confidence. While no correlation was found between ALP usage and improved academic results, students had a positive perception of the ALP. Positive attitudes towards an ALP can foster intrinsic motivation, potentially encouraging self-driven, long-term learning habits even if immediate academic improvements are not evident (White, 2020).

In general, however, ALPs have demonstrated positive impacts on learning performance, engagement, motivation, and satisfaction across various disciplines, age groups, and types of adaptation.

5.3. The role of learning analytics

As mentioned in Subsection 5.1, integrating learner analytics (LA) into ALPs offers clear benefits for educators. LA involves interpreting learner data to understand their learning process and behaviors more deeply (Liu et al., 2017a). It provides a "real-time view of student progress that is not available in other teaching methods (Dziuban et al., 2018). Since ALPs already collect student data (e.g. test scores, engagement levels) to refine the learner model and drive adaptation, inherent access is provided to the information necessary to create comprehensive LA visualizations. After a series of data processing and aggregation, LA can then be visualized on a dashboard, enabling live progress tracking. For example, Moltudal's ALP directly depicts students' competence levels using color-codes like red, yellow and green to facilitate quick assessment by teachers (Moltudal et al., 2022). YiXue's ALP offers dashboards that monitor student progress, presenting their submissions and response durations for each question (Cui et al., 2018). Teachers can monitor LA before and after lessons to continuously adjust their instructional strategies according to student needs, addressing common class misconceptions. (Rincon-Flores et al., 2024).

Additional data processing, such as merging LA with other school data, can provide further insights, like tracking performance trends over time and identifying areas for curriculum improvement (Aristizábal, 2018). A notable example is González-Castro et al.'s LA dashboard, which features item characteristic curves (which shows how likely students are going to answer a question correctly based on their ability) and item information curves (which indicates how much information a question provides about a learner's ability), informing instructors on each question's difficulty level and effectiveness. These visualizations have been positively acknowledged by instructors for usefulness in redesigning course content and assessments (González-Castro et al., 2021). Students' data can be further used to build classification models that predict future academic performance as part of an Early Warning System. Predicted at-risk students can be surfaced in the LA dashboards, allowing instructors to identify them and provide timely intervention (Alam, 2023).

LA visualizations can also empower students by enabling them to make data-driven decisions. These visualizations allow students to compare their progress with peers and reflect on their learning behaviors (Vesin et al., 2018). By fostering self-regulated learning (Anna Mavroudi & Krogstie, 2018), students become more active in goal-setting, strategy use, self-evaluation, help-seeking, and perseverance (Harati et al., 2021), leading to better learning outcomes. This aligns with the idea that ALPs can enhance students' metacognitive skills, helping them assess and adjust their learning strategies (Kem, 2022), and promoting more effective knowledge acquisition (Eau et al., 2019).

A related concept to LA is the Open Learner Model (OLM), which externalizes a student's learner model to make their progress and learning attributes transparent. For instance, an OLM may visualize competencies, assessment performance, and other learner characteristics (Abyaa et al., 2019). Besides increasing motivation and supporting self-evaluation, an OLM adds transparency to ALP recommendations. RiPPLE, an ALP by Khosravi et al., implemented an OLM allowing undergraduates to view their mastery levels across topics. Most users agreed that these visualizations improved their understanding of the ALP's recommendations and increased their trust in the system (Khosravi et al., 2020).

5.4. Challenges to ALP implementation

While ALPs show promise in enhancing educational outcomes, their implementation faces several challenges. Privacy and security of learner data are significant concerns as ALPs become more widespread (Li et al., 2021). Zawacki-Richter et al. noted a lack of focus on privacy issues in many studies (Zawacki-Richter et al., 2019), even though substantial data is collected whenever students engage with ALPs. The accuracy of personalized adaptation requires sensitive data collection, such as location and emotional state, which may discomfort users. To address these concerns, ALP developers and stakeholders must establish data governance frameworks, implement privacy-preserving data storage and processing, and ensure compliance with relevant regulations.

Institutional challenges also exist. Muñoz et al. highlighted the lack of leadership support and resistance to adopting innovative technologies in some educational institutions (Muñoz et al., 2022). Similarly, a Delphi study comparing South African and Swiss universities identified common obstacles, including "institutional commitment to adaptive learning" and limited "financial and personnel resources" (Mirata et al., 2020). Effective ALP implementation requires dedicated IT support, financial investment, personnel, and time. For instance, faculty collaboration with instructional designers at the University of Central Florida can take six or more academic semesters to develop a single adaptive course (Cavanagh et al., 2020).

Educators also require training and support to effectively use ALPs. A study on the Smart Science Initiative in Australia revealed that most teachers did not use the ALP's advanced analytics, preferring traditional classroom techniques and expressing uncertainty about using the tools (Ng & Fergusson, 2019). Students may also face adaptation challenges. For example, Danish teachers in a professional development ALP reported anxiety when their personalized learning paths did not cover the entire curriculum, leading them to study all materials instead of their designated paths (academic fear of missing out), resulting in inefficient learning practices (Petersen & Gundersen, 2019). It is crucial to guide both teachers and students on how to use ALPs to maximize their benefits.

