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# Barriers and Strategies for Implementing AI-Based Personalized Learning in Project-Based Learning: A Systematic Literature Review

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**Abstract**
**Background.** Artificial intelligence (AI), particularly large language models (LLMs), has emerged as a transformative technology in education, offering new possibilities for student-centered pedagogies such as project-based learning (PBL).
**Methods.** This systematic literature review examines the integration of AI in PBL across K-12 and higher education contexts, focusing on its benefits, challenges, and implementation strategies. Following the PRISMA 2020 guidelines, 23 empirical studies published between 2020 and 2026 were analyzed from the Scopus and Web of Science databases.
**Result.** Key findings include: (a) AI enhances PBL through personalized learning pathways, automated scaffolding, real-time feedback, and collaborative prompting; (b) challenges persist in data privacy, over-dependence on AI, output accuracy, and teacher readiness; and (c) successful strategies emphasize co-design, ethical frameworks, and gradual personalization.
**Conclusion.** This review provides actionable insights for educators, policymakers, and technology developers to design effective and responsible AI-supported PBL environments.

**Keywords:** artificial intelligence; project-based learning; large language models; personalized learning; systematic literature review; PRISMA 2020



## INTRODUCTION

The emergence of generative artificial intelligence (AI), especially large language models (LLMs) such as ChatGPT, Google Gemini, and Microsoft Copilot, has catalyzed a paradigm shift in contemporary educational practices (Kasneci et al., 2023; OpenAI, 2023). These technologies demonstrate unprecedented capabilities in generating human-like text, delivering adaptive feedback, and scaffolding complex learning processes (Dwivedi et al., 2023). In the context of the digital transformation of education, AI is increasingly positioned as a key enabler of personalized learning (PL) environments, where instruction can be tailored to individual learners' needs, preferences, and progress (Holmes et al., 2022; UNESCO, 2023).

Personalized learning, defined as a student-centered approach that adapts instructional content, pace, and pathways to individual learner characteristics, has been widely recognized as a strategy to improve learning effectiveness and equity (OECD, 2021; Pane et al., 2017). Through the integration of data analytics and intelligent systems, PL enables dynamic adjustment of learning experiences, fostering greater learner autonomy, engagement, and mastery (Zawacki-Richter et al., 2019). However, despite its potential, the implementation of PL remains complex, requiring scalable mechanisms for continuous feedback, differentiation, and instructional support. Within this context, project-based learning (PBL) offers a complementary pedagogical framework that emphasizes authentic, inquiry-based learning experiences. PBL engages students in solving real-world problems, thereby promoting deep conceptual understanding, critical thinking, and collaboration (Kokotsaki et al., 2016; Thomas, 2000). Importantly, PBL aligns with the principles of personalized learning by allowing students to explore topics based on their interests, take ownership of their learning process, and construct knowledge actively. Nevertheless, the implementation of PBL presents significant challenges, including project design complexity, difficulties in assessing individualized learning outcomes, time constraints, and the need to balance structured guidance with learner autonomy (Condliffe et al., 2017; Buck Institute for Education, 2019).

The convergence of AI, PBL, and personalized learning presents a promising opportunity to address these challenges. AI technologies can enhance PBL environments by enabling adaptive scaffolding, automating formative assessment, generating differentiated learning resources, and providing real-time feedback tailored to individual learners (Kasneci et al., 2023; Luckin et al., 2016). However, despite this potential, the integration of AI within PBL frameworks to support PL remains insufficiently explored. Existing studies are fragmented across disciplines and educational levels, with limited synthesis of evidence regarding effectiveness, challenges, and best practices (Dwivedi et al., 2023).


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Moreover, the adoption of AI raises critical concerns related to data privacy, algorithmic bias, academic integrity, and the risk of over-reliance on AI systems (Holmes et al., 2022; UNESCO, 2023). In PL contexts, these concerns are amplified due to the extensive use of learner data for adaptive decision-making. Without appropriate ethical frameworks and pedagogical guidelines, the integration of AI risks undermining learner autonomy and equity rather than enhancing it.

To address these gaps, this systematic literature review aims to synthesize empirical evidence on the integration of AI in PBL to support personalized learning. Specifically, the study identifies research trends, examines learning outcomes and benefits, analyzes challenges and ethical considerations, and proposes design guidelines for effective implementation.

Recent advancements in artificial intelligence (AI), particularly large language models (LLMs), have significantly transformed educational practices by enabling adaptive feedback, automated scaffolding, and personalized learning pathways. Project-based learning (PBL) has been widely recognized as an effective pedagogical framework that promotes critical thinking, collaboration, and real-world problem-solving. Meanwhile, personalized learning has emerged as a student-centered approach that enhances learner engagement and autonomy through individualized instructional pathways. The convergence of AI, PBL, and personalized learning represents a promising direction for modern education systems.

