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Effectiveness Challenges and Strategies of AI-Powered Learning Platforms for Personalised Learning

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Abstract. AI functions are increasingly embedded in learning management systems, adaptive tutoring, and analytics dashboards, making "AI-powered learning platforms" a practical route for delivering personalised learning at scale. Evidence from meta-analyses and selected empirical trials indicates that adaptive systems can produce small-to-moderate achievement gains, especially when recommendations respond to learners' current mastery rather than offering uniform digital practice. Yet the credibility of these gains is often contested: reported benefits are uneven across learners and settings, core algorithmic decisions remain difficult to interpret for teachers and students, and many evaluations rely on short time windows that say little about motivation, equity, retention, or transfer. Building on this literature, the paper frames effectiveness as a multidimensional construct (cognitive, behavioural, affective, and equity-related outcomes) and proposes a socio-technical account linking platform design, learner data and behaviour, teacher orchestration, and institutional governance. On this basis, it outlines actionable strategies—curricular alignment, transparent and auditable data infrastructures, structured learner support, and ethical oversight—to strengthen both the educational value and the trustworthiness of AI-enabled personalisation.

Keywords: Artificial Intelligence, Personalised Learning, Adaptive Learning Technologies, Learning Analytics, Instructional Design

1. Introduction

1.1. Research context and significance

AI has moved beyond isolated pilots and is now folded into everyday instructional workflows—diagnostic quizzes, adaptive homework, automated feedback, and analytics dashboards that inform lesson planning. Syntheses of technology-supported personalised learning suggest measurable achievement benefits on average, but they also show that effects depend heavily on design choices and classroom integration, not merely on the presence of "AI" features [1]. Meanwhile, rapid institutional uptake has positioned AI-enabled platforms as both a commercial product category and a policy instrument for scaling differentiation, particularly in systems where large classes make individualised support difficult to sustain. The practical question, therefore, is no longer whether platforms can generate gains in principle, but under what conditions they do so in routine practice

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and for which learners. Global figures show a rapid increase in institutional investment, with schools and universities adopting AI tools for adaptive practice, automated feedback and learning analytics dashboards to support more personalised instruction [2]. A white paper on intelligent adaptive learning in K-12 education summarises large-scale pilots in several provinces and cities, highlighting the rapid growth of adaptive homework systems, subject-specific intelligent tutoring systems and integrated teaching-assessment platforms [3]. This research topic holds significant practical, commercial and social relevance. On the one hand, AI-powered learning platforms are becoming an important product category for education technology companies. On the other hand, for schools and governments, these platforms represent a potential lever to personalise learning at scale, support students who are struggling and improve equity. Against this backdrop of rapid adoption and commercial growth, this section reviews the existing empirical evidence on the effectiveness of AI-powered learning platforms for personalised learning.

1.2. Literature review: evidence and limitations

The existing research on AI and technology-supported personalised learning can be roughly divided into three strands: meta-analytic and systematic review evidence on learning outcomes, studies of specific adaptive tools and intelligent tutoring systems, and work on learning analytics and AI in particular subject domains or countries. This section synthesises evidence from each of these strands to establish the current state of knowledge.

First, a meta-analysis of technology-supported personalised learning in low- and middle-income countries synthesised 16 randomised controlled trials involving over 50,000 school-aged learners and reported an overall effect size of 0.18 on learning outcomes [1]. Earlier meta-analytic work on intelligent tutoring systems (ITS) reported that ITS use generally leads to higher test scores than conventional non-adaptive instruction and can sometimes approach the effectiveness of individual human tutoring. However, there is substantial variation across subjects and implementation conditions [4].

Second, a study of personalised adaptive learning modules embedded into higher education courses found that students using adaptive tools achieved higher course grades and reported more positive learning experiences than those in non-adaptive versions of the same course [5]. Another study integrating an adaptive learning tool into online and face-to-face business statistics courses reported that more students achieved top grades and that overall satisfaction improved once the adaptive tool was carefully aligned with course objectives and assessments [6]. In medical education, a randomised controlled trial of an AI-driven personalised learning platform that combined reinforcement learning, natural language processing and collaborative filtering found moderate to large effects on post-test performance compared with traditional lecture-based teaching, with particularly strong benefits for lower-achieving students [7].

