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AI-Driven Personalized Learning in Higher Education: A Systematic Review Through the Lens of Bloom's Taxonomy

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ABSTRACT

Background: *Artificial intelligence has increasingly been adopted to support personalized learning in higher education; however, existing research remains fragmented with limited synthesis of how AI-driven personalization aligns with cognitive learning outcomes, particularly those defined by Bloom's taxonomy. While generative AI has gained attention, its pedagogical role relative to earlier analytics-based and intelligent tutoring approaches remains insufficiently examined.* ***Method:*** *This study presents a systematic literature review conducted in accordance with PRISMA-2020 guidelines. Peer-reviewed studies published between 2015 and 2025 were identified through Scopus, Web of Science, IEEE Xplore, ACM Digital Library, ERIC, SpringerLink, and ScienceDirect. Following screening and quality assessment, 25 studies were included for synthesis.* ***Key Findings:*** *The analysis indicates that AI-driven personalization predominantly supports lower-order cognitive processes, including remembering, understanding, and application. Learning analytics and intelligent tutoring systems primarily enable adaptive feedback and content sequencing, while generative AI shows emerging potential for supporting higher-order cognition, though empirical evidence remains limited.* ***Implications:*** *The findings highlight the need for cognitively aligned AI system design in higher education. Future AI-based learning tools should explicitly integrate Bloom's taxonomy to ensure pedagogical coherence, transparency, and meaningful support for higher-order learning outcomes.*

Keywords: *Artificial intelligence, personalized learning, generative AI, higher education, Bloom's taxonomy*

PURPOSE AND SCOPE OF THE REVIEW

Digital technologies have been rapidly developing, constantly transforming the sphere of higher education, and artificial intelligence (AI) became one of the strongest factors of modern teaching and learning processes. Initial uses of AI in education were centered on intelligent tutoring systems and antegrading systems that operated on a rule-. But with the recent improvements in Generative AI, especially the large language models (LLMs), and transformer-based architectures, there has been a substantial change to educational technology (Xia et al., 2025). Generative AI can serve to generate human-like text, adaptive explanations, feedback, and learning content in real time compared to previous systems, which can create new modes of interaction between learners and educational systems (Gonsalves, 2024). With the rise in the use of these tools in universities, the role of these tools in pedagogy is an important issue of scholastic debate. Attending to learner diversity is one of the major challenges in higher learning. Students vary in their background knowledge, learning speed, cognitive capacity, and motivation, but in most cases of traditional principles of instruction, they promote standardized curriculum, and unified scales of assessment (Kwan et al., 2025). This has resulted in the increased popularity of personalized learning, a model that aligns teaching content, feedback, and learning pathways with the needs of the individual learners. A lot of human labor and scaling was historically challenging and personalization had to be intensive. Generative AI systems are providing new opportunities that include adaptive content generation, personalized feedback and scaffold at scale (Almatrafi & Johri, 2025). Generative AI is becoming a possible answer to the traditional shortcomings of individualized higher education.

The educational potential of generative AI remains valid not only because of its technological complexity but also its correspondence with the existing theories of learning. It is considered to be one of the most powerful frameworks of the concept of cognitive learning outcomes developed by Bloom in the middle of the 20th century and then revised (Adnans et al., n.d.). It defines the lower and higher levels of learning including skills like remembering and understanding as well as analyzing, evaluating, and creating. Blooms taxonomy is one of the most popular approaches in designing curricula, assessment, and learning outcomes in higher education institutions (Jackson, 2025). To test the usefulness of generative AI systems in teaching and learning, it is necessary to investigate their ability or failures to assist at various levels of thinking. The current studies on generative AI in education are growing fast and are still disjointed. A significant proportion of research is dedicated to system development or usability or short-term performance results, and fewer directly study the alignment of AI-based personalization with the goals of cognitive learning (AlAfnan & Al, 2024). Besides, even though some systems purport to lead to improvement in higher-order thinking, there is sparse-scale evidence to indicate how these alleged improvements are implemented, quantified, or conceptualized. This gap confirms the necessity of a systematic synthesis of the empirical and design-driven research that can explore generative AI in the cognitive perspective (Shanto et al., 2025).

This systematic literature review aims to critically review the application of generative AI systems to support personalized learning in higher education with particular focus on its interaction with the Bloom taxonomy. This review aims to determine how personalization mechanisms as adaptive content generation, learner modeling, and automated feedback are designed and implemented, and aligned with the various levels of cognitive learning. This review will help to understand whether existing generative AI applications mainly support lower-order learning or are effective scaffolding higher-order cognitive capacities through the synthesis of existing empirical evidence (Chan & Wong, 2025). The review is restricted to peer-reviewed articles with a higher education setting published between 2015 and 2025, or the timeframe within which generative AI studies have grown at a fast pace. The review is limited to systems that include generative models and show some kind of personalization, but not studies that are purely conceptual, policy-oriented, or not related to cognitive learning outcomes. This review will contribute to the provision of a rigorous and comprehensible insight on the pedagogical role of generative AI in personalized higher education by adopting a systematic methodology and pre-determined quality assessment criteria.

RESEARCH QUESTIONS

1. RQ1: How are AI-driven personalization approaches, including generative AI, applied to support learning in higher education?
2. RQ2: How do AI-driven personalized learning systems target, model, or scaffold cognitive learning outcomes across Bloom's taxonomy?
3. RQ3: What personalization mechanisms (e.g., learner modeling, adaptive content generation, and automated feedback) are implemented in AI-driven systems?
4. RQ4: What empirical evidence exists regarding the impact of AI-driven personalization on cognitive learning outcomes and pedagogical effectiveness?
5. RQ5: What methodological, technical, and pedagogical limitations are reported in the literature on AI-driven personalized learning in higher education?

METHODOLOGY

Search Strategy

The reliability, reproducibility and completeness of a systematic literature review depend on a comprehensive and transparent search strategy. The search strategy in this research was crafted to find high-quality empirical and design research that explored the application of generative AI to personalized learning in higher education with a particular focus on cognitive learning outcomes in the taxonomy of Bloom. The strategy will adhere to the guidelines of the systematic review because it explicitly specifies databases, search terms, and filtering criteria to reduce bias but cover the maximum number of relevant studies. The search process was designed to include interdisciplinary research that has taken place in the fields of education, computer science, artificial intelligence, and learning sciences. Since such rapid development of generative AI technologies, the approach focuses on depth and breadth to cover both the baseline literature and more recent ideas. This systematic literature review was conducted in accordance with the PRISMA-2020 guidelines.