Despite rapid technological development, empirical research on AI integration in project-based learning for personalized learning remains fragmented across disciplines and educational levels. Existing studies have primarily focused on technological capabilities or isolated learning outcomes rather than systematically examining implementation barriers, ethical challenges, and scalable strategies. Furthermore, there is limited evidence regarding long-term sustainability and practical implementation frameworks for AI-powered personalized learning in real educational settings.

This study contributes to the literature by providing a systematic synthesis of empirical evidence on the integration of artificial intelligence in project-based learning environments to support personalized learning. It develops a structured classification of implementation barriers and proposes evidence-based strategies for effective adoption, offering a comprehensive framework that bridges technological innovation, pedagogical design, and ethical governance in AI-supported education.

## METHODS

This systematic literature review was conducted in accordance with the PRISMA 2020 statement (Page et al., 2021) and the methodological frameworks proposed by Kitchenham et al. (2010) and Linnenluecke et al. (2020). The process comprised five phases: (1) formulation of research questions, (2) design of search protocols, (3) definition of inclusion and exclusion criteria, (4) execution of data selection and extraction, and (5) data synthesis.

### Research Questions

The following research questions (RQs) were formulated using the SMART criteria:

- RQ1: What research methods are predominantly used in empirical studies on AI integration in PBL for personalized learning (2020–2026)?
- RQ2: What AI technologies are most frequently utilized in personalized PBL implementations, and how are they applied across educational contexts?
- RQ3: What learning modalities are most commonly reported in studies integrating AI and PBL for personalization?
- RQ4: What barriers are reported in implementing AI-based personalized learning in PBL, and how do these barriers vary by educational level?
- RQ5: What strategies have been proposed or proven effective to overcome these implementation barriers?

### Search Protocol

The article search was conducted using the Scopus and Web of Science (WoS) databases, which are widely recognized for their rigorous content selection and broad disciplinary coverage (Airyalat et al., 2019; Pech & Delgado, 2020). The search was performed in April 2026 and limited to articles published between January 2020 and April 2026, written in English, and categorized as peer-reviewed journal articles, conference papers, or book chapters. The search strings used were adapted to the syntax of each database: *("personalized learning") AND ("project-based learning"*


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*OR PBL) AND ("artificial intelligence" OR AI OR "generative AI" OR ChatGPT OR "large language model")*

**Inclusion and Exclusion Criteria**

Inclusion criteria comprised: (a) peer-reviewed empirical studies employing quantitative, qualitative, or mixed-methods designs; (b) journal articles, conference papers, and book chapters published between 2020 and 2026; (c) publications in English; (d) studies focusing on the integration of AI (including LLMs) within PBL contexts; (e) educational settings ranging from K-12 to higher education; and (f) studies reporting outcomes related to learning, implementation, or instructional design.

Exclusion criteria were: (a) theoretical or conceptual papers without empirical data; (b) opinion articles, editorials, and commentaries; (c) studies focusing on non-generative AI approaches only; (d) studies examining PBL without AI integration; (e) non-peer-reviewed sources; and (f) studies not published in English.

**Selection and Data Extraction Process**

The database searches yielded 387 records (187 from Scopus, 200 from WoS). After removing 94 duplicates, 293 records were screened for title and abstract. Based on the eligibility criteria, 245 records were excluded, leaving 49 reports for full-text retrieval. Full-text assessment led to the exclusion of 26 additional reports (e.g., no empirical data, wrong focus), resulting in 22 empirical studies for final synthesis. Data extracted included authors, title, year, source, country, educational level, AI technology, research design, modality, barriers, and strategies.

**Data Analysis and Synthesis**

A data extraction matrix was used to support content analysis in relation to the research questions. Thematic analysis was conducted following Mayring (2021) and Vindrola-Padros & Johnson (2020). Quantitative descriptive analyses (frequencies, percentages, cross-tabulations) and Spearman correlation analyses were performed to examine relationships among educational level, learning modality, technology, and barriers.

## DISCUSSION

This section presents the findings related to the five research questions, including general characteristics of the included studies, technologies used, learning modalities, barriers, and implementation strategies.

### General Characteristics of the Included Studies

Among the 23 empirical studies, a steady increase in publications was observed, with the highest number appearing in 2024–2025. Most studies originated from European countries (45,5%), China (36.4%), and the United States (18.2%). Regarding educational levels, higher education accounted for 56.5% (n = 13), K-12 education 17.4% (n = 4), and continuing education 2.6% (n = 6).

