Decoupling Personalised and Adaptive Learning in AI-Enhanced Education: A Narrative Review and Conceptual Clarification

Harvinder Kaur Dharam Singh[1], Siti Khadijah Mohamad[1*]
[1]Faculty of Education, Open University Malaysia, Malaysia
**Corresponding author: Siti Khadijah Mohamad (siti_khadijah@oum.edu.my)*

Received: 27 November 2025
Received in revised form: 12 December 2025
Accepted: 14 December 2025
Published: 18 December 2025

ABSTRACT

Personalised learning and adaptive learning are often treated as the same idea in AI-enhanced education, even though they represent different pedagogical purposes. This narrative review examines ten contemporary studies, including work on intelligent tutoring systems, adaptive platforms, multi-agent AI, and human-centred AI frameworks, in order to clarify the distinction between these two concepts. The review shows that personalised learning involves intentional, human-centred customisation based on learner goals, preferences, identity, and context. In contrast, adaptive learning relies on algorithmic, real-time adjustments based on performance data. While AI systems are increasingly sophisticated in adaptivity, they rarely achieve genuine personalisation, often limiting learner agency and overlooking socio-emotional or cultural dimensions. This review also introduces a conceptual model that positions personalisation and adaptivity as related but distinct constructs requiring different pedagogical intentions, data models, and levels of human oversight. Understanding this distinction is essential to prevent misinterpretation, guide responsible AI adoption, and ensure that automation supports rather than replaces human judgement. The paper concludes with recommendations for educators, instructional designers, and AI developers to integrate AI in ways that are transparent, ethical, and centred on meaningful learner autonomy.

Keywords
Artificial intelligence; Personalised learning; Adaptive learning; Narrative review; AI-enhanced education

Introduction

Artificial intelligence (AI) continues to transform the landscape of education, driving renewed interest in personalised learning (PL) and adaptive learning (AL) as strategies to enhance learner experience, efficiency, and autonomy. Across higher education, clinical training, STEM fields, and professional learning, AI-driven systems promise tailored pathways, instant feedback, and dynamic content adjustments. Yet, as the field expands, so too does the conceptual confusion surrounding personalisation and adaptivity. Many systems labelled "personalised" are, in reality, predominantly adaptive, driven by algorithmic responses to performance data rather than learner preferences, identities, or goals. The distinction is not trivial as each concept implies different pedagogical commitments, ethical implications, and AI design requirements.

The conflation of PL and AL is clearly visible across contemporary literature. For example, AI agents for adaptive learning emphasise real-time monitoring, autonomous scaffolding, and automated decision-making, focusing primarily on performance optimisation rather than learner agency (Hedi et al., 2025). In dental education, AI-enhanced simulations provide tailored pathways for clinical skill development, yet these pathways are shaped more by competence-based adaptivity than by holistic personalisation anchored in learner background or learning identity (Hu et al., 2025). Meanwhile, human-centred frameworks in AI-enhanced education argue that algorithmic personalisation cannot be meaningful without socio-emotional, cultural, and contextual considerations. These are elements that most adaptive systems do not capture (Lata, 2024). Similarly, pedagogical analyses of personalised learning highlight the tension between algorithmic automation and genuine pedagogical intentionality, noting that most AI systems focus on adaptive feedback rather than comprehensive learner-centred design (Vorobyeva et al., 2025).

These tensions demonstrate that the terms personalised learning and adaptive learning are often treated as synonyms, even though their pedagogical, technological, and ethical foundations differ substantially. Such conflation narrows scholarly discourse and risks creating digital ecosystems where learners are shaped by data-driven automation rather than empowered by meaningful choice, reflection, and agency. To advance conceptual clarity, this narrative review focuses on decoupling personalisation and adaptivity by mapping their distinct purposes, assumptions, and pedagogical implications, and examining how AI systems mediate their overlap. This distinction is urgently needed, not only to refine theoretical discourse but to guide educators, policymakers, and AI designers in creating systems that align with genuine educational values rather than purely algorithmic optimisation.

Literature Review

AI-enhanced education is shaped by the convergence of several technological capabilities, i.e. intelligent tutoring systems (ITS), large language models (LLMs), multi-agent systems, retrieval-augmented generation (RAG), virtual simulations, and predictive analytics. These technologies enable complex forms of automation, making adaptive learning systems increasingly sophisticated. For instance, multi-agent intelligent tutoring architectures provide real-time monitoring, performance analysis, and dynamic scaffolding as the core features of adaptive learning systems (Hedi et al., 2025). Similarly, AI-driven VR simulations allow dental students to practise skills repeatedly while receiving personalised analytics on performance patterns, providing a hybrid form of adaptivity and skill-specific customisation (Hu et al., 2025). At the same time, the pedagogical goals of personalised learning extend beyond performance optimisation. Personalisation involves tailoring learning experiences based on learner contexts, identities, motivations, cultural backgrounds, and learning preferences. Yet many AI systems do not collect or meaningfully interpret such contextual data. As highlighted in human-centred AI education research, algorithmic systems alone cannot personalise socio-emotional experiences, cultural relevance, or motivational alignment. These elements are essential for authentic personalisation (Lata, 2024). This aligns with broader concerns about ethical implementation, including risks of bias, depersonalisation, teacher marginalisation, and over-automation of learning processes, highlighted across multiple papers. The literature emphasises that without intentional pedagogical frameworks, AI-enabled adaptivity may inadvertently reproduce inequities or limit learner autonomy. Thus, while AI has advanced the technical capabilities for adaptivity, personalisation remains a pedagogical and human-centred endeavour that requires more than data-driven decision-making. This narrative review situates itself within this critical tension and proposes a clear conceptual decoupling to address the challenges arising from conflation of the two concepts. The specific aims are to:

