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Personalized Learning in Secondary and Higher Education: A Systematic Literature Review of Technology-Enhanced Approaches

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Abstract: The personalization of learning and teaching processes represents an advanced approach to education that adapts content, pace, and teaching methods to the individual needs and preferences of students. This approach relies on analyzing diverse student characteristics, such as their knowledge level, progress, learning style, and interests. Achieving these goals is significantly supported by the use of information and communication technology, which facilitates and enhances the implementation of personalization in technology-enhanced learning (TEL). The primary objective of personalization is to increase student engagement, motivation, and support in achieving learning outcomes through individualized learning paths, real-time progress tracking, and feedback. This systematic literature review examines existing personalization approaches in secondary and higher education, supported by technology. The study investigates their effectiveness and provides recommendations for future research. Results reveal that personalized teaching methods—primarily through recommender systems, adaptive learning platforms, and algorithm-driven models—are effective in tailoring educational experiences by leveraging diverse student data, such as demographics, prior achievements, learning styles, and digital engagement. The review shows a predominant focus on higher education, particularly in subjects related to computer science and digital technologies. Quantitative evaluations complemented by qualitative insights, consistently indicate that personalization enhances content mastery, motivation, and overall satisfaction, with no significant negative effects identified.

Keywords: *Personalization, secondary and higher education, student motivation, systematic literature review, technology-enhanced learning.*

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Introduction

The traditional one-size-fits-all approach to education, long prevalent in teaching practice, has proven insufficient in addressing the diversity of students' prior knowledge, learning styles, pace, and motivation (Avidov-Ungar & Zamir, 2024). Modern students often process information quickly, but may struggle to maintain focus when content is not engaging (Kirschner & De Bruyckere, 2017). These changing characteristics of learners require more flexible and responsive teaching approaches that can adapt to individual needs.

Personalized learning is a response to this challenge by tailoring educational content, pace of learning, and teaching strategies to the unique profile of the learner. Supported by recent advances in technology-enhanced learning (TEL), personalization has become increasingly important in both research and practice. TEL tools facilitate individualized learning paths, real-time feedback, and progress tracking by leveraging various student data such as prior achievements, learning preferences, cognitive characteristics, and behavioral patterns (Bernacki et al., 2021; Contrino et al., 2024; Xie et al., 2019).

As an educational model, personalized learning emphasizes active student engagement, self-directed learning, and alignment between instructional design and the needs of learners. It promotes inclusion and equity by matching resources to different learner profiles, including those with learning difficulties or accessibility needs (Alsobhi & Alyoubi, 2019). Technology plays a crucial role in enabling such personalization through methods such as recommender systems,

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adaptive platforms, and intelligent feedback mechanisms (Ahku & Panchoo, 2019; Suwita et al., 2019). Some approaches also involve students and parents as partners in learning, while others emphasize the evolving role of teachers and the importance of authentic, competency-based tasks (Chookaew et al., 2015).

Despite the growing number of studies on digital personalization in education, existing systematic literature reviews (SLRs) have primarily focused on primary education or general digital learning environments (Shemshack & Spector, 2020; Van Schoors et al., 2021). There remains a lack of focused, up-to-date SLRs that examine how personalization is implemented specifically in secondary and higher education, particularly in light of recent technological advances. Given the increasing diversity of learners and the rapid development of adaptive tools, a current synthesis is needed to understand how these technologies support personalization at these critical stages of education.

Secondary and higher education are important stages in a student's academic journey where personalized learning can significantly improve outcomes by addressing individual needs and fostering deeper engagement. Secondary education marks the transition from a broad-based curriculum to more specialized subjects, and personalization supports this transition by designing learning experiences that engage students and promote their success (Van Schoors et al., 2021). In higher education, where students are expanding their knowledge within their chosen disciplines, personalized learning has great potential to support the development of subject-specific expertise and enable independent learning (Gonzalez & Chiappe, 2024). Furthermore, personalization at these stages fosters important skills such as problem solving and self-regulation and empowers students to take more responsibility for their education and prepare for lifelong learning and career flexibility (Mironova et al., 2016; Van Schoors et al., 2021).

This study presents a systematic literature review (SLR) (Okoli, 2015) on the application of personalization in teaching processes in secondary and higher education. It provides an overview of current methods, techniques, and types of research, identifies subject areas and levels of education where personalization is applied, and examines the impact on students. The review offers insights and recommendations to guide future research, with a focus on secondary schools and universities.

Literature Review

Many authors emphasize the benefits of digital personalized learning in educational practice, particularly its impact on improving learning outcomes. One of the most comprehensive systematic literature reviews on personalized learning and teaching was conducted by Van Schoors et al. (2021). The study examined research on digital personalized learning in primary and secondary schools over a 25-year period, from 1995 to 2020. This systematic review examines various aspects, including the conceptualization, adaptive dimensions, and implementation of digital personalized learning tools and their impact. The results show that digital personalized learning has a positive impact on student engagement and performance, underlining its importance for modern education.

Shemshack and Spector (2020) noted a growing interest in the fields of Educational Data Mining (EDM) and Learning Analytics (LA) in relation to the personalization of learning and teaching processes. Personalized learning, which adapts instruction to individual learners' needs, has gained traction due to advancements in technology, particularly adaptive learning systems and big data analytics. Adaptive learning systems are becoming increasingly relevant due to their ability to scale personalized education efficiently. However, a clear definition and standardized framework are needed to advance research and implementation.

Gonzalez and Chiappe (2024) conducted a systematic literature review on learning analytics to identify its potential for enhancing learning personalization. Their analysis identified 12 key factors of learning analytics for personalization, including continuous and formative assessment, monitoring, support, feedback, dashboards, data types, intelligent teaching, self-regulated learning, game-based learning, social learning networks, alert systems, and learning styles. These features are particularly relevant for promoting equitable access to education, as they allow educators to identify and address inequities in student progress and engagement through data-driven interventions. Dashboards and alert systems, for example, enable real-time monitoring of student performance, so that support can be targeted where it is most needed, while formative assessments and personalized feedback help bridge learning gaps effectively. By integrating these tools into digital learning environments, learning analytics not only supports individualization, but also promotes inclusion through the continuous improvement of assessment and feedback mechanisms. This highlights the need to further explore innovative approaches to personalization, particularly those that leverage advanced technologies, to address the challenges of ensuring equitable learning opportunities for all students.