Databases

A variety of academic databases were selected to be very comprehensive in terms of the disciplines of interest. Scopus and Web of Science became core databases because they are a wide index of high-impact, peer-reviewed journals and conference proceedings in the education, technology, and social sciences. These databases are robust citation tracking databases, which facilitate recognition of impactful studies and research trends. IEEE Xplore and ACM Digital Library were added to retrieve technical and system-oriented articles, especially works on generative models, intelligent tutoring systems and adaptive learning technologies. These databases are required to find the engineering and computer-science contributions that might not be obvious in education-oriented journals. SpringerLink and ScienceDirect were chosen as the library to seek interdisciplinary studies in the boundary of artificial intelligence, educational technology, and cognitive science. These websites provide a huge amount of empirical research and experimental reviews on how higher education learning systems are applicable. ERIC was added to provide coverage of research, which focuses on education by withholding back studies that focus on pedagogy, learning outcomes, and instructional design. Google Scholar was further utilized to only perform backward snowballing to determine other relevant studies referenced in major articles to increase completeness and retain quality assurance.

Search Terms

Systematic search terms were developed in a way that suggests the main ideas of the review: generative AI technologies, personalized learning mechanisms, higher education settings, and cognitive learning outcomes consistent with the Bloom taxonomy. An organized Boolean search query was created in order to guarantee consistency across databases and permit minor syntax modifications where necessary. The initial element of the search query narrowed on generative AI technologies, like the words "generative AI, large language model, LLM, ChatGPT, GPT, generative transformer, and neural text generation. The selection of these terms was aimed at covering both general and model-specific areas, and it was crucial to include the studies that would define the generative systems in various ways. The second one was based on personalized learning testing words like personalized learning, adaptive learning, intelligent tutoring, and learner modeling.

They were selected as these are key terms that can encompass a variety of approaches to personalization, including adaptive content delivery, personalized feedback, and evaluation. The third element confined the context to higher education as it would include words like higher education, university, undergraduate, and graduate. This made sure that those studies that were done in the school or informal level of learning were filtered out at the search stage. The last element was aimed at cognitive learning results, especially Bloom's taxonomy, and the following terms were used: Bloom taxonomy, cognitive skills, learning outcomes and the level of knowledge. The addition of these terms made it possible to find the studies that specifically mention the Bloom taxonomy and include those studies that refer to the development of cognitive skills in a more indirect manner. The Boolean operator AND was used to combine these components to provide conceptual alignment, whereas the Boolean operator OR was used within a specific component to include terminology variants. This method is more precise and more recall exhibiting, minimizing irrelevant findings and minimizing the chance of omitting relevant research.

Filters

A set of filters was continuously used across databases to further narrow the search results and make them relevant. First, the search was restricted in the years between 2015 and 2025. The period is associated with the appearance of models and generative AI applications using transformers and their fast evolution, which allowed capturing not only early foundational work but also the latest progress. Second, the search filter was limited to publications in English language. This choice was intended to provide a similar interpretation and methodological check-up, and to recognize the practical limitations of analysis systematizing.

Third, only peer-reviewed journal articles, conference papers, systematic reviews, and experimental studies were included with the help of document type filter. Visions that are not peer-reviewed, including editorials, opinion pieces, technical blogs, and unpublished manuscripts, were locked out to uphold academic rigor and reliability. Domain restrictions were to restrict the scope to higher education context only. Articles that dealt solely with K12 education, corporate training, or unstructured learning situations were locked out, although they could have been using generative AI or personalization. This has made sure that the findings have a direct application to teaching and learning at university level. All of these filters made the review more valid because it makes sure that the included studies are not old, of high quality, contextually relevant, and aimed at meeting the research objectives. The search was conducted for studies published between January 2015 and December 2024.

INCLUSION AND EXCLUSION CRITERIA

Transparency, rigor, and reproducibility of a systematic literature review depend largely on clear inclusion and exclusion criteria. The criteria in this paper were constructed critically to fit the goal of the review which is to discuss the ways generative AI aids in personalized learning in higher education in a lens of the Bloom taxonomy. The criteria can be used to specify the scope of the review, minimize selection bias and ensure that only high-quality and relevant studies are included in the synthesis. Inclusion criteria were intended to help include studies that offer relevant empirical results or descriptive accounts of systems in the context of generative AI-based personalization and cognitive learning impacts. The exclusion criteria were used to ensure that the studies that fall outside the educational, methodological, or conceptual scope of the review are excluded. Combined, these criteria provide a sense of coherence in the chosen literature and allow a narrow analysis of how generative AI can be used in higher education in a pedagogically relevant way. In this review, AI-driven personalization refers to systems that adapt content, feedback, assessment, or learning pathways based on learner data using artificial intelligence techniques, including generative models, learning analytics, or intelligent tutoring mechanisms.

Inclusion Criteria

The inclusion criteria were set in the studies included in this review based on all predefined criteria of inclusion to be used to warrant relevance to both technological and pedagogical aspects of the research topic. First, they had to be eligible studies, meaning they must have used generative AI models (e.g. large language models, transformer-based architectures or other generative text or feedback systems). This requirement was necessary to make sure that the review dealt specifically with generative methods as opposed to either rule-based or non-generative intelligent tutoring systems. Second, the research had to take place in a higher learning institution, such as a university, college, or other institution of tertiary level. This limitation had to be so, in order to make it relevant to the learning objectives, teaching practice and cognitive expectation that comes with the higher education setting. Third, studies were needed to exhibit a type of personalization or learner adaptation. These consisted of adaptive content, personalized feedback, learner modeling, recommender systems, or active assessment systems.

The research involving the use of generative AI without adaptation to the particular learner was not included in the studies, as it was not relevant to the research topic of the personalized learning. Fourth, research had to mention Bloom taxonomy directly or discuss cognitive abilities that can be rationally mapped into Bloom cognitive levels. It enabled both direct and inferred tests of the way in which systems of generative AI interact with various kinds of cognitive activities. Lastly, empirical evidence, experimental results, or descriptions of system design and evaluation studies that appeared in the literature were restricted to only studies providing such information. This made sure that the review was based on verifiable research but not speculation or a completely conceptual discussion. Studies were included if Bloom's taxonomy was explicitly referenced or if cognitive outcomes could be reasonably inferred and mapped to Bloom's cognitive levels based on the reported learning tasks and assessments.