To foster support for ALPs, Georgia State University launched workshops for course coordinators and support staff, providing insights into ALP benefits, design, and evaluation, and encouraging community dialogue around adaptive learning (Tesene, 2018). Mirata et al. further recommend hiring instructional designers to collaborate with faculty on adaptive course design, providing high-quality training for both educators and students, and incorporating adaptive learning into institutional strategies to promote innovation (Mirata et al., 2020). Additionally, involving faculty and students in ALP development and testing can enhance usability and satisfaction. Colorado Technical University held focus group discussions with faculty and students after each course pilot, allowing the team to gather feedback and make key adjustments before a larger rollout (Dziuban et al., 2017).

6. Future trends

The future of ALPs is set to see major advancements across key areas. Technological developments, especially in artificial intelligence and big data, will continue to enhance ALPs' personalization capabilities. As data-driven decision-making grows in education, ALPs will play a vital role in shaping policy, instructional innovation, and promoting educational equity. The following sections explore these trends in detail.

ALPs are expected to integrate advanced technologies such as augmented reality (AR), virtual reality (VR), gamification, and large language models (LLMs), creating immersive and personalized learning environments. For instance, adaptive 3D virtual environments can tailor learning scenes by highlighting, hiding, or organizing 3D objects based on individual learner needs (Scott et al., 2017). Similarly, narrative-driven educational games provide adaptive scaffolding, adjusting feedback and hints to match each learner's unique needs (Alam et al., 2018). Min et al.'s Engage game, which uses block-based programming to teach computational thinking, captures students' in-game interactions to infer affective states and gameplay skills, dynamically adapting challenges and plotlines to personalize learning experiences (Min et al., 2020). Gamification elements in ALPs also boost motivation. For example, Hassan et al. tailored gamified experiences based on learning styles in a computer science course, showing increased motivation and reduced dropout rates (Muhammad Awais Hassan et al., 2021).

The use of chatbots in ALPs is also likely to grow, as the use of LLMs gain more prominence in the field. Chatbots leverage LLMs to offer students instant feedback personalized to their answers, simulating a private tutor (Sajja et al., 2023). ArgueTutor, a chatbot that provides feedback on persuasive writing, improved the quality of student arguments and received positive user satisfaction (Wambsganss et al., 2021). LearningPartnerBot by Kaiss et al. can answer students' queries and suggest relevant learning recommendations based on students' learning styles (e.g. suggesting text materials for verbal learners, videos for visual learners). It was shown that using the chatbot led to more beginners progressing to intermediate and advanced programming proficiency levels (Kaiss et al., 2023). SAMCares, a chatbot for Sam Houston State University, uses a technology called Retrieval-Augmented Generation to enrich an LLM's knowledge with course-specific materials from an external database. As such, the LLM is able to provide answers adapted to students' questions with increased accuracy (Faruqui et al., 2024). Beyond providing adaptive feedback and explanations, the presence of an encouraging chatbot can also improve student motivation by creating a supportive learning environment (Ruan et al., 2019).

Trends are also emerging in the ALP development process itself. Heffernan et al. propose that ALPs could leverage crowdsourcing from teachers and students to diversify available resources, such as tailored feedback for common misconceptions. PeerASSIST, a feature allowing students to share problem-solving approaches, demonstrates this approach, addressing the challenge of scaling learning resources in a growing ALP user base (Heffernan et al., 2016). Simplified development tools, like domain-specific language frameworks, further reduce technical barriers, enabling more educators to design adaptive virtual environments (Meacham et al., 2020).

Future ALPs will harness real-time data analysis, emotional insights, and behavioral tracking to dynamically adjust content and strategies, supporting highly personalized learning paths. These platforms will also allow interdisciplinary learning by seamlessly integrating various subjects. As ALPs increasingly rely on learner data, privacy and security will become essential. Advanced technologies like federated learning and data anonymization will protect user privacy while enabling robust data analysis, reducing potential security risks.

Beyond instructional applications, ALPs will increasingly contribute to educational policy by providing critical data for promoting educational equity, resource distribution, and performance assessment. Policy support for ALPs will foster widespread adoption, especially in schools from diverse socio-economic backgrounds.

In the coming years, ALPs will drive instructional innovation, policy reform, and equitable access to personalized learning. Recognized as the foundation for next-generation e-learning (Gurcan et al., 2021), ALPs will reshape traditional education through continuous technological advancements and the datafication of educational systems. However, balancing privacy, security, and equity will remain essential. Future research will focus on addressing these challenges while unlocking the full potential of ALPs to create more efficient and inclusive educational systems.

7. Conclusion

This review examines the current application of ALPs in education, focusing on design principles, evaluation methods, algorithms, and impacts on learning. ALPs address the limitations of traditional “one-size-fits-all” and “teach-to-the-middle” approaches (Shelle et al., 2018) by leveraging AI to create learner-centered platforms tailored to individual needs and abilities (Soofi & Ahmed, 2019). Highlighting successful ALP implementations across K-12 and higher education, this review demonstrates that adapting instruction to students’ unique learning profiles enhances performance, motivation, and engagement.

