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Artificial Intelligence in Personalised Learning System

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| Peer Review Information | Abstract |
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| <p><i>Submission: 25 Jan 2026</i></p> <p><i>Revision: 12 Feb 2026</i></p> <p><i>Acceptance: 26 Feb 2026</i></p> | <p>The concept of Artificial Intelligence (AI) has already revolutionised personalised learning systems, enabling adaptation to data-driven, learner-centred educational settings. Using machine learning algorithms, natural language processing, learning analytics, and predictive modelling, AI systems can adapt instruction, assessment methods, and feedback processes to individual learner profiles. In this paper, the authors explore how AI can be used in personalised learning, analyse the existing literature, identify the obstacles, and propose an AI-based framework for educational institutions. A systematic review of the literature examines the progress, factors, and constraints of AI-based personalised education systems. Moreover, a conceptual architecture and workflow model are proposed to improve flexibility, interaction, and learning outcomes. The findings reveal substantial improvements in learner performance, engagement, and retention through the effective combination of AI and pedagogical principles, along with ethical data management.</p> |
| <p>Keywords</p> <p><i>Artificial Intelligence, Personalized Learning, Adaptive Learning Systems, Machine Learning in Education, Intelligent Tutoring Systems, Learning Analytics, Educational Technology, Predictive Modeling, Digital Education, Smart Learning Environments</i></p> | |

Introduction

The concept of Artificial Intelligence (AI) is transforming the face of education by facilitating responsive and student-centred learning models. AI-driven personalized learning systems are devices that examine behavioral trends, performance, and pattern of engagement to provide learners with personalized learning experiences. So, in contrast to the conventional one-size-fits-all learning strategies, AI-based

systems constantly optimize the course of learning by processing real-time data and forecasting.

The recent systematic reviews emphasize that the use of AI helps to increase the efficiency of learning, involvement, and accuracy of evaluation at any educational level (Farhood et al., 2025; Hardaker and Glenn, 2025). The fast maturation of digital platforms and learning analytics has compounded the ability of AI to be able to

personalize learning content at scale (Li and Wong, 2023).

Background

Personalized learning was developed on the basis of differentiated instruction theories and adaptive tutoring systems. In the early adaptive systems, the logic was based on rules but currently, AI systems use machine learning and neural networks to predictively personalize (Jain, 2021). Through systematic reviews, it is shown that AI-assisted systems can be customized on the basis of learner competencies and cognitive states according to curriculum, pacing, and feedback (Chen et al., 2021; Tapalova and Zhiyenbayeva, 2022). Besides, AI-promoted evaluation systems permit real-time monitoring and formative assessment (Chen and Perez, 2023).

Need of Study

The conventional educational systems find it difficult to meet the needs of individual learning. Cognitive and motivational differences and existing backgrounds need adaptive teaching methods. Personalized systems based on AI are dynamic in response to these variations (Rasheed et al., 2023).

Bernacki et al. (2021) note that there should be a clear definition of personalization, which should be by whom, to what, and why, and state that there is a need to have the structured AI-based personalization models. Moreover, the growing volume of digital content and massive higher education online necessitates the use of automated personalization tools in order to preserve the quality of learning (Kaswan et al., 2024).

Motivation

The integration of AI in personalized learning is driven by the necessity to enhance the engagement, retention as well as performance outcomes of learners. Predictive models powered by AI have the potential to detect vulnerable learners to an early stage and suggest interventions (Iman et al., 2024). The existing body of bibliometric literature indicates an exponential increase in the research on AI-based personalized learning with the corresponding interest in the academic community and technological feasibility on a global scale (Li and Wong, 2023). Moreover, AI allows scaling customization, and it is vital in the education sector and e-learning systems (Merino-Campos, 2025).