Exclusion Criteria

The use of the exclusion criteria ensured the maintenance of the methodological integrity and the thematic focus of the review. Articles focusing on K-12 education alone, vocational training, corporate learning or informal learning were not included because these areas of education vary significantly in goals of instruction, autonomy and cognitive demands compared to higher education. Also excluded were research studies that were not done using generative AI models. This encompassed research on conventional intelligent tutoring systems, adaptive learning systems guided by predefined rules or non-generative machine learning systems. The omission of such studies was done to provide conceptual purity and avoid overlap with previous generations of educational technology. Purely conceptual, ethical, policy-oriented, and opinion-based studies were not considered since they did not provide empirical data or a system-level analysis. Although these studies can be of great help, those studies lack the evidence that would help determine the personalization mechanisms or cognitive learning outcomes.

Non-peer-reviewed sources (preprints that have never been reviewed formally, technical reports, blog posts, and industry white papers) were also filtered out to provide academic rigor and reliability. The only exceptions were done in cases of backward snowballing where such sources resulted in peer-reviewed publications. The literature that had no explicit connection to personalization of learning or to cognitive performance was a filtering criterion, despite the use of a generative AI in learning contexts. This criterion helped to be sure that all the studies incorporated were related directly to the main theme of the review personalized learning and the taxonomy of Bloom in higher education. Studies focusing exclusively on K-12 education were excluded due to substantial differences in curricular structure, learner autonomy, and cognitive expectations compared to higher education contexts.

SCREENING PROCEDURE

PRISMA Stages

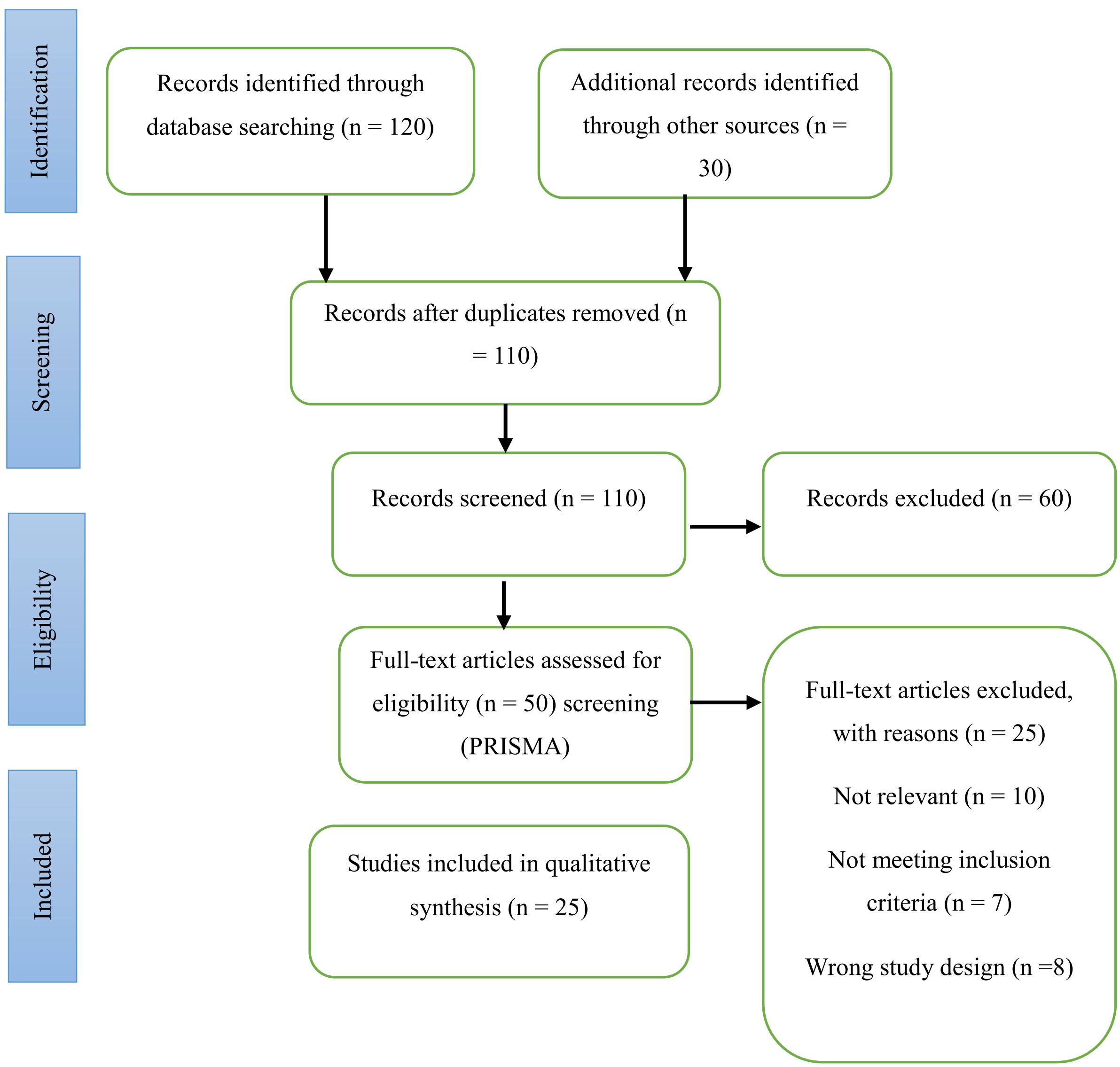

Figure 1: PRISMA Diagram

Inter-Rater Agreement

To achieve objectivity, consistency and methodological rigor in the screening process inter-rater agreement was rigorously evaluated in the stage of study selection of this systematic literature review. The records retrieved were screened by two independent reviewers at the title-abstract screening phase and the full-text eligibility assessment phase. Independent screening minimized possible selection biasness and increased the robustness of inclusion decisions. Inter-rater reliability was derived by Cohen -Kappa (-) statistical coefficient, which is common standard statistical coefficient to measure the agreement between the two reviewers, not by chance. The Cohen 2 values are between 1 and -1 with the larger coefficient implying the stronger level of agreement. As per standard systematic review criteria, a level of agreement that will be considered to be substantial was adopted as an indicator of 0.70 and above. The inclusion threshold indicates a reasonable degree of homogeneity across all the studies included in a systematic review and justifies the validity of the screening procedure.