Labadze et al. (2023) examined the use of AI-based conversational agents in education from 2018 to 2023, emphasizing their role in personalization. Tools like ChatGPT, Bard, and Socratic assist teachers by automating administrative tasks, customizing content, and generating engaging questions aligned with learning objectives. Teachers can also use these agents to create tailored educational materials that cater to different learning styles. For students, conversational agents provide detailed feedback, guide problem-solving, and support self-testing to reinforce knowledge and prepare for exams. They also promote independent learning by encouraging critical thinking and exploration of complex topics. Many students recognize their value in skill development and academic support. Despite these advantages, concerns remain about reliability, fairness, academic integrity, and privacy. Misinformation and ethical dilemmas pose challenges to their widespread adoption. To address these issues, the study highlights the need for digital literacy training for teachers and students, ensuring they can effectively and critically use AI tools. Additionally, implementing transparent policies on data use and AI ethics can help build trust and promote responsible integration in education.

Suwita et al. (2019) explored the key components of personalized e-learning in higher education, focusing on approaches, content personalization techniques, and standards. Their study provides a comprehensive framework for implementing personalized e-learning, demonstrating its potential to enhance learning quality and adapt to students' needs. This framework is particularly beneficial for higher education institutions and researchers, emphasizing the importance of understanding student learning styles to design more effective e-learning systems.

An examination of the existing literature reveals that personalization in the learning and teaching process is an important element of contemporary education. The studies examined underline the growing significance of personalized learning strategies. The results of the studies consistently show that personalization has a positive impact on student motivation, promotes student engagement and enables more effective achievement of learning outcomes. However, the analysis also points to a continued need for high-quality, systematic literature reviews to further explore the benefits of personalization for educational purposes and to identify effective and scalable approaches, methods, and techniques. Despite the growing interest in personalized learning, there remains a limited number of comprehensive systematic literature reviews (SLRs) that synthesize existing findings and provide a structured overview of current advancements. A new SLR is necessary to bridge this gap, offering an updated analysis that incorporates the most recent studies and identifies emerging trends in personalized education. The increasing volume of published research emphasizes the need to incorporate the most recent studies, especially those exploring the evolving methods of personalization in technology-enhanced learning (TEL).

Existing reviews also have some limitations. Many focus primarily on personalization in primary education, leaving secondary and higher education contexts underexplored. Others lack subject-specific focus—particularly in foundational disciplines like mathematics—and tend to concentrate on general personalization concepts. In addition, most adopt narrow methodological approaches, often relying solely on quantitative data without integrating qualitative insights or design-based frameworks. These gaps limit the depth and applicability of their findings and highlight the need for a broader, more targeted synthesis.

This systematic literature review aims to fill this gap by identifying and analyzing key studies on the application of personalization in secondary and higher education, particularly those integrated with technology. By synthesizing current research, this paper seeks to contribute to ongoing discussions in the field of personalized education and offer actionable recommendations for future research.

Methodology

Systematic literature reviews (SLRs) provide a structured approach to synthesizing scientific research, using rigorous analytical methods to collect and process data. This study employs an SLR methodology based on the frameworks established by Okoli (2015) with modified guidelines developed specifically for research in information sciences. These methods are particularly suited to address the interdisciplinary nature of research that integrates social and technical sciences, as is the case in the fields of technology-enhanced learning and the application of information and communication technology. By applying this approach, the study ensures a comprehensive and systematic examination of the relevant literature and thus fulfills the requirements for high-quality, evidence-based research.

Purpose and Research Questions

The aim of this systematic literature review is to explore the possibilities of personalizing learning and teaching through technology, with a particular focus on secondary and higher education. The review seeks to provide practical recommendations for future research and implementation by examining how personalized learning approaches are applied at these educational levels.

To systematically address the gaps identified in the reviewed literature, the study is guided by five research questions. These questions were formulated to explore areas where prior research has been limited, fragmented, or lacking in synthesis:

RQ1: What methods and techniques are used for personalization in the teaching process in secondary and higher education?

RQ2: What types of student data are utilized in the implementation of personalized methods and techniques?

RQ3: In which student age groups, subjects, and activities is personalization applied?

RQ4: What types of research have been conducted to evaluate the effectiveness of personalization in the teaching process?

RQ5: Does personalization in the teaching process have a positive impact on achievement of learning outcomes and/or motivation and/or engagement in secondary and higher education, and in what ways?Although personalized approaches are increasingly used in education, there is no overview of the methods and techniques used specifically in secondary and higher education. Existing reviews often take a broad conceptual or technological perspective and do not systematically categorize the range of personalization techniques applied at these levels so RQ1 addresses this gap.

Although many studies refer to the use of student data, they rarely specify the types or explain how such data are used in the personalization process. As a result, it remains unclear what kinds of data drive adaptive decisions in practice. RQ2 examines what types of data are used for personalization to clarify how systems adapt to individual learners.

Previous reviews have tended to focus on primary education or on narrow subject areas, which limits the understanding of where personalization is currently being implemented. RQ3 examines the educational contexts in which personalization is applied, including age groups, subject areas, and types of learning activities, to identify underrepresented areas and learner groups.

The assessment of personalization effectiveness varies widely across studies, and prior literature has not consistently mapped the range of methodological approaches used. RQ4 explores the research designs and methods used to evaluate effectiveness to better understand current evaluation practices and inform future study design.

Although positive effects of personalization are frequently reported, the extent and consistency of reported benefits remain insufficiently synthesized across existing reviews. RQ5 focuses on how personalized approaches affect student learning outcomes, academic performance, motivation, and satisfaction.

Taken together, these five research questions provide a comprehensive understanding of how personalization is implemented and evaluated in secondary and higher education and aim to advance research and practice in this area.