Third, in programming education, intelligent tutoring systems that deliver adaptive exercises and tailored feedback have been shown to enhance programming skills, reduce anxiety and improve satisfaction, particularly for students with some initial proficiency [8]. A systematic review of AI-driven intelligent tutoring systems in K-12 education suggests that such systems can support the mastery of core concepts and procedural skills, while also emphasising the importance of alignment with curriculum standards and teacher involvement in orchestration [9].

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1.3. Research gaps and questions

Although the literature is expanding, three gaps remain. First, many outcome studies emphasise short-term test scores or course grades, while giving limited attention to broader outcomes such as self-regulated learning, longer-term retention, and equity across student groups. Second, AI platforms are often treated as black boxes, with insufficient analysis of how design choices - such as the pedagogical logic of recommendations and the transparency of system outputs - interact with learner characteristics and teacher practices. Third, implementation conditions are unevenly reported, particularly when training, infrastructure, or curricular alignment is inadequate, and failure modes begin to surface. In response, this paper asks: (1) Which socio-technical factors most strongly shape platform effectiveness? (2) Which validity risks undermine the robustness and fairness of reported impacts? (3) What design, pedagogical, and governance strategies can mitigate these risks?

1.4. Analytical framework and structure

The paper takes a socio-technical systems perspective. Rather than treating the platform as "just an algorithm," it considers how algorithms, data practices, and human decisions come together in everyday use. On this view, outcomes depend on the interaction between platform design, learner needs, teacher orchestration, and institutional governance, across cognitive, behavioural, affective, and equity dimensions. This approach moves the question from "Does it work?" to "When, how, and for whom does it work—and what is gained or lost along the way?"

2. AI Learning platforms: components, processes and implementation contexts

AI-powered learning platforms typically bring together functions that were once delivered by separate systems, including content management, assessment engines, tutoring-like supports, recommendation services, and learning analytics dashboards. Industry reports and provider descriptions often portray adaptive platforms as continuously collecting learners' response data, updating a learner model, and using it to select content, tasks, and feedback tailored to each learner [10]. In practice, this data-driven loop—diagnose, adapt, respond, and monitor—constitutes a central mechanism through which platform-based personalisation is enacted.

In school and higher education settings, this mechanism is commonly realised as a cycle of diagnostic assessment, adaptive sequencing, immediate feedback, and analytics-supported monitoring. Diagnostic tests and interaction logs are used to infer mastery levels and flag learners at risk of underperformance. Based on these estimates, the system adjusts task difficulty, pacing, and practice sequences, often aiming to keep activities appropriately challenging (sometimes discussed in terms of learners' zone of proximal development). Learners may receive instant feedback, hints, and occasional explanations, while teachers and administrators consult dashboards that summarise progress at individual and cohort levels, surface common misconceptions, and identify learners who may need additional support [5,11]. Although this basic cycle recurs across contexts, implementation varies substantially across systems and regions.

In China, AI learning platforms are closely linked to national smart education initiatives. A white paper on intelligent adaptive learning in K-12 education documents large-scale deployment of adaptive homework systems and integrated platforms in multiple provinces [3]. Schools use these systems to assign differentiated practice, monitor errors, and generate reports for parents, including automated grading, personalised learning paths, and predictive analytics for identifying at-risk students. At the same time, some higher education institutions integrate adaptive modules into large

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gateway courses such as mathematics, statistics and programming, where AI tools support personalised practice and data-driven feedback for diverse cohorts [5,8].

A typical scenario can be described as follows. In a junior secondary mathematics class in an urban district, students complete diagnostic tests on an AI platform at the beginning of a unit. The platform groups students into different levels and assigns them tailored exercise sets. Those who struggle receive more basic items with worked examples; those who show higher mastery move quickly to application and challenge problems. During and after class, the teacher uses the dashboard to identify which topics cause the most difficulty and adjusts the lesson plans accordingly. In principle, this kind of arrangement promises to make differentiation more manageable in large classes and to support both high- and low-achieving students more systematically. However, the actual effects depend on how the platform is designed and how teachers and students use it in daily practice.