However, challenges related to privacy and institutional support remain and require careful consideration. To expand ALP adoption and fully realize its potential, future research should focus on refining personalized learning pathways while ensuring user privacy and equitable access. Educators and developers can use insights from this review to guide the implementation and optimization of ALPs, addressing essential design factors and anticipating challenges in specific educational contexts. With technological advances and adaptive educational policies, ALPs are well-positioned for broader global adoption, offering personalized solutions to meet diverse learner needs.

CRediT authorship contribution statement

Le Ying Tan: Writing – original draft, Validation, Formal analysis, Data curation, Conceptualization. **Shiyu Hu:** Writing – review & editing, Validation, Conceptualization. **Darren J. Yeo:** Writing – review & editing, Supervision, Project administration, Conceptualization. **Kang Hao Cheong:** Writing – review & editing, Validation, Formal analysis, Supervision, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This work was supported by the Singapore Ministry of Education (MOE) Tertiary Education Research Fund (TRF) under Grant No. MOE2022-TRF-029.

References

Abolnejadian, M., Alipour, S., & Taeb, K. (2024). Leveraging chatgpt for adaptive learning through personalized prompt-based instruction: A cs1 education case study. In *Extended abstracts of the CHI conference on human factors in computing systems, CHI EA '24*. New York, NY, USA: Association for Computing Machinery.

Abyaa, A., Khalidi Idrissi, M., & Bennani, S. (2019). Learner modelling: Systematic review of the literature from the last 5 years. *Educational Technology Research and Development*, *67*, 1105–1143.

Afini Normadhi, N. B., Shuib, L., Md Nasir, H. N., Bimba, A., Idris, N., & Balakrishnan, V. (2019). Identification of personal traits in adaptive learning environment: Systematic literature review. *Computers and Education*, *130*, 168–190.

Aggarwal, D. (2023). Integration of innovative technological developments and AI with education for an adaptive learning pedagogy. *China Petroleum Processing and Petrochemical Technology*, *23*, 709–714.

Alam, A. (2022). Employing adaptive learning and intelligent tutoring robots for virtual classrooms and smart campuses: Reforming education in the age of artificial intelligence. In R. N. Shaw, S. Das, V. Piuri, & M. Bianchini (Eds.), *Advanced computing and intelligent technologies* (pp. 395–406).

Alam, A. (2023). The secret sauce of student success: Cracking the code by navigating the path to personalized learning with educational data mining. In *2023 2nd international conference on smart technologies and systems for next generation computing (ICSTSN)* (pp. 1–8).

Alam, A., Ullah, S., & Ali, N. (2018). The effect of learning-based adaptivity on students' performance in 3d-virtual learning environments. *IEEE Access*, *6*, 3400–3407.

Aleven, V., McLaughlin, E. A., Glenn, R. A., & Koedinger, K. R. (2016). *Instruction based on adaptive learning technologies*. *Handbook of research on learning and instruction*. Routledge.

Anna Mavroudi, M. G., & Krogstie, J. (2018). Supporting adaptive learning pathways through the use of learning analytics: Developments, challenges and future opportunities. *Interactive Learning Environments*, *26*(2), 206–220.

Apoki, U. C., Al-Chalabi, H. K. M., & Crisan, G. C. (2020). From digital learning resources to adaptive learning objects: An overview. In D. Simian, & L. F. Stoica (Eds.), *Modelling and development of intelligent systems* (pp. 18–32). Cham: Springer International Publishing.

Aristizábal, J. A. (2018). Using learning analytics to improve students' reading skills: A case study in an American international school with English as an additional language (EAL) students. *Education and Learning Research Journal*, *17*, 193–214.

Arsovic, B., & Stefanovic, N. (2020). E-learning based on the adaptive learning model: Case study in Serbia. *Sādhanā*, *45*, 266.

Awais Hassan, M., Habiba, U., Khalid, H., Shoaib, M., & Arshad, S. (2019). An adaptive feedback system to improve student performance based on collaborative behavior. *IEEE Access*, *7*, 107171–107178.

Azzi, I., Jeghal, A., Radouane, A., Yahyaouy, A., & Tairi, H. (2020). A robust classification to predict learning styles in adaptive e-learning systems. *Education and Information Technologies*, *25*, 437–448.

Bartolomé, A., Castañeda, L., & Adell, J. (2018). Personalisation in educational technology: The absence of underlying pedagogies. *International Journal of Educational Technology in Higher Education*, *15*(14).

Bauer, M., Bräuer, C., Schuldt, J., & Krömker, H. (2019). Adaptive e-learning for supporting motivation in the context of engineering science. In S. Nazir, A.-M. Teperi, & A. Polak-Sopińska (Eds.), *Advances in human factors in training, education, and learning sciences* (pp. 409–422). Cham: Springer International Publishing.