Together, these questions seek to offer a thorough understanding of personalized learning in secondary and higher education and to inform future research and development in the field.

Protocol

The research protocol defined the scope of the review, focusing on scientific journals and conference proceedings that address personalization in education at the secondary and higher education levels, published in English within the past ten years. This 10-year period was chosen to reflect the latest trends in technology-enhanced personalized learning, particularly with regard to the rapid advances in AI, learning analytics and digital platforms. The protocol included a systematic search of two highly relevant bibliographic databases, Web of Science and Scopus. Furthermore, specific inclusion and exclusion criteria were established to ensure the relevance and quality of the selected studies, and these criteria are explained later in the paper. During this phase, roles and responsibilities for conducting the review process were clearly defined and agreed upon.

Database Search

The Scopus and Web of Science databases were searched with the same query at the end of July 2024. To find papers related to personalization in secondary and higher education (and not elementary education), restrictions were applied to the abstract and title, searching keywords such as "persona*", "learn*", "secondary", "university", "higher education", "education*" and "technolog*", while excluding abstracts containing the keywords "primary school" and "elementary school". Searching with the same query and the appropriate formulation (syntax) returned 499 articles in the Web of Science database and 1,952 articles in the Scopus database. The query formulation (syntax) for the Web of Science database was: TI= (persona*) AND (AB= (persona*)) AND (AB= (secondary) OR AB= (university) OR AB= ("higher education")) AND (AB =(education*) OR AB= (learn*)) AND AB= (technolog*)) NOT (AB= ("primary school") OR AB= ("elementary school")).

The query formulation (syntax) for the Scopus database was: (TITLE (persona*) AND ABS (persona*) AND (ABS (secondary) OR ABS (university) OR ABS ("higher education")) AND (ABS (education*) OR ABS (learn*)) AND (technolog*) AND NOT ABS ("primary school") AND NOT ("elementary school")).

Due to the large number of papers that met the search criteria, an additional selection was made to reduce the number of contributions by applying specific inclusion and exclusion criteria. This step allowed the elimination of a significant number of papers without the need for detailed review or reading. Duplicates (papers found by searching both databases) were also removed.

A time limit was set and only recent papers published between January 2014 and July 2024 were analyzed. Furthermore, only articles from journals and conference proceedings in English were included in the analysis. After applying these basic inclusion and exclusion criteria, as shown in Table 1, 1,599 papers remained for further analysis.

Table 1. Basic Inclusion and Exclusion Criteria

No	Included	Excluded
1.	Articles from 2014 to 2024	Articles older than 2014
2.	Primary studies published in journals and conference proceedings	Review papers and book chapters
3.	Articles written in English	Articles not written in English

Quality Appraisal

In this step, a further quality assessment was carried out, including the exclusion of articles of insufficient quality on the basis of abstracts or a superficial review of the text without detailed reading. The criteria for quality assessment are listed in Table 2. A superficial review excluded papers that did not describe the research conducted and its results, that were not fully accessible, that did not refer to secondary and higher education, and that did not describe methods and techniques supported by information and communication technologies to implement personalization.

Table 2. Additional Inclusion and Exclusion Criteria

No	Included	Excluded
1.	Papers that describe the research results	Papers that do not describe the research results or where the research has not yet been conducted
2.	Papers fully written in English and fully accessible	Papers with only an abstract in English or those not fully accessible
3.	Papers related to education	Papers not related to education
4.	Papers related to secondary school students and university students	Papers not related to secondary school students or university students
5.	Papers that describe methods and techniques for personalizing the learning and teaching process with the help of digital technology	Papers that do not describe methods and techniques for personalizing the learning and teaching process with the help of digital technology
6.	Papers that describe the application of methods and techniques for personalization	Papers that do not describe the application of methods and techniques for personalization

The author conducted a critical evaluation of the abstracts of 1,599 selected papers to determine their suitability for further analysis. A quality assessment checklist based on a four-point scale was used in the process. For each of the six inclusion and exclusion criteria, the first author (coder) had to decide to what extent the paper met one of the options: 'yes', 'no', 'unclear', and 'not applicable'. The reliability of this process was assessed using intercoder agreement (O'Connor & Joffe, 2020). An additional coder (the second author) evaluated the quality of 25% of randomly selected papers using the same scale ('yes', 'no', 'unclear', and 'not applicable'). To measure intercoder agreement, Cohen's kappa coefficient (Altman, 1990; Cohen, 1960). Coding disagreements between the first and second coders were assessed using Cohen's kappa coefficient (0.92) and resolved through a consensus process. The coders jointly reviewed all disagreements and discussed the reasons for each rating. The third author's role was to provide an objective decision in the event of unresolved disagreements, ensuring consistency, neutrality, and methodological rigor in the coding process.

To ensure consistency during the quality appraisal phase, specific indicators were used to assess each inclusion criterion. For criterion 1, papers that presented clear research results based on the data collected were included; papers without results were excluded. Criterion 2 required the availability of the full text in English, and papers that were only available as abstracts or in other languages were excluded. Criterion 3 focused on relevance to the field of education and included studies on learning, teaching or educational technologies, while excluding papers from unrelated fields. For criterion 4, only papers dealing with secondary school or university students were included, while studies on other population groups were excluded. Criterion 5 required a detailed description of personalization methods or techniques based on digital technologies, while papers without such content were excluded. Finally, criterion 6 required evidence of the application of these techniques, such as experimental use or implementation in the classroom, while purely theoretical or conceptual discussions were excluded. For further analysis, 21 papers remained that met all the inclusion and exclusion criteria.

Data Extraction

After selecting the articles for inclusion in the review, the first author systematically extracted relevant data from each study. The data collection process was guided by the research questions defined during the initial phase of the study. The second and third authors reviewed the extracted data and suggested corrections to ensure accuracy and consistency. This process resulted in the creation of a detailed final table summarizing data from the 21 selected papers, which were further analysed in the next step.