At the initial screening stage, duplicates were eliminated followed by independent evaluation of all records by both reviewers. The next step involved the calculation of agreement scores to assess the consistency of exclusion and inclusion judgments. In case of any discrepancies, they were recorded and checked systematically. The major causes of disagreements were in the interpretational differences in the relevance of the studies and the inclusion of generative components of AI or the scope of the personalization mechanisms. All the disputes were dealt with by a process of structuring the conflict resolution. Detailed discussion of the reviewers was done to redefine the objectives of the study, the inclusion criterion, and the methodological requirements. In case of the inability to come to a consensus after discussion, it was re-examined in accordance with the set criteria until the agreement was reached. This cyclic approach was transparent and consistent, as well as compliant with the scope and goals of the review. The use of Cohen-Kappa and a systematic conflict resolution process improved the methodological soundness of the screening process and made sure that the ultimate collection of included studies was chosen by a rigorous and reproducible method.

Data Extraction

Author(s) & Year	**AI Approach**	**Educational Context**	**Personalization Mechanism**	**Bloom Level(s) Addressed**	**Type of Evidence**	**Key Outcomes / Focus**	**Relevance**
Aleven et al. (2016)	Intelligent Tutoring System (ITS)	Higher Education	Adaptive hints, help-seeking	Understand, Apply	Experimental study	Improved learning with guided support	High
Baker (2016)	Learning Analytics	Higher Education	Data-driven personalization	Understand, Apply	Conceptual + applied cases	Personalized learning pathways	Medium
Baker et al. (2016)	Learning Analytics / EDM	Higher Education	Learner modeling	Apply, Analyze	Review chapter	Analytics-driven adaptation	Medium
Bender et al. (2021)	Generative AI (LLMs)	HE / General	Not personalized (risk-focused)	Analyze, Evaluate	Critical analysis	Risks of LLM deployment	Contextual

Author(s) & Year	AI Approach	Educational Context	Personalization Mechanism	Bloom Level(s) Addressed	Type of Evidence	Key Outcomes / Focus	Relevance
Noushad (2024)	Pedagogical Framework	Higher Education	Outcome-based alignment	Understand, Apply, Analyze	Conceptual	Cognitive outcome design	High
Adams (2015)	Pedagogical Taxonomy	Higher Education (Medical)	Instructional alignment	All Bloom levels	Conceptual review	Cognitive classification	High
Jitpaisarnwattana et al. (2021)	Learning Analytics	MOOC (HE)	Adaptive & social learning	Understand, Apply	Mixed methods	Enhanced learner interaction	High
Chiu et al. (2023)	AI (Multiple Approaches)	Higher Education	Multiple AI approaches	Understand–Evaluate	Systematic review	AI opportunities & challenges	High
Yuvaraj et al. (2025)	Affective AI	Higher Education	Emotion-aware adaptation	Understand, Apply	Bibliometric + review	Engagement & affect	Medium
De Bruyckere et al. (2019)	Conceptual / Critical	Higher Education	Not personalized	Analyze, Evaluate	Critical analysis	Learning misconceptions	Contextual
Macfarlane (2020)	Conceptual (Non-AI)	Higher Education	Not personalized	Analyze	Conceptual	Student learning myths	Contextual
Pedro et al. (2019)	AI in Education	Higher Education	Adaptive systems	Understand, Apply	Policy analysis	AI challenges & opportunities	Medium
Tretow-Fish & Khalid (2023)	Learning Analytics	Higher Education	Adaptive dashboards	Understand, Analyze	Systematic review	Evaluation methods	High
Kalyuga (2023)	Instructional Theory	Higher Education	Expertise-based guidance	Apply, Analyze	Theoretical analysis	Task complexity management	High
Darwazeh & Branch (2015)	Pedagogical Framework	Higher Education	Instructional alignment	All Bloom levels	Conference study	Taxonomy refinement	High

Author(s) & Year	AI Approach	Educational Context	Personalization Mechanism	Bloom Level(s) Addressed	Type of Evidence	Key Outcomes / Focus	Relevance
Luckin & Holmes (2016)	AI in Education	Higher Education	Adaptive intelligence	Understand–Analyze	Conceptual framework	AI-supported learning	High
Mollick & Mollick (2023)	Generative AI (LLMs)	Higher Education	Prompt-based personalization	Analyze, Evaluate, Create	Design-based analysis	AI-assisted learning tasks	High
Terziev et al. (2020)	Intelligent Systems	Higher Education	Adaptive intelligence	Understand, Apply	Conference study	Education–industry link	Medium
Osadcha et al. (2020)	Adaptive Learning Systems	Higher Education	Individual learning paths	Apply, Analyze	Systematic review	Personalized trajectories	High
Dever et al. (2023)	Intelligent Tutoring / Agents	Higher Education	Adaptive scaffolding	Analyze, Evaluate	Experimental	Improved metacognition	High
Mirari (2022)	Adaptive Learning Systems	Higher Education	Personalized content	Understand, Apply	Empirical study	Improved performance	High
Salas-Pilco & Yang (2022)	AI Applications	Higher Education	Adaptive systems	Understand–Analyze	Systematic review	Regional AI adoption	Medium
Luo et al. (2025)	AI-based Learning Tools	Higher Education	Personalized AI tools	Apply–Evaluate	Systematic review	Design & assessment trends	High
Bahrami et al. (2022)	AI Models (Methodological)	Reference	Not personalized	—	Meta-analysis	Methodological rigor	Contextual
Suthar et al. (2024)	Infrastructure (Edge/Fog)	Higher Education	Infrastructure support	—	Applied study	System efficiency	Low–Medium

The analyzed articles show the development of artificial intelligence-assisted personalized learning in postsecondary education that ranges between the initial analytics-based and rule-based systems to the latest generation and cognitively adaptive systemology. Previous background literature, including the personal works of Aleven et al. (2016), and Baker (2016), focuses on intelligent tutoring systems and learning analytics as means to provide adaptive support, although usually to lower- to mid-level cognitive functions, including understanding, application, and guided problem solving. The studies form the pedagogical foundations of personalization which are mostly based on rules or data-informed understandings instead of on generative skills. Research based on education-focused data mining and analytics (e.g., Baker et al., 2016; Jitpaisarnwattana et al., 2021; Tretow-Fish & Khalid, 2023) emphasize the learner modeling, dashboard-based feedback, and adaptive pathways. Although they enhance interaction and observation, their cognitive correspondence is unclear, and the explicit correspondence to the taxonomy offered by Bloom is usually scarce.