1. Clarify conceptual distinctions between personalised learning and adaptive learning.
2. Synthesise findings across ten contemporary AI-enhanced education studies.
3. Identify pedagogical, ethical, and technological implications of conflating both terms.
4. Propose a conceptual clarification model for future research and practice.

Methods

This study employed a narrative review design, chosen for its suitability in synthesising heterogeneous literature, clarifying conceptual ambiguities, and constructing theoretical insights in fields where empirical findings and conceptual definitions remain inconsistent. Unlike systematic reviews, which primarily focus on procedural exhaustiveness, the narrative review approach enables the researcher to critically interpret diverse theoretical claims, methodological assumptions, and conceptual overlaps across educational technology studies. This design aligns with the aim of the article, i.e. to distinguish and clarify the constructs of personalised learning and adaptive learning within AI-enhanced educational ecosystems, and to develop an integrative conceptual model based on contemporary scholarship.

To ensure breadth and depth, a multi-stage search strategy was used. The search covered peer-reviewed articles published between 2021 and 2025, corresponding with the period of rapid expansion in AI-enhanced personalised learning systems. Searches were conducted across well-known databases such as Scopus and Web of Science. Search terms were combined using Boolean operators such as “personalised learning” OR “personalization”; “adaptive learning” OR “adaptive systems”; “AI-enhanced education” OR “artificial intelligence in education”; “learning analytics" AND "personalisation"; "intelligent tutoring systems"; "AI agents" AND "education"; and "multi-agent systems" AND learning.

Studies were included if they met the following criteria: (1) focused explicitly on AI, personalised learning, or adaptive learning; (2) discussed theoretical foundations, conceptual frameworks, or system architectures; (3) provided empirical, conceptual, or design-based evidence relevant to PL or AL; and (4) were available in full-text form. Studies were excluded if they (1) focused solely on machine learning optimisation with no educational connection; and (2) described general AI applications without reference to learning design.

Although the ten studies provide strong conceptual insights, their small number limits the generalisability of the findings across the broader and rapidly expanding AI-education landscape. As a narrative review, the aim is interpretive rather than exhaustive, but this limitation should be acknowledged when considering the scope of the conclusions.

The narrative analysis was guided by interpretive thematic synthesis, which is common in narrative reviews focusing on emerging or conceptually fluid phenomena. The analysis proceeded in three iterative cycles: (1) Concept identification and coding; (2) Cross-study comparison and pattern recognition; and (3) integrative conceptual synthesis.

These distinctions formed the foundation for the PAL Matrix (Personalisation–Adaptivity Learning Matrix), that is the conceptual model introduced in this narrative review. The model synthesises how personalisation and adaptivity interact without collapsing into each other, by articulating four quadrants that represent distinct configurations of AI-enhanced learning.

Results and Discussion

Theme 1: Conceptualising Personalised Learning

Personalised learning has traditionally been understood as a learner-centred approach designed to tailor instruction to individual needs, preferences, motivations, identities, and aspirations. In contemporary discourse, it is often presented as an educational ideal. This ideal promises to honour each learner's uniqueness while empowering them to take greater control of their learning trajectory. However, as artificial intelligence becomes increasingly embedded within educational systems, the meaning of personalisation has expanded, blurred, and sometimes become contentious. Across the ten studies examined, personalised learning consistently emerges as a construct grounded in human agency, cultural relevance, intentional instructional design, and meaningful learner empowerment. Yet a clear gap exists between the pedagogical vision of personalisation and the ways AI-driven systems operationalise it in practice.

A central theme in the reviewed literature is the notion of personalised learning as a form of human-centred intentionality. Scholars working in human-centred AI argue that adjusting content through algorithms does not, in itself, constitute personalisation. For personalisation to be meaningful, it must be rooted in human judgement, teacher intention, learner identity, and socio-emotional understanding. Lata (2024) articulates this most clearly, emphasising that personalisation must consider learners' backgrounds, strengths, interests, and socio-cultural contexts. These are dimensions that AI systems cannot independently interpret or nuance. This perspective reinforces the argument that personalisation is about designing learning experiences that genuinely "fit the learner," rather than simply calibrating task difficulty or sequencing based on computational logic. In this view, personalisation remains an inherently pedagogical and relational construct that cannot be reduced to algorithmic manipulation.