Analysis

By querying the databases and applying the initial inclusion and exclusion criteria (Table 1), a total of 1,599 papers were identified for further consideration. After applying additional, more specific inclusion and exclusion criteria (Table 2), the final number of papers was narrowed down to 21 (Figure 1). This review focused exclusively on primary studies that reported research results and addressed personalization in the context of secondary and higher education.

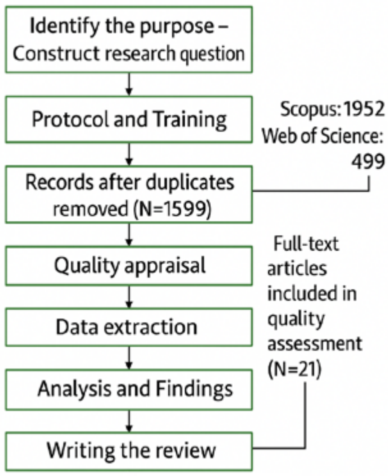

Figure 1. Process Flow of the Systematic Literature Review

Figure 2 presents the distribution of analysed papers by year of publication. The data indicate an overall upward trend, with the highest number of studies published in 2024 by mid-July (5 papers), suggesting increasing research interest in personalized learning in recent years.

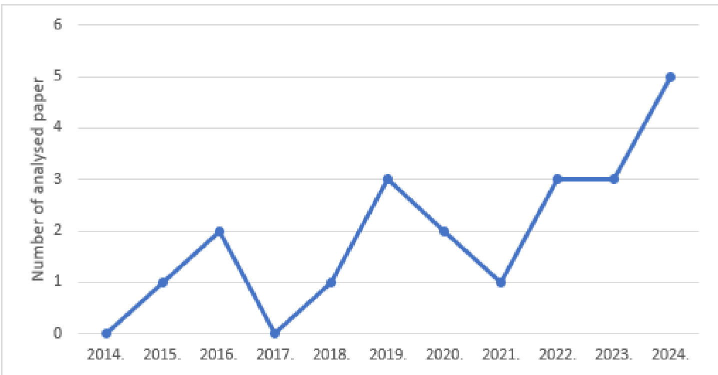

Figure 2. Number of Analysed Papers by Year of Publication

Figure 3. illustrates the ratio of analysed papers related to application of personalization in secondary and higher education, expressed as a percentage. The analysis reveals a significant difference in research focus between the two educational levels. Specifically, 86% of the studies pertain to higher education, whereas only 14% are focused on secondary education.

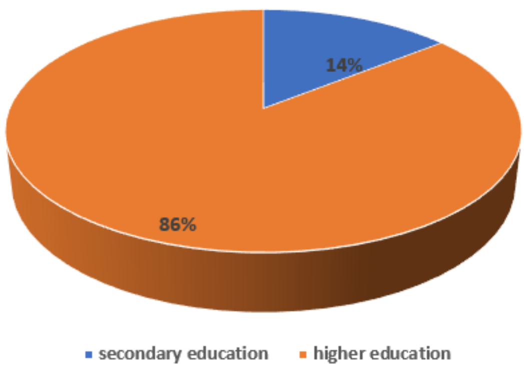

Figure 3. The Ratio of Analysed Papers Related to Secondary and Higher Education.

Figure 4. shows the distribution of subjects or areas in which personalization methods were applied. This distribution highlights a strong focus on computer science and technology-related disciplines in the context of personalized learning.

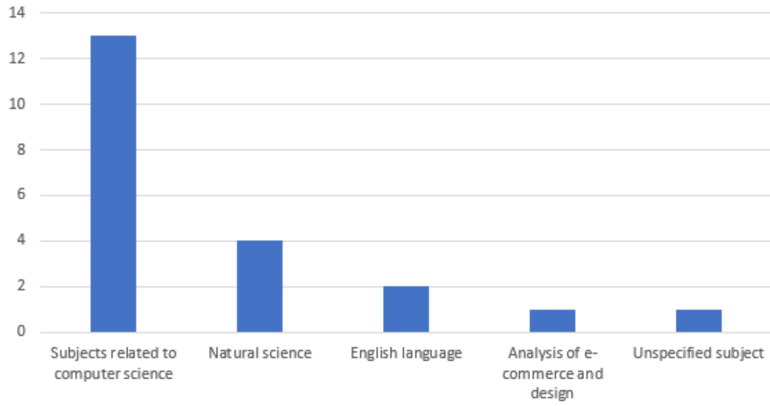

Figure 4. Subjects or Areas in Which Personalization was Applied

Results

This chapter presents results collected from the systematic literature review in relation to the research questions. All papers analyzed are labeled S1 to S21 and these labels are references in the reminder of the paper (see Appendix).

RQ1 - What methods and techniques are used for personalization in the teaching process in secondary and higher education?

The analyzed studies applied a variety of personalization methods that can be grouped into six main categories (Table 3.).

Table 3. Personalization Methods/Techniques of Examined Studies

Methods/Techniques	Description	Study Labels
Recommender and Sequencing Systems	Systems that use recommender system techniques to suggest personalized learning paths, content, or activities based on prior performance and learner profiles.	S1, S13, S16, S17
AI and Machine Learning Techniques	Personalization techniques based on artificial intelligence and machine learning, including deep learning, clustering algorithms, and neural networks, used to adapt content and tasks in real time.	S5, S8, S11, S12
Learning Analytics-Based Adaptation	Personalization based on analysis of students' interaction patterns, learning behavior, and preferences to adjust learning materials and pathways.	S6, S7, S18
Rule-Based Personalization Models	Systems that use predefined logic or structured design models to offer flexible content delivery, navigation options, assessment types, and learning paths aligned with learners' choices and needs.	S9, S14, S15
Diagnostics-Driven Personalization for Specific Learner Needs	Personalization aimed at students with specific educational needs (e.g., dyslexia or low prior knowledge), using diagnostic techniques such as item response theory and dual adaptation mechanisms to support accessibility and learning outcomes.	S10, S17, S19
AI-Supported Scaffolding Techniques	Techniques that apply artificial intelligence to provide educational scaffolds, supporting students in managing and regulating their learning process with personalized assistance.	S20, S21