Another strand of scholarship concentrates on instructional theory and cognitive frameworks, such as the taxonomy or cognitive load theory by Bloom (Adams, 2015; Darwazeh and Branch, 2015; Kalyuga, 2023; Noushad, 2024). These articles give good theoretical foundations to learning goals and cognitive development but largely do not specify the application of AI-based personalization. They manage to do this by specifying cognitive targets, not illustrating technological enactment. The more recent investigations are an indication of a transition towards generative and more advanced AI systems. Articles by Mollick and Mollick (2023), Dever et al. (2023), and Luo et al. (2025) demonstrate how higher-order cognitive skills, such as analysis, evaluation, and self-controlled learning, can be supported using AI-based tools and pedagogical agents. These studies indicate more consistency with the higher levels of Bloom, especially in cases where adaptive scaffolding and feedback are incorporated. According to systematic reviews (e.g., Chiu et al., 2023; Salas-Pilco and Yang, 2022; Yuvaraj et al., 2025), despite the growing use of AI in higher education, there is still partial evidence on long-term higher-order effects. Also, critical views (Bender et al., 2021; De Bruyckere et al., 2019; Macfarlane, 2020) warn about unquestioning embrace, which entails ethical, cognitive, and pedagogical dangers. This comparison demonstrates that the mismatch between technological innovation and explicit cognitive congruence has existed, and it is necessary to implement generative AI-based systems with strong pedagogical foundations and empirically established in connection with the Bloom taxonomy.

Quality Assessment

A structured quality evaluation procedure was implemented on all the studies used in this systematic literature review to guarantee methodological rigor and reliability. The evaluation combined both the Mixed Methods Appraisal Tool (MMAT) and AI-specific quality indicators, permitting the review of the quality of educational research and technical soundness of generative AI systems. The MMAT was chosen since it can be used to review research studies of various research designs, such as qualitative, quantitative, and mixed-methods research studies. When applying MMAT, every study was rated in accordance with main criteria, including clarity of the research questions, suitability of research methods, soundness of data collection processes, sufficiency of data analysis, and sensibility between findings and conclusions. This guaranteed that there were only studies of quality to put in the synthesis. Besides MMAT, AI-specific quality indicators, provided to overcome the problems peculiar to learning systems based on generative AI. Such indicators evaluated the openness of AI model use, comprehensibility in explaining system architecture, management of known constraints like hallucinations or bias, and whether the personalization mechanisms were explicable. Reproducibility was also considered, with datasets, laboratory settings, and procedures reported. All criteria were marked on 02 scale (0 = not addressed, 1 = partially addressed, 2 = fully addressed). The mixed evaluation allowed an even-handed judgment on pedagogic validity and technical credibility. This two-layered quality judgement ensured the quality of the review results and the strong comparability of the studies included.

Table 1: MMAT-Based Quality Assessment of Included Studies

Author(s) & Year	Study Type	MMAT Score (0–10)	Quality Level	Justification (Brief)
Aleven et al. (2016)	Experimental (ITS)	9	High	Clear research questions, controlled design, validated outcomes
Baker (2016)	Conceptual + applied	6	Moderate	Applied cases but limited empirical validation
Baker et al. (2016)	Review chapter	6	Moderate	Synthesizes analytics methods, no primary experimentation
Bender et al. (2021)	Critical analysis	4	Low / Contextual	Theoretical critique, no educational intervention
Noushad (2024)	Conceptual framework	4	Low / Contextual	Pedagogical theory, no empirical testing
Adams (2015)	Conceptual review	4	Low / Contextual	Taxonomy-focused, non-empirical
Jitpaisarnwattana et al. (2021)	Mixed methods	8	High	Clear data sources, learner analytics, empirical validation
Chiu et al. (2023)	Systematic review	8	High	PRISMA-based, rigorous synthesis
Yuvaraj et al. (2025)	Bibliometric + review	6	Moderate	Strong mapping, limited learning outcome validation
De Bruyckere et al. (2019)	Critical analysis	4	Low / Contextual	Theoretical critique, no system evaluation
Macfarlane (2020)	Conceptual	4	Low / Contextual	Theoretical discussion only
Pedro et al. (2019)	Policy analysis	6	Moderate	Evidence-informed but not experimental
Tretow-Fish & Khalid (2023)	Systematic review	8	High	Clear evaluation framework and synthesis
Kalyuga (2023)	Theoretical analysis	4	Low / Contextual	Cognitive theory, no AI system testing
Darwazeh & Branch (2015)	Conference study	5	Moderate	Conceptual refinement with limited validation

Author(s) & Year	Study Type	MMAT Score (0–10)	Quality Level	Justification (Brief)
Luckin & Holmes (2016)	Conceptual framework	4	Low / Contextual	Visionary framework, no empirical data
Mollick & Mollick (2023)	Design-based analysis	7	Moderate	Practical classroom use, limited controlled evaluation
Terziev et al. (2020)	Conference study	5	Moderate	Applied context, limited methodological detail
Osadcha et al. (2020)	Systematic review	7	Moderate	Structured review, heterogeneous evidence
Dever et al. (2023)	Experimental	9	High	Strong experimental design, cognitive measures
Mirari (2022)	Empirical study	8	High	Clear intervention and outcome measures
Salas-Pilco & Yang (2022)	Systematic review	8	High	Methodologically rigorous regional synthesis
Luo et al. (2025)	Systematic review	9	High	Strong methodology, clear evaluation criteria
Bahrami et al. (2022)	Meta-analysis (method ref.)	3	Low / Contextual	Methodological reference, not educational
Suthar et al. (2024)	Applied infrastructure study	3	Low / Contextual	Technical focus, no learning outcomes

RESULTS

Descriptive Results

Table 2: AI Type (from tags)

Category	Count (n)	Percent
AI in education (broad)	4	16%
EdTech infrastructure (non-AI pedagogy)	1	4%
Generative AI / LLM	2	8%
ITS / Pedagogical agents	2	8%
Learning analytics / EDM	4	16%
Not specified	8	32%
Other / Out-of-scope	1	4%
Pedagogical framework / theory	3	12%
Total	25	100%

Table 1 shows the spread of the AI types in the selected studies. The biggest share of literature represents the category of Not specified (32%), which means that much of the literature talks about AI-enabled learning without a precise account of the technological model. There is an equal representation of learning analytics and educational data mining, broad AI-in-education (16% apiece), which demonstrate their continued importance to the research. By comparison, systems based on generative AI or large language models are explicitly evident in the literature only 8% of the literature reviewed. This dispersion implies that although the AI-assisted personalization interest is rising, generative AI implementations with clearly stated concerns are not yet as common in the existing literature as they could be.