3. Analysis of effectiveness: factors, challenges and validity issues

3.1. Key factors enhancing effectiveness

3.1.1. Data-driven adaptive sequencing and targeted practice

Meta-analytic and empirical findings suggest that data-driven adaptive sequencing and targeted practice are key factors contributing to the positive impact of AI learning platforms. The meta-analysis of technology-supported personalised learning mentioned above shows that interventions with strong adaptivity, where the system continuously adjusts difficulty and content based on learner performance, achieve larger learning gains than those with weak or no adaptivity [1]. A meta-analysis of intelligent tutoring systems likewise reports that ITS use leads to higher test scores than non-adaptive instruction, partly because the system can diagnose misconceptions and provide targeted practice and feedback [4].

Evidence across meta-analytic syntheses and tool-specific studies converges on a similar mechanism: when a platform can estimate mastery with reasonable accuracy and align recommended tasks with curricular objectives, it can allocate practice time more efficiently—reducing unproductive repetition for advanced learners while providing structured scaffolding for those who struggle [5-8]. Importantly, this mechanism is conditional. Gains are more plausible when adaptivity is frequent and instructionally interpretable, and less plausible when learner models rely on thin behavioural proxies or when "personalisation" is reduced to difficulty adjustment without attention to conceptual progression.

3.1.2. Supporting engagement and self-regulated learning

A second influencing factor concerns how AI learning platforms support engagement and self-regulated learning. Adaptive systems that offer timely feedback, progress visualisations, and goal-setting tools can make learning trajectories more visible and manageable—for example, through progress bars, mastery indicators, and personalised goal prompts. A systematic review of learning analytics for personalised learning suggests that dashboards and alerts can encourage students to monitor their learning and respond to early warning signals when they fall behind [10]. Related work also notes that progress indicators are most productive when they are easy to interpret and non-threatening, such as by clarifying success criteria and allowing learners some choice in learning paths [11].

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Perceived usefulness also matters: when learners see recommendations as helping them select suitable tasks while preserving flexibility, they are more likely to persist through difficulty. In one medical education study, students using an AI platform spent more time on autonomous study and participated more actively in class discussions, indicating gains in both behavioural and cognitive engagement [7]. Taken together, these features can function as scaffolds for self-regulated learning, particularly for learners who have not yet developed robust strategies on their own.

3.1.3. Data-informed instructional decision-making and formative assessment

A third positive factor concerns data-informed teaching. AI learning platforms collect large amounts of interaction data that can be transformed into actionable information for teachers. Dashboards can show which knowledge points are difficult for the class, which students are at risk and which tasks are most frequently answered incorrectly, including heat maps of class performance, individual student profiles, and real-time alerts for struggling learners. The systematic reviews on personalised learning and learning analytics indicate that when teachers use such information as a basis for formative assessment—such as re-teaching difficult concepts, grouping students strategically, or providing targeted feedback—learning outcomes tend to improve [10,11].

In higher education, instructors using adaptive tools in business statistics and other quantitative courses have leveraged platform data to redesign lectures and practical sessions, focusing on topics with low mastery rates and utilising class time more efficiently [5,6]. For example, one study reported a 15% increase in student engagement and a 20% reduction in failure rates after implementing data-informed teaching strategies. In Chinese schools, AI platforms are frequently utilised to generate diagnostic reports that inform teachers' lesson preparation and remedial activities [3].

3.2. Key challenges and validity risks

Despite these positive influences, several problems and risks can undermine the overall effectiveness and validity of AI-powered personalised learning.

3.2.1. Algorithmic opacity and limited pedagogical scope

Teachers and students experience many AI learning platforms as "algorithmic black boxes". Users can see that different learners receive different tasks. Still, they cannot easily understand how the system estimates mastery, why a particular sequence is recommended, or which pedagogical model underlies these decisions. Reviews of intelligent tutoring systems and learning analytics research point out that explanations of system behaviour are often minimal, and that transparency is not yet a central design principle [9,11].

When the pedagogical logic of the platform is unclear, teachers may struggle to integrate the system into coherent lesson designs. For example, teachers may not know whether the platform is focusing on conceptual understanding, procedural practice or test-taking strategies. As a result, there can be a mismatch between what teachers emphasise in class and what the platform emphasises in practice sessions. Moreover, some AI platforms implicitly equate personalisation with "more practice at the right difficulty" and rarely support higher-order skills such as inquiry, collaboration or critical thinking. This narrow logic risks producing gains in item-level performance without corresponding improvements in deeper understanding or transferable skills.

