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Review article

# Personalized adaptive learning in higher education: A scoping review of key characteristics and impact on academic performance and engagement

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ABSTRACT

*Introduction:* Higher education institutions face persistent challenges of student retention and academic progress. Personalized adaptive learning has the potential to address these issues as it leverages educational technology to tailor learning pathways according to individual student needs.
*Objective:* To elucidate the key characteristics of personalized adaptive learning in higher education and its impact on academic performance and engagement.
*Methods:* The Joanna Briggs Institute scoping review methodology was followed. Key international databases were searched to retrieve articles. The titles and abstracts of selected studies were imported into Covidence. Peer-reviewed journal articles, theses, and dissertations focusing on undergraduate students engaged in personalized adaptive learning, published between 2012 and 2024 were included. Data was extracted and charted in Covidence. Results were summarised through a narrative synthesis and visually presented in a PRISMA-ScR flow diagram.
*Results:* This review included 69 eligible studies. The findings reveal insights into the multifaceted nature of personalized adaptive learning, which include platforms, implementation strategies, perceived strengths and limitations by instructors and students. Pre-knowledge quizzes were reported as the most common indicator for activating adaptive content delivery, and McGraw-Hill's Connect LearnSmart and Moodle were the most utilized adaptive platforms. Improved academic performance was reported by 41 of the studies (n = 41, 59 %), and 25 studies (n = 25, 36 %) indicated increased student engagement.
*Conclusion:* This study highlights the potential of personalized adaptive learning to positively impact academic performance, student engagement and learning, despite technological limitations. Further research is encouraged to address technological challenges, build on strengths and refine implementation and application of personalized adaptive learning in higher education.

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## 1. Introduction

In today's rapidly evolving landscape of higher education, educators are constantly adapting to changes driven by digitization, global events such as the COVID-19 pandemic, and the Fourth Industrial Revolution [1]. The progression of educational technology, including learning management systems, big data, and analytics, is disrupting higher education institutions and driving digital transformation [2,3]. This has resulted in innovative teaching strategies and increased flexibility in teaching and learning, providing cost-effective access to unlimited educational resources regardless of geographical location [2,4].

Despite these advances, higher education institutions continue to face challenges regarding student success and throughput rates [1,5]. Student engagement, involving interactions between learners, educators and content, as well as leaners and computer interfaces, is essential for effective learning, particularly in online or hybrid learning environments [6].

The advent of personalized adaptive learning has significantly transformed higher education by combining personalized learning principles with adaptive learning technologies. This integration has led to more effective, efficient, and engaging educational experiences tailored to individual learner needs. The development of personalized adaptive learning has been shaped by numerous innovations over the past century, from Dewey's progressive education in 1916 to recent advancements in AI-powered adaptive learning systems [7] and integrative personalized adaptive learning ecosystems that leverage artificial intelligence and machine learning algorithms to analyze learner behavior, predict performance, and offer tailored interventions [8,9]. The theoretical foundations of personalized adaptive learning draw from a rich tapestry of educational and psychological theories. These range from Behaviorism to more recent contributions like Connectivism and Learning Analytics [10–12]. This progression demonstrates a shift from viewing learning as a purely behavioral process to understanding it as a complex, personalized, and adaptive phenomenon influenced by cognitive, social, and technological factors.

Personalized adaptive learning, defined [13] as "a technology-empowered effective pedagogy which can adaptively adjust teaching strategies timely based on real-time monitored (enabled by smart technology) learners' differences and changes in individual characteristics, performance, and personal development" [13], has the potential to address long-standing challenges in higher education. These include the scalability of individualized instruction, engagement in online learning environments, and the accommodation of diverse learner populations. This is supported by Muñoz et al. [14], who reported that adaptive learning should be further explored with regard to adaptive techniques and technology, as the core of personalized adaptive learning focuses on data-driven learning design informed by the individual user characteristics [13]. The design and delivery of personalized adaptive learning pathways can be based on various single or multimodal data sources, including pre-test questionnaires [15], student confidence levels [16], and activity logs from learning management systems [17,18]. Learning pathways have also been designed to adapt content delivery format based on student learning styles [19,20]. Existing literature has described the application of personalized adaptive learning platforms across various educational fields, such as engineering, humanities, information technology, health sciences, and veterinary science [21–25].

A variety of definitions and terminology exists for the key concepts associated with personalized and adaptive learning across different fields. An initial taxonomy was proposed for adaptivity in learning that considers its design and evaluation at the micro and macro levels [26]. A literature-driven taxonomy was later developed to categorize literature in the domain of personalized learning systems according to content, learner model and learning environment [27]. The Personalized adaptive learning framework guides the implementation of personalized adaptive learning as a teaching and learning strategy to suit learning differences among individual students [13]. This data-driven design framework is based on constructivism, which can potentially improve learning design in the development of personalized learning activities or pathways [28].

Personalized learning shows promise in fostering equity in learning [29] and enhancing student success [30]. This is particularly interesting to higher education institutions in the global South, facing a diverse student population entering university programs that are not tailored to their individual learning needs. These students face multiple barriers to learning, including systemic and historical barriers, gender and racial inclusivity, and socioeconomic divides that can influence access to technology, infrastructure, and educational resources [31]. Personalized content delivery, which allows for student differences based on a variety of indicators, can promote academic progression and student success [32]. Previous systematic reviews have determined trends in the literature and identified four major research domains in adaptive learning: deep learning in educational data analysis, adaptive learning models in AI education, intelligent tutoring systems, and modeling technology for feature modeling and knowledge tracing [33]. It did, not investigate the benefits and shortcomings of adaptive learning systems or synthesize the most frequently utilized technology and data collection practices applied in adaptive learning systems [33]. Additionally, future meta-analysis studies are recommended to accurately assess the effectiveness of adaptive learning systems [33]. Previous studies on adaptive learning remain dissipated and focus on one or more of the many different aspects related to the implementation and technology of adaptive learning systems. The current study aims to address gaps in adaptive learning research by providing a comprehensive synthesis of the characteristics and impact of personalized adaptive learning systems on academic performance and student engagement.

A scoping review was selected as an appropriate method to assess the nature and extent of the existing literature to map descriptions of the key characteristics of personalized adaptive learning, the platforms utilized, implementation strategies, indicators used as triggers for content delivery, type of content delivered, impact on learning and academic performance, and perceived strengths and limitations of personalized adaptive learning systems. To meet our study aim we formulated the following review question: What are the key characteristics and impact of personalized adaptive learning on academic performance, student engagement, and learning in higher education?

## 2. Methodology

### 2.1. Inclusion criteria

#### 2.1.1. Participants

This review included studies on higher education, undergraduate students from all year levels, and any field of study or academic program in any faculty at a tertiary educational institution that has participated in personalized adaptive learning.

#### 2.1.2. Concept

This study aims to map descriptions of personalized adaptive learning, which can be defined as a pedagogical approach implemented to individualize student learning by selecting and delivering content or learning objects based on students' learning preferences, behaviors, knowledge, academic achievement, and learning analytics [13].

#### 2.1.3. Context

Higher education is an umbrella term for various tertiary and post-secondary learning institutions, including colleges and universities that provide professional, technical, and vocational training and offer a degree or credentials. The terms' higher education and university' are used interchangeably [34]. This scoping review focused on studies concerned with higher education settings, which included universities and technical and vocational education and training (TVET) colleges.

### 2.2. Exclusion criteria

Studies with no abstract available in the database, as screening of study abstracts formed part of the search strategy for this review.

Studies that were published before 2012 due to the rapid advancement of educational technology and the field of learning analytics.

Studies published after July 2024, as the literature search were conducted until June 30, 2024; therefore, later publications from 2024 were excluded.

Studies in which the full text cannot be translated into English. All languages were included in the search strategy as the researchers first aimed to translate the full text into English.

This scoping review did not include systematic reviews, conference proceedings, commentaries, opinion pieces, editorials, or grey literature.

### 2.3. Methods

The scoping review was conducted following the Joanna Briggs Institute (JBI) scoping review methodology as described in the 2015 Joanna Briggs Institute Reviewers' Manual [35,36].

#### 2.3.1. Search strategy

An initial literature search was conducted using MEDLINE Ultimate (EBSCOHost) to locate peer-reviewed published articles, theses, and dissertations related to the subject matter. The search strategy for MEDLINE Ultimate (EBSCOHost) was constructed by extracting keywords from the titles and abstracts of relevant articles and the index terms used to characterize these articles in the initial search results.

#### 2.3.2. Study selection

Step 1: Literature search: The literature search included the following primary databases for peer-reviewed journal articles on education, health science education, educational technology, and data science: MEDLINE Ultimate (EBSCOHost), ERIC (EBSCOHost), CINAHL Complete (EBSCOhost), SCOPUS, and Web of Science, Cochrane Library Database of Systematic Reviews, and Joanna Briggs Institute Evidence-Based-Practice Database (OvidSP). A secondary database, ProQuest Dissertations and Theses

**Table 1**
Search string and filters.

| Database | MEDLINE Ultimate (via EBSCOHost) |
|---|---|
| Search string with BOOLEAN operators | university student OR degree learner OR degree student OR higher education learner OR higher education student OR students, health occupations OR undergraduate learner OR undergraduate student OR university learner AND personalized adaptive learning OR adaptive and personalized learning OR adaptive learning AND higher education OR education, professional OR post-secondary education OR university OR tertiary education |
| Search filters and limitations applied | Text availability: Abstract & Full text,<br>Publication date: 12 years,<br>Species: Humans,<br>Journal: MEDLINE,<br>Age: All Adult 19+ years |

Global, was included in the search to identify relevant theses and dissertations. Systematic reviews and grey literature were excluded.

The search strings and filters listed in Table 1 were applied for the literature search.

The search strategy, which included all the search filters and keywords, was modified according to the search function of each database.