The reviewed studies employed a variety of personalization methods, which can be grouped into six categories. Recommender and sequencing systems (S1, S13, S16, S17) leveraged learner profiles and performance data to dynamically suggest personalized learning paths, activities, or content, aligning with individual progress and goals. AI and machine learning techniques (S5, S8, S11, S12) used algorithms such as deep learning, clustering, and neural networks to analyze complex data sets and provide real-time personalization based on students' behaviors, preferences, or predicted needs. Learning analytics-based adaptation (S6, S7, S18) focused on analyzing learning patterns and student interactions to adjust learning materials and paths, offering data-driven flexibility throughout the learning process. Rule-based personalization models (S9, S14, S15) applied structured logic to provide flexible navigation, content delivery, and assessment formats aligned with learner choices, allowing students greater autonomy in progressing through the material. Diagnostics-driven personalization (S10, S17, S19) supported students with specific needs by using diagnostic techniques such as item response theory or dual adaptation mechanisms to tailor content accessibility and address learning gaps. Finally, AI-supported scaffolding techniques (S20, S21) used intelligent agents to provide real time, adaptive guidance and support, helping students regulate their own learning and stay engaged. These approaches demonstrate the evolving sophistication of technology-enhanced personalization in education, aiming to optimize learning through tailored experiences based on diverse student data.

RQ2. What types of student data are utilized in the implementation of personalized methods and techniques?

The reviewed studies utilized a diverse range of student data types to support personalization, which can be grouped into several main categories (Table 4).

Table 4. Data Used for Personalization of Examined Studies

Data Used for Personalization	**Study Labels**
Demographic context	S2, S3, S13
System interactions	S19
Interests and motivation	S13
User behavior	S1, S6, S8, S12, S13, S19
Learning styles	S7, S10, S11, S14, S15, S18
Prior achievements	S4, S9, S14, S15, S16, S17, S20
Other	S3, S5, S8, S10, S11, S13, S16, S21

Demographic context (S2, S3, S13) includes data such as age, gender, language background, and socioeconomic status, providing a foundational understanding of learners' environments and informing inclusive instructional design. System interactions (S19), such as real-time input or engagement with digital content, enable the dynamic adjustment of strategies and content based on student responses. Interests and motivation (S13) also play a role, allowing content to be aligned with personal aspirations or preferences, which fosters greater engagement. User behavior (S1, S6, S8, S12, S13, S19) is a key data source, capturing metrics such as time on task, interaction patterns, and activity sequences, which are used to drive adaptive learning systems. Learning styles (S7, S10, S11, S14, S15, S18) are frequently incorporated to tailor delivery methods to how students best absorb information. Prior achievements (S4, S9, S14, S15, S16, S17, S20), such as past performance, test scores, and academic history, are commonly used to inform personalized learning paths that match students' current proficiency levels. In addition to the main categories, several studies employed unique or composite data types such as psychological traits (e.g., Big Five Personality traits in S5) and cognitive misconceptions identified through item response theory (S17), which were grouped under "Other" due to their distinct nature. These examples highlight emerging directions in personalization research such as the use of psychometric and cognitive profiling that go beyond conventional data categories.

RQ3. In which student age groups, subjects, and activities is personalization applied?

The application of personalization in the examined studies spans different age groups (Table 5.) and subject areas (Table 6.), with a clear emphasis on university-level education.

Table 5. Age Group of Examined Studies

Age Group	**Study Labels**
High School	S3, S7, S19
University	S1, S2, S4, S5, S6, S8, S9, S10, S11, S12, S13, S14, S15, S16, S17, S18, S21, S21

Table 6. Subject/Activity of Examined Studies

Subject/Activity	**Study Labels**
AI in Education	S21
Language	S12, S13
Mathematics	S16, S20
Chemistry	S8
Physics	S7
Unspecified	S11
Programming/Computer Science	S1, S2, S3, S4, S5, S6, S9, S10, S14, S15, S16, S17, S18, S19

As shown in Table 5, only three studies (S3, S7, S19) targeted high school students, while the remaining 18 focused on university students (S1, S2, S4, S5, S6, S8, S9, S10, S11, S12, S13, S14, S15, S16, S17, S18, S20, S21). This distribution suggests that higher education offers more opportunities or perhaps more available infrastructure for implementing advanced personalization techniques. Regarding subject areas, the majority of studies applied personalization within Programming and Computer Science contexts (S1, S2, S3, S4, S5, S6, S9, S10, S14, S15, S16, S17, S18, S19), confirming a strong concentration in technology-oriented disciplines. In addition, Mathematics was represented in two studies (S16, S20), while Physics (S7) and Chemistry (S8) appeared less frequently. Language learning was addressed in two studies (S12, S13), and AI in education was explored in one study (S21). Only one study (S11) did not specify the subject area, applying personalization across several different courses. In terms of educational activities, personalization was primarily used to support content mastery, with the exception of S1, where it was applied specifically to problem solving. These findings indicate a strong alignment between personalization research and technologically advanced or computational domains, while also revealing limited application in non-STEM subjects and at the secondary education level.

RQ4. What types of research have been conducted to evaluate the effectiveness of personalization in the teaching process?

All studies utilized quantitative research methods, including experiments and surveys, while three studies (S3, S11, S16) incorporated qualitative research to provide additional depth and context. In S3, interviews were conducted to develop educational personas and gather detailed demographic data, as well as to understand the goals and challenges of users. In S11, a qualitative phase was integrated to complement the quantitative analysis, offering a deeper exploration of participants' experiences and perceptions with an artificial intelligence-based learning platform. This phase involved semi-structured interviews with students, teachers, and administrative staff. Similarly, in S16, a qualitative evaluation was conducted to assess the personalized materials used in the experiment. This evaluation included input from both professors and students, focusing on their satisfaction and perspectives on the effectiveness of the materials.