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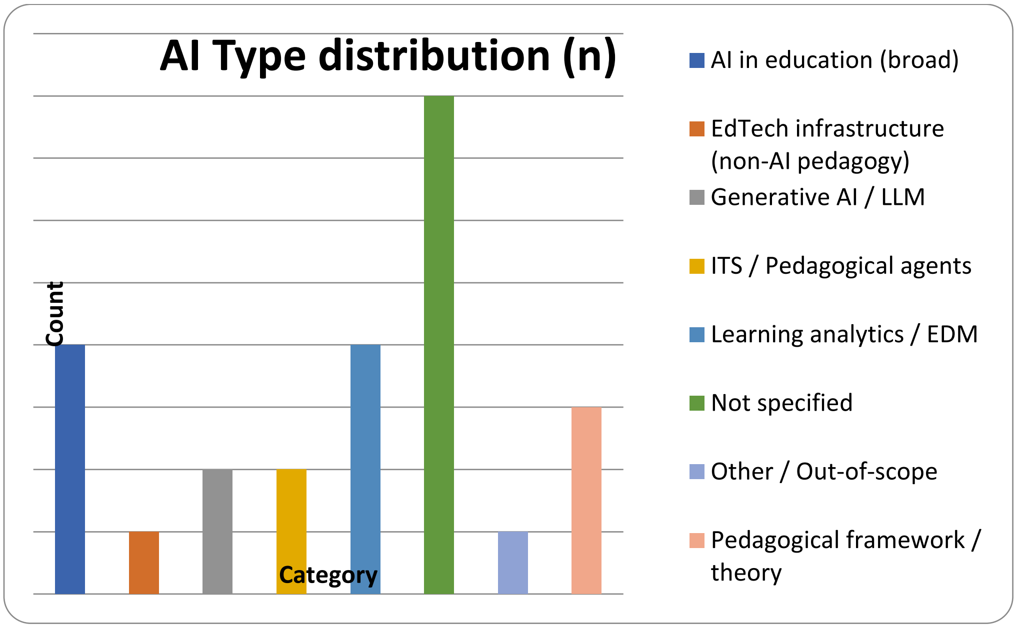

Table 3: Evaluation Method

Category	Count (n)	Percent
Conceptual / chapter	4	16%
Conference paper (method varies)	4	16%
Meta-analysis	1	4%
Not specified / varies	11	44%
Preprint (method varies)	1	4%
Systematic review	4	16%
Total	25	100%

Table 3 outlines the methods of evaluation used in the included studies. A significant fraction of the literature (44%) fails to explicitly and consistently use an identified method of evaluation, and there is a lack of consistency in the rigor of the methods. The proportion of conceptual or book chapter contributions and systematic reviews is equal, 16% each, suggesting high theoretical synthesis and secondary analysis. Mixed methodology conference papers also reflect 16% of the research in the field, as the research is exploratory and emerging. Empirical meta-analyses and preprint studies have a low representation. Altogether, the distribution indicates that strong experimental analysis is not deeply developed in the research on AI-assisted personalized learning.

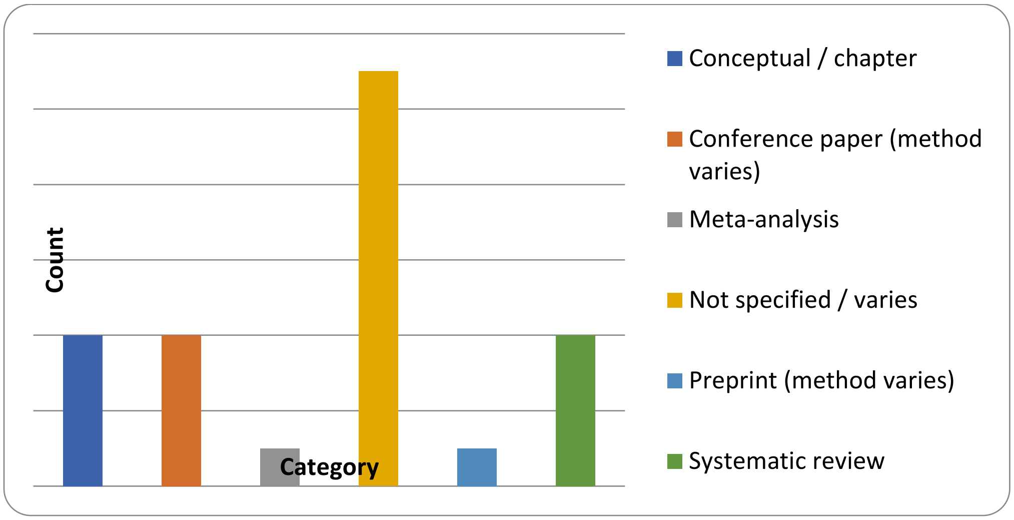

Table 4: Context

Category	Count (n)	Percent
Education (general)	19	76%
Higher education	4	16%
MOOC (higher education-related)	1	4%
Non-education	1	4%
Total	25	100%

Table 3 provides the context sensitivity of the analyzed articles. Most of the literature (76 percentage) is located within general educational context, meaning that numerous studies do not specify the specific level of education on which they are supported by AI. Only 16 percent of the studies are directly oriented to higher education, and a minor percentage cover MOOC-based learning environment in terms of tertiary education. Only very few research works can be contained out of an educational context. This dispersion indicates that, regardless of the increasing attention to the AI-driven personalization, there is light empirically-based studies explicitly placed in higher education settings.

Thematic Synthesis

The thematic synthesis identified five prevalent themes representing the conceptualization and implementation of artificial intelligence-assisted personalization in higher education. These themes represent different degrees of technological maturity and pedagogical alignment in the reviewed studies.

Generative Feedback Systems: The use of generative and instructional feedback became one of the key personalization mechanisms arisen. Weaver et al. (2024) highlight the instructional authority of comments in instructing training that structured and punctual remarks notably aid in reflective learning and teaching enhancement. Clark and Mayer (2023) give evidence-based principles of effective multimedia and e-learning feedback and emphasize the role of adaptive feedback in improving learner understanding and interest. These studies collectively signal a heavy focus on feedback as a fundamental personalization tool; though feedback efficacy is generally justified, its operational definition via generative AI is still rather instructive than all-generative.

Personalized Content Generation: Adaptive and collaborative learning techniques were aimed at personalized content delivery. Akuma and Ndera (2021) suggest the adaptive hypermedia system that fits the preferences of learners, showing that personalized content paths can enhance the engagement of learners. Chetlen et al. (2020) are concerned with collaborative and peer-based learning settings, where the content is personalized in the course of social interaction instead of being produced by algorithms. Although the two studies emphasize on personalization, the use of established structures implies a lack of generative autonomy, which points to moderate strength of this theme.