Step 2: Screening of titles and abstracts: All citations identified in the search were uploaded to Covidence, an online systematic review platform [37]. All duplicates in the uploaded citations were automatically removed. The authors conducted a pilot study to screen 10 % of the identified titles and abstracts to test the inclusion criteria before screening full text articles. The first author screened all titles and abstracts based on the inclusion criteria of the scoping review. The second and third authors screened 10 % of titles for quality control. Differences between the authors regarding the inclusion of a study were discussed to reach a consensus. Covidence calculated the interrater reliability metric for title and abstract reviews using Cohen's Kappa coefficient, which yielded results between reviewer one and two as 0.37, and 0.55 between reviewer one and three. This indicated a fair to moderate level of agreement between the authors in classifying the articles into the same category [38,39].

Step 3: Screening of full-text articles: The first author evaluated the full-text articles of the selected citations in accordance with the inclusion criteria, and 20 % of the full-text citations were reviewed by the second and third authors. The reasons for excluding evidence sources that did not meet the inclusion criteria in the full-text review were recorded in Covidence and are reported in the results section. Differences between the authors' decisions regarding the inclusion or exclusion of full-text articles in the selection process were flagged as conflicts in Covidence. The authors discussed each conflict to reach consensus. After discussion, the third author included or excluded relevant studies on Covidence.

Step 4: Data Extraction: Data extraction from the included articles was performed using a data extraction tool created in Covidence by the authors. The draft data extraction tool was piloted by the authors before the data extraction process commenced. Each author extracted three selected studies and charted relevant data. The extracted data from each author were compared and discussed to reach an agreement on understanding the concepts and terminology of the data extraction tool. The data extraction tool was revised as required and no further changes were made to the instrument after the data extraction process began.

The first author extracted data from full-text articles of the selected citations per inclusion criteria, and the second and third authors extracted data from 20 % of the full-text citations. The extracted data from each author was compared in Covidence. Any differences in the extracted data were discussed by the authors to reach a consensus before they were accepted into the final results section.

The following data were extracted from the included studies: 1) study characteristics (year of publication, country, source type, research aim and objectives, research design, population, sample size, and context); 2) key characteristics of personalized adaptive learning (platform used, implementation, indicators for implementation, type of content delivered, and strengths and limitations); and 3) impact of personalized adaptive learning on student learning, academic performance, and engagement.

Step 5: Data charting and synthesis: The data extraction results for Covidence were exported to an Excel spreadsheet. The extracted data were cleaned to improve the quality, remove duplicate or irrelevant information, and identify and correct missing data or errors prior to analysis. The data was charted to indicate how the results relate to the research questions. A narrative synthesis was compiled to summarize the results and visually present using a PRISMA-ScR flow diagram, data chart, tables, and graphs. The JBI Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews, PRISMA-ScR Checklist was used a reporting guideline [40].

## 3. Results

### 3.1. Literature search outcomes

The number of search hits per database is presented in Table 2.

**Table 2**
Number of search hits per database.

| Database | Number of search hits |
|---|---|
| ProQuest Dissertations & Theses Global | 345 |
| SCOPUS | 180 |
| Unspecified | 106 |
| Web of Science | 105 |
| MEDLINE Complete via EBSCOHost | 104 |
| ERIC via EBSCOHost | 90 |
| Cochrane Library | 41 |
| CINAHL Complete via EBSCOHost | 11 |
| JBI Evidence Synthesis | 6 |
| **Total number of search hits:** | **988** |

Nine hundred and eighty-eight references (n = 988) were imported into the Covidence software. Following automatic removal of duplicates (n = 109), 879 abstracts were screened. Of the 879 abstracts evaluated, 192 met the inclusion criteria for further review and 687 were categorized as irrelevant. The scoping review process was monitored through adherence to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines [40]. After reviewing 192 full texts, 123 studies were excluded because they did not meet the inclusion criteria, and 69 studies were included in this scoping review. The identification and extraction process of our study is presented in Fig. 1 as a Preferred Reporting Items for Systematic Reviews and Meta-analyses extension for scoping review (PRISMA-ScR) flow diagram [40].

A summary of the extracted data on the key characteristics and the impact of personalized adaptive learning from the included studies is presented in the data chart in Table 3.

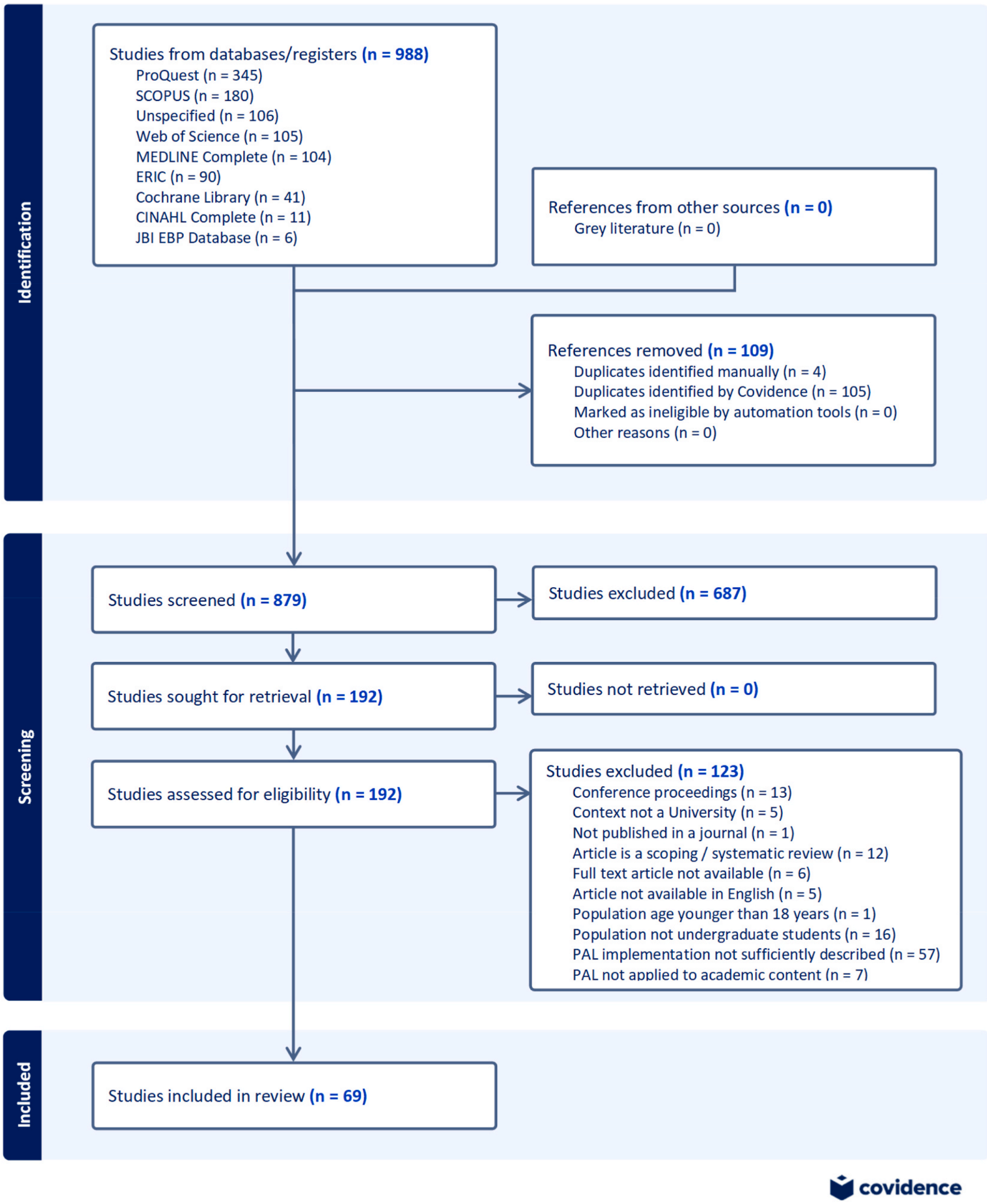


**Fig. 1.** PRISMA-ScR flow diagram of the review process [37].

**Table 3**
Data chart on the key characteristics and impact of personalized adaptive learning.

| Author | Personalized adaptive learning measures | Content delivered through personalized adaptive learning | Strengths of personalized adaptive learning | Limitations of personalized adaptive learning | Impact on academic performance |
|---|---|---|---|---|---|
| Aljabali et al. (2020) [41] | Student (social/behavioral) attributes based on self-rated measures; Learning profiles - self-rated | Academic teaching content; Self-assessment quizzes | Personalization and customization of learning. | None reported | Increased student success |
| Alkore Alshalabi, (2016) [42] | Pre-knowledge quiz/test; Learning profiles - self-rated | Academic teaching content | Personalization and customization of learning | None reported | Increased student success |
| Alshammari & Qtaish, (2019) [43] | Pre-knowledge quiz/test; Learning profiles - self-rated | Academic teaching content | Improve learning outcomes and quality of learning. | Other: Limited ability for students to control the learning process | Increased student success |
| Alsobhi & Alyoubi, (2019) [19] | Learning profiles - self-rated | Not reported | Improve learning outcomes and quality of learning. | None reported | No impact reported |
| Alwadei, (2019) [44] | Pre-knowledge quiz/test; Multi-modal data | Academic teaching content; Other: Revision course | Personalization and customization of learning | Other: Focus on outcomes measures, such as cognitive performance, rather than learning processes | Increased student success |
| Alwadei et al. (2023) [45] | Student engagement based on Learning Analytics (Activity logs/Clickstreams); Pre-knowledge quiz/test; Academic performance averages; Student (social/behavioural) attributes based on self-rated measures | Academic teaching content; Self-assessment quizzes | Personalization and customization of learning; Improve learning outcomes and quality of learning | Technological limitations | Increased student success |
| Azevedo et al. (2024) [46] | None reported | Academic teaching content | Personalization and customization of learning; Improve learning outcomes and quality of learning; Increase engagement and motivation | None reported | No impact reported |
| Bamba Adewumi, (2020) [47] | Pre-knowledge quiz/test | Homework assignments; Tutorials/ Remedial teaching | Increase engagement and motivation; improve teaching efficiency. | Students tried to use a 14-day free trial to avoid paying a costly access fee. | Increased student success |
| Basitere et al. (2023) [48] | None reported | Self-assessment quizzes | Improve learning outcomes and quality of learning; Other: Timely student feedback & use of visual modes to explain concepts | Technological limitations; Other: Interactive platforms are expensive and not all students have prior experience with technology. | Increased student success |
| Benchoff et al. (2018) [49] | Pre-knowledge quiz/test; Learning profiles - self-rated | Academic teaching content; Self-assessment quizzes | Improve learning outcomes and quality of learning. | Other: Attempts had to be limited to avoid trial and error by students. | Increased student success |
| Cerezo et al. (2020) [50] | Student (social/behavioral) attributes based on self-rated measures; Other: Self-regulating strategies | Other: Self-regulating strategies for learning | Personalization and customization of learning. | None reported | Other: Increase in self-regulation strategies. |
| Chrysafiadi et al. (2023) [51] | Pre-knowledge quiz/test | Academic teaching content | Personalization and customization of learning; Improve learning outcomes and quality of learning; Increase engagement and motivation; Improve teaching efficiency | None reported | Increased student success |
| Clark & Kaw, (2020) [52] | Pre-knowledge quiz/test; Academic performance averages; Multi-modal data; Student (social/behavioral) attributes based on self-rated measures | Other: Pre-class preparations for flipped classroom | Improve learning outcomes and quality of learning. | Other: Effort required to program the platform and have content ready for implementation. | Increased student success |
| Contrino et al.’ (2024) [53] | Student engagement based on Learning Analytics (Activity logs/Clickstreams); Pre- | Academic teaching content | Personalization and customization of learning; | Technological limitations; Attitudinal limitations | Increased student success |