Across the studies, personalised learning is also strongly associated with learner agency and autonomy. Pedagogical traditions such as self-directed learning, constructivism, and differentiated instruction all position the learner as an active participant in shaping their learning journey. Consistent with these traditions, personalised learning in theory emphasises the ability of learners to exercise choice, set goals, navigate flexible pathways, and engage with content in ways that align with their personal aspirations and needs. AI-enhanced environments can support such agency by allowing learners to control pacing, select preferred modalities, personalise projects, access multimodal resources, or request feedback aligned with their goals. However, the evidence from the reviewed studies suggests that many AI systems marketed as personalised do not prioritise learner agency. Instead, they rely heavily on system-driven recommendations, performance-based modelling, and automated sequencing. Multi-agent systems such as AIA-PAL offer sophisticated personalised dialogue and instructional support, yet these personalisations are ultimately driven by the system's analytics rather than by learner-initiated decisions (Hedi et al., 2025). This disconnect reveals a recurring tension: while personalisation in theory centres on learner autonomy, personalisation in practice often remains algorithm-centric and directive.

Another significant conceptualisation of personalised learning emphasises the integration of cognitive and socio-emotional dimensions. Scholars argue that personalisation must address the whole learner, including their emotions, motivations, cultural backgrounds, identities, and self-efficacy. Lata (2024) stresses that AI-driven personalisation must incorporate socio-emotional and cultural considerations to avoid becoming a narrow, technocentric practice that undermines educational equity and wellbeing. Similarly, pedagogical studies such as those by Vorobyeva et al. (2025) highlight the need for educators to interpret learner profiles holistically when designing personalised learning environments. Their work demonstrates that personalisation is not purely technical. It is a pedagogical commitment that requires human interpretation and contextual sensitivity. However, most AI tools reviewed across the ten studies focus primarily on modelling performance, and at best, basic affective states. They rarely account for learners' motivations, cultural contexts, learning histories, or identities, leaving significant dimensions of personalisation underrepresented.

Contextual relevance also plays a critical role in conceptualisations of personalised learning. Personalisation, as described in the literature, should reflect the learner's environment, goals, and future trajectory. In professional programmes such as dental education, AI-enhanced personalisation often focuses on aligning learning activities with clinical competency levels. For example, Hu et al. (2025) describe learning pathways customised to the learner's evolving clinical skills. While such designs demonstrate contextual tailoring, they remain constrained by performance-oriented interpretations of personalisation, as broader aspects of learner identity, aspirations, or socio-emotional needs remain beyond the system's modelling capacity. This observation highlights a broader limitation of AI-driven personalisation. Although it is contextual in some respects, it often remains procedural and functional rather than holistic and human-centred.

A final insight emerging across the literature is the idea of personalisation as co-construction. In educational theory, personalisation involves ongoing dialogue, negotiation, and sense-making between the learner and the learning environment. LLMs and conversational agents offer new possibilities for dialogic personalisation by enabling interactive explanations, clarifications, and exploratory discussion. Systems such as AIA-PAL (Artificial Intelligence Agents for Personalized Adaptive Learning) demonstrate how multi-agent conversational architectures can create more responsive learning experiences. However, the conversations remain shaped by the system's pre-defined pedagogical logic and training data (Hedi et al., 2025). While the dialogue may be dynamic, it does not necessarily equate to personalised co-construction in the humanistic sense. The learner's influence remains limited by what the system is programmed to respond to and prioritise.

Taken together, these conceptual threads reveal a persistent discrepancy between the pedagogical aspirations of personalised learning and the algorithmic realities of AI-driven implementations. Personalised learning, as conceptualised across the reviewed literature, is fundamentally about human intention, learner agency, holistic development, and meaningful co-construction. AI-enhanced systems, while capable of supporting elements of this vision, often focus narrowly on performance optimisation and automated decision-making. This tension underscores the need for clearer conceptual boundaries, and for design approaches that preserve the human-centred essence of personalisation within AI-mediated learning environments.

Theme 2: Conceptualising Adaptive Learning

Adaptive learning is consistently portrayed in the reviewed literature as a technical capability embedded within AI-driven systems rather than as a pedagogical construct centred on learner identity or agency. While personalised learning focuses on who the learner is, adaptive learning concentrates on what the learner does. It is fundamentally a data-driven process that interprets learner behaviours, evaluates performance in real time, and adjusts instructional pathways accordingly. Across the ten studies, adaptivity emerges as a form of algorithmic optimisation rather than a holistic approach to learning design, raising important questions about the extent to which adaptive systems can, or should be considered personalised. At the same time, the reviewed studies also highlight contexts where adaptive learning offers clear pedagogical advantages. Adaptive systems are particularly effective in domains that require procedural mastery, structured skill progression, or repeated practice with immediate feedback. For example, adaptive VR for clinical dentistry, adaptive mathematics platforms, and language learning engines can reduce cognitive overload by sequencing tasks responsively and correcting misconceptions at the point of error. These benefits demonstrate that AL, when used for well-defined competencies and transparent instructional goals, can meaningfully strengthen learning efficiency and learner confidence.