Automated Assessment and Scaffolding: The intelligent tutoring perspectives were the key approaches to automated assessment and scaffolding. Hasan et al. (2020) discuss the history of evolution of intelligent to affective tutoring systems, explaining that adaptive assessment and emotional scaffolding are new steps. Nedrehagen et al. (2024) investigate dialogic formative feedback, highlighting the practice of scaffolding using interactive assessment. Even though both studies attest to criminological automation, empirical confirmation of long-term cognitive effects is still constrained which reflects semi-implementation strength.

Learner Modeling: The data-driven cognitive representations covered the learner modeling. Gan et al. (2020) introduce sophisticated methods of knowledge tracking that simulate dynamic cognitive statuses of learners and make them adapt responsively. Sahin and Yurdugul (2020) offers a more analytical approach on the field of educational data mining and learning analytics, includes the historical development and future prospects. The theme has high technical funding but less pedagogical explanation of learner models has typically been understudied.

Cognitive Alignment Gaps: There were cognitive alignment gaps among studies. Adhikari (2024) revisits the updated Bloom taxonomy which substantiates its significance in scaffolded cognitive development. Biggs et al. (2022) also focus on positive alignment of learning goals, teaching and assessment. Regardless of this intensive theoretical basis, numerous AI-based systems do not actively incorporate the Bloom levels of cognition, posing an ongoing gap between technology implementation and pedagogical purpose.

Table 5: Mapping of AI Personalization Mechanisms to Bloom's Cognitive Levels

AI Personalization Mechanism	Remember / Understand	Apply	Analyze	Evaluate	Create
Learning analytics dashboards	✔	✔	⍰	✕	✕
Intelligent tutoring systems (ITS)	✔	✔	✔	⍰	✕
Adaptive content sequencing	✔	✔	⍰	✕	✕
Automated feedback systems	✔	✔	⍰	⍰	✕
Generative AI (LLMs, agents)	✔	✔	✔	✔	⍰

The mapping indicates that AI-driven personalization predominantly supports lower-order cognitive processes (remembering, understanding, and application), while higher-order levels particularly evaluation and creation remain under-represented and are mainly addressed by generative AI-based systems.

Analytical Synthesis

This analytical synthesis will incorporate the result of the reviewed studies by relating the types of AI models, personalization mechanisms, and how they correspond with cognitive learning results in higher education. Throughout the literature, a strong contrast between analytics-informed and rule-directed systems, intelligent tutoring system (ITS), and emergent generation AI approaches, with regard to their cognitive and pedagogical reach. In research, AI-driven personalization mainly aids the lower-order cognitive functions, particularly, remembering, understanding and application. Learning analytics systems and adaptive hypermedia platforms are based on structured learner data, with preset rules controlling the instructional decision, and are useful in procedural learning and performance optimization (Lin et al., 2023). Intelligent tutoring and affect-aware systems use interaction-level data to adapt instructional pace, feedback, and scaffolding, yet their cognitive value is still heavily focused on the lower levels of Bloom taxonomy.

Generative AI-based systems, in contrast, have a higher scaffolding capability of higher-order cognitive processes, such as analysis and evaluation, with dialogic interaction, reflective feedback, and generation of open-ended tasks. The empirical data on the basis of long-term returns in the analysis and development stages, however, is limited and fragmented. In most instances, more high-order engagement is documented indirectly via learner reflexivity or self-managed learning tests instead of the proper cognitive design (Harnas et al., 2024). Cognitive alignment often disintegrates when the personalization mechanisms are incentivized by behavioral or performance statistics with a non-clear mapping to instructional goals based on the Bloom taxonomy. Feedback and adaptive content delivery, especially based on analytically generated content, can successfully reinforce conceptual knowledge and procedural knowledge but seldom go beyond that, to the deliberate support of synthesis, evaluation, or creative knowledge building (Meng et al., 2025).

Increased engagement and task completion, and short-term performance gains are predominant in the reported learning outcomes (Rajabalee & Santally, 2021). Adaptive feedback and scaffolding are valuable components of self-regulation but have little solid basis of developing high-order cognition in the long term based on AI-based personalization, which points to a warning gap between the technological potential and the pedagogical will.

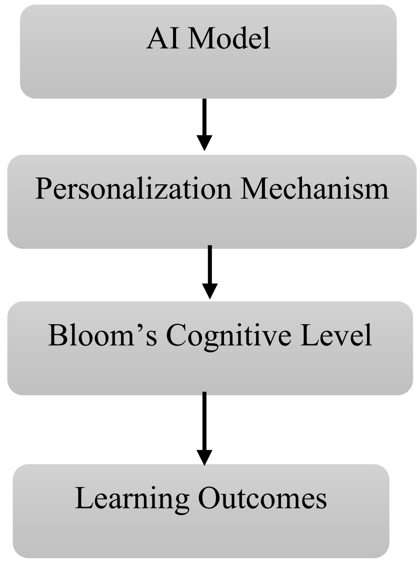

Figure 2: Model–personalization cognition outcome framework for AI-supported personalized learning.

Gap Analysis

The literature synthesis creates a number of significant gaps in the research, technical, and pedagogical aspects. There are research gaps such as minimal use of rigorous experimental designs and longitudinal evaluations. Other studies utilize short-term interventions, limited samples, or descriptive studies, which do not allow concluding on lasting learning effects. Moreover, assessment is frequently determined by measures of engagement or satisfaction instead of solid testing of cognitive growth, more especially assessing higher levels of the taxonomy of Bloom. There are still technical discrepancies in the development and reporting of AI-based personalization systems. Some studies have a restricted level of transparency of model architecture, source of data, and adaptation logic, thereby limiting reproducibility and comparability. Also, the issues of explainability, bias, and addressing inaccurate or misleading output of the system are not addressed in detail. Although adaptive and affective systems have potential, the majority of research does not specifically assess the impact of technical design selection on cognitive learning mechanisms. The strongest gaps are those of pedagogy. Even though the taxonomy by Bloom is often cited as a reference guide, it is seldom operationalized in system design or evaluation plans.

The majority of the current AI-assisted learning systems prioritize lower-order thinking, and few studies have empirically examined analysis, appraisal, and invention. Positive congruence between learning goals, personalization processes, and evaluation is not well-developed. To fill these gaps, it is necessary to use integrated research designs that need to combine technical innovation with clear cognitive theory so that AI-based personalization has a significant purpose in supporting higher-order learning in higher education.