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**Table 3** (*continued*)

| Author | Personalized adaptive learning measures | Content delivered through personalized adaptive learning | Strengths of personalized adaptive learning | Limitations of personalized adaptive learning | Impact on academic performance |
|---|---|---|---|---|---|
| | knowledge quiz/test; Academic performance averages | | Improve learning outcomes and quality of learning | | |
| Deng et al. (2019) [54] | Learning profiles - self-rated | Academic teaching content | Improve learning outcomes and quality of learning; improve teaching efficiency. | Other: Limited consideration of advanced student behavior | Increased student success |
| Dietrich et al. (2021) [55] | Pre-knowledge quiz/test; Other: Questionnaires on motivation | Academic teaching content | Improve teaching efficiency. | Other: No student collaboration and no individualized prompts to support students in using self-regulated learning strategies. | Increased student success |
| Dry et al. (2018) [56] | Student engagement based on Learning Analytics; Academic performance averages; Student (social/behavioral) attributes based on self-rated measures; | Academic teaching content | Personalization and customization of learning. | Technological limitations | Increased student success |
| Duffy & Azevedo, (2015) [57] | Pre-knowledge quiz/test; Student (social/behavioral) attributes based on self-rated measures | Academic teaching content | Improve learning outcomes and quality of learning. | Other: Scaffolds are not sufficient to improve comprehension and achievement outcome | No impact reported |
| Dziuban et al. (2018) [58] | Pre-knowledge quiz/test | Academic teaching content | Personalization and customization of learning; improve teaching efficiency; accessibility. | None reported | No impact reported |
| Eau et al. (2022) [59] | Pre-knowledge quiz/test | Homework assignments | Improve teaching efficiency. | None reported | Increased student success |
| Eichler & Peeples, (2013) [60] | Pre-knowledge quiz/test; Academic performance averages | Homework assignments | Improve learning outcomes and quality of learning. | Technological limitations; Time and resource limitations | Increased student success |
| Ennouamani et al. (2020) [61] | Pre-knowledge quiz/test; Academic performance averages; Learning profiles - self-rated; Student (social/behavioral) attributes based on self-rated measures | Academic teaching content | Improve learning outcomes and quality of learning; accessibility. | Other: Limited multimedia formats of content presentation | Increased student success |
| Eryilmaz & Adabashi, (2020) [62] | Pre-knowledge quiz/test | Other: Learning Excel | Personalization and customization of learning; improve learning outcomes and quality of learning; improve teaching efficiency. | None reported | Increased student success |
| Gransden et al. (2024) [63] | Student engagement based on Learning Analytics (Activity logs/Clickstreams) | Other: Referencing & student systems | Personalization and customization of learning; Improve learning outcomes and quality of learning; Increase engagement and motivation | Technological limitations | Increased student success |
| Harati et al. (2021) [64] | Pre-knowledge quiz/test; Student (social/behavioral) attributes based on self-rated measures | Academic teaching content | Personalization and customization of learning. | Other: Adaptive technology requires autonomous and independent learners with high SRL skills | No impact reported, SRL scores decreased |
| Heras et al. (2020) [65] | Learning profiles - self-rated; Other: Student's educational preferences in terms of interactivity level, preferred language and preferred format. | Academic teaching content | Personalization and customization of learning. | Other: Textual explanations not suited for all learners. | No impact reported |
| Hinkle et al. (2020) [66] | Pre-knowledge quiz/test | Academic teaching content | Improve learning outcomes and quality of learning during a disaster. | None reported | No impact reported |
| Horvers et al. (2024) [67] | Pre-knowledge quiz/test; Physiological data; Student (social/behavioural) attributes based on self-rated measures; Affective state of students | Academic teaching content | Personalization and customization of learning; Improve learning outcomes and quality of learning; Increase engagement and motivation | Technological limitations | No impact reported |

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**Table 3** (*continued*)

| Author | Personalized adaptive learning measures | Content delivered through personalized adaptive learning | Strengths of personalized adaptive learning | Limitations of personalized adaptive learning | Impact on academic performance |
|---|---|---|---|---|---|
| Hsieh et al. (2013) [24] | Pre-knowledge quiz/test; Learning profiles - self-rated | Tutorials/ Remedial teaching | Personalization and customization of learning; improve learning outcomes and quality of learning. | Other: Fail to reflect if teaching materials match learner preferences. | Increased student success |
| Huang & Shiu, (2012) [68] | Pre-knowledge quiz/test | Other: Web design - related to their field of study | Personalization and customization of learning; improve teaching efficiency. | Perception limitations | Increased student success |
| Ipinnaiye et al. (2024) [69] | Student engagement based on Learning Analytics (Activity logs/Clickstreams); Confidence level on content related questions | Academic teaching content | Personalization and customization of learning; Improve learning outcomes and quality of learning; Increase engagement and motivation | Pedagogical limitations; Logistical limitations | Increased student success |
| Jang et al. (2017) [16] | Multi-modal data; Learning profiles - self-rated; Student (social/behavioral) attributes based on self-rated measures; Other: Confidence level on content related questions | Academic teaching content | Personalization and customization of learning. | Technological limitations; Other: Lacks tactile interactions with patients. | No impact reported |
| Janson et al. (2022) [70] | Student engagement based on Learning Analytics (Activity logs/Clickstreams) | Academic teaching content | None reported | Technological limitations | No impact reported |
| Jeong et al. (2012) [71] | Pre-knowledge quiz/test | Other: English | Improve teaching efficiency; improve learning outcomes and quality of learning. | None reported | Increased student success |
| Jeong & Choi, (2013) [72] | Pre-knowledge quiz/test | Other: English | Personalization and customization of learning; accessibility. | None reported | Increased student success |
| Kaoropthai et al. (2019) [73] | Pre-knowledge quiz/test | Tutorials/ Remedial teaching | Personalization and customization of learning. | Other: Limited consideration of individual learner variables | Increased student success |
| Khosravi et al. (2019) [74] | Student engagement based on Learning Analytics; Academic performance averages | Academic teaching content | None reported | None reported | Increased student success |
| Kolpikova et al. (2019) [75] | Pre-knowledge quiz/test | Self-assessment quizzes | None reported | Time and resource limitations | No impact reported |
| Kunzler, (2012) [76] | Other: Student errors | Homework assignments | Improve teaching efficiency | Technological limitations; time and resource limitations. | Increased student success |
| Latham et al. (2014) [77] | Pre-knowledge quiz/test; Learning profiles - self-rated | Tutorials/ Remedial teaching | Personalization and customization of learning; increase engagement and motivation. | Time and resource limitations; Other: the algorithm not adaptive to emotional factors such as boredom and frustration that affect learning. | Increased student success |
| Leas, (2015) [20] | Pre-knowledge quiz/test; Learning profiles - self-rated | Academic teaching content | None reported | None reported | No impact reported |
| Lim et al. (2023) [78] | Academic performance averages | Not reported | Personalization and customization of learning; Improve learning outcomes and quality of learning | None reported | Increased student success |
| Lim et al. (2024) [79] | Student engagement based on Learning Analytics (Activity logs/Clickstreams) | Academic teaching content | Personalization and customization of learning; Improve learning outcomes and quality of learning | Technological limitations | No impact reported |
| Lv, (2024) [80] | Student (social/behavioural) attributes based on self-rated measures; Other: Competency indicators | Academic teaching content | Personalization and customization of learning; Improve learning outcomes and quality of learning; Increase engagement and motivation | None reported | Increased student success |
| Maaliw III, (2020) [81] | Student engagement based on Learning Analytics Learning profiles - self-rated | Academic teaching content | Personalization and customization of learning. | Technological limitations | No impact reported |