In addition to the various qualitative benefits, several studies have also provided quantitative evidence of the effectiveness of personalization. For example, Ingkavara et al. (2022) reported significantly higher post-test and learning gain scores for the experimental group using a personalized, self-regulated online learning environment compared to the control group. M. Wang and Lv (2022) observed 96.67% student satisfaction and 85% accuracy in their personalized learning model, indicating improved performance and reliability of the system. These examples illustrate how personalization can lead to measurable improvements in learning outcomes. However, comparative metrics or effect sizes were not reported in all studies, suggesting a need for more consistent and rigorous evaluation of impact in future research.

RQ5. Does personalization in the teaching process have a positive impact on the achievement of learning outcomes and/or motivation in secondary and higher education, and in what way?

All studies concluded that personalization in the teaching and learning process has a positive impact on students, enhancing both their mastery of teaching content and their motivation to learn. Positive effects, including greater satisfaction with the overall learning experience and increased motivation, were reported in eight studies (S1, S3, S9, S12, S14, S16, S19, S21). Improved communication between students and professors was noted in one study (S4), while 16 studies (S1, S2, S5, S6, S7, S8, S10, S11, S12, S13, S14, S15, S17, S18, S19, S20) highlighted faster and more effective mastery of learning outcomes, along with better final results.

These findings were supported by data collected through surveys, pre- and post-tests of student knowledge, and comparative analysis between experimental groups. In these studies, one group used traditional methods while the other group adopted personalized approaches, demonstrating the benefits of personalization in achieving better academic outcomes. All studies concluded that the personalization of the teaching and learning process positively affects students, whether in terms of mastering teaching content or motivation to learn.

It is important to note that no study showed negative effects of personalization on students.

Conclusions

The upward trend in publications on the topic of personalization underlines the growing importance of this topic in educational research. This study confirms prior findings on the benefits of personalization while identifying new insights on educational levels, subject coverage, and the diversity of applied methods. It also highlights methodological considerations that should inform future research and practice.

For RQ1, the analysis shows various methods and techniques enabled by technology, including AI, recommender systems and adaptive platforms. These tools personalize learning by leveraging data such as prior achievements, learning styles and behavioral patterns. This aligns with the findings of Van Schoors et al. (2021), who emphasize the positive impact of digital tools on engagement and achievement in primary and secondary education. Our study extends these findings to secondary and higher education and shows that adaptive systems dynamically tailor content and tasks. Unlike many previous reviews that focused on conceptual or technical aspects, our study highlights real-world applications of personalization techniques in educational settings and synthesizes reported impact. We also observed the growing role of algorithm-based personalization, including machine learning and deep learning techniques, which supports and extends the findings of Labadze et al. (2023). Several studies employed AI-driven strategies that incorporate elements of predictive modeling and learner diagnostics. These findings highlight the potential of integrating personalization features into widely used learning platforms, which could improve scalability and expand access to tailored educational experiences.

In relation to RQ2, the results confirm the importance of multiple types of student data for effective personalization. Demographics, prior achievements, learning styles, interests, and real-time feedback are all critical. Learning analytics and feedback mechanisms support real-time monitoring and customization. These findings support Gonzalez and Chiappe (2024), who identified key personalization factors in learning analytics. Our study shows how these types of data influence the design of personalized systems and pedagogical strategies at all levels of education.

In answering RQ3, our study revealed that personalization is primarily used in higher education, especially in STEM subjects. This focus differs from the findings of previous reviews, such as Van Schoors et al. (2021), which report a broader application of personalization approaches in primary education. In contrast, our review shows that secondary education remains underrepresented, with only a few studies referring to this level. While the strong presence of personalization in higher education may reflect better technological infrastructure and institutional flexibility, it also reveals a gap in its broader application. Although STEM subjects dominate, other areas remain underexplored despite their potential benefits. This narrow focus suggests that research on personalization may be unintentionally limited, focusing primarily on specific levels and disciplines. Expanding personalization efforts to secondary education and a broader range of subjects could improve equity and accessibility, especially for students who may benefit from tailored support for different learning needs.

For RQ4, most studies relied on quantitative methods, while a few combined these with qualitative approaches to explore learner' experiences and contextual factors. These mixed approaches provided more comprehensive insights into how personalization is perceived and implemented in practice. Despite the generally positive findings, the lack of consistent metrics and reporting of effect sizes limits comparability between studies. The use of mixed methods and iterative research designs, such as Design-Based Research (DBR), offers the potential for a deeper understanding and more robust evaluation of personalization in authentic educational environments. Emphasizing user-centered feedback alongside outcome measures can strengthen future research by capturing both effectiveness and relevance to learners.

Regarding RQ5, all included studies reported positive effects of personalization on learning outcomes, motivation and satisfaction. Students showed improved content mastery, academic performance, and engagement. Several studies used experimental or comparative designs, with some using surveys and pre/post-tests to evaluate effectiveness, supporting the value of personalization in secondary and higher education. These consistently positive results highlight the potential of personalized approaches to enhance student achievement and reflect a broader shift toward data-driven customization of content and pacing. Despite varied implementations, the common focus on measurable improvements suggests a strong link between personalization and learning outcomes. These findings offer new insights into the practical application of personalization across different subjects and levels of education and highlight the need for continued development.

While all included studies reported positive outcomes, this consistency may reflect prevailing trends in reporting rather than a lack of challenge. The lack of negative findings contrasts with concerns raised by Masters (2023) and suggests that studies showing limited or adverse effects of personalization may have been underreported or unpublished. This highlights the need for balanced reporting and suggests that wider inclusion of diverse studies could further enrich the understanding of effectiveness. In addition to the advantages mentioned above, personalization also raises important ethical and practical considerations. There are potential risks associated with the use of AI and big student data, including reduced transparency, privacy concerns and the possibility of reinforcing existing inequalities. Over-reliance on algorithmic systems can disadvantage students whose learning behaviors do not align with predefined models. These issues highlight the need for greater attention to transparency, data control and human oversight in the development and implementation of personalized learning tools. Strengthening the digital literacy of educators and students will also be crucial to ensure critical engagement with these systems. Future research should explore these challenges in more detail to support responsible and equitable use of personalization in education.