A central characteristic of adaptive learning is its reliance on real-time performance-driven adjustment. In technical frameworks such as AIA-PAL, adaptivity is implemented through continuous monitoring, learner modelling, and dynamic scaffolding. The system evaluates learner actions, identifies patterns of error, estimates mastery levels, and modifies task difficulty or the degree of support as needed. Hedi et al. (2025) describe how multi-agent AI structures bring together decision-making tools, retrieval-augmented generation for validation, and specialised tutor agents to deliver instruction with minimal human intervention. These systems prioritise efficiency, accuracy, and speed. Adaptivity, in this sense, is entirely behaviourally anchored. It responds to what the learner has demonstrated rather than to their preferences, cultural background, or identity. This aligns with traditional intelligent tutoring system (ITS) models, where adaptivity is defined almost exclusively as alignment to performance progression.

Another strong thread in the literature is the use of adaptive systems to automate learning pathways. In professional contexts such as dental clinical training, adaptive VR and machine learning systems analyse learners' skills, identify weaknesses, and adjust practice tasks to reinforce specific competencies (Hu et al., 2025). Although these adjustments may appear "tailored," they remain competence-driven and performance-oriented rather than grounded in broader personalisation principles. Vorobyeva et al. (2025) show that adaptive systems often control what learners see next, how much feedback they receive, and which content is delivered. These decisions are guided not by learner agency but by algorithmic optimisation. Adaptivity, therefore, functions as a system-led mechanism that determines the most efficient instructional sequence based on measurable outcomes.

Several studies also highlight the increasing role of predictive modelling in adaptive learning. Machine learning tools are frequently used to anticipate learner performance, identify potential risk, and pre-emptively adjust content sequencing. Lata (2024) notes that predictive analytics can support instruction by forecasting learner needs and offering proactive recommendations. However, she warns that predictive modelling can reinforce algorithmic bias and may unintentionally restrict learner autonomy. When systems predict what a learner "needs" or "should" do, they also prescribe what the learner "must" do, potentially resulting in deterministic pathways that narrow rather than expand learning opportunities. Thus, adaptivity can become overly prescriptive, behaviourist, and reductionist, foregrounding performance metrics over learner choice.

Mastery-based progression is another hallmark of adaptive learning. Most adaptive systems require learners to demonstrate competence before advancing to the next task or level, a design especially evident in clinical and procedural training contexts. Studies by Hu et al. (2025) and Vorobyeva et al. (2025) illustrate how adaptive systems prioritise mastery, error reduction, and procedural accuracy. The goal is to optimise the learner's progression through precise and incremental improvements. While effective for skill acquisition, this approach differs profoundly from personalised learning, which emphasises creativity, exploration, self-expression, and multimodal engagement.

Adaptive learning, in contrast, is narrower in scope and more aligned with performance optimisation than with holistic learner development.

A recurring concern in the literature is that adaptive systems can inadvertently diminish human agency. When algorithms dictate pacing, sequencing, and instructional choices, teachers may have reduced control over the learning process, and learners may have fewer opportunities to make decisions about their learning paths. Both Lata (2024) and Vorobyeva et al. (2025) caution that adaptive systems are sometimes implemented not to support teachers and learners, but to replace human judgement under the guise of "personalisation." This can result in a subtle but significant erosion of pedagogical autonomy and can shift decision-making power from educators to opaque computational models. The risk is heightened when adaptivity is presented as inherently beneficial without consideration of its potential to constrain learners or oversimplify complex learning realities.

Across all ten papers, adaptive learning is consistently portrayed as a data-centred construct. It is measurement-driven, algorithm-mediated, and grounded in computational analytics. Whether embedded in multi-agent architectures, VR simulations, learning analytics dashboards, or predictive modelling tools, adaptivity remains anchored in performance-responsive decision rules. It is automated, optimisation-oriented, and mastery-focused. Although these systems can significantly improve task efficiency, accuracy, and learning flow, they do not inherently support identity, autonomy, socio-cultural context, or emotional development. These elements are the hallmarks of genuine personalisation.

In summary, adaptive learning emerges from the reviewed studies as a powerful but limited construct. It excels at automating pathways, regulating difficulty, predicting performance, and optimising skill mastery. However, its algorithmic nature places it in stark contrast with personalised learning, which is holistic, agency-driven, and grounded in human interpretation. Recognising adaptivity as fundamentally performance-based rather than person-based is therefore essential for avoiding conceptual confusion and ensuring that AI-enhanced learning systems are designed and implemented with clarity and pedagogical integrity.

Theme 3: Personalised Learning is not Adaptive Learning

Although the terms PL and AL are frequently used interchangeably in AI-enhanced education, the literature shows that they represent fundamentally different pedagogical and technological constructs. Conflating the two creates conceptual ambiguity, obscures theoretical clarity, and leads to the misalignment of AI systems with educational intentions. Drawing on the ten studies reviewed, this section unpacks the critical distinctions between PL and AL by examining their divergent purposes, assumptions, logics, and outcomes.