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**Table 3** (*continued*)

| Author | Personalized adaptive learning measures | Content delivered through personalized adaptive learning | Strengths of personalized adaptive learning | Limitations of personalized adaptive learning | Impact on academic performance |
|---|---|---|---|---|---|
| Manly, (2024) [82] | Pre-knowledge quiz/test; Academic performance averages | Academic teaching content | Personalization and customization of learning; Improve learning outcomes and quality of learning; Accessibility | None reported | Increased student success |
| Mejeh et al. (2024) [83] | Student (social/behavioural) attributes based on self-rated measures | Other: Self-Regulated Learning strategies | Personalization and customization of learning; Improve learning outcomes and quality of learning; Increase engagement and motivation; Other: data analysis | Technological limitations; Limited personalization | No impact reported |
| Miller et al. (2019) [84] | Pre-knowledge quiz/test | Homework assignments | Personalization and customization of learning. | Other: Weighting, number of attempts allowed and rigid due dates may impact completion rates | No significant impact reported |
| Mwambe et al. (2020) [85] | Student engagement based on Learning Analytics; Pre-knowledge quiz/test; Academic performance averages; Physiological data; Other: Reading time. | Academic teaching content | Personalization and customization of learning. | None reported | Increased student success |
| Papamitsiou et al. (2020) [86] | Student engagement based on Learning Analytics; Pre-knowledge quiz/test; Physiological data; Student (social/behavioral) attributes based on self-rated measures | Self-assessment quizzes | Personalization and customization of learning; increase engagement and motivation. | None reported | No impact reported |
| Polly et al. (2014) [87] | Pre-knowledge quiz/test | Academic teaching content; Tutorials/ Remedial teaching | Increase engagement and motivation; improve learning outcomes and quality of learning. | None reported | No impact reported |
| Premlatha et al. (2016) [88] | Student engagement based on Learning Analytics; Multi-modal data; Learning profiles - objective | Academic teaching content | Personalization and customization of learning. | None reported | No impact reported |
| Putra et al. (2021) [21] | Pre-knowledge quiz/test | Academic teaching content | Personalization and customization of learning; improve teaching efficiency and data analysis. | Time and resource limitations | No significant impact reported |
| Renn et al. (2021) [89] | Student engagement based on Learning Analytics; Pre-knowledge quiz/test | Homework assignments | Improve learning outcomes and quality of learning; improve teaching efficiency. | Other: Designed to supplement classroom instruction, cannot replace teaching | Increased student success |
| Samofalova et al. (2023) [90] | Pre-knowledge quiz/test; Learning profiles - self-rated | Academic teaching content | Personalization and customization of learning; Improve learning outcomes and quality of learning; Increase engagement and motivation | Attitudinal limitations | Increased student success |
| Scarpiello, (2021) [30] | Pre-knowledge quiz/test | Homework assignments | Personalization and customization of learning; improve learning outcomes and quality of learning. | Other: Student adjustment to online instruction | Increased student success |
| Sense et al. (2021) [91] | Pre-knowledge quiz/test | Academic teaching content | Personalization and customization of learning; increase engagement and motivation. | Technological limitations | No impact reported |
| Smyrnova-Trybulska et al. (2022) [92] | Learning profiles - objective | Academic teaching content | Personalization and customization of learning. | Time and resource limitations | Increased student success |
| Troussas, Chrysafiadi et al. | Student engagement based on Learning Analytics; Learning profiles - objective; Affective state of students; Other: | Academic teaching content | Personalization and customization of learning; improve learning outcomes and quality of learning. | None reported | No impact reported |

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**Table 3** (*continued*)

| Author | Personalized adaptive learning measures | Content delivered through personalized adaptive learning | Strengths of personalized adaptive learning | Limitations of personalized adaptive learning | Impact on academic performance |
|---|---|---|---|---|---|
| (2021) [93] | Usability and User experience instruments | | | | |
| Troussas, Krouska et al. (2021a) [94] | Pre-knowledge quiz/test; Academic performance averages | Academic teaching content | Personalization and customization of learning; improve learning outcomes and quality of learning. | Technological limitations | Increased student success |
| Troussas, Krouska et al. (2021b) [95] | Pre-knowledge quiz/test; Academic performance averages; Other: Degree of misconceptions between student mistakes and student performance | Academic teaching content | Personalization and customization of learning; improve learning outcomes and quality of learning. | Technological limitations | No impact reported |
| White, (2020) [96] | Confidence level on content related questions; Other: Content knowledge | Academic teaching content | Personalization and customization of learning. | Technological limitations; Other: Poor match between test questions and content, Reading and difficulty levels of questions set by test bank vs instructor may differ. | No impact reported |
| Wu et al. (2018) [97] | Pre-knowledge quiz/test | Other: Learning Excel | Personalization and customization of learning; improve learning outcomes and quality of learning. | Other: Limited consideration of individual learner variables and not providing dynamic scaffoldings for them. | Increased student success |
| Xie et al. (2019) [98] | Pre-knowledge quiz/test | Other: English second language - word learning | Personalization and customization of learning. | Time and resource limitations | Increased student success |
| Xu et al. (2014) [99] | Pre-knowledge quiz/test | Academic teaching content; Self-assessment quizzes | Personalization and customization of learning. | None reported | Increased student success |
| Yang et al. (2013) [100] | Pre-knowledge quiz/test; Learning profiles - self-rated | Academic teaching content | Improve learning outcomes and quality of learning. | Other: Not considering the difficulty levels of the learning materials. | Increased student success |
| Yang et al. (2014) [101] | Pre-knowledge quiz/test; Other: Critical thinking and language tests | Academic teaching content | Personalization and customization of learning. | Other: Not allowing learners to progress from one proficiency level to another. | Other: Improved critical-thinking skills |
| Yousaf et al. (2023) [102] | Pre-knowledge quiz/test | Academic teaching content | Personalization and customization of learning; Increase engagement and motivation | None reported | Increased student success |
| Zhu & Wang, (2020) [103] | Student engagement based on Learning Analytics; Pre-knowledge quiz/test; Academic performance averages; Other: Student perception survey | Academic teaching content | Increase engagement and motivation. | Technological limitations; Other: Limited data analytics | Increased student success |

### *3. 2. Study characteristics*

#### *3.2.1. Distribution by publication year, source and country*

Personalized adaptive learning is a growing area of research interest. Fig. 2 presents a literature mapping graph illustrating the resonance and evolution of personalized adaptive learning in higher education from 2012 to 2024, showcasing relevant publications, key authors according to citation counts, and the interconnections between various publications in this rapidly developing field.

The 69 included articles reflected an increasing number of publications since 2012. A decrease was seen in 2015 that remained at two publications per year (n = 2, 4 %) in 2016, and one in 2017 (n = 1, 2 %). An upward trend in publications was noted from 2018 (n = 4, 8 %) to 2019 (n = 9, 17 %), with the most publications on the research topic in 2020 (n = 13, 25 %). Of the 69 included studies published in the last twelve years, 40 (58 %) were published between 2020 and 2024 as seen in Fig. 3.

The majority of the 69 included articles were from peer-reviewed journals (n = 63, 91 %) and six (n = 6, 9 %) were dissertations. Nearly one third of the studies were from the United States (n = 20, 29 %), followed by Taiwan with the second highest number of publications (n = 5, 7 %). Four publications were from Greece (n = 4, 6 %) and Australia, China, Spain and Germany each had three publications (n = 3, 4 %) that were included in the scoping review. The other countries with two publications each (n = 2, 3 %) were Canada, Republic of Korea, Saudi Arabia, Netherlands, United Kingdom, Ireland and Russia. The remaining countries had one