Birjali, M., Beni-Hssane, A., & Erritali, M. (2018). A novel adaptive e-learning model based on big data by using competence-based knowledge and social learner activities. *Applied Soft Computing*, *69*, 14–32.

Bloom, B. S. (1984). The 2 sigma problem: The search for methods of group instruction as effective as one-to-one tutoring. *Educational Researcher*, *13*(6), 4–16.

Bremgartner, V., de Magalhães Netto, J. F., & de Menezes, C. S. (2015). Adaptation resources in virtual learning environments under constructivist approach: A systematic review. In *2015 IEEE frontiers in education conference (FIE)* (pp. 1–8).

Brinton, C. G., Rill, R., Ha, S., Chiang, M., Smith, R., & Ju, W. (2015). Individualization for education at scale: Miic design and preliminary evaluation. *IEEE Transactions on Learning Technologies*, *8*(1), 136–148.

Cavanagh, T., Chen, B., Lahcen, R. A. M., & Paradiso, J. (2020). Constructing a design framework and pedagogical approach for adaptive learning in higher education: A practitioner's perspective. *International Review of Research in Open and Distance Learning*, *21*(1), 173–197.

Chen, C.-H. (2014). An adaptive scaffolding e-learning system for middle school students' physics learning. *Australasian Journal of Educational Technology*, *30*(3).

Chen, Y., Li, X., Liu, J., & Ying, Z. (2018). Recommendation system for adaptive learning. *Applied Psychological Measurement*, *42*(1), 24–41.

Cui, W., Xue, Z., & Thai, K.-P. (2018). Performance comparison of an AI-based adaptive learning system in China. In *2018 Chinese automation congress (CAC)* (pp. 3170–3175).

Deng, Y., Lu, D., Chung, C.-J., Huang, D., & Zeng, Z. (2018). Personalized learning in a virtual hands-on lab platform for computer science education. In *2018 IEEE frontiers in education conference (FIE)* (pp. 1–8).

Dolenc, K., & Aberšek, B. (2015). Tech8 intelligent and adaptive e-learning system: Integration into technology and science classrooms in lower secondary schools. *Computers and Education*, *82*, 354–365.

Dziuban, C., Howlin, C., Moskal, P., Johnson, C., Parker, L., & Campbell, M. (2018). Adaptive learning: A stabilizing influence across disciplines and universities. *Online Learning*, *22*, 7–39.

Dziuban, C., Moskal, P., Cassisi, J., & Fawcett, A. (2016). Adaptive learning in psychology: Wayfinding in the digital age. *Online Learning*, *20*(3).

Dziuban, C. D., Moskal, P. D., Johnson, C., & Evans, D. (2017). Adaptive learning: A tale of two contexts. *Current Issues in Emerging eLearning*, 4.

Eau, G., Judah, K., & Shahid, H. (2019). How can adaptive platforms improve student learning outcomes? A case study of open educational resources and adaptive learning platforms. *SSRN Electronic Journal*.

El-Sabagh, H. A. (2021). Adaptive e-learning environment based on learning styles and its impact on development students' engagement. *International Journal of Educational Technology in Higher Education, 18:53*.

Elmaadaway, M., & Abouelenein, Y. (2023). In-service teachers' tpack development through an adaptive e-learning environment (ale). *Educational Information Technology*, *28*, 8273–8298.

Ennouamani, S., Mahani, Z., & Akharraz, L. (2020). A context-aware mobile learning system for adapting learning content and format of presentation: Design, validation and evaluation. *Education and Information Technologies*, *25*, 3919–3955.

Essa, A. (2016). A possible future for next generation adaptive learning systems. *Smart Learning Environments*, *3*, 16.

Farmer, E. C., Catalano, A. J., & Halpern, A. J. (2020). Exploring student preference between textbook chapters and adaptive learning lessons in an introductory environmental geology course. *TechTrends*, *64*, 150–157.

Faruqui, S. H. A., Tasnim, N., Basith, I. I., Obeidat, S., & Yildiz, F. (2024). Integrating A.I. in higher education: Protocol for a pilot study with 'samcares: An adaptive learning hub'. arXiv.

Fatahi, S. (2019). An experimental study on an adaptive e-learning environment based on learner's personality and emotion. *Education and Information Technologies*, *24*, 2225–2241.

Gamage, S. H. P. W., Ayres, J. R., & Behrend, M. B. (2022). A systematic review on trends in using moodle for teaching and learning. *International Journal of STEM Education*, *9*(9).

Gligorea, I., Cioca, M., Oancea, R., Gorski, A.-T., Gorski, H., & Tudorache, P. (2023). Adaptive learning using artificial intelligence in e-learning: A literature review. *Education Sciences*, *13*(12).

González-Castro, N., Muñoz-Merino, P. J., Alario-Hoyos, C., & Delgado Kloos, C. (2021). Adaptive learning module for a conversational agent to support MOOC learners. *Australasian Journal of Educational Technology*, *37*(2), 24–44.