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3.2.2. Data quality issues, algorithmic bias and equity concerns

The effectiveness of AI-driven personalisation depends on the quality and representativeness of the data used to train and run the system. In many cases, learner models are primarily built on clickstream data and responses to closed-ended questions. These data capture only certain aspects of learning and can be noisy, incomplete or misinterpreted. The meta-analysis of technology-supported personalised learning notes that most interventions are concentrated in mathematics and literacy and often take place in relatively well-resourced settings [1]. The learning analytics review also highlights that datasets often come from early-adopting institutions, which may not be representative of all schools and universities [11].

If training data are biased towards high-performing schools or particular regions, algorithms may perform less accurately for students from under-resourced backgrounds. For example, learners from rural or low-income contexts may have different interaction patterns, device access or language backgrounds, which can affect how the system interprets their behaviour. In such cases, the introduction of AI tools may unintentionally widen existing gaps rather than narrow them.

Additionally, data quality issues such as missing logs, unstable internet connections, or inconsistent platform usage can compromise the accuracy of learner models. If recommendations are based on incomplete or misleading data, personalisation may be ineffective or even counterproductive.

3.2.3. Implementation barriers and excessive automation

A third set of problems relates to implementation and the risk of over-reliance on automation. The large-scale adoption of AI learning platforms requires substantial investment in hardware, connectivity, technical support, and teacher training. The Chinese white paper on intelligent adaptive learning notes that many schools still face challenges in integrating platforms with existing teaching routines, and that teachers need targeted professional development to use data and adaptive functions effectively [3].

Without sufficient training and time for reflective practice, teachers may use AI platforms primarily as homework assignment tools that deliver standardised practice, rather than as integrated components of instructional design. Large-scale adoption is not a plug-and-play change; it requires stable infrastructure, technical support, and, most importantly, time and training for teachers to develop data-informed routines. Without such capacity, platforms are often used in the narrowest way—as homework delivery and grading systems—while the interpretive and pedagogical work is left untouched. A related risk is automation overreach: decision-making may drift toward "follow the dashboard" practices, which can erode teacher agency and reduce opportunities for human–AI co-design, especially when platform metrics are treated as authoritative rather than provisional signals.

When decision-making is handed too readily to algorithms, teacher agency can be weakened. Teachers may feel pressured to follow platform recommendations even when these conflict with their professional judgement or knowledge of local contexts. Over time, this can reduce the space for human–AI co-design and critical reflection on how personalisation should be realised in specific classrooms, as shown in Table 1.

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Table 1. A summary framework of enhancing factors and key challenges for AI-powered personalised learning

Key Factors Enhancing Effectiveness	Key Challenges and Validity Risks
Data-Driven Adaptive Sequencing & Targeted Practice: Continuous adjustment based on performance. Alignment with curriculum goals.	Algorithmic Opacity & Limited Pedagogical Scope: "Black-box" algorithms hinder trust. Narrow focus on low-order skills.
Supporting Engagement & Self-Regulated Learning: Immediate feedback and progress visualisation. Scaffolds for learner autonomy.	Data Quality Issues & Algorithmic Bias: Non-representative training data. Risk of exacerbating equity gaps.
Data-Informed Instructional Decision-Making: Actionable dashboards for teachers. Supports formative assessment and differentiation.	Implementation Barriers & Excessive Automation: Insufficient teacher training and support. Risk of undermining teacher agency.

4. Strategic pathways for trustworthy and effective implementation

4.1. Foster pedagogical co-design and human-AI orchestration

First, AI learning platforms should be explicitly aligned with curriculum standards, course objectives and teachers' pedagogical plans. Rather than treating the platform as a generic, stand-alone tool, schools and universities can clarify which competencies they expect the platform to support (for example, conceptual understanding, procedural fluency, application or exam preparation) and how these relate to the platform's learner model and content structure. Adaptive functions can then be configured to scaffold learning in stages—for instance, from conceptual exploration to guided practice and then to transfer—rather than focusing only on repetitive practice.