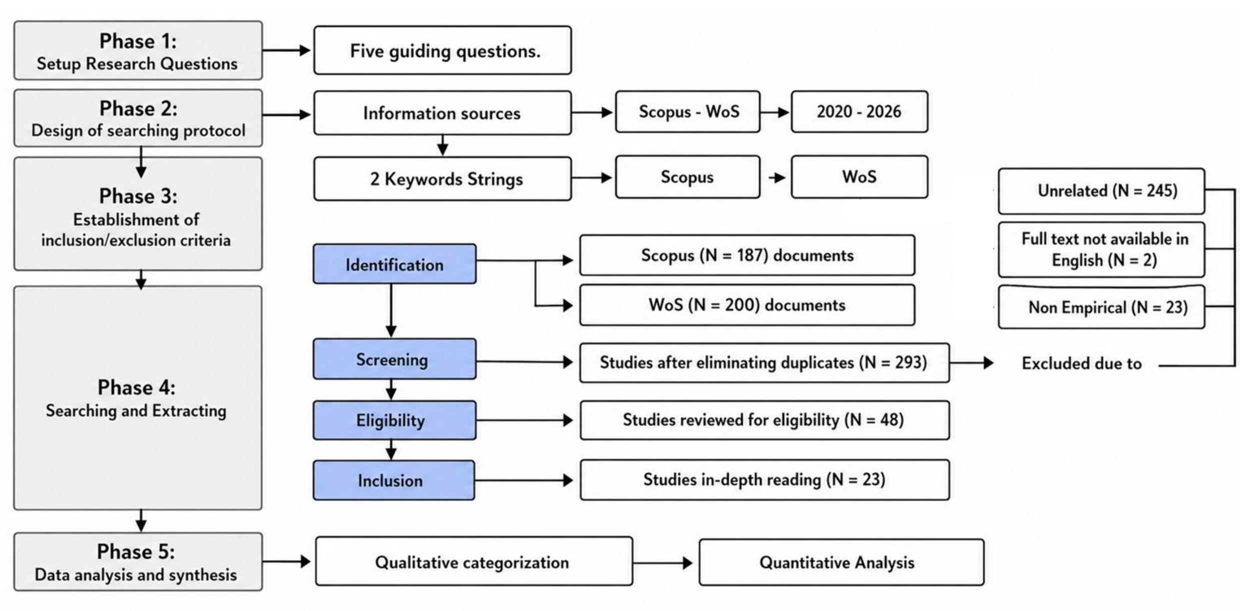


Figure 1. PRISMA 2020 flow diagram.

### Research Methods (RQ1)

The distribution of research methods showed a preference for mixed-methods approaches (n = 10, 43.5%), followed by quantitative (n = 7, 30.4%) and qualitative (n = 6, 26.1%). Mixed methods allowed a comprehensive understanding of both learning outcomes and implementation processes. For example, Perifanou and Economides (2025) combined questionnaires with focus group discussions to examine collaborative use of GenAI tools in PBL.

**AI Technologies Used (RQ2)**

Table 1 summarizes the AI technologies most frequently utilized in personalized PBL implementations. Large language models (LLMs) and ChatGPT were the most prevalent (29.6%), primarily used for project ideation, research, report drafting, and art generation. Intelligent tutoring systems (ITS) accounted for 22.2%, providing conceptual scaffolding and adaptive practice.

Table 1. AI technologies used in personalized PBL implementations.

| AI Technology | Frequency (n) | % | Typical PBL Context |
|---|---|---|---|
| Large Language Models / ChatGPT | 16 | 29.6% | Project ideation, research, drafting, art generation |
| Intelligent Tutoring Systems | 12 | 22.2% | Conceptual scaffolding, adaptive practice |
| Learning Analytics | 10 | 18.5% | Progress tracking, pathway recommendations |
| Chatbot / Virtual Assistant | 8 | 14.8% | Real-time support, instant feedback |
| AI for Assessment | 4 | 7.4% | Project evaluation, personalized rubrics |
| Combined technologies | 3 | 5.6% | Integrated PBL environments |

| | | | |
|---|---|---|---|
| Other (e.g., generative AI for art) | 1 | 1.9% | Creative project-based tasks |

**Learning Modalities (RQ3)**

E-learning was the dominant modality in higher education (65.5% of higher education studies), while blended learning was more common in elementary and secondary schools (58.3% and 62.5%, respectively). Only four studies (7.7%) reported fully face-to-face AI-PBL implementation.