Grawemeyer, B., Mavrikis, M., Holmes, W., et al. (2017). Affective learning: Improving engagement and enhancing learning with affect-aware feedback. *User Modeling and User-Adapted Interaction*, *27*(1), 119–158.

Gumbheer, C. P., Khedo, K. K., & Bungaleea, A. (2022). Personalized and adaptive context-aware mobile learning: Review, challenges and future directions. *Education and Information Technologies*, *27*, 7491–7517.

Gupta, S., Ojeh, N., Sa, B., Majumder, M. A. A., Singh, K., & Adams, O. P. (2020). Use of an adaptive e-learning platform as a formative assessment tool in the cardiovascular system course component of an MBBSprogramme. *Advances in Medical Education and Practice*, *11*, 989–996.

Gurcan, F., Ozyurt, O., & Cagitay, N. E. (2021). Investigation of emerging trends in the e-learning field using latent Dirichlet allocation. *International Review of Research in Open and Distance Learning*, *22*(2), 1–18.

Gómez, S., Zervas, P., Sampson, D. G., & Fabregat, R. (2014). Context-aware adaptive and personalized mobile learning delivery supported by uolmp. *Journal of King Saud University: Computer and Information Sciences*, *26*(1 Supplement), 47–61. Current Advances in Digital Learning Technologies.

Harati, H., Sujo-Montes, L., Tu, C.-H., Armfield, S. J. W., & Yen, C.-J. (2021). Assessment and learning in knowledge spaces (aleks) adaptive system impact on students' perception and self-regulated learning skills. *Education Sciences*, *11*(10).

Heffernan, N. T., Ostrow, K. S., Kelly, K., Selent, D., Van Inwegen, E. G., Xiong, X., & Williams, J. J. (2016). The future of adaptive learning: Does the crowd hold the key? *International Journal of Artificial Intelligence in Education*.

Hengbin Yan, J. L., & Liu, Y. (2018). Efl pronunciation training with computer-assisted adaptive peer review. *English Language Teaching*, *11*.

Hubalovsky, S., Hubalovska, M., & Musilek, M. (2019). Assessment of the influence of adaptive e-learning on learning effectiveness of primary school pupils. *Computers in Human Behavior*, *92*, 691–705.

Hwang, G.-J., Sung, H.-Y., Chang, S.-C., & Huang, X.-C. (2020). A fuzzy expert system-based adaptive learning approach to improving students' learning performances by considering affective and cognitive factors. *Computers and Education: Artificial Intelligence*, *1*, Article 100003.

Idris, N., Hashim, S. Z. M., Samsudin, R., & Ahmad, N. B. H. (2017). Intelligent learning model based on significant weight of domain knowledge concept for adaptive e-learning. *International Journal on Advanced Science Engineering Information Technology*, *7*.

Ifenthaler, D., Gibson, D. C., & Zheng, L. (2018). The dynamics of learning engagement in challenge-based online learning. In *2018 IEEE 18th international conference on advanced learning technologies (ICALT)* (pp. 178–182).

Imhof, C., Bergamin, P., & McGarrity, S. (2020). *Implementation of adaptive learning systems: Current state and potential*. Cham: Springer International Publishing (pp. 93–115).

Jando, E., Meyliana, Hidayanto, A. N., Prabowo, H., Warnars, H. L. H. S., & Sasmoko (2017). Personalized e-learning model: A systematic literature review. In *2017 international conference on information management and technology (ICIMTech)* (pp. 238–243).

Kaiss, W., Mansouri, K., & Poirier, F. (2023). Effectiveness of an adaptive learning chatbot on students' learning outcomes based on learning styles. *International Journal: Emerging Technologies in Learning*, *18*(13), 250–261.

Kardan, A. A., Aziz, M., & Shahpasand, M. (2015). Adaptive systems: A content analysis on technical side for e-learning environments. *Artificial Intelligence Review*, *44*, 365–391.

Kaw, A., Clark, R., Delgado, E., & Abate, N. (2019). Analyzing the use of adaptive learning in a flipped classroom for preclass learning. *Computer Applications in Engineering Education*, *27*(3), 663–678.

Kem, D. (2022). Personalised and adaptive learning: Emerging learning platforms in the era of digital and smart learning. *International Journal of Social Science and Human Research*, *5*, 385–391.

Khanal, S. S., Prasad, P., Alsadoon, A., & Maag, A. (2020). A systematic review: Machine learning based recommendation systems for e-learning. *Education and Information Technologies*, *25*, 2635–2664.

Khosravi, H., Sadiq, S., & Gasevic, D. (2020). Development and adoption of an adaptive learning system: Reflections and lessons learned. In *Proceedings of the 51st ACM technical symposium on computer science education, SIGCSE '20* (pp. 58–64). New York, NY, USA: Association for Computing Machinery.

Krouska, A., Troussas, C., & Virvou, M. (2019). Computerized adaptive assessment using accumulative learning activities based on revised bloom's taxonomy. In M. Virvou, F. Kumeno, & K. Oikonomou (Eds.), *Knowledge-based software engineering: 2018* (pp. 252–258). Cham: Springer International Publishing.