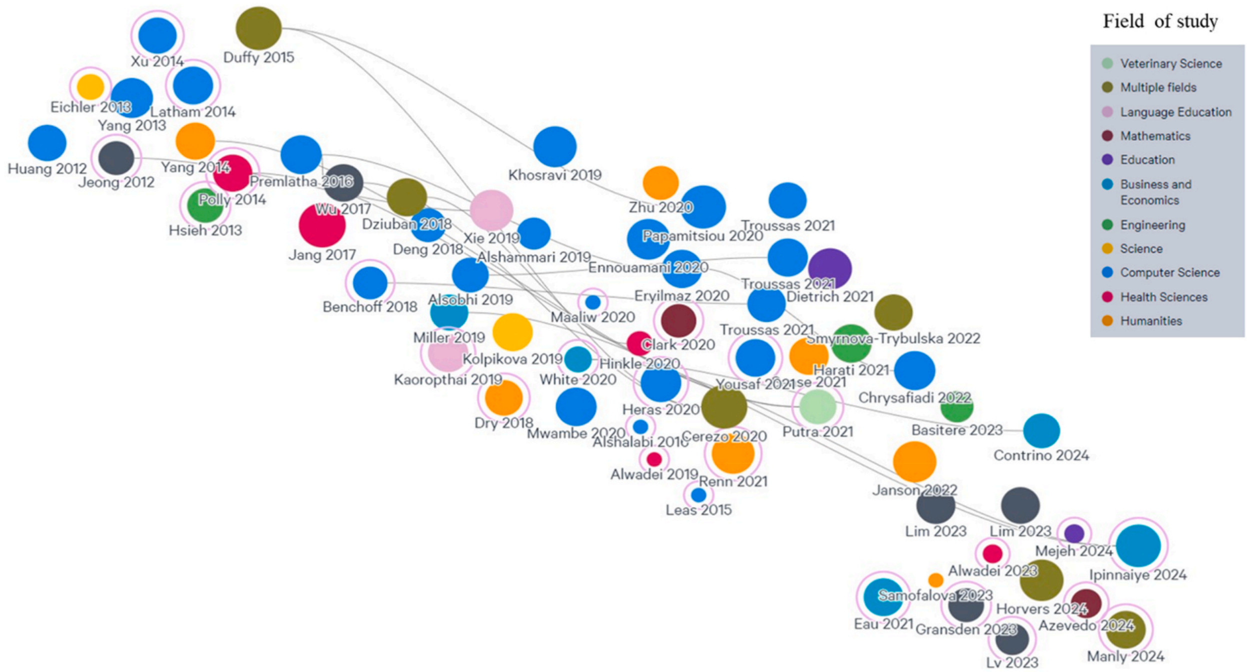


**Fig. 2.** Literature map of Personalized Adaptive Learning (PAL) in higher education (2012–2024).

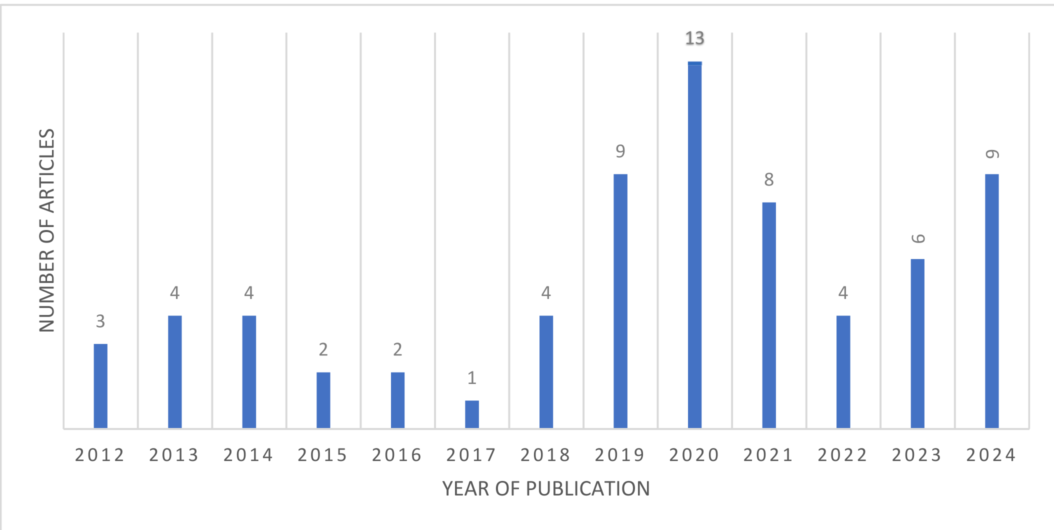


**Fig. 3.** Number of articles per year of publication.

publication each (n = 1, 1 %). The countries from which the publications were included in the scoping review are shown on the world map in Fig. 4.

### 3.2.2. *Distribution by population characteristics*

Over ninety percent of the research (n = 63, 91 %) was conducted at universities, followed by TVET Colleges (n = 3, 4 %), and three studies (n = 3, 4 %) were charted as other because it did not specify the context. The participants in the 69 included studies were undergraduate students from different academic programs and fields of study. Most of the studies were from Information Technology (n = 23, 33 %), followed by humanities and economic and business sciences with 6 studies each (n = 6, 9 %), health sciences (n = 5, 7 %), natural and agricultural sciences (n = 4, 6 %), Three studies were from engineering (n = 3, 4 %), two from education (n = 2, 3 %) and one was from veterinary sciences (n = 1, 1 %). Eight of the 69 studies were categorized as other: mixed if the research was conducted across multiple fields of study (n = 8, 12 %), and eleven of the articles did not specify the field of study (n = 11, 16 %) and

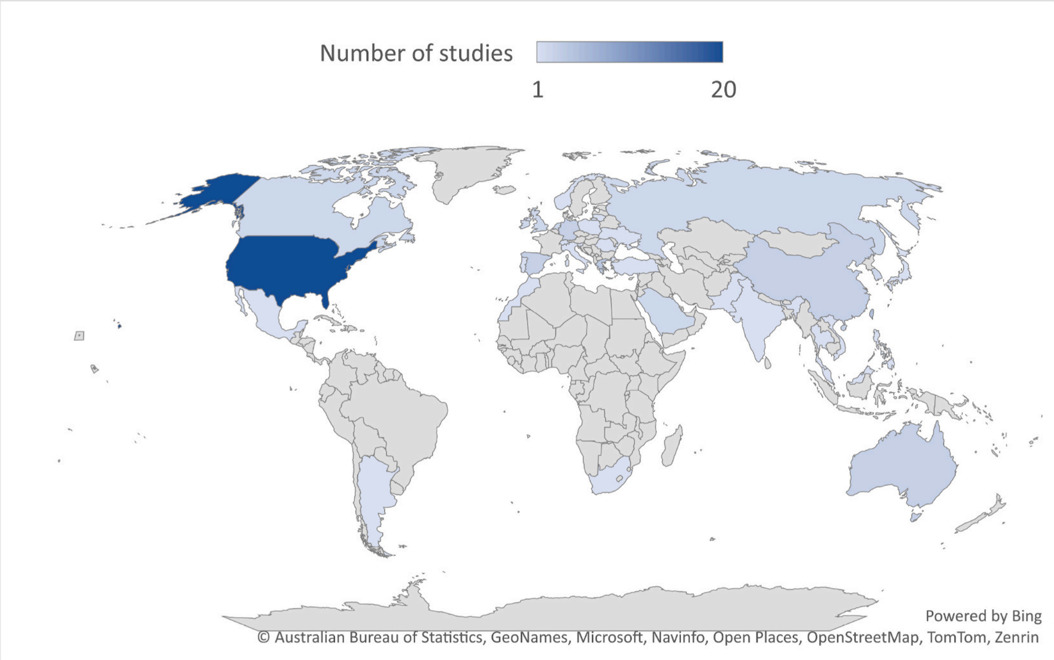


**Fig. 4.** Publications by country.

were categorized as other: unspecified. Fig. 5 shows the number of articles per field of study.

### 3.2.3. Distribution by research design

Various study designs have been implemented to investigate the effects of personalized adaptive learning on student learning. The most common research designs were experimental (n = 21, 30 %) quasi-experimental (n = 21, 30 %), correlational (n = 6, 9 %), mixed method (n = 6, 9 %), other (n = 6, 9 %), survey (n = 4, 6 %), descriptive (n = 3, 4 %), and case study design (n = 2, 3 %).

### 3.2.4. Aims and objectives of included studies

A wide range of studies has examined the effectiveness and impact of adaptive learning systems in various educational contexts [44] and the development of adaptive learning system prototypes [89]. The included studies aimed to explore various objectives, including evaluating the role of customization in courses [76], identifying individual student needs using adaptive learning techniques

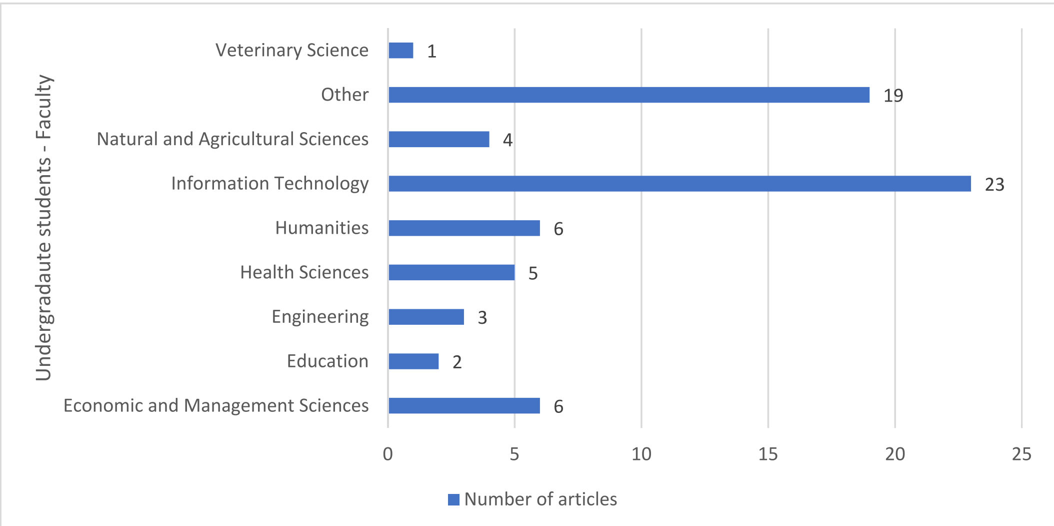


**Fig. 5.** Number of articles per field of study.

[42], and analyzing the impact of specific adaptive learning platforms [30]. Other studies compared the effectiveness of adaptive e-learning in different teaching techniques and classroom settings [18], developed personalized remedial learning systems [24], and evaluated user-centric adaptive systems [68]. Furthermore, the influence of adaptive learning on the development of self-regulated learning skills [50], as well as the impact of gamified learning models [41], intelligent tutoring systems [89], and adaptive learning in diverse subject areas such as English second language [98], computer science [20], and veterinary dermatology [21] were investigated.

#### 3.2.5. Distribution by sample size

The sample size of the participants varied greatly between the studies (min = 17, max = 12714). The mean sample size of the included studies was 390.2 with a median of 120 and a standard deviation of 1528.5. Studies with a sample size below 100 participants were categorized as small, sample sizes between 100 and 250 participants were medium, and those with more than 250 participants were considered large [104–106]. The 69 studies included in this scoping review consisted mostly of small-sample studies (n = 28, 41 %), medium-sample size studies (n = 24, 35 %), and the least number of studies had a large sample size (n = 17, 25 %). Studies from the Faculties of Humanities and Information Technology had noticeably larger sample sizes.

### 3.3. Key characteristics of personalized adaptive learning

#### 3.3.1. Distribution by personalized adaptive learning platform

Researchers have used a variety of terms interchangeably in the investigation of personalized adaptive learning platforms [66], such as adaptive learning systems [68], adaptive courseware [59], or adaptive technology [96], intelligent tutoring systems [50], adaptive algorithms [89], model-based adaptive fact-learning systems [91], adaptive e-learning systems [19], and intelligent agent-supported virtual learning environments [107], adaptive virtual learning environment [81], bioinformatics-based adaptive systems [85], context-aware mobile learning systems [61], or personalized remedial learning systems [24].

The platforms used for implementing personalized adaptive learning have varied widely across studies. The Moodle learning management system (n = 6, 9 %) and McGraw-Hill's Connect LearnSmart (n = 6, 9 %) were the most prevalent platforms, followed by Smart Sparrow (n = 3, 4 %) and Realizeit (n = 3, 4 %). Three studies used mobile apps (n = 3, 4 %), whereas only one of the included studies used the Blackboard Learning Management System (n = 1, 1 %). Of the 69 included studies, 28 used different platforms from those mentioned or developed their own platforms for delivering content through adaptive learning pathways (n = 33, 48 %). Lastly, seven of the included studies did not specify the adaptive learning platform used in their research (n = 11, 16 %).