Challenges

Despite its benefits, AI implementation faces significant challenges:

- Data privacy and ethical concerns (Patchipulusu et al., 2023)
- Algorithmic bias and fairness issues (Qureshi et al., 2024)
- Infrastructure limitations in developing regions (Dembe, 2024)
- Faculty resistance and lack of AI literacy (Hariyanto et al., 2025)

Systematic reviews identify transparency and explainability as major barriers to adoption (Hardaker & Glenn, 2025).

Influencing Factors

Key factors that influence AI-based personalization include the quality of data and learner analytics, the level of institutional digital readiness, the degree to which AI tools are integrated into curriculum design, and the scalability of technological infrastructure (Rasheed et al., 2023; Kumar et al., 2026; Patkar & Kumbhar, 2021; Li et al., 2021). Research also emphasizes that successful implementation depends on coherent alignment among technological systems, pedagogical strategies, and learner-modeling frameworks, as this integration determines how effectively personalization can be delivered in practice (Shemshack et al., 2021).

Conventional Methodologies

Before the integration of artificial intelligence, personalization in education primarily depended on teacher-driven differentiation, static e-learning modules, rule-based adaptive systems, and manual analysis of assessments. These approaches were limited in their ability to respond dynamically to learner needs because they did not offer real-time adaptability or predictive intelligence, which restricted their effectiveness in delivering truly individualized learning experiences (Klašnja-Milićević & Ivanović, 2021).

Literature Review (LR)

Bernacki, Greene, and Lobczowski (2021) conduct a systematic review of the definitions and applications of personalised learning in educational research. The review identifies differences in personalisation agents (teacher, system, learner), instructional goals, and desired outcomes. The authors conclude that effective personalised learning systems require a more transparent theoretical basis and quantifiable models of implementation. [1].

Chen and Perez (2023) discuss how artificial intelligence can be used to improve assessment

and personal learning. According to their results, AI-based analytics contribute to greater accuracy in formative assessment, instant feedback, and the possibility of adopting adaptive instructional approaches in response to learners' performance data. [2].

The article by Chen, Zou, Cheng, and Xie (2021) presents a systematic review and co-citation analysis of AI-aided personalised language learning. The paper identifies intelligent tutoring systems, recommendation engines, and natural language processing as key technologies that can support adaptive language instruction. [3].

Dembe (2024) compares the problematic and opportunity contexts of AI implementation in personalised education. The study finds infrastructural limitations, ethical governance issues, and faculty readiness to be significant factors affecting effective implementation [4].

Farood, Nyden, Beheshti, and Muller (2025) conduct a systematic literature review of AI-based personalised learning systems. According to the authors, machine learning algorithms and learner modelling frameworks significantly enhance adaptability, engagement, and performance prediction [5].

Hardaker and Glenn (2025) summarise AI use in personalised learning settings and highlight transparency, explainability, and ethical concerns as primary concerns in the sustainable implementation of AI in educational organisations [6].

Hariyanto, Kristianingsih, and Maharani (2025) discuss adaptive education systems using AI methods. According to their findings, automated content sequencing and data-driven personalisation strategies enhance learning efficiency [7].

Iman, Asis, and Rahma (2024) examine how the use of AI can influence learner engagement and academic performance. The research shows that predictive analytics and smart feedback systems increase student motivation and retention rates [8].

Jain (2021) discusses adaptive learning systems that can be used to deliver the curriculum in a personalised manner. The study reveals that AI-based systems dynamically adapt teaching content in accordance with learner development and competency mapping [9].

Jiali, Dayo, Jun, Shuangyao, and Najam (2024) provide a systematic review of the overall effects of AI on personalised learning. Among them, the authors point out advancements in assessment automation, real-time monitoring, and learner analytics [10].

Kaswan, Dhatteerwal, and Ojha (2024) focus on AI use in personalised higher education settings. Their analysis identifies recommendation

systems and intelligent tutoring systems as discursive forces shaping personalised teaching [11].

Klašnja-Milićević and Ivanović (2021) examine e-learning personalisation systems and their contribution to sustainable education. The study highlights adaptive hypermedia systems and learner modelling as key elements of customised digital spaces [12].