A foundational difference lies in what each construct positions at the centre of the learning process. Personalised learning is anchored in the learner as a human being. It requires attention to motivations, context, identity, interests, cultural background, and socio-emotional needs. Its core logic is relational and pedagogical, grounded in intentional instructional design rather than technical automation. Lata (2024) underscores that genuine personalisation requires understanding "the child behind the data." This includes recognising their lived experiences, aspirations, and emotional realities. Adaptive learning, by contrast, centres on learner data rather than the learner. It relies on performance metrics, error patterns, mastery estimates, and behavioural indicators to determine the next step in a learning pathway. As Vorobyeva et al. (2025) point out, many systems marketed as personalised are in fact adaptive, offering performance-driven adjustments rather than holistic personalisation. Fundamentally, personalisation operationalises human values, whereas adaptivity operationalises computational logic.

This foundational distinction shapes how each construct approaches learner choice. Personalised learning frameworks typically foreground learner autonomy by encouraging choice of pace, goals, modality, context, pathway, and representation. The learner plays an active role in shaping how learning unfolds. Adaptive learning, however, tends to minimise choice because it optimises pathways based on statistical predictions rather than learner preferences. In multi-agent systems such as AIA-PAL, learners receive highly tailored assistance, yet the system, not the learner, determines the next activity, level of scaffolding, or difficulty adjustment (Hedi et al., 2025). Personalisation thus expands learner control, whereas adaptivity consolidates system control for the sake of optimisation.

Another defining difference lies in the scope of what each construct seeks to address. Personalised learning focuses on the whole learner. It incorporates contextual relevance, socio-emotional needs, cultural alignment, learning history, identity development, and personal goals. Adaptive learning focuses almost exclusively on competence. It is concerned with skill mastery, error reduction, performance accuracy, and the remediation of knowledge gaps. For instance, in dental education, adaptive simulations tailor clinical tasks to learners' skill levels (Hu et al., 2025). Although such tailoring appears personalised, it responds only to performance progression, not to learner motivations or socio-cultural contexts. This distinction reinforces the idea that personalisation attends to the learner in full, whereas adaptivity attends only to what can be measured.

The contrast also extends to the origins and logic of each construct. Personalised learning is fundamentally design-driven. It begins with pedagogical commitments that include differentiated instruction, multimodal content design, curated resources, socio-emotional scaffolding, and reflective learning opportunities. Adaptivity, on the other hand, is data-driven. It depends on learner modelling, predictive analytics, rule-based algorithms, machine-learning classification, and automated feedback systems. Vorobyeva et al. (2025) emphasise that personalisation evolves from human-led instructional design, whereas adaptivity emerges from the technical capabilities of AI systems. Teachers can personalise without AI, but adaptivity cannot exist without computational automation.

This divergence also influences the types of learning outcomes each construct supports. Personalised learning is oriented toward identity formation, motivation, self-awareness, belonging, self-efficacy, and reflective capacity. It fosters the learner's sense of purpose and personal agency. Adaptive learning supports mastery, efficient progression, cognitive reinforcement, and procedural accuracy. It strengthens performance but does not inherently foster meaning-making or identity development. Human-centred AI scholars argue that identity work cannot be automated as it requires relational scaffolding and intentional pedagogical care that adaptive systems cannot replicate. Adaptivity may reinforce mastery, but without personalisation, mastery becomes disconnected from meaning, relevance, or learner purpose.

Another conceptual difference often overlooked is that personalisation can exist without AI, but adaptivity cannot. Teachers have always personalised learning through observation, differentiation, dialogue, and relational understanding. These practices long predate AI and do not rely on computational mechanisms. Adaptive learning, by contrast, originates entirely from technological automation. It has no analogue outside algorithmic logic. This reinforces why conflating PL and AL distorts the meaning of personalisation and risks replacing pedagogical intentionality with technological determinism.

Finally, personalisation and adaptivity differ in their value orientation. Personalised learning explicitly values the human by prioritising empathy, cultural responsiveness, socio-emotional support, dialogue, and ethical care. Adaptive learning, on the other hand, optimises the machine by focusing on analytic efficiency, error detection, predictive accuracy, and computational modelling. Personalisation is value-laden, shaped by educational philosophies and learner wellbeing. Adaptivity is value-neutral, shaped by mathematical optimisation and system logic. This distinction has ethical implications, particularly regarding learner agency, surveillance, bias, and control. When adaptive systems replace or override teacher judgement under the banner of "personalisation," they risk reducing education to a technical exercise devoid of relational meaning.

Collectively, these distinctions illustrate why equating personalised learning with adaptive learning creates conceptual confusion and operational risks. Personalisation is pedagogical, intentional, and human-centred. Adaptivity is technical, automated, and data-centred. Understanding their differences is essential for building AI-enhanced learning environments that support rather than undermine the core values of education.