#### 3.3.2. Distribution by indicators for content delivery

The use of pre-knowledge quizzes as an indicator for activating adaptive learning pathways was the most prevalent (n = 40, 58 %), followed by student engagement based on learning analytics such as activity logs and clickstreams (n = 15, 22 %). Four of the included studies used learning profiles as an adaptive learning indicator (n = 4, 6 %), and two studies used student social or behavioral attributes based on self-rated measures (n = 10, 14 %). One study used students' self-rated confidence levels to answer content-related questions (n = 3, 4 %). The type of error made by students while practising or applying concepts learned on the platform was used as another measure (n = 1, 1 %), as well as student profiling based on multimodal data (n = 4, 6 %).

#### 3.3.3. Distribution by type of content delivered through personalized adaptive learning

The majority of the included studies used adaptive learning strategies for the delivery of academic teaching content and self-assessment quizzes (n = 44, 64 %), homework assignments were second (n = 7, 10 %), three studies used adaptive learning for tutorials or remedial teaching (n = 7, 10 %), and three used adaptive learning for student self-assessment quizzes (n = 3, 4 %). Two of the included studies taught Excel to students (n = 2, 3 %), two studies delivered self-regulation for learning strategies to students (n = 2, 3 %), and two studies did not specify the type of content delivered through the platform (n = 2, 3 %).

#### 3.3.4. Distribution by strengths of personalized adaptive learning

The use of personalized adaptive learning has been recognized by researchers as a valuable and versatile tool with numerous advantages. One of the key strengths that has emerged is personalization and customization (n = 43, 62 %), followed by improvement in learning outcomes and quality of learning (n = 25, 36 %), and improvement in teaching efficiency (n = 6, 9 %). The positive impact of personalized adaptive learning on student engagement and motivation (n = 14, 20 %) has been acknowledged by instructors, as well as the accessibility of learning content (n = 3, 4 %). Other strengths of personalized adaptive learning (n = 35, 51 %) mentioned in the studies, include its potential to enhance academic performance [42], support self-paced and efficient learning [23], and offer benefits such as augment clinical training by mirroring clinical reasoning [89], and reduce anxiety in subjects such as mathematics [15]. Its ability to provide personalized feedback [23], promote active and self-regulated learning [57], and maintain educational continuity during disruptions is valued [66], along with increased student satisfaction [18]. It also allows students to practice their skills [89] and make mistakes during a safe learning process [87]. Repetition of learning is facilitated by allowing students multiple attempts in completing learning activities [49]. The ability of an adaptive system to evaluate student ability [68], predict academic performance [56] and identify at-risk students [54] are further recognized as advantageous features.

#### 3.3.5. Distribution by limitations of personalized adaptive learning

Personalized adaptive learning faces constraints that are complex in nature, including technological limitations (n = 22, 32 %), time and resource limitations (n = 7, 10 %), pedagogical limitations (n = 3, 4 %), student attitudinal limitations (n = 2, 3 %), and perception of the use of the platform as an additional workload (n = 1, 1 %). One study reported instructor perceptions regarding the use of the personalized adaptive learning platform as a limitation (n = 1, 1 %), and 36 studies included other limitations (n = 36, 52 %). Other limitations include challenges in programming and content preparation by instructors [52], restricted student control over the learning process [43], and the need for high self-regulation among learners [64]. Limitations also encompass inadequacies in system algorithms to account for diverse student characteristics, leading to potential impacts on learning outcomes [77], difficulties faced by students in adapting to online courses [30], and the costs associated with access codes [15]. A focus primarily on academic performance, rather than holistic learning processes, also detracts from its effectiveness. Some of the technological limitations mentioned in the studies include lack of safeguards in the online system [48], lack of feedback for incorrect answers and practical issues with students being marked incorrect due to spelling/case errors in question types other than MCQs [63]. Adaptive learning can limit the authentic learning experience of students [108], and students may show different emotional responses in a controlled laboratory setting compared to their regular class environment [67]. Furthermore, adaptive learning technology used only trace data such as mouse clicks, page navigation, and keystrokes and did not incorporate other modalities like audio or video data on students [48], and system algorithms do not consider diverse student characteristics such as boredom and frustration [109], emotional state [110], or variables like self-regulation for learning and attitude, which can impact learning [111].

#### 3.3.6. Implementation strategies utilized in personalized adaptive learning

The 69 studies included in this scoping review yielded several key insights, including the use of a variety of personalized adaptive learning systems to tailor learning or remediation by providing individualized learning pathways [15,24,59]. Studies have reported a variety of indicators used as triggers for activating adaptive content delivery, such as students' individual knowledge levels [21,59,66], behavior [50], and self-rated learning styles or preferences [54,65]. Sensory modalities [85,112], cognitive styles [56], and dyslexia [19], have also been used as indicators to tailor personalized learning activities. Complex adaptive algorithms built into adaptive learning platforms [19,42,58] use a single indicator, such as a pre-knowledge quiz mark [21,59,62], a combination of indicators [56,113], or multimodal profiling data [16] to alter or guide the generation of personalized learning paths that align content delivery to individual students. The duration for which personalized adaptive learning was implemented varied widely across studies, ranging from its application in an online revision tutorial [77] to the duration of a course [66]. The instructor's role in terms of learning design, content creation, monitoring, student,- and technical support remains central to the implementation and effectiveness of personalized adaptive learning [59,64], despite the computerized functioning of adaptive algorithms.

### 3. 4. Impact of personalized adaptive learning on academic performance, student engagement and learning

#### 3.4.1. Distribution by impact on academic performance

Of the 69 reviewed studies, 41 reported an increase in students' academic performance (n = 41, 59 %), whereas 28 reported no impact on academic performance (n = 28, 41 %). Seven studies did not have academic performance as an outcome measure but reported additional student improvements such as an increase in the critical thinking skills of students [23], increased acquisition of core competencies, and the use of self-regulation strategies for learning [50]. In contrast, one study noted a decrease in students' self-regulation scores [64]. One study specifically noted an increase in the academic performance of high-performing students and women following the implementation of personalized adaptive learning, although it had no negative impact on the performance of other students [59].

#### 3.4.2. Distribution by impact on student engagement

Forty-four studies did not report the impact of personalized adaptive learning on student engagement as an outcome (n = 44, 64 %), while 25 studies indicated an increase in student engagement during the implementation of personalized adaptive learning (n = 25, 36 %) [61,64]. Two studies noted an increase in students' engagement with learning resources [21,57]. According to one study, the use of the platform motivated students to learn [51] but another study reported a decrease in student engagement due to isolation created by individual learning pathways [53].

#### 3.4.3. Impact of personalized adaptive learning on students' learning

Several studies have indicated that an adaptive learning system enhances students' learning processes [42] and has a significant impact on academic performance [15], as seen in higher post-test scores [44], higher exam marks [60], and improvement in critical thinking skills [23]. Students who completed LearnSmart with a 100 % score had higher final course grades [96]. However, using the LearnSmart platform did not have a significant impact on exam grades. One study reported that rigid deadlines for the completion of LearnSmart assignments had a negative impact on completion rates, whereas students with a flexible completion regime performed better in LearnSmart assignments and exams [84]. Improvement in short- and medium-term learning outcomes after the completion of adaptive learning tasks was reported in another study [43]. Students who used the adaptive system performed significantly better in assessments [56]; it decreased their mental load and increased their belief in learning progress [113]. A student's chance of success was greater if they completed many adaptive activities and practised and revised the content [58]. These findings are contrary to those of another study indicating that customization did not have an effect on student grades [76], and the completion of adaptive pre-class reading questions did not influence students' actual or perceived preparedness for class and had no impact on exam results [75]. An unexpected finding was that self-regulated learning scores of students decreased significantly after four months of instruction on the ALEKS platform [64].

Tailored content delivery is also a way to retain student engagement, regardless of a student's motivation [112], whereas another study reported that adaptive learning can improve student motivation [65]. Adaptive learning also had an impact on low-achieving students, who showed significant improvement [24]. Students showed an increased interest in the course, and enthusiastic students had the highest assessment scores after the implementation of adaptive learning [88]. One study presented a framework and architecture of an adaptive system and did not report the outcomes of its application [81]. It was also noted that the student variables that showed an association with task performance could be used to inform the further development of individual learning pathways [16].

## 4. Discussion

### 4.1. Study characteristics

Our findings highlight an increasing number of publications on personalized adaptive learning from 2018 onwards. The surge in publications between 2020 and 2024 may be attributed to the increased use of educational technology as a result of emergency remote teaching (ERT) during the Covid 19 pandemic [114,115], the innovation and advancement of adaptive learning technologies [116], and its potential to transform higher education through tailored educational offerings [117] and creating meaningful and effective student learning experiences [118]. The prominence of adaptive learning has been emphasized as one of the educational technologies that is expected to make the most significant impression on higher education [119]. The advancement of computer technologies has had a direct impact on the development of adaptive systems and strategies for personalized learning as new technologies enable rich and diverse learning content and learning experiences, as well as more advanced personalization system features. Commonalities were noted in the benefits and methods utilized in personalized learning and adaptive learning technologies to create tailored educational experiences. The intersectionality between personalized learning and adaptive learning technologies can be described as two concepts that are not separate entities, but rather intertwined approaches that is focussed on adapting content to student's needs through the integration of technology based on student tracking metrics.

North America, Asia, Europe, parts of South America, and Australia had a higher representation in the number of published studies. The dominance of the United States in the included studies, and other developed countries such as Australia reflects the significant value placed on personalized adaptive learning within leading educational systems, while the overall involvement of countries from diverse regions such as Europe, Asia, South America, and the Middle East shows a global interest in seeking educational technology solutions to improve student learning. However, there is a clear underrepresentation of Africa, Eastern Europe, and Central and Southern Asia. Similar trends have been noted in studies on Computational Thinking in schools [120] and higher education settings [121]. Underrepresented countries may not have the technological resources, access to online platforms, or necessary expertise for the implementation of personalized adaptive learning due to a lack of funding or skills development opportunities, follow more traditional teaching or delivery modes for curricula, or may still be in the initial stages of implementing such technologies [122]. To improve the implementation of personalized adaptive learning in developing countries, future development should focus on enhancing technological infrastructure, creating culturally relevant content [123], and developing low-resource solutions [124]. Capacity building through international collaborations is important [125], as is establishing comprehensive policy frameworks [126], sustainable funding models [127] and robust monitoring and evaluation systems [128]. To succeed, future approaches should integrate adaptive learning with existing educational systems [129] and develop offline capabilities to address connectivity issues [130]. By addressing these areas, personalized adaptive learning can be effectively implemented and scaled in underrepresented developing countries, potentially narrowing the global educational technology gap.