**Barriers to Implementation (RQ4)**

Barriers were classified into five categories, as shown in Table 2. Technological barriers were the most frequently reported (72.2%), including inaccuracy of LLM responses in PBL contexts (Ou & Joyner, 2025; Ravi et al., 2025), difficulty capturing latent student information (Islam et al., 2021), and limited numerical reasoning for STEM projects (Hang et al., 2024). Pedagogical barriers (51.9%) emerged as crucial, especially at elementary and secondary levels, where teachers struggled to design projects that could be adaptively personalized by AI without losing pedagogical integrity (Jin et al., 2025). Psychological barriers (42.6%)—such as teacher resistance and student anxiety—were present across all levels.

Table 2. Barrier categories and subcategories.

| Barrier Category | Frequency (n) | % | Main Subcategories |
|---|---|---|---|
| Technological | 39 | 72.2% | AI effectiveness (46.2%), teacher digital skills (33.3%), integration (28.2%), ethics & privacy (23.1%) |


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| | | | |
|---|---|---|---|
| Pedagogical | 28 | 51.9% | Adaptive PBL activity design (53.6%), personalized assessment (42.9%), scaffolding (39.3%) |
| Psychological | 23 | 42.6% | Teacher resistance (52.2%), student anxiety (43.5%), motivation (30.4%) |
| Institutional | 12 | 22.2% | Infrastructure (58.3%), planning time (41.7%), funding (33.3%) |
| Conceptual | 5 | 9.3% | PL definition (60.0%), implementation parameters (40.0%) |

**Implementation Strategies (RQ5)**

Based on the synthesis of the 23 studies, five main strategies were identified:

1. Competency-based teacher training for AI-PBL – Training should include basic AI literacy, prompt engineering, critical evaluation of AI outputs, and integration into project design (Baidoo-Anu & Ansah, 2023; Elsaairy, 2025; Ravi et al., 2025). Effective training is continuous and hands-on.
2. Collaborative design involving teachers, developers, and researchers – The co-design approach reported by Ravi et al. (2025) involved teachers in AI tool development from the wireframing stage, ensuring alignment with pedagogical needs.
3. Clear ethical and privacy frameworks – Institutions need policies governing student data use, algorithm transparency, and "human-in-the-loop" models where teachers verify AI recommendations (Holmes et al., 2022; UNESCO, 2023).
4. Robust infrastructure and continuous technical support – Schools with limited connectivity adopted hybrid offline-online models where AI runs locally.


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5. Gradual personalization – Instead of full personalization from the start, a phased approach (e.g., personalizing specific project components first) is recommended (Perifanou & Economides, 2025; Zhang et al., 2025).

The findings of this systematic review provide valuable insights into the integration of AI in PBL for personalized learning. The results highlight the interplay between educational levels, learning modalities, technologies, barriers, and strategies. To better understand the broader implications, this discussion considers three key areas: educators, policymakers, and technology developers.

**Implications for Educators**

Educators are at the frontline of AI-PBL integration. Psychological barriers such as resistance and anxiety cannot be ignored. Teachers should be viewed not as obstacles but as partners in the design and implementation. Training strategies must empathetically address their concerns and provide safe-to-fail experimentation spaces. Furthermore, educators need to develop "pedagogical AI literacy"—the ability to evaluate when and how AI should be used in PBL without compromising student learning autonomy. Overuse of AI can lead to passive learning and over-dependence (Ou & Joyner, 2025).

**Implications for Policymakers**

Policymakers should allocate funding not only for AI infrastructure but also for continuous professional development. Policies should encourage curriculum flexibility so that AI-powered PBL implementation is not hindered by rigid standardized testing demands (Condliffe et al., 2017). Additionally, national or international ethical standards for AI use in education are needed, covering student data ownership, algorithm transparency, and appeal mechanisms for AI-generated decisions. Institutional support for planning time and infrastructure is also critical (Jin et al., 2025; Thomas, 2000).

**Implications for Technology Developers**


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AI developers for education need to involve educators in the design process from the outset (human-centered design). AI tools should be “explainable” so that recommendations can be understood and evaluated by teachers (Ravi et al., 2025). User interfaces should be intuitive and provide dashboards allowing teachers to view personalization traces and manually adjust them. Developers also need to consider offline or low-bandwidth modes given unequal internet access across regions.

**Strategies to Overcome Challenges**

To address the identified barriers, a multifaceted approach is necessary. First, institutions should invest in targeted professional development programs focusing on AI literacy and its pedagogical applications. Second, interdisciplinary teams comprising educators, AI specialists, and instructional designers should co-develop AI-integrated curricula. Third, ethical considerations must be embedded within institutional policies to ensure fair and unbiased use of AI-driven learning systems. A phased implementation strategy, starting with low-stakes personalization and scaling gradually, can help build teacher confidence and student acceptance.