DISCUSSION

This review systematically explored the idea of AI-based personalized learning in higher education in the context of the Bloom taxonomy, especially the way various AI strategies support cognitive learning outcomes. Theoretically speaking, the taxonomy of Bloom can serve as a clear-cut guideline to differentiate between lower- and high-order mental processes and still serves as a key aspect in the curriculum creation and evaluation in advanced education. The incorporation of this framework into AI-infused personalization systems is still uneven, however, the gap between pedagogic theory and technology remains to be persistent. The evidence reviewed in this paper shows that the majority of AI-based personalization systems are more dominant in supporting the lower levels of cognition, especially in the remembering, understanding and application. Systems based on analytics and smart tutoring systems (e.g., Aleven et al., 2016; Baker, 2016; Jitpaisarnwattana et al., 2021) are shown to be equally effective in adaptive feedback, procedural scaffolding, and performance optimization. The fact that these systems are based on collected and organized data about learners and preset rules renders them quite applicable in the tracking of progression and the promotion of foundational learning but restricts their ability to promote higher-level thinking. This trend is also supported by systematic reviews in the area of learning analytics and it is identified that explicit alignment of cognition frequently does not exist or is implicit (Tretow-Fish and Khalid, 2023; Chiu et al., 2023).

Generative AI-based methods, on the contrary, demonstrate a growing potential and possibility to access higher-order thinking, especially analysis and evaluation. According to studies that use large language models as design-based and exploratory (e.g., Mollick and Mollick, 2023; Luo et al., 2025), dialogic interaction, prompted reflection, and generation of open-ended tasks can help students engage with the task more in-depth. Nevertheless, there is still limited empirical support in regard to the sustained gains in the evaluation and creation level. Numerous studies mention short-term involvement or self-reported learning effects not compared with rigorously evaluated cognitive gains which is also emphasized by critical and conceptual reviews (Bender et al., 2021; De Bruyckere et al., 2019). Consequently, the assertions of improvement in the higher-binding brain functions by generative AI must be viewed with suspicion. In terms of implications, the findings indicate the opportunities and limitations of AI-based personalized learning in higher learning. Pedagogically, the findings indicate that AI systems need to be clearly cognitive-minded, as opposed to relying on the assumption that personalization will lead to deeper learning. Generative AI has likely to have similar promising affordances to support higher-order thinking, but this must be done intentionally through teaching design and powerful assessment. To the researchers, a more empirically sound validation is important due to the absence of longitudinal and experimentally sound studies. To teachers and schools, this discussion suggests that the use of AI should be guided by pedagogical objectives based on the Bloom taxonomy, and not just efficiency or engagement rates.

REPORTING PLAN

This systematic review of the literature is reported using the best practices that guarantee transparency, rigor, and reproducibility. The review applies PRISMA (Preferred Reporting Items to Systematic Reviews and Meta-Analyses) 2020 guidelines, which gives a systematic framework of recording every step of the review process. The compliance with PRISMA is manifested by well-reported search strategy, inclusion and exclusion criteria, screening procedures, data extraction methods and procedures of quality assessment. The identification, screening, eligibility and inclusion of the studies, and the reasons why they were excluded at any point are described using a PRISMA flow diagram. Such a systematic method increases methodological transparency and makes readers evaluate the reliability and thoroughness of the review. The overall report is well structured into digestible chapter by chapter format to help in easing the flow between the conceptual base to synthesis of the analysis. The background shows theoretical grounds connected to generative AI, personalized learning, and the taxonomy proposed by Bloom, which gives the concise understanding in the following analysis. The methodologies explains the systematic review method, such as search strategy, screening, inclusion and exclusion rules, data extraction framework, and quality evaluation approaches. The results and discussion chapter describe and themes the synthesized studies and indicate implications of the AI-assisted personalized learning suggesting how these findings relate to the current theory and practice. The research by summarizing main insights, research gaps, and future research directions. Accessible and complete reporting is ensured and supplementary materials such as detailed search strings and extraction matrices are given in appendices.

CONTRIBUTIONS OF THE STUDY

- This review provides a structured synthesis of how different AI approaches including learning analytics, intelligent tutoring systems, and emerging generative AI align with specific levels of Bloom's taxonomy, offering a clear evidence-based overview of their cognitive focus in higher education contexts.

- By comparing empirical and design-based studies, the review reveals that most AI-driven personalization mechanisms predominantly support lower-order cognitive processes (remembering, understanding, and applying), while higher-order levels (analyzing, evaluating, and creating) remain under-represented and weakly operationalized.

- The study distinguishes the pedagogical affordances and limitations of generative AI in relation to traditional analytics-driven systems, highlighting that generative models show emerging potential for higher-order cognitive engagement but lack robust empirical validation.

- Based on synthesized evidence, the review offers actionable insights for educators, researchers, and system designers, emphasizing the need for explicit Bloom-aligned instructional design, transparent personalization mechanisms, and cognitively grounded evaluation when deploying AI-driven learning systems in higher education.

FUTURE RESEARCH DIRECTIONS

- Future research should move beyond short-term interventions and cross-sectional evaluations by employing longitudinal and quasi-experimental designs. Such studies are necessary to examine the sustained effects of AI-driven personalization on students' cognitive development across multiple levels of Bloom's taxonomy, particularly higher-order skills such as analysis, evaluation, and creation.

- There is a need for AI-based learning systems that operationalize Bloom's taxonomy directly within their design logic, personalization mechanisms, and assessment strategies. Future studies should explicitly map instructional prompts, adaptive feedback, and content generation to specific cognitive levels and evaluate whether these mappings result in measurable cognitive gains.

- As AI systems increasingly influence instructional pathways and assessment, future research should prioritize explainable AI (XAI) approaches that allow educators and learners to understand how personalization decisions are made. Transparent learner modeling and interpretable feedback mechanisms are critical for pedagogical trust, ethical deployment, and meaningful instructional alignment.

- Rather than positioning AI as a replacement for instructional expertise, future research should investigate models of effective teacher–AI collaboration. Studies should explore how educators can guide, regulate, and contextualize AI-generated feedback and content to support higher-order cognition, reflective learning, and pedagogical coherence in higher education.

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APPENDICES

Appendix A: Search Strings

("generative AI" OR "large language model" OR LLM OR ChatGPT)

AND ("personalized learning" OR "adaptive learning" OR "intelligent tutoring")

AND ("higher education" OR university OR undergraduate)

AND ("Bloom's taxonomy" OR cognitive learning outcomes)