The significance of research on personalized adaptive learning in university settings across a diverse range of educational fields, with a noticeable presence in information technology, natural and agricultural sciences, and the humanities, highlights the direct relevance and practical applications of these systems across disciplines in higher education. In several studies, personalized adaptive learning positively influenced student success and engagement, especially in quantitative disciplines like mathematics and engineering [48,131]. This suggests that adaptive learning techniques may be particularly effective in subjects where learning progress can be systematically quantified and adapted to individual learning paths. However, the effectiveness of personalized adaptive learning varies, with some studies reporting no significant impact on student success or engagement [84,132]. This variance could be attributed to different implementation strategies, the inherent complexity of the subject matter, or varying degrees of adaptation in the personalized adaptive learning systems used. There appears to be a consistent positive outcome in STEM fields [103], likely due to the structured nature of problems and solutions in these areas which align well with adaptive learning systems that adjust based on student performance. The impact in non-STEM fields is less pronounced, possibly due to the subjective nature of content and the difficulty in measuring engagement and performance through adaptive systems [56]. The analysis indicates that while personalized adaptive learning has the potential to enhance learning outcomes significantly, its effectiveness is highly contingent on the subject area, the design and implementation of the system, and the specific educational context [44,133]. This highlights the necessity for tailored approaches in the deployment of personalized adaptive learning systems, taking into consideration the unique challenges and opportunities within different academic disciplines [51,69].

The studies included in our analysis utilized a diverse range of research designs, which contributed to a robust evidence base in the field through various rigorous scientific approaches. The breadth of research designs offers valuable insights for educators into the evolving nature of educational research practices and informs evidence-based decisions for the integration of adaptive learning systems in various educational settings. The wide range of sample sizes observed among the included studies is important in the interpretation of their findings to provide insight into potential biases associated with reported effect sizes, as studies with small sample sizes may report larger effect sizes [105]. Recognizing the influence of sample size on reported outcomes contributes to the critical evaluation and interpretation of the reliability and generalizability of reported outcomes [105].

### 4.2. Key characteristics of personalized adaptive learning

Regarding the first research question on the key characteristics of personalized adaptive learning in higher education, our findings reveal the multifaceted nature of personalized adaptive learning. The investigation of its core characteristics such as the platforms utilized, implementation strategies, indicators and triggers for adaptation, the content delivered, and a critical analysis of its strengths and limitations, provides a comprehensive overview of the current state and effectiveness of these systems in higher education settings.

Our study highlighted a wide range of terms used interchangeably to describe personalized adaptive learning platforms, indicating a lack of standardized nomenclature in the field. This is supported by Cavanagh [134] who described the variation of terminology as a hurdle for the implementation of adaptive learning. Two studies have also proposed the use of a uniform taxonomy for adaptive learning [26,27]. The lack of established standards in personalized adaptive learning research presents both challenges and opportunities for growth. On the one hand, it can make it difficult to compare and synthesize findings from different studies. On the other hand, this diversity of approaches and vocabularies showcases the field's adaptability and potential for innovation in various educational contexts. Efforts to develop a consistent taxonomy could enhance the coherence and effectiveness of personalized adaptive learning research and implementation strategies.

Surprisingly, significant variations were found in the platforms used to implement personalized adaptive learning. This diversity emphasizes the adaptability and potential of continuous new developments in the field of personalized adaptive learning systems, to cater to various educational needs and contexts. This is supported by Jing et al. [33] and Gligorea et al. [118] who described new developments in adaptive learning software over time, with the latest emerging systems combining Artificial Intelligence with adaptive systems to improve personalization and the learning experience of students [33]. These future developments, referred to as Adaptive Learning 3.0, aim to improve the integration between different components of the learning experience through data science, Artificial Intelligence, and machine learning [135].

Implementation strategies highlight the importance of tailoring learning or remediation through individualized learning pathways. Customization is achieved by utilizing various indicators, including students' knowledge levels, behavior, preferences, and even cognitive styles. These findings are consistent with the literature, as Taylor et al. [32] also found four categories of adaptive mechanisms. Interestingly, we found that pre-knowledge quizzes were predominantly used as content delivery indicators. This suggests a focus on the assessment of students' understanding of content to effectively tailor learning paths. This differs from the findings of Soler Costa et al. [136], who suggested that fair assessment of students' competences in personalized and adaptive learning may be difficult. The content delivered through personalized adaptive learning mainly included academic teaching content, self-assessment quizzes, and homework assignments, showing a comprehensive approach to covering the learning process from concept introduction to practice and assessment.

Personalized adaptive learning faces multiple limitations including technological, time, resource, and pedagogical constraints. This supports the findings of a previous study that described technological challenges in the implementation of adaptive learning [137]. These challenges highlight the complexity of implementing effective adaptive learning solutions. Some of the key areas that require investigation include enhancing technological capabilities to better accommodate diverse learner characteristics [138], optimizing resource allocation, and improving pedagogical integration [7]. Additionally, researchers should focus on fostering student engagement [139], developing more holistic assessment methods [29], and refining adaptive algorithms to account for emotional states and self-regulation abilities [116]. Efforts to create more authentic learning experiences within personalized adaptive learning environments [140] and provide effective support for instructors [141] are also crucial. By addressing these areas, future personalized adaptive learning research can work towards overcoming identified obstacles and developing more effective, inclusive, and comprehensive adaptive learning systems that align with the evolving needs of contemporary education.

Despite some limitations, personalized adaptive learning is recognized for its strengths in personalization, improving learning outcomes, enhancing teaching efficiency, and motivating students. Research shows that personalized adaptive learning significantly enhances student engagement and academic achievement. Adaptive systems increase student motivation and make learning more relevant [142]. However, effectiveness varies with individual student traits, benefiting those with higher initial motivation the most [143]. Studies demonstrate that personalized adaptive learning improves performance across contexts, especially for low-achieving students [98], but its impact is more pronounced in STEM subjects compared to humanities [144]. Despite its potential, the success of personalized adaptive learning depends on the subject, student characteristics, and implementation strategies, pointing to a need for further research in diverse educational settings.

### 4.3. Impact of personalized adaptive learning

In relation to the second research question on the impact of personalized adaptive learning on academic performance, student engagement, and learning, the results have uncovered outcomes that carry significant implications, highlighting how this innovative educational approach tailors the learning experience to meet individual student needs, thereby fostering a more effective and engaging learning environment.

#### 4.3.1. Academic performance

Previous studies have noted the positive impact of personalized adaptive learning on academic performance [145]. In accordance with these earlier findings, our results revealed that 41 of the reviewed studies (n = 41, 59 %) observed an increase in students' academic performance after implementing personalized adaptive learning. This indicates that for the majority of cases, personalized adaptive learning can effectively enhance learning outcomes by tailoring educational content and strategies to meet individual students' needs.

An unexpected finding was that the positive impact was not limited to overall academic performance metrics; some studies highlighted the increased acquisition of core competencies [89] and critical thinking skills [113], as well as improved self-regulation strategies for learning [50]. These findings support those of Zhang et al. [145], who reported improved active learning behaviors, attitude, self-efficacy, and levels of motivation, in addition to the improved academic performance noted among students following a personalized learning intervention. The study outcomes that do not directly measure academic performance are nonetheless indicative of the broader educational impact of personalized adaptive learning and suggest that the benefits of personalized adaptive learning extend beyond traditional academic performance measures. For instance, the improvement in critical thinking and self-regulation skills may indicate the potential of personalized adaptive learning to contribute to the holistic development of students, fostering deeper engagement with the material and enhancing essential skills for lifelong learning.

Contrary to this finding, 28 of the studies (n = 28, 41 %) reported no significant impact on academic performance from the use of personalized adaptive learning. A possible explanation for this variability in outcomes might be the complexity of educational interventions and suggests that the effectiveness of personalized adaptive learning may depend on various factors, including the specific implementation strategy, subject matter, and context in which it is used [136,146]. The integration of personalized adaptive learning into curricula critically affects its success; poor integration or inadequate support can lead to subpar outcomes [141]. The effectiveness of personalized adaptive learning also varies by discipline, with some subjects being more suitable for adaptive learning [139]. Factors like student demographics, prior knowledge, and learning environments also play a role. For example, one study found that AI's effectiveness in education, including adaptive learning, is context-dependent [147]. These inconsistencies highlight the need for further research into personalized adaptive learning, focusing on conditions, strategies, and learner characteristics that enhance its effectiveness.

While the majority of studies report positive outcomes, the mixed results regarding the impact of personalized adaptive learning on academic performance cautions against viewing personalized adaptive learning as a universal solution to educational challenges.

#### 4.3.2. *Student engagement*

The impact of personalized adaptive learning on student engagement presents a complex picture with mixed results and areas of concern.

Several studies have found that adapting instruction to student interests and providing personalized motivation, can enhance engagement and performance [148,149]. The results of our study showed that an increase in student engagement during the implementation of personalized adaptive learning was reported in 25 of the included studies (n = 25, 36 %). This finding is consistent with that of Lynch and Ghergulescu [150] who reported that 88 % of learners experienced flow-a state of complete engagement in the activity-with the use of a personalized adaptive learning system. These findings highlight the potential of personalized adaptive learning to enhance student involvement by providing learning experiences tailored to individual needs, interests, and readiness levels. The personalization inherent in personalized adaptive learning can make learning more relevant and motivating for students, potentially leading to higher engagement levels. This is consistent with the findings of Apoki et al. [151] who explored the role of pedagogical agents in personalized adaptive learning to improve performance, motivation, and engagement.