Li, F., He, Y., & Xue, Q. (2021). Progress, challenges and countermeasures of adaptive learning: A systematic review. *Educational Technology & Society*, *24*(3), 238–255.

Li, H., Cui, W., Xu, Z., Zhu, Z., & Feng, M. (2018). Yixue adaptive learning system and its promise on improving student learning. In *Proceedings of the 10th international conference on computer supported education (CSEDU 2018)* (pp. 45–52).

Li, J., & Li, Q. (2024). Enhancing educational design capabilities through interactive mobile and adaptive learning platforms: An empirical study. *International Journal of Interactive Mobile Technologies*, *18*(08), 87–101.

Lim, L., Lim, S. H., & Lim, R. W. Y. (2022). Measuring learner satisfaction of an adaptive learning system. *Behavioral Sciences*, *12*(8).

Liu, M., Kang, J., Zou, W., Lee, H., Pan, Z., & Corliss, S. (2017a). Using data to understand how to better design adaptive learning. *Technology, Knowledge and Learning*, *22*, 271–298.

Liu, M., McKelroy, E., Corliss, S. B., & Carrigan, J. (2017b). Investigating the effect of an adaptive learning intervention on students' learning. *Educational Technology Research and Development*, *65*, 1605–1625.

Liu, T. C. (2022). A case study of the adaptive learning platform in a Taiwanese elementary school: Precision education from teachers' perspectives. *Education and Information Technologies*, *27*, 6295–6316.

Louhab, F. E., Bahnasse, A., & Talea, M. (2018). Towards an adaptive formative assessment in context-aware mobile learning. *Procedia Computer Science*, *135*, 441–448. The 3rd International Conference on Computer Science and Computational Intelligence (ICCSCI 2018): Empowering Smart Technology in Digital Era for a Better Life.

Madani, Y., Ezzikouri, H., Erritali, M., & Hssina, B. (2020). Finding optimal pedagogical content in an adaptive e-learning platform using a new recommendation approach and reinforcement learning. *Journal of Ambient Intelligence and Humanized Computing*, *11*, 3921–3936.

Maravanyika, M., Dlodlo, N., & Jere, N. (2017). An adaptive recommender-system based framework for personalised teaching and learning on e-learning platforms. In *2017 IST-Africa week conference (IST-Africa)* (pp. 1–9).

Marienko, M. V., Nosenko, Y., & Shyshkina, M. P. (2020). Personalization of learning using adaptive technologies and augmented reality. arXiv, arXiv:2011.05802 [abs].

Martin, A. J., & Maria, D. M. (2019). Adaptation using machine learning for personalized elearning environment based on students preference. *International Journal of Innovative Technology and Exploring Engineering*, *8*(10), 4064–4069.

Martin, F., Chen, Y., Moore, R. L., & Westine, C. D. (2020). Systematic review of adaptive learning research designs, context, strategies, and technologies from 2009 to 2018. *Educational Technology Research and Development*, *68*, 1903–1929.

Meacham, S., Pech, V., & Nauck, D. (2020). AdaptiveVLE: An integrated framework for personalized online education using MPS jetbrains domain-specific modeling environment. *IEEE Access*, *8*, 184621–184632.

Min, W., Mott, B., Park, K., Taylor, S., Akram, B., Wiebe, E., Boyer, K. E., & Lester, J. (2020). Promoting computer science learning with block-based programming and narrative-centered gameplay. In *2020 IEEE conference on games (CoG)* (pp. 654–657).

Mirata, V., Hirt, F., Bergamin, P., & van der Westhuizen, C. (2020). Challenges and contexts in establishing adaptive learning in higher education: Findings from a delphi study. *International Journal of Educational Technology in Higher Education*, *17:32*.

Mohammad, T., & Alshammari, A. Q. (2019). Effective adaptive e-learning systems according to learning style and knowledge level. *Journal of Information Technology Education: Research*, *18*, 529–547.

Moltudal, S. H., Krumsvik, R. J., & Høydal, K. L. (2022). Adaptive learning technology in primary education: Implications for professional teacher knowledge and classroom management. *Frontiers in Education*, *7*.

Morze, N., Varchenko-Trotsenko, L., Terletska, T., & Smyrnova-Trybulska, E. (2021). Implementation of adaptive learning at higher education institutions by means of moodle LMS. *Journal of Physics. Conference Series*, *1840*(1), Article 012062.

Mousavinasab, E., Zarifsanaiey, N., Kalhori, S. R. N., Rakhshan, M., Keikha, L., & Saeedi, M. G. (2021). Intelligent tutoring systems: A systematic review of characteristics, applications, and evaluation methods. *Interactive Learning Environments*, *29*(1), 142–163.

Muhammad Awais Hassan, Ume Habiba, F. M., & Shoaib, M. (2021). Adaptive gamification in e-learning based on students' learning styles. *Interactive Learning Environments*, *29*(4), 545–565.