Limitations

One of the main limitations of this systematic literature review is that the search was restricted to only two bibliographic databases (Web of Science and Scopus). Although these reputable databases were selected to identify the highest quality articles, it is possible that access to a larger number of digital databases could have led to different outcomes. Another limitation relates to the wording of the query used to search for articles in digital databases. Using a narrower query with specific keywords may have limited the identification of relevant articles. A broader or more diverse set of keywords might have led to the discovery of a larger number of articles, as different authors often use different terminology for the same concepts. This means that some studies may have been overlooked due to terminological discrepancies, affecting the completeness of the search results. One of the limitations concerns the inclusion and exclusion criteria. By excluding papers in which the research is described narratively without providing a detailed methodological framework or specific findings, the number of papers analyzed was significantly reduced. This approach ensured that the focus was on rigorously detailed studies, but may have led to the exclusion of other potentially relevant research that did not meet these specific criteria.

Although all included studies met the inclusion criteria, there were differences in the level of methodological detail. In some cases, more comprehensive descriptions of sampling strategies, study design or personalization techniques would have improved the interpretation of results. These differences may affect the depth of insight and clarity of understanding of the findings. Almost all studies reported positive effects of personalization, while there were no studies that showed no or negative outcomes. This overrepresentation of positive results raises the possibility of publication bias, which could lead to an overestimation of the actual impact of personalization on student achievement.

Recommendations for Future Research and Practice

Scope of Application and Target Groups

To fully exploit the potential of personalization in education, targeted efforts should be made to extend its application to areas and groups that have been little researched to date. One recommendation is to focus more on the secondary education. Personalized approaches can play an important role at this stage by addressing different learning needs. By adapting content, pace and teaching strategies to younger learners, personalization could improve academic outcomes and foster greater engagement and motivation.

Another recommendation is to expand the application of personalization techniques to underrepresented subjects. Certain subjects have received limited attention in current research despite their importance to education. Mathematics in particular is underrepresented in current research on personalization, despite being a foundational subject with significant potential for tailored interventions. Personalized approaches in mathematics could help to address different prior knowledge, reduce anxiety associated with the subject and improve problem-solving skills, leading to better understanding and achievement.

Personalization could also be integrated into practical learning contexts, such as project-based learning, vocational training and internships. Personalized guidance and feedback in these environments can help align learning experiences with individual career aspirations, making education more relevant and competency-based. By addressing specific needs and goals, personalization in practical contexts could improve students' preparation for future jobs and contribute to their long-term career success.

Future research should apply Design-Based Research (DBR) methods specifically in STEM subjects (e.g., mathematics and physics) to iteratively develop and evaluate adaptive learning environments in real secondary school classrooms. Researchers should also explore the use of learning analytics dashboards in these subjects to provide teachers with real-time insights into student performance and engagement. This would enable timely instructional adjustments and support data-informed decision-making in classrooms. Additionally, personalization should be extended to underrepresented subjects in current research, including language learning and humanities, by adapting content to students' comprehension levels, interests, and learning profiles.

Methodological Approaches

Appropriate research methods are needed to advance the understanding and implementation of personalization in education. While quantitative methods dominate current studies and effectively measure outcomes such as achievement and engagement, they often ignore the experiences of learners and teachers. To address this gap, the use of mixed methods approaches is recommended. By combining quantitative metrics with qualitative findings (e.g., from interviews, focus groups), researchers can gain a more comprehensive understanding of the impact of personalization in specific settings and on individual students.

Design-Based Research (DBR) is another promising methodological framework that offers a practical way to bridge the gap between theory and practice. By integrating iterative cycles of design, implementation, and refinement in authentic educational settings, the DBR approach allows researchers and practitioners to collaboratively explore how personalization techniques work in real-world contexts, evaluate their effectiveness, and tailor them to the needs of diverse learners.

Applying such methods can ensure that research on personalization not only advances theoretical knowledge, but also leads to actionable strategies for improving educational practice, particularly in addressing the diverse needs and interests of secondary and university students.

Technology Advancements

Recommender systems are among the promising technologies that are advancing personalized education across various fields. By continuously adapting to students' individual needs and characteristics, these systems increase engagement and ensure that learning experiences are tailored and effective. AI-driven advancements provide numerous opportunities to deepen this personalization, such as predictive analytics and real-time feedback systems that can proactively identify potential challenges and deliver targeted interventions.

AI technologies enable the creation of highly personalized content, assignments and learning paths based on learners' individual profiles. In addition, the integration of AI with learning analytics supports the collection and analysis of detailed data on student interactions, progress and behaviour. This allows educators to monitor performance in real time, uncover trends and make data-driven adjustments to optimize personalized learning strategies.

To facilitate wider adoption of personalization, educational institutions should provide professional development programs that train teachers in the ethical and effective use of AI-driven tools. These programs should include guidelines on data privacy, bias mitigation, algorithmic transparency, and how to critically interpret system feedback.

This paper presents a systematic literature review of the application of personalization in secondary and higher education, highlighting the methods used and their educational impact. Our analysis of 21 studies shows that personalization is most commonly implemented in higher education and STEM-related disciplines. It improves learning outcomes, motivation and student satisfaction and is supported by technologies such as recommender systems, adaptive platforms and AI-driven analytics.

The primary scientific contribution of this review is to offer a structured, comparative synthesis of personalization methods and the use of student data in underexplored contexts, particularly in secondary education. It also highlights the concentration of research efforts and identifies gaps, such as the limited use of rigorous experimental designs and the lack of attention to ethical concerns.

Looking ahead, the successful implementation of personalization in education requires more than just technical solutions. Ethical safeguards, professional development for teachers and digital literacy for students must be integrated into policy and practice. When used responsibly, personalization has the potential to support equitable, inclusive and adaptive education for a broad range of learners.

We call on researchers to address current gaps in subject diversity, study quality, and experimental control, and on policymakers to ensure that personalization is implemented with ethical foresight and practical support.

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Generative AI Statement

The authors did not use generative AI or AI-assisted technologies to create, analyze or interpret content. InstaText, a non-generative AI tool, was used under human supervision exclusively to improve the language, clarity and readability of the manuscript. All content was reviewed and verified by the authors.