The positive impact on engagement is further highlighted by reports that personalized adaptive learning serves as a motivation for future learning [61]. This suggests that when students perceive learning to be aligned with their personal goals and abilities, they are more likely to develop a positive disposition towards continued education. The noted increase in students' engagement with learning resources in one study [57] emphasizes the potential of personalized adaptive learning to encourage deeper exploration and utilization of available materials. Increased interaction with learning resources can lead to a more active and self-directed learning process. This finding is consistent with that of Zhang et al. [145], who reported that personalized adaptive learning resulted in an increase in the active learning behaviors of students.

Our scoping review revealed that 44 out of 69 studies (64 %) did not report student engagement as a primary outcome of personalized adaptive learning. This indicates a research focus predominantly on academic performance, with less emphasis on engagement effects. This gap in literature requires attention, possibly due to methodological and conceptual challenges. Measuring and quantifying engagement is particularly difficult, as it is a complex, multidimensional construct [152]. Researchers might avoid engagement as a primary focus due to these complexities, often assuming that improved performance implies increased engagement. A recent study argue that engagement is a key factor in promoting self-regulated learning, which is essential for success in personalized learning environments [153]. However, studies have shown that enhanced performance in personalized learning environments does not necessarily correlate with higher emotional or cognitive engagement [154]. Additionally, engagement is sometimes seen as a mediating factor rather than an outcome, perceived merely as a pathway to better academic performance. This view neglects the intrinsic value of engagement and its long-term impact on student attitudes towards learning [155]. Despite these challenges, student engagement remains important in personalized adaptive learning contexts and warrants more targeted research on how personalized adaptive learning influences various aspects of student engagement, including emotional, behavioral, and cognitive engagement. Future studies should aim to develop robust methodologies for measuring engagement in adaptive learning contexts and explore its relationship with both short-term performance and long-term learning outcomes.

An unexpected concern raised by one study is the potential for personalized adaptive learning to decrease student engagement due to the isolation created by individual learning pathways [64]. This finding highlights a possible drawback of highly personalized learning environments, where the lack of social interaction and collaborative learning opportunities may negatively affect some students' engagement levels. This finding reflects those of Taylor et al. [32] who also reported that the lack of interaction in adaptive systems may lead to student isolation. Although personalization can significantly enhance engagement by making learning more relevant and motivating, it is crucial to balance individual learning paths with opportunities for social interaction and collaboration, to prevent feelings of isolation.

#### *4.3.3. Student learning*

This study presents a compelling case for the adoption of personalized adaptive learning in various learning environments, with evidence pointing to its potential to improve academic performance, enhance the learning process, and support individual students' needs [113,156]. However, mixed results regarding the impact on academic progress and the decrease in self-regulated learning scores [64] indicate that the implementation of personalized adaptive learning needs to be carefully considered and tailored to the specific context and student population. In accordance with these mixed results, previous studies have reported that the implementation of personalized adaptive learning must be carefully considered, taking into account the diverse learning styles and needs of students [136,146,157].

Several studies have highlighted that personalized adaptive learning systems can enhance the learning process, leading to improved academic performance [43,56,74], higher post-test scores [68], and exam marks [60]. This finding is consistent with that of Holthaus and Pancar [158], who reported significant learning progress in students who actively participated in adaptive learning. This suggests that adaptive learning can effectively tailor educational content to meet individual students' needs and enhance understanding and retention. Improvements in critical thinking skills and short-to medium-term learning outcomes [43,113] further indicate the potential of personalized adaptive learning to contribute not only to rote learning but also to deeper cognitive skills development. By decreasing students' mental load and increasing their belief in learning progress [113], personalized adaptive learning systems can make learning more accessible and manageable, potentially increasing students' persistence and success rates. The findings suggest a relationship between the extent of engagement in adaptive activities and student success, highlighting the importance of active participation and practice in the learning process. This aspect needs to be explored further in future studies. The effectiveness of combining online adaptive learning with in-person activities and the importance of tailored content delivery in retaining engagement and improving motivation indicate the benefits of a holistic blended learning approach [145].

While some studies reported a significant impact on learning, others found no effect of personalized adaptive learning on student learning and performance. This variability indicates that the impact of personalized adaptive learning may depend on how it is integrated into a broader educational experience. The negative impact of rigid deadlines on completion rates versus the positive outcomes of a flexible completion regime [84] emphasizes the need for adaptability not only in learning content but also in course management and assignment deadlines. Active engagement with adaptive learning activities should be encouraged as a key component of student success, and personalized adaptive learning should be leveraged to provide targeted support to students with diverse learning preferences and needs.

### *4.4. Study limitations*

This scoping review revealed several limitations that need to be considered when interpreting the findings. Publication bias is a concern because most of the studies were published in peer-reviewed journals, which may have led to a bias towards positive or significant results. Additionally, the concentration of studies in the United States may limit the generalizability of the findings. The limited timeframe of the last twelve years, with a peak in publications in 2020, may have overlooked earlier developments in personalized adaptive learning practices. Study design variability, sample size heterogeneity, and platform reporting bias present methodological challenges, making it difficult to make direct comparisons and generalize the findings. The indicator selection bias and focus on specific outcome measures may limit the comprehensive understanding of personalized adaptive learning, and the lack of thorough exploration of instructor and student perspective representation, coupled with the absence of qualitative data, adds a layer of complexity to the interpretation of the challenges and strengths associated with personalized adaptive learning.

### *4. 5. Recommendations*

Future research should aim to address the research gap on the long-term effects of personalized adaptive learning by conducting longitudinal studies to assess the sustained impact of personalized adaptive learning over extended periods, by tracking academic performance trends and engagement levels among students who have experienced personalized adaptive learning delivery throughout their academic journey. Future studies can also explore innovative solutions to address the technological limitations highlighted by instructors by developing more advanced adaptive learning systems that consider multiple student characteristics and reduce programming and content preparation efforts required for the implementation of personalized adaptive learning.

## 5. Conclusion

Personalized adaptive learning is characterized by the implementation of sophisticated system algorithms to personalize student learning experiences by delivering content or learning pathways informed by specific metrics such as quiz marks, learning analytics, or student characteristics. This study, comprising 69 articles from 2012 to 2024, revealed diverse publication trends, multifaceted characteristics, and impact on learning. The results supported the positive impact of personalized adaptive learning on teaching and learning outcomes and highlighted its role in personalizing the learning experience, offering self-paced learning, real-time feedback, and flexibility, signifying its pivotal role in creating a dynamic and effective learning environment. Some of the technological limitations mentioned in the studies include lack of safeguards in the online system [48], lack of feedback for incorrect answers and practical issues with students being marked incorrect due to spelling/case errors in question types other than MCQs [63]. Adaptive learning can limit the authentic learning experience of students [108], and students may show different emotional responses in a controlled laboratory setting compared to their regular class environment [67]. Furthermore, adaptive learning technology used only trace data such as mouse clicks, page navigation, and keystrokes and did not incorporate other modalities like audio or video data on students [48], and system algorithms do not consider diverse student characteristics such as boredom and frustration [109], emotional state [110], or variables like self-regulation for learning and attitude, which can impact learning [111]. While acknowledging inherent challenges and limitations, such as technological and resource constraints, this study emphasizes the strengths and potential of personalized adaptive learning in higher education to cater to individual needs, improve academic performance and enhance student engagement. The impact of personalized adaptive learning on student engagement and academic performance is promising, with 41 studies (59 %) reporting a significant impact on academic performance and 25 studies (36 %) reporting increased student engagement. Twenty-eight studies ($n = 28$, 41 %) did however not report on the impact of personalized adaptive learning on academic performance and 44 studies (64 %) did not report on any discernible increase in student engagement. Overall, this research advocates for the implementation of personalized adaptive learning into existing educational frameworks.

The implementation of adaptive learning systems in higher education will require a strategic and layered approach that aligns these systems with institutional goals and curricula to achieve specific educational objectives [159] To support this alignment, comprehensive faculty development is required which includes both technical training and pedagogical support [160]. Additionally, the integration must ensure compatibility with existing Learning Management Systems and customization to address varied academic needs and contextual relevance [161,162]. Safeguarding data privacy and ensuring ethical use of information are also critical [163]. An effective adoption process should be phased and scalable, allowing for adjustments based on initial experiences [164], and sustained by continuous evaluation [165]. Moreover, a robust technical infrastructure is essential [142], along with alignment with accreditation standards and effective change management strategies to foster a culture receptive to new technologies [166,167].

To enhance the field of personalized adaptive learning, future research should concentrate on several critical areas. These include the integration and outcomes of personalized adaptive learning in different educational contexts, the development of more advanced learner models, the improvement of real-time adaptation algorithms, the integration of multimodal data for comprehensive learner profiling [168], and the enhancement of content recommendation systems. Artificial intelligence (AI) has the potential to play a pivotal role in these advancements, by analysing large educational datasets to uncover learning patterns, empowering intelligent tutoring systems with natural language processing capabilities [169,170], automating the creation and curation of personalized content [139], and offering predictive analytics for early intervention [171]. The goal of these research efforts should be to create and evaluate AI-driven learning systems that can adapt to each learner's unique needs, preferences, and progress in real-time, to optimize educational outcomes and student learning experiences [172].

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## CRediT authorship contribution statement

**Eileen du Plooy:** Writing – original draft, Visualization, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Daleen Casteleijn:** Writing – review & editing, Validation, Supervision, Methodology, Investigation, Conceptualization. **Denise Franzsen:** Writing – review & editing, Validation, Supervision, Methodology, Investigation, Conceptualization.

## Author agreement

All the authors provided approval of the submitted manuscript.

## Data availability declaration

The data that support the findings of this study are available from the corresponding author upon reasonable request.

## Ethical declaration

This study was reviewed and approved by the University of the Witwatersrand Human Research Ethics Committee (non-medical) with the approval number: H22/10/07, October 21, 2022.

## Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Eileen du Plooy reports Covidence systematic review software was provided by Research Masterminds Success Academy. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2024.e39630.

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