Second, platforms should be designed for human–AI orchestration. Teachers need transparent information about how the system estimates mastery and generates recommendations, and they need flexible controls to override or modify adaptive paths. Platform use is most defensible when it is tethered to explicit learning goals. Institutions can begin by specifying which competencies a platform is expected to support in a given course or grade (e.g., conceptual understanding versus exam-oriented fluency), and then checking whether the platform's content structure and mastery model actually represent those competencies. When the platform does not fit the curriculum or local constraints, "more adaptivity" rarely fixes the issue. The practical response is either to reconfigure the system or to limit its use to tasks it can support reliably. Orchestration is just as critical. Teachers need signals they can interpret and control points they can act on—understanding why a recommendation appears, reshaping task sequences, and overriding the system when professional judgement and contextual knowledge point elsewhere [5,11]. Co-design routines such as pilot–feedback–iteration make these controls easier to use and help prevent dashboards from displacing teacher judgement.

More broadly, a design-based approach can bring teachers, students, and developers into the same improvement loop. By testing AI-supported activities in real classrooms and feeding observations back into redesign, teams can refine algorithms, interfaces, and content in ways that respond to pedagogical needs. This kind of collaboration is one route toward reducing misalignment and enabling context-sensitive use of AI.

4.2. Establish robust data governance and multidimensional evaluation

Evaluation designs need to reflect the paper's multidimensional view of effectiveness. In addition to immediate achievement outcomes, studies can incorporate indicators of motivation and self-regulation, and include delayed measures that speak to retention or transfer. Equity analyses are

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stronger when subgroup reporting is planned in advance and paired with routine checks for model drift (e.g., systematic under- or over-estimation for particular groups). Finally, platform logs may support internal improvement, but scaling decisions are more defensible when they also rely on external measures aligned with curricular standards.

4.3. Empower learners and institutions through capacity building and ethical governance

A third group of suggestions relates to learners and institutional governance. From the learner side, AI learning platforms can incorporate features that explicitly support self-regulation and data literacy. Goal-setting modules, learning plans and reflective prompts can encourage students to use platform feedback actively rather than passively. Visualisations of learning progress should be understandable, emphasising growth and effort instead of ranking, so as to avoid discouraging lower-achieving students [5]. Teachers can integrate short classroom activities that guide students in interpreting dashboard information, planning their study time, and responding constructively to difficulties.

For institutional governance, schools and universities can develop clear policies regarding data protection, algorithmic transparency and responsible AI use. Such policies can define acceptable uses of student data, outline procedures for obtaining informed consent, and establish mechanisms for addressing concerns about fairness or errors. In parallel, leadership can support cross-functional teams that bring together educators, instructional designers, technologists, and data specialists to oversee platform selection, configuration, and monitoring [2,3,12].

Comprehensive professional development programs are essential to cultivate "AI-literate" educators who are "AI-aware": they understand basic concepts of AI and learning analytics, recognise both opportunities and risks, and can participate in governance discussions. When institutional strategies, capacity-building and classroom practice are aligned, AI learning platforms are more likely to produce sustained and equitable benefits rather than short-lived or uneven effects.

5. Conclusion

5.1. Synthesis of evidence and core tension

AI-powered learning platforms have created new possibilities for implementing personalised learning at scale. Evidence from meta-analyses, systematic reviews, and empirical trials shows that when well-designed and integrated, such platforms can generate small to moderate improvements in learning outcomes, enhance engagement and self-regulation, and support data-informed teaching. These platforms primarily operate through data-driven adaptation, support for self-regulated learning, and enabling data-informed teaching, with strongly adaptive systems producing meaningful gains when properly aligned with curriculum goals.

Validity is the sticking point. In AI-enabled teaching and assessment, validity fractures through opaque algorithms, narrow pedagogical logic that rewards what is easy to count, uneven data that amplifies advantage, automation that erodes teacher judgment, and evaluation routines tuned to short-term score bumps over durable outcomes. Opacity is the first obstacle. A quick stress test shows it: submit the same 300-word essay ten times and the feedback swings from "excellent coherence" to "missing a thesis," while the model offers fluent rationales without traceable evidence. Poor data misleads very quickly. When datasets under-represent bilingual learners, "personalised" recommendations can steer them toward remedial drills, and the system then reports gains only because the benchmark has been narrowed. Design, not technology, drives this drift. That drift calls

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for an integrated response—co-designing human–AI orchestration, enforcing data governance with multidimensional evaluation, and building capacity for ethical stewardship that restores learner, institutional, and teacher agency.