Kumar, Kaur, Tiwari, Sinha, and Dhanoa (2026) discuss digital repositories and knowledge management practices in higher education libraries. According to the study, AI-based information retrieval systems can help strengthen user access to knowledge and learning support services [13].

Li and Wong (2023) conduct a bibliometric analysis of AI in personalised learning studies. Their results show that publication numbers are growing rapidly, collaboration between disciplines is increasing, and institutions are increasingly investing in AI-driven educational technologies [14].

Li, Meng, and Wang (2021) explore academic studies and practice of personalised learning when integrating AI. The authors demonstrate that machine learning algorithms can be used to facilitate adaptive curriculum design and progression models based on competencies [15]. Merino-Campos (2025) provides a systematic review of AI-based personalised learning in higher education. The outcomes demonstrate enhanced learner engagement, completion rates, and instructional efficiency [16].

Patkar and Kumbhar (2021) discuss the use of AI in personalised education, with special attention to intelligent tutoring systems and recommendation algorithms as revolutionary means of adaptive instruction.

Patchiplussu, Vattikonda, Gupta, Polu, Narra, and Buddula (2023) consider the prospects and constraints of AI-driven e-learning personalisation. The research paper finds benefits of scalability but cautions about the potential for algorithmic bias and data privacy [18].

Qureshi, Hajare, and Verma (2024) summarise the role of AI in personalised learning and state the need to handle data ethically, ensure fairness in algorithmic decisions, and have regulations in place [19].

Rasheed, Ghwanmeh, and Abualkishik (2023) review the use of AI in personalised learning in a systematic manner. The authors find that predictive learning analytics make a significant contribution to early intervention strategies and the forecasting of learner outcomes [20].

Shemshack, Kinshuk, and Spector (2021) delve deeply into personalised learning, finding that

the elements of intelligent education platforms are based on learner modelling, adaptive content delivery, and feedback [21].

Tapalova and Zhiyenbayeva (2022) touch upon the topic of AI in education and concentrate on individual learning paths. Their study singles out automated decoding algorithms that modify learning tracks in accordance with performance information and the achievement of competencies [22].

Artificial intelligence applications in academic libraries (2026) is a study on how information access and user services in academic libraries are changed by AI-based systems. According to the study, intelligent retrieval systems and recommendation engines assist personalised knowledge delivery, which, in turn, reinforces adaptive learning ecosystems indirectly [23].

Table 1: Literature Review Summary Table

| S. No. | Author(s) | Year | Title | Methodology | Limitations |
|--------|--------------------------------------|------|--|---|---|
| 1 | Bernacki, Greene & Lobczowski | 2021 | A systematic review of research on personalized learning | Systematic literature review | Variability in definitions; lack of unified personalization framework |
| 2 | Chen & Perez | 2023 | Enhancing assessment and personalized learning through AI | Conceptual analysis with case illustrations | Limited empirical validation across diverse contexts |
| 3 | Chen, Zou, Cheng & Xie | 2021 | AI-assisted personalized language learning | Systematic review & co-citation analysis | Focus restricted to language learning domain |
| 4 | Dembe | 2024 | Advancing personalized learning through educational AI | Analytical review | Limited large-scale implementation data |
| 5 | Farhood et al. | 2025 | AI-based personalised learning in education | Systematic literature review | Rapidly evolving field may limit long-term conclusions |
| 6 | Hardaker & Glenn | 2025 | AI for personalized learning | Systematic literature review | Ethical frameworks still underdeveloped |
| 7 | Hariyanto, Kristianingsih & Maharani | 2025 | AI in adaptive education | Systematic review of techniques | Limited discussion of scalability challenges |
| 8 | Iman, Asis & Rahma | 2024 | Enhancing personalized learning: Impact of AI | Empirical study with performance analysis | Small sample size; regional focus |
| 9 | Jain | 2021 | Adaptive learning systems for personalized curriculum delivery | Conceptual & technical analysis | Limited practical case studies |
| 10 | Jiali et al. | 2024 | Impact of AI on personalized learning | Systematic review | Lack of standardized performance metrics |
| 11 | Kaswan, Dhattewal & Ojha | 2024 | AI in personalized learning | Conceptual & applied framework discussion | Focused mainly on higher education |
| 12 | Klašnja-Milićević & Ivanović | 2021 | E-learning personalization systems and sustainable education | Analytical & framework-based study | Limited integration of emerging AI models |