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Appendix: Overview of Analyzed Characteristics in Selected Papers

Study Labels	Personalization Methods/Techniques	Data Used for Personalization	Subject/ Activity	Age Group	Sample Size	Research Type	Results
S1 (Prisco et al., 2020)	Recommendation system (based on ELO model) for specific educational goals for each student, aiming to align student capabilities with task difficulty	Interaction history and task performance data	Computer Science - Problem Solving	1st Year University	42 students	Quantitative	Positive: Better performance and higher student engagement
S2 (Chang et al., 2022)	Personalized service compatible with Moodle system for personalized processing with self-improvement mechanism	Synced user profiles from the student information management system	Programming	University	41 students	Quantitative	Positive: Better final test results and smaller average score gap on final exam compared to before
S3 (Zanudin et al., 2021)	Persona concept based on demographic data, goals, and challenges of users when using educational applications	Demographic data, user goals, and challenges	Computer Science	High School	29 students	Quantitative and qualitative	Positive: High satisfaction with learning process applying the persona concept
S4 (Ahku & Panchoo, 2019)	Web platform that works and optimizes learning paths for personalized learning	Results from prior knowledge assessments	Programming	University	20 students	Quantitative	Positive: Better communication between students and professors, better progress monitoring through the application
S5 (Tseng et al., 2023)	Mathematical model for assessing personality traits	Personality traits assessed via Big Five Personality questionnaire	Game Development	University	Phase 1: 30 students Phase 2: 16 students	Quantitative	Positive: Improvement in performing academic tasks
S6 (Liu et al., 2020)	Personalized learning path recommendations based on students' learning styles, based on in-depth analysis of students' learning logs in online environments	Learning logs from online environments	E-commerce System Analysis, Design	University	60 students	Quantitative	Positive: Better results (final grades)
S7 (Ingkavara et al., 2022)	Use of a personalized approach for implementing self-regulated online learning to provide appropriate learning paths and materials matching students' learning preferences	Learning preferences collected through questionnaires	Physics	High School	292 students	Quantitative	Positive: Better results
S8 (M. Wang & Lv, 2022)	Personalized educational model constructed based on the distributed computing method and deep learning clustering algorithm (DL)	Learning data and user search history	Chemistry	University	463 students	Quantitative	Positive: Faster mastery of material for better academic success
S9 (Hui, 2023)	Personalized learning paths (regardless of prior knowledge) based on 4 main features (alternative paths, flexible time, multiple test attempts, and multiple options in programming)	Pre-test results	Human-Computer Interaction	University - 3rd Year	360 students	Quantitative	Positive: Positive impact on learning experience

Study Labels	Personalization Methods/Techniques	Data Used for Personalization	Subject/ Activity	Age Group	Sample Size	Research Type	Results
S10 (Alsobhi & Alyoubi, 2019)	Adaptive e-learning system DAELMS (Dyslexia adaptive e-learning management system) customized for dyslexia	Learning style data and dyslexia type	Computer Science Subjects	University	48 students	Quantitative	Positive: Improves mastering learning outcomes
S11 (Naseer et al., 2024)	AI-driven adaptive educational platform using advanced deep learning algorithms	Student performance data and learning preferences	Unspecified subjects	University	240 students	Quantitative and Qualitative	Positive: Positive impact on mastering learning outcomes and better performance
S12 (Zhang, 2024)	Personalized system for learning English based on a trilingual concept using specific algorithms such as BP and k-means clustering algorithm	Student data collected through learning interactions	English Language	University	630 students	Quantitative	Positive: Increased pass rate and student satisfaction
S13 (Wu, 2024)	Personalized smart teaching model based on students' needs using web mining, SOM neural network, and hybrid recommendation algorithm	Learning habits, hobbies, age, study program, and system logs	English Language	University	103 students	Quantitative	Positive: Improves mastering learning outcomes
S14 (Mironova et al., 2016)	Hybrid and flexible learning model	Prior knowledge and preferred learning styles	Computer Science	University	Undetermined	Quantitative	Positive: Positive impact on mastering learning outcomes and increased motivation
S15 (Chookaew et al., 2015)	Personalized support system for learning based on multiple sources of personalized information	Prior knowledge and preferred learning styles	Programming	University - 1st Year	54 students	Quantitative	Positive: Improves mastering learning outcomes
S16 (Garrido et al., 2016)	myPTutor – e-learning model using AI-based planning techniques to create fully personalized learning paths in the form of sequences of learning objects (LOs) that meet both pedagogical and student requirements	Student profile data and prior knowledge	Discrete Mathematics, Natural Sciences, Metaheuristics, Structured Programming	University	Undetermined	Quantitative and Qualitative	Positive: Higher satisfaction with the learning process
S17 (Maddalora, 2019)	Personalized learning model based on item response theory	Prior knowledge and misconceptions about the material	Programming	University	40 students	Quantitative	Positive: Improves mastering learning outcomes
S18 (Deng et al., 2018)	Personalized learning platform ThoTh Lab that identifies learning style and recommends further activities and personalized materials	Learning style questionnaire results	Computer Science Subjects	University	103 students	Quantitative	Positive: Improves mastering learning outcomes and leads to better academic success
S19 (Wongwatkit & Panjaburee, 2024)	Recommended learning system based on a double adaptation mechanism	Learning time, question responses, and system feedback logs	Computer Science	High School	336 students	Quantitative	Positive: Positive impact on mastering learning outcomes and greater motivation

Study Labels	Personalization Methods/Techniques	Data Used for Personalization	Subject/ Activity	Age Group	Sample Size	Research Type	Results
S20 (Contrino et al., 2024)	CogBooks – adaptive learning system applied to flexible, interactive courses using technology	Prior knowledge and test results	Statistical Decision Methods	University	530 students	Quantitative	Positive: Improves success
S21 (Lim et al., 2024)	Educational scaffolds supporting self-regulated learning, managed by AI	Personal student data collected prior to the experiment	Artificial Intelligence, Differentiation in Schools, Educational Scaffolding	University	59 students	Quantitative	Positive: Positive impact on the learning process