Bringing the reviewed evidence together, three points answer the guiding questions of this paper. First, effectiveness is most consistently associated with curriculum-aligned adaptivity, feedback that supports learners' self-monitoring, and teacher use of platform data for formative decisions. Second, the same mechanisms generate validity risks when they are opaque, data-poor, or implemented as substitutes for pedagogy: black-box recommendations can misalign with classroom goals, biased or incomplete traces can distort learner models, and automation can narrow teaching to what is easiest to measure. Third, the central tension is therefore socio-technical rather than purely technical: platform impact depends on how design choices, teacher judgement, and institutional governance jointly shape what "personalisation" means in practice.

5.2. Theoretical and practical implications

For developers, the implication is to design for interpretability and instructional actionability—outputs that explain "why this task" and map to plausible teaching responses, not only to predictive accuracy. For schools and policymakers, the implication is to treat adoption as capacity building: infrastructure, professional development, and evaluation practices must be planned alongside procurement. Socially, personalised learning will not automatically advance equity; equity outcomes require deliberate monitoring of subgroup effects and safeguards that prevent differential error rates from accumulating over time.

5.3. Limitations and future research trajectories

This paper is limited by its reliance on secondary evidence, which varies in methodological quality and often underreports implementation details. Future work would benefit from multi-site, longitudinal designs that track platform use over semesters or school years, combining learning outcomes with process measures (e.g., how teachers interpret dashboards; how students respond to feedback) and equity diagnostics (e.g., model drift and subgroup performance). Mixed-method approaches—linking platform logs with classroom observations and interviews—are particularly important for testing whether reported gains reflect durable learning rather than short-term practice effects.

Overall, the promise of AI-enabled personalisation lies less in automation per se than in disciplined orchestration: using computational adaptation to expand teachers' options while keeping educational goals, fairness, and accountability as design constraints.

References

[1] Major, L., Francis, G. A., & Tsapali, M. (2021). The effectiveness of technology-supported personalised learning in low-and middle-income countries: A meta-analysis. British Journal of Educational Technology, 52(5), 1935-1964.

[2] Engageli. (2025). 20 statistics on AI in education to guide your learning strategy in 2025. Engageli Blog. https: //www.engageli.com/blog/ai-in-education-statistics.

[3] Ernst & Young. (2021). China's AI adaptive learning industry whitepaper. EY Greater China. https: //www.ey.com/content/dam/ey-unified-site/ey-com/en-cn/insights/education/documents/ey-china-ai-adaptive-learning-industry-whitepaper-en.pdf.

[4] Ma, W., Adesope, O. O., Nesbit, J. C., & Liu, Q. (2014). Intelligent tutoring systems and learning outcomes: A meta-analysis. Journal of Educational Psychology, 106(4), 901.

DOI: 10.54254/2754-1169/2026.LD32107

[5] Tariq, M. U. (2024). Navigating the personalisation pathway: Implementing adaptive learning technologies in higher education. In Adaptive Learning Technologies for Higher Education (pp. 265-291). IGI Global.
[6] Contrino, M. F., Reyes-Millán, M., Vázquez-Villegas, P., & Membrillo-Hernández, J. (2024). Using an adaptive learning tool to improve student performance and satisfaction in online and face-to-face education for a more personalised approach. Smart Learning Environments, 11(1), 6.
[7] Chen, Y. (2025). Evaluation of the impact of an AI-driven personalised learning platform on medical students' learning performance. Frontiers in Medicine, 12, 1610012.
[8] Fodouop Kouam, A. W. (2024). The effectiveness of intelligent tutoring systems in supporting students with varying levels of programming experience. Discover Education, 3(1), 278.
[9] Inuwa, A. U., Sulaiman, S., & Samsudin, R. (2025). Systematic Literature Review on Artificial Intelligence-Driven Personalized Learning. International Journal of Advanced Computer Science & Applications, 16(6).
[10] Fariani, R. I., Junus, K., & Santoso, H. B. (2023). A systematic literature review on personalised learning in the higher education context. Technology, Knowledge and Learning, 28(2), 449-476.
[11] Avella, J. T., Kebritchi, M., Nunn, S. G., & Kanai, T. (2016). Learning analytics methods, benefits, and challenges in higher education: A systematic literature review. Online Learning, 20(2), 13-29.
[12] Coursera. (2025). Adaptive learning platforms: How AI powers personalised learning. Coursera. https: //www.coursera.org/articles/adaptive-learning-platforms.