Theme 4: How AI Systems Actually Implement Personalisation and Adaptivity

A comparative analysis of the ten reviewed papers reveals a striking pattern. While many AI-enhanced systems claim to deliver personalised learning, most actually implement adaptive learning. This theme synthesises how each study operationalises PL and AL, clarifying the specific mechanisms through which AI systems respond to learners and exposing the conceptual contradictions embedded in contemporary implementations.
The AIA-PAL framework, presented by Hedi et al. (2025), provides one of the most advanced examples of adaptive architecture in the dataset. The system employs real-time monitoring, behaviour-based decision-making, and multiple specialised agents, including tutor, teacher, and practical agents, to deliver dynamic scaffolding aligned to learner performance. Retrieval-augmented generation (RAG) is incorporated to increase precision and reduce hallucination, further enhancing the system's adaptive consistency. Although the authors describe the system as personalised, the review finds that its form of personalisation is limited to adaptive personalisation. These adjustments are rooted in performance, analytics, and automated decision pathways rather than in a holistic understanding of the learner. As Hedi et al. (2025) emphasise, this reflects a wider pattern within AI-enhanced education where adaptivity is framed rhetorically as personalisation, contributing to conceptual conflation in the field.

Similar trends appear in the AI-driven innovations reported in dental education. Studies by Hu et al. (2025) describe VR clinical simulations combined with machine learning models that assess learner skill levels and modify tasks accordingly. These systems can tailor clinical scenarios based on learner competence and adjust the difficulty or nature of training tasks to scaffold skill mastery. While such customisation is valuable for procedural learning, it remains competence-based rather than genuinely personalised. Important dimensions such as learner identity, motivation, cultural background, and emotional needs are not modelled. The system offers targeted tailoring, but it is rightly characterised as competency-driven adaptivity rather than holistic personalisation.

In contrast, Lata's (2024) work provides one of the strongest articulations of what personalisation should entail beyond adaptive mechanisms. She foregrounds socio-emotional needs, cultural responsiveness, inclusion, teacher empowerment, and the ethical use of AI. These dimensions are often absent from adaptive systems. Her work stresses participatory design, reduced algorithmic bias, and the need for learners to be seen and understood beyond data patterns. Lata (2024) critiques prevailing adaptive systems for being reductive and argues that personalisation cannot be achieved through algorithmic modulation alone. Carefully attending to learners' contexts, relationships, and identities is essential. The paper thus strongly reinforces the conceptual distinction between personalisation and adaptivity.

Vorobyeva et al. (2025) also contribute significantly to understanding the pedagogical requirements of genuine personalisation. They emphasise learner expectations, alignment between pedagogy and technology, curriculum integration, teacher readiness, and professional-context relevance as key determinants of effective personalised learning. Their analysis highlights that while many AI systems are advertised as personalised, they largely follow adaptive logic, lacking sophisticated learner modelling that includes motivational, socio-emotional, or cultural factors. Without explicit pedagogical intentionality, AI-driven personalised learning risks devolving into technocratic automation, detaching instructional decisions from learners' lived realities.

Across the remaining papers, including those by Merino-Campos (2025), Li and Wong (2023), Iqbal (2023), du Plooy et al. (2024), Sajja et al. (2024), and Major et al. (2021), several recurring patterns further illustrate how AI systems predominantly operationalise adaptivity rather than personalisation. First, there is a heavy reliance on adaptive engines that identify error patterns, adjust task difficulty, detect performance gaps, and generate targeted feedback. Such systems regulate learning pathways based on behavioural and cognitive indicators, even when authors use personalised learning terminology. Second, personalisation, when implemented, often takes the form of superficial user profiling. This includes tracking preferred modalities, individual pacing, or dashboard customisations. While these features offer flexibility, they do not constitute deep personalisation grounded in context, identity, or socio-emotional understanding.

Another important trend is the marginalisation of teachers. Several studies describe systems that automate decision-making to the extent that teacher involvement is reduced to oversight rather than active instruction. Automated feedback frequently replaces human feedback, and algorithmic sequencing displaces teacher judgement. The result is enhanced adaptivity but diminished pedagogical personalisation, since meaningful personalisation traditionally relies on teacher insight, relational understanding, and human-centred discretion.

Ethical concerns permeate multiple papers as well. Issues of privacy, algorithmic bias, misinterpretation of learner data, depersonalisation, heightened surveillance, inequitable access, and the erosion of teacher roles underscore the risks that arise when adaptive systems are assumed to be inherently beneficial or are misrepresented as personalised. These concerns are tightly linked to the conflation of PL and AL. When automated adaptivity is mistaken for personalisation, stakeholders may underestimate the ethical implications of shifting decision-making power from humans to algorithms.

A further systemic pattern is the prioritisation of efficiency over meaning. Adaptive systems aim to optimise performance progression, accelerate mastery, reduce cognitive load, and respond automatically to learner behaviour. Personalised learning, however, seeks to cultivate meaning, identity, motivation, and empowerment. The ten papers collectively reveal that AI systems overwhelmingly privilege optimisation, often at the expense of the deeper human dimensions of learning. This demonstrates why adaptive systems, though valuable for procedural mastery, cannot fulfil the broader promises of personalised learning without deliberate human-centred design.