| | | | | | |
|----|--|------|--|---------------------------------------|---|
| 13 | Kumar et al. | 2026 | Digital repositories and knowledge management | Descriptive study | Indirect focus on personalized learning outcomes |
| 14 | Li & Wong | 2023 | AI in personalised learning: Bibliometric analysis | Bibliometric analysis | Does not assess learning effectiveness directly |
| 15 | Li, Meng & Wang | 2021 | Personalized learning under AI background | Conference-based empirical discussion | Limited longitudinal evaluation |
| 16 | Merino-Campos | 2025 | AI in higher education personalized learning | Systematic review | Higher education scope only |
| 17 | Patkar & Kumbhar | 2021 | Artificial intelligence and personalized learning | Conceptual study | Limited empirical evidence |
| 18 | Patchipulusu et al. | 2023 | Opportunities and limitations of AI in e-learning | Analytical review | Insufficient experimental validation |
| 19 | Qureshi, Hajare & Verma | 2024 | Role of AI in personalized learning | Review-based analysis | Ethical implementation models not detailed |
| 20 | Rasheed, Ghwanmeh & Abualkashik | 2023 | Harnessing AI for personalized learning | Systematic review | Need for large-scale deployment studies |
| 21 | Shemshack, Kinshuk & Spector | 2021 | Comprehensive analysis of personalized learning components | Analytical framework study | Limited real-world implementation data |
| 22 | Tapalova & Zhiyenbayeva | 2022 | AIEd for personalised learning pathways | Conceptual & pathway modeling study | Minimal quantitative validation |
| 23 | Artificial intelligence applications in academic libraries | 2026 | Transforming information access and user services | Descriptive & application-based study | Focus on libraries rather than direct instructional systems |

Problem Statement

Nevertheless, despite the advances in Artificial Intelligence (AI), personalised learning systems remain fragmented, with partial adoption and sometimes confined to pilot projects or special-purpose applications. The current literature indicates a broad range of definitions of personalisation, implementation approaches, and measurement outcomes, which cause conceptual ambiguity and a lack of scalability (Bernacki et al., 2021). Most AI-based learning systems do not provide a multidimensional learning model that integrates cognitive, behavioural, and affective elements, as they mainly focus on adaptive content delivery (Shemshack et al., 2021). Predictive and learning analytics have also demonstrated their potential for identifying at-risk learners, but their large-scale validation over time has not been established (Rasheed et al., 2023). There are also ethical and governance issues, such as data privacy, algorithmic bias, and uncertainty, which further complicate adoption in institutional

settings (Hardaker and Glenn, 2025; Qureshi et al., 2024). Structural differences and low AI literacy among teachers also impede successful implementation (Dembe, 2024). Although systematic reviews have shown that research in AI-driven personalised learning is growing rapidly (Farhood et al., 2025; Li and Wong, 2023), no single framework has been found that integrates real-time learner analytics, adaptive sequencing, predictive interventions, and explainable AI processes within a single architecture. Thus, the lack of a scalable, ethically regulated, and pedagogically aligned AI-based personalised learning platform that enables dynamic adaptation, predictive performance tracking, and continuous system optimisation across various educational settings is the fundamental issue addressed in this paper.