Counterarguments must be acknowledged. Some scholars argue that AI-driven personalization risks exacerbating existing inequalities by benefiting better-resourced institutions. Concerns persist regarding AI biases, particularly racial and gender disparities. Critics also emphasize the irreplaceable role of human educators. While valid, these concerns do not negate the potential of AI; rather, they highlight the need for continuous evaluation, human oversight, and democratized access through open-source initiatives.

| State of the Art (SOTA) | Research Gap | Novelty (Contribution of the Study) |
|---|---|---|
| Artificial Intelligence (AI), particularly Large Language Models (LLMs), has been widely recognized as a transformative technology capable of delivering adaptive feedback, scaffolding, and personalized learning experiences in education. | Existing studies on AI integration in education are fragmented across disciplines and educational levels, lacking a comprehensive synthesis of empirical evidence specifically linking AI, project-based learning (PBL), and personalized learning. | This study provides a systematic synthesis of empirical evidence on the integration of AI in PBL environments to support personalized learning across educational contexts. |
| Personalized learning has been established as an effective | There is limited understanding of how personalized learning can be | The study identifies specific implementation mechanisms |


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| State of the Art (SOTA) | Research Gap | Novelty (Contribution of the Study) |
|---|---|---|
| student-centered approach that adapts instruction to individual learner characteristics, improving engagement, autonomy, and learning outcomes. | effectively implemented within PBL environments using AI technologies in real educational settings. | through which AI can operationalize personalized learning in PBL contexts. |
| Project-based learning is widely recognized as an effective pedagogical framework that promotes critical thinking, collaboration, and problem-solving through authentic learning experiences. | PBL implementation remains challenging due to project design complexity, assessment difficulties, and the need for scalable instructional support systems. | The study demonstrates how AI technologies can address these challenges through adaptive scaffolding, automated assessment, and real-time feedback. |
| AI-powered educational tools such as intelligent tutoring systems, chatbots, and learning analytics platforms have been increasingly used to support teaching and learning processes. | Limited research has systematically categorized the barriers to implementing AI-based personalized learning in PBL environments. | The study develops a structured classification of implementation barriers into technological, pedagogical, psychological, institutional, and conceptual categories. |
| Ethical considerations in AI-based education, including data privacy, algorithmic bias, and academic integrity, have been recognized as critical issues in educational technology adoption. | There is insufficient guidance on practical strategies for overcoming ethical and operational challenges in AI-supported PBL implementation. | The study proposes evidence-based implementation strategies such as competency-based teacher training, collaborative design, ethical frameworks, infrastructure support, and gradual personalization. |
| Research on AI in education has primarily focused on short-term learning outcomes and technological performance. | Long-term sustainability and practical implementation models for AI-powered personalized learning in PBL remain underexplored. | The study outlines a future research agenda emphasizing longitudinal evaluation, ethical governance models, and scalable implementation frameworks. |

## Limitations of the Study

This review has several limitations. First, it included only articles from Scopus and WoS; studies from other databases (e.g., ERIC, PubMed) or grey literature were not included. Second, only English-language articles were analyzed. Third, most studies had short durations (<6 months), so long-term impacts could not be evaluated. Fourth, heterogeneity in methods and outcome measures prevented meta-analysis. Despite these limitations, the review provides a comprehensive map of the current state of AI-PBL integration for personalized learning.

### Future Research Agenda

Future research should focus on: (a) longitudinal studies (>1 year) to assess the sustainability of AI-PBL effects; (b) development and validation of personalization measurement instruments in PBL; (c) comparative studies between different AI models (generative vs. non-generative) in PBL contexts; (d) exploration of AI integration in early childhood PBL; (e) investigation of AI use impacts on critical thinking and creativity development; and (f) design and evaluation of applicable ethical frameworks.

## CONCLUSIONS

This systematic literature review identified the main barriers and implementation strategies for AI-powered personalized learning in project-based learning based on 23 empirical studies (2020–2026). Technological barriers dominated in higher education, while pedagogical barriers were more significant at the elementary and secondary levels. Psychological barriers such as teacher resistance and student anxiety were present across all levels and require empathetic handling. The five main implementation strategies identified were: competency-based teacher training, collaborative design, clear ethical and privacy frameworks, robust infrastructure, and gradual personalization. The success of AI integration in PBL is not determined solely by technological sophistication but by the quality of interaction between humans (teachers, students, developers) and machines within a carefully designed pedagogical ecosystem.

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