Synthesising insights across all ten studies yields four overarching conclusions. First, adaptivity dominates AI-enhanced education. Despite frequent references to "personalised learning," the majority of systems remain fundamentally performance-driven and algorithmically regulated. Second, personalisation is regularly under-theorised. Many authors use the term superficially, defining it simply as "tailoring learning to the individual," thereby permitting vague and ambiguous interpretations. Third, a clear tension exists between what AI systems emphasise and what educators value. AI systems prioritise performance metrics, whereas educators emphasise learner development, agency, and context. This tension fuels continued conflation of the two constructs. Finally, significant ethical and pedagogical risks arise when personalisation is treated as synonymous with adaptivity. These include the loss of learner autonomy, misalignment with educational intentions, marginalisation of teachers, and the depersonalisation of learning experiences.

Overall, the comparative analysis confirms that while AI systems excel at adaptive adjustments, they do not yet embody the holistic, intentional, and relational vision of personalised learning. Mislabelling adaptive systems as personalised masks important conceptual differences and limits the potential for AI to meaningfully support educational equity, human agency, and learner identity.

Theme 5: Ethical, Pedagogical, and Equity Implications of Decoupling Personalised and Adaptive Learning

Adaptive learning systems depend heavily on extensive data collection, including behavioural traces, performance trends, response times, error patterns, clickstream analytics, and in some cases biometric indicators such as motion data in VR-based clinical training. While these data streams enable real-time adaptation, they also introduce significant concerns around privacy, surveillance, and ethical data governance.

One emerging risk is surveillance creep. Systems such as Hu et al.'s (2025) AI-enhanced dental simulations continuously track every movement, decision, and procedural error to improve performance feedback. Although these features support mastery-based progression, they simultaneously expand the level of monitoring to an intensity that exceeds traditional educational norms. Lata (2024) warns that when such adaptivity is misrepresented as personalisation, intrusive data practices are often justified as acts of individual care, masking the fact that such systems primarily optimise performance metrics rather than support learner autonomy or dignity.

e-ISSN 2600-8572 | DOI: https://doi.org/10.11113/itlj.v9.203

Algorithmic bias is another major concern. Studies across the review highlight how adaptive models, when trained on homogeneous datasets, may misinterpret the behaviours of multilingual learners, culturally diverse student populations, or neurodivergent learners. This can lead to unfair labelling, such as categorising learners as "struggling" or "slow", based on culturally insensitive or context-blind metrics. Vorobyeva et al. (2025) emphasise that many adaptive systems are deployed with insufficient attention to cultural diversity, thereby amplifying inequities rather than addressing them.

Compounding these issues is the lack of transparency surrounding data collection and algorithmic decision-making. Learners seldom understand what data is being collected, how it shapes their learning path, or how algorithmic decisions influence progression. This undermines informed consent and reduces learner agency, giving AI systems disproportionate power over educational trajectories.

Decoupling PL from AL reveals a deep set of pedagogical tensions around teacher agency, curriculum design, and the purpose of learning itself. One central concern is the marginalisation of teachers. Several papers describe how adaptive systems automate feedback, pacing, task sequencing, and difficulty regulation. While these automations enhance efficiency, they strip teachers of critical pedagogical roles and reduce opportunities for relational, context-sensitive instruction. Lata (2024) highlights that without intentional personalisation strategies, teachers risk becoming system supervisors rather than pedagogical decision-makers, eroding their professional expertise.

Adaptive systems also risk narrowing the curriculum. Because they optimise for measurable outcomes, they often prioritise procedural mastery over complex domains such as creativity, inquiry, socio-emotional learning, and interdisciplinary thinking. While adaptivity is highly effective in competency-driven domains like dentistry, it is insufficient for learning experiences that require reflection, cultural interpretation, or collaborative meaning-making.
Moreover, adaptivity tends to reduce learning to a pursuit of efficiency. It emphasises faster mastery, minimal cognitive load, and streamlined progression. Yet, education is not merely about efficiency; meaningful learning often requires moments of struggle, uncertainty, exploration, and reflection. When personalisation is reduced to algorithmic optimisation, learning becomes mechanistic rather than transformational.

Equity considerations further underscore the need to separate PL from AL. Adaptive systems require stable connectivity, reliable infrastructure, and updated devices. Learners in low-resource contexts may receive less accurate adaptation or may not receive any adaptation at all. This can lead to widening gaps between resource-rich and resource-poor educational environments. Such outcomes contradict the equity aspirations often attached to the rhetoric of "personalised learning."

Cultural and linguistic bias pose additional threats. When adaptive models are trained on narrow datasets, they may misinterpret or penalise culturally diverse learning behaviours. Neurodivergent learners may also be misread by systems optimised for normative behavioural patterns. Vorobyeva et al. (2025) stress that without culturally aware pedagogical frameworks, any form of adaptive personalisation risks being superficial or even harmful.

A deeper paradox also emerges. While personalisation aims to promote equity by meeting learners where they are, adaptive systems may inadvertently produce personalised inequality. Predictive algorithms can track learners early, narrow their future pathways, and prematurely judge readiness or capability, especially if the system misinterprets signals from disadvantaged learners. Human-mediated personalisation is therefore essential to counterbalance algorithmic determinism and to ensure fairness.