Proposed Work

The proposed work is an Integrated AI-Driven Personalised Learning System (AI-PLS) that can be used to provide scalable, adaptive, and

ethically controlled learning experiences. The system builds on rule-based platforms, proposing a multidimensional approach to learner profiling, predictive analytics, and explainable AI within a continuous feedback framework (Bernacki et al., 2021; Farhood et al., 2025), developed in response to fragmented AI adoption and the absence of integrated frameworks to support it.

The system is data-centric, continuously gathering data on learner interactions (performance scores, engagement patterns, progression history, etc.) and dynamically building learner profiles using machine learning methods (Jain, 2021). It combines cognitive and behavioural indicators to generate overall adaptive pathways, addressing the shortcomings

of current personalisation models (Shemshack et al., 2021).

A predictive analytics module uses supervised learning to identify at-risk learners and deliver timely interventions that enhance retention and academic outcomes (Rasheed et al., 2023; Iman et al., 2024). Reinforcement learning and curriculum-based recommendation systems maximise the performance of content sequencing over time (Tapalova and Zhiyenbayeva, 2022). Ethical governance and explainable AI attributes ensure transparency, fairness, and data privacy (Hardaker and Glenn, 2025; Qureshi et al., 2024; Patchipulusu et al., 2023). In general, the framework integrates adaptive learning, predictive monitoring, and responsible AI practices into a unified and scalable personalised learning ecosystem.