Murray, M. C., & Pérez, J. (2015). Informing and performing: A study comparing adaptive learning to traditional learning. *Informing Science: The International Journal of an Emerging Transdiscipline*, *18*, 111–125.

Muñoz, J. L. R., Ojeda, F. M., Jurado, D. L. A., Peña, P. F. P., Carranza, C. P. M., Berríos, H. Q., Molina, S. U., Farfan, A. R. M., Arias-Gonzáles, J. L., & Vasquez-Pauca, M. J. (2022). Systematic review of adaptive learning technology for learning in higher education. *Eurasian Journal of Educational Research*, *98*, 221–233.

Nabizadeh, A. H., Gonçalves, D., Gama, S., Jorge, J., & Rafsanjani, H. N. (2020). Adaptive learning path recommender approach using auxiliary learning objects. *Computers and Education*, *147*, Article 103777.

Nakic, J., Granic, A., & Glavinic, V. (2015). Anatomy of student models in adaptive learning systems: A systematic literature review of individual differences from 2001 to 2013. *Journal of Educational Computing Research*, *51*(4), 459–489.

Ng, W., & Fergusson, J. (2019). Technology-enhanced science partnership initiative: Impact on secondary science teachers. *Research in Science Education*, *49*, 219–242.

Orsi Koch Delgado, H., de Azevedo Fay, A., Sebastiany, M. J., & Cortina Silva, A. D. (2020). Artificial intelligence adaptive learning tools: The teaching of English in focus. *Brazilian English Language Teaching Journal*, *11*(2), Article e38749.

Osadcha, K., Osadchyi, V., Semerikov, S., Chemerys, H., & Chorna, A. (2020). The review of the adaptive learning systems for the formation of individual educational trajectory. In *Proceedings of the 16th international conference on ICT in education, research and industrial applications. Integration, harmonization and knowledge transfer. Volume II: Workshops*. CEUR-WS.org.

Pardos, Z. A., Tang, S., Davis, D., & Le, C. V. (2017). Enabling real-time adaptivity in MOOCs with a personalized next-step recommendation framework. In *Proceedings of the fourth (2017) ACM conference on learning @ scale, l@s '17* (pp. 23–32). New York, NY, USA: Association for Computing Machinery.

Peng, H., Ma, S., & Spector, J. M. (2019). Personalized adaptive learning: An emerging pedagogical approach enabled by a smart learning environment. *Smart Learning Environments*, *6*(9).

Petersen, A. K., & Gundersen, P. (2019). Challenges in designing personalised learning paths in spocs. *Designs for Learning*, *11*, 72–79.

Premlatha, K. R., & Geetha, T. V. (2015). Learning content design and learner adaptation for adaptive e-learning environment: A survey. *Artificial Intelligence Review*, *44*, 443–465.

Rincon-Flores, E., Castano, L., Guerrero Solis, S., et al. (2024). Improving the learning-teaching process through adaptive learning strategy. *Smart Learning Environments*, *11*, 27.

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

Romero, C., & Ventura, S. (2020). Educational data mining and learning analytics: An updated survey. *WIREs Data Mining and Knowledge Discovery*, *10*(3).

Rosen, Y., Rushkin, I., Rubin, R., Munson, L., Ang, A., Weber, G., Lopez, G., & Tingley, D. (2018). The effects of adaptive learning in a massive open online course on learners' skill development. In *Proceedings of the fifth annual ACM conference on learning at scale, l@s '18*. New York, NY, USA: Association for Computing Machinery.

Ruan, S., Jiang, L., Xu, J., Tham, B. J.-K., Qiu, Z., Zhu, Y., Murnane, E. L., Brunskill, E., & Landay, J. A. (2019). Quizbot: A dialogue-based adaptive learning system for factual knowledge. In *Proceedings of the 2019 CHI conference on human factors in computing systems, CHI '19* (pp. 1–13). New York, NY, USA: Association for Computing Machinery.

Said, G. R. E. (2019). Context-aware adaptive m-learning: Implicit indicators of learning performance, perceived usefulness, and willingness to use. *Computers in Education Journal*, *10*.

Saito, T., & Watanobe, Y. (2020). Learning path recommendation system for programming education based on neural networks. *International Journal of Distance Education Technologies*, *18*(1), 36–64.

Sajja, R., Sermet, Y., Cikmaz, M., Cwiertny, D., & Demir, I. (2023). Artificial intelligence-enabled intelligent assistant for personalized and adaptive learning in higher education. arXiv.

Sayed, W. S., Noeman, A. M., Abdellatif, A., Abdelrazek, M., Badawy, M. G., Hamed, A., & El-Tantawy, S. (2023). AI-based adaptive personalized content presentation and exercises navigation for an effective and engaging e-learning platform. *Multimedia Tools and Applications*, *82*, 3303–3333.

Scheiter, K., Schubert, C., Schüler, A., Schmidt, H., Zimmermann, G., Wassermann, B., Krebs, M.-C., & Eder, T. (2019). Adaptive multimedia: Using gaze-contingent instructional guidance to provide personalized processing support. *Computers and Education*, *139*, 31–47.