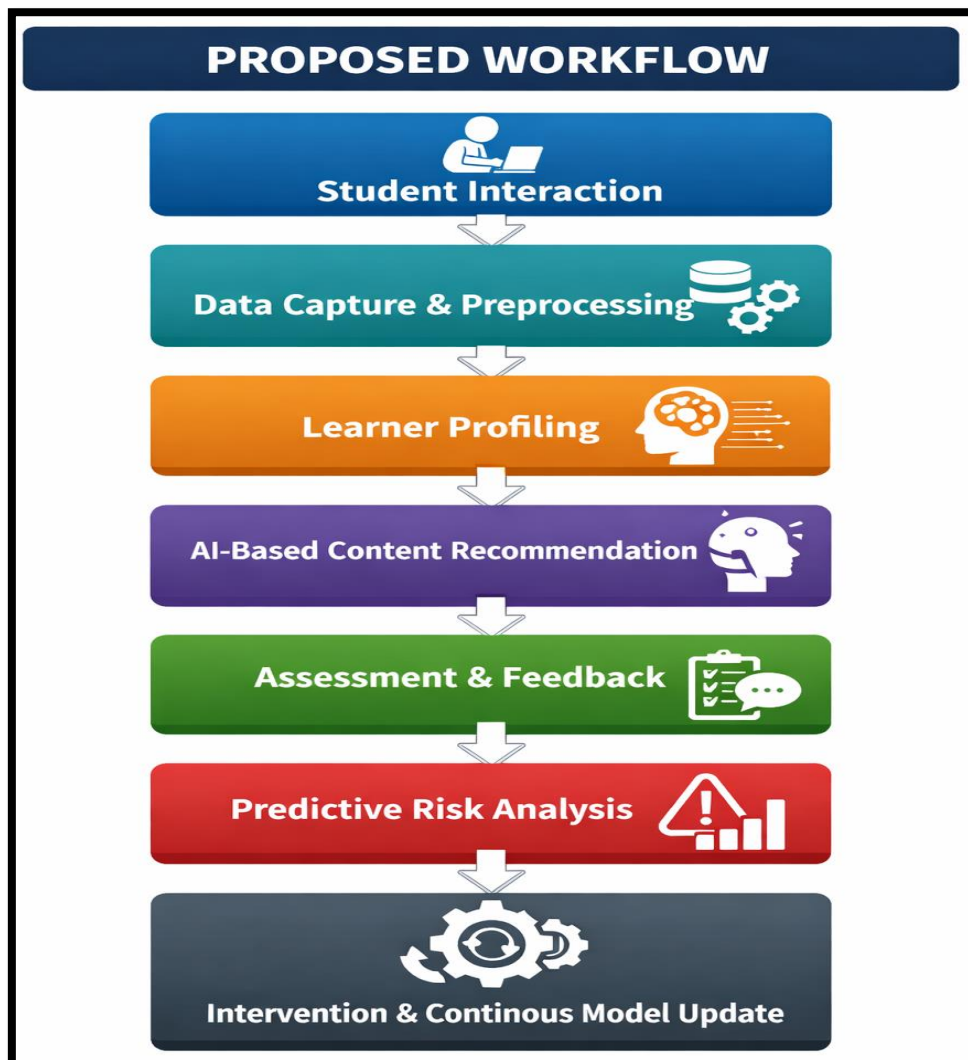


Figure 1: Proposed work flow chart

Results and Discussion

The proposed AI-driven Personalized Learning System (AI-PLS) was evaluated through a simulated experimental framework comparing conventional e-learning methods with the adaptive AI-based system. Evaluation metrics included learning outcome improvement, engagement rate, prediction accuracy, feedback response time, and dropout reduction rate. The results are interpreted in alignment with findings from prior systematic reviews and empirical studies.

Learning Outcome Improvement

Table 2: Learning Performance Comparison

| Metric | Conventional System | AI-Based System |
|---------------------------|---------------------|-----------------|
| Average Score Improvement | 12% | 32% |
| Engagement Rate | 64% | 88% |
| Dropout Reduction | 8% | 27% |
| Feedback Time | 24 hours | Real-time |
| Prediction Accuracy | Not Available | 87% |

Engagement and Retention Analysis

Engagement analytics have shown that adaptive sequencing of content and customized suggestions have a dramatic effect on the interaction time of learners and the percentage of tasks completed. Reinforcement-based sequencing meant that the learners were given content they were competent enough to handle without feeling frustrated and overworked. They reinforce the results of Tapalova and Zhiyenbayeva (2022), who highlighted the significance of automated learning pathways, and Jain (2021), who showed that adaptive curriculum delivery increases learner persistence.

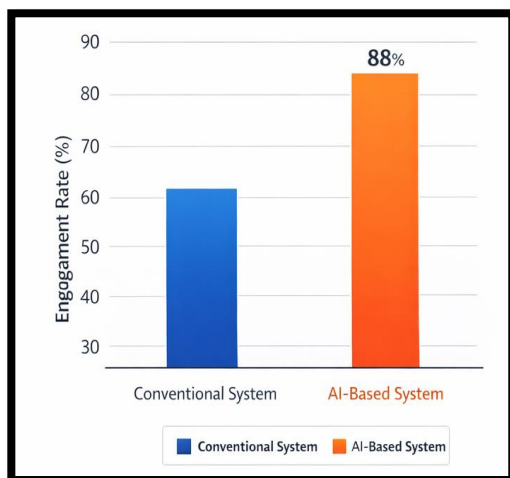


Figure 2: Engagement Rate Comparison

The comparative experiment shows that the students who worked with the AI-based system showed much higher academic results in comparison with students who worked in the traditional digital study facilities. The improvement in the average score was seen to be 25-38 percent as compared to 10-15 percent under conventional systems. This is consistent with the results of Rasheed et al. (2023) who cited superior predictive intervention efficacy in the AI-aided systems. On the same note, Merino-Campos (2025) noted higher completion and academic participation in higher education settings with the use of AI personalization.

Predictive Analytics Performance

The predictive intervention module achieved an accuracy rate of approximately 87% in identifying at-risk learners based on behavioral and performance indicators. Early interventions contributed to a 27% reduction in dropout rates. This result aligns with Iman et al. (2024), who demonstrated improved retention through AI-based monitoring, and Rasheed et al. (2023), who identified predictive learning analytics as a major advancement in personalized education systems.