Scott, E., Soria, A., & Campo, M. (2017). Adaptive 3d virtual learning environments—a review of the literature. *IEEE Transactions on Learning Technologies*, *10*(3), 262–276.

Sein Minn (2022). AI-assisted knowledge assessment techniques for adaptive learning environments. *Computers and Education: Artificial Intelligence*, *3*, Article 100050.

Sharma, N., Doherty, I., & Dong, C. (2017). Adaptive learning in medical education: The final piece of technology enhanced learning? *The Ulster Medical Journal*, *86*(3), 198–200.

Shawky, D., & Badawi, A. (2019). *Towards a personalized learning experience using reinforcement learning*. Cham: Springer International Publishing (pp. 169–187).

Shelle, G., Earnesty, D., Pilkenton, A., & Powell, E. (2018). Adaptive learning: An innovative method for online teaching and learning. *The Journal of Extension*, *56*.

Soofi, A. A., & Ahmed, M. U. (2019). A systematic review of domains, techniques, delivery modes and validation methods for intelligent tutoring systems. *International Journal of Advanced Computer Science and Applications*, *10*(3).

Talaghzi, J., Bennane, A., Himmi, M. M., Bellafkih, M., & Benomar, A. (2020). Online adaptive learning: A review of literature. In *Proceedings of the 13th international conference on intelligent systems: Theories and applications, SITA'20*. New York, NY, USA: Association for Computing Machinery.

Taylor, D. L., Yeung, M., & Bashet, A. Z. (2021). *Personalized and adaptive learning*. Cham: Springer International Publishing (pp. 17–34).

Tesene, M. M. (2018). Adaptable selectivity: A case study in evaluating and selecting adaptive learning courseware at Georgia state university. *Current Issues in Emerging eLearning*, *5*.

Thalmann, S. (2014). Adaptation criteria for the personalised delivery of learning materials: A multi-stage empirical investigation. *Australasian Journal of Educational Technology*, *30*(1).

Troussas, C., Krouska, A., & Sgouropoulou, C. (2021). A novel teaching strategy through adaptive learning activities for computer programming. *IEEE Transactions on Education*, *64*(2), 103–109.

Truong, H. M. (2016). Integrating learning styles and adaptive e-learning system: Current developments, problems and opportunities. *Computers in Human Behavior*, *55*, 1185–1193.

Vesin, B., Mangaroska, K., & Giannakos, M. (2018). Learning in smart environments: User-centered design and analytics of an adaptive learning system. *Smart Learning Environments*, *5*(24).

Villesseche, J., Le Bohec, O., Quaireau, C., Nogues, J., Besnard, A.-L., Oriez, S., De La Haye, F., Noel, Y., & Lavandier, K. (2019). Enhancing reading skills through adaptive e-learning. *Interactive Technology and Smart Education*, *16*, 2–17.

Wambsganss, T., Kueng, T., Soellner, M., & Leimeister, J. M. (2021). Arguetutor: An adaptive dialog-based learning system for argumentation skills. In *Proceedings of the 2021 CHI conference on human factors in computing systems, CHI '21*. New York, NY, USA: Association for Computing Machinery.

Wan, S., & Niu, Z. (2020). A hybrid e-learning recommendation approach based on learners' influence propagation. *IEEE Transactions on Knowledge and Data Engineering*, *32*(5), 827–840.

Wang, S., Christensen, C., Cui, W., Tong, R., Yarnall, L., Shear, L., & Feng, M. (2023). When adaptive learning is effective learning: Comparison of an adaptive learning system to teacher-led instruction. *Interactive Learning Environments*, *31*(2), 793–803.

White, G. (2020). Adaptive learning technology relationship with student learning outcomes. *Journal of Information Technology Education: Research*, *19*, 113–130.

Wu, C.-H., Chen, Y.-S., & Chen, T.-C. (2017). An adaptive e-learning system for enhancing learning performance: Based on dynamic scaffolding theory. *Eurasia Journal of Mathematics, Science and Technology Education*, *14*, 903–913.

Wu, T.-T., Lee, H.-Y., Wang, W.-S., et al. (2023). Leveraging computer vision for adaptive learning in stem education: Effect of engagement and self-efficacy. *International Journal of Educational Technology in Higher Education*, *20*(53).

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

Yuksel, B. F., Oleson, K. B., Harrison, L., Peck, E. M., Afergan, D., Chang, R., & Jacob, R. J. (2016). Learn piano with Bach: An adaptive learning interface that adjusts task difficulty based on brain state. In *Proceedings of the 2016 CHI conference on human factors in computing systems, CHI '16* (pp. 5372–5384). New York, NY, USA: Association for Computing Machinery.

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – where are the educators? *International Journal of Educational Technology in Higher Education*, *16*, 39.

Özyurt, O., & Özyurt, H. (2015). Learning style based individualized adaptive e-learning environments: Content analysis of the articles published from 2005 to 2014. *Computers in Human Behavior*, *52*, 349–358.