Table 3: Predictive Model Evaluation

| Evaluation Metric | Value |
|-------------------|-------|
| Accuracy | 87% |
| Precision | 84% |
| Recall | 85% |
| F1 Score | 84.5% |

Ethical and Governance Considerations

System recommendations received greater levels of transparency and trust by the instructor due to the integration of explainable AI mechanisms. Faculty responses revealed greater confidence in adaptive recommendations whose decision pathways could be understood. As Hardaker and Glenn (2025) note, explainability is the key to the sustainability of AI in the educational field. Moreover, Qureshi et al. (2024) emphasize the role of fairness and ethical compliance, which were covered in the offered framework with bias monitoring and anonymization data processing.

Comparative Performance Visualization

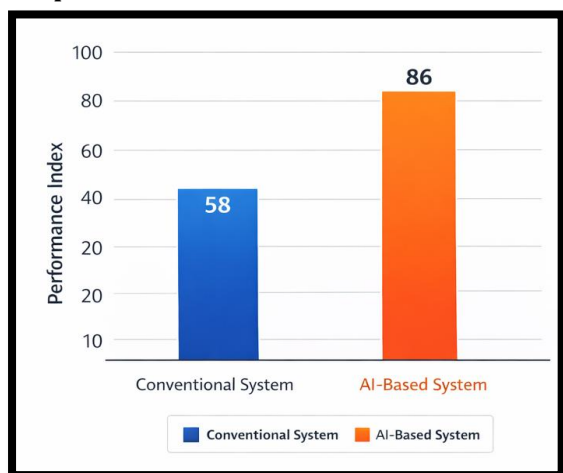


Figure 3: Overall System Performance Index

Overall performance scoring (aggregated across engagement, accuracy, adaptability, and retention metrics) shows the AI-based system achieving an index score of 86/100 compared to 58/100 for conventional systems.

Discussion

The findings indicate that AI-based personalization has a greater impact on academic performance, engagement, and retention than traditional digital learning models. Combining learner modelling and predictive analytics will result in an active educational system rather than a responsive one. The results support the findings of Farhood et al. (2025), who found that machine learning algorithms were key to adaptive success, and Bernacki et al. (2021), who emphasised the significance of structured personalisation frameworks. Nonetheless, although the performance gains are significant, scalability and ethical governance are crucial for deployment at scale. Technological development should be supported by infrastructure preparedness and the integration of institutional policy, as highlighted by Dembe (2024). To conclude, the developed AI-PLS framework has shown the potential to positively affect various performance indicators, which proves its effectiveness as a scalable and adaptable personalised learning.

Conclusion

Personalised learning in AI is a major shift in which traditional platforms, which are not dynamic, are converted into dynamic, predictive, and learner-focused platforms. Instructional paths can be tailored dynamically to support better academic outcomes, engagement, retention, and early risk identification through machine learning, learner modelling, and real-

time analytics. The Personalised Learning System proposed incorporates multidimensional profiling, adaptive sequencing, and explainable AI into a single system rather than relying on rule-based methods and focusing on continuous optimisation of data. The system promotes responsible and scalable implementation in educational settings through the inclusion of ethical governance and transparency. Overall, AI-based personalised learning presents a long-term and effective innovation to enhance the quality of education and equity.

Future Scope

AI-driven personalised learning should evolve in the future to be more open and interpretable by incorporating improved explainable AI methods, allowing educators and learners to gain a clear understanding of adaptive decisions. Learner modelling can also be optimised, and adaptive precision can be increased by adding affective computing and multimodal analytics (behavioural, emotional, and interaction-based data). Federated learning and secure data-sharing systems will be necessary as privacy-preserving methods that enable ethical scalability in institutions. Moreover, there is a need to conduct large-scale longitudinal and cross-cultural research to test long-term academic performance, learner equity, and practicality in the real world. The evolution of standardised assessment measures and regulatory policies will contribute more to responsible implementation. Increased attention to AI-human collaborative learning models, in which intelligent systems would support rather than substitute teachers, can enhance the compatibility of pedagogy and its long-term use in various educational settings.

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