Conceptual Clarification Model: Decoupling Personalised and Adaptive Learning in AI-Enhanced Education

This section presents the conceptual clarification model developed from the synthesis of ten contemporary studies on AI-enhanced learning. The model advances the argument that PL and AL, although frequently intertwined in the literature, represent fundamentally different constructs that must be conceptually separated before they can be meaningfully integrated. This clarification serves as the original theoretical contribution of the review and offers a foundation for educators, instructional designers, technologists, and policymakers working with AI-driven educational systems. The model rests on three core principles. The first is that personalisation and adaptivity are inherently distinct. The second is that they may intersect but should not be collapsed into one another. The third is that effective AI-enhanced learning emerges only when both are orchestrated intentionally rather than assumed to be interchangeable.

The model reframes the relationship between personalisation and adaptivity across four key dimensions, i.e. purpose, core logic, agency, and pedagogical orientation. Examining these dimensions reveals the foundational distinctions between the two constructs. First, personalisation and adaptivity differ in their underlying purpose. Personalised learning emphasises human development, meaning-making, and the cultivation of learner identity, agency, and socio-emotional growth. By contrast, adaptive learning is designed to optimise performance by adjusting content, pacing, and difficulty in response to real-time learner data. Although these purposes can complement one another, they spring from different pedagogical intentions and cannot be treated as equivalent.

Second, the constructs differ in their core logic. Personalised learning is grounded in pedagogical design, relying on educator judgment, relational understanding of learners, and the intentional shaping of learning pathways. Adaptive learning, however, operates on computational logic: algorithmic modelling, rule-based sequencing, and automated behavioural tracking. Personalisation is value-driven, reflecting human interpretation and contextual awareness, while adaptivity is automated and focused on efficiency. This distinction further illustrates why the two constructs must not be conflated.

Third, personalisation and adaptivity diverge in the type of agency they promote. Personalised learning expands learner autonomy by offering choices in pace, modality, goals, and contextual pathways. Adaptive learning, on the other hand, reduces agency by delegating decisions to algorithms that predict and direct the learner's next steps. These different forms of agency shape the learner's experience and influence the ethical implications of AI use in education. They also demonstrate that learner choice and algorithmic control are not interchangeable but represent competing logics that must be intentionally reconciled.

Finally, the pedagogical orientation of the two constructs differs. Personalisation is inherently holistic, integrating cognitive, emotional, cultural, and contextual dimensions of learning. Adaptivity is instrumental and procedural, focused primarily on cognitive mastery and task efficiency. Although both orientations are legitimate, neither is sufficient on its own. AI-enhanced education must recognise, and respect the distinct contributions of each pedagogical stance.

From these distinctions emerges the PAL Matrix (Personalisation–Adaptivity Learning Matrix), a conceptual tool that maps PL and AL across two axes, i.e. the degree of personalisation and the degree of adaptivity. These axes produce four quadrants that reflect the different ways learning environments can be configured (see Figure 1).

e-ISSN 2600-8572 | DOI: https://doi.org/10.11113/itlj.v9.203

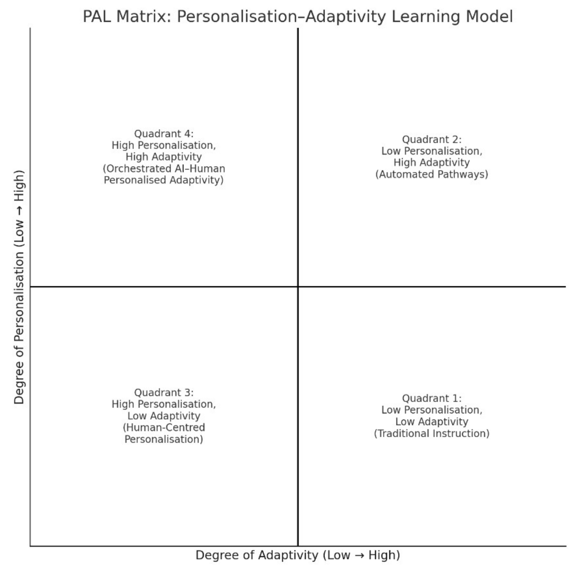

Figure 1. PAL Matrix (Personalisation–Adaptivity Learning Matrix)

The first quadrant, representing low personalisation and low adaptivity, captures traditional instruction characterised by fixed pacing, standardised content, and minimal learner agency. AI plays no meaningful role here.

The second quadrant reflects low personalisation but high adaptivity and represents the majority of current AI systems. Intelligent tutoring systems, AI-driven VR simulations, and multi-agent systems such as AIA-PAL fall into this category. These systems are highly responsive to performance data and automated in their sequencing, but they do not incorporate contextual, cultural, or identity-based dimensions of learning. Although often marketed as "personalised learning," they exemplify adaptivity rather than genuine personalisation.

The third quadrant, high personalisation but low adaptivity, represents human-centred personalised learning environments. These are typically designed by educators who intentionally shape learning pathways through flexible curricula, learner choice, socio-emotional integration, and culturally responsive pedagogy. AI involvement is minimal or absent. This quadrant captures the essence of personalised learning as a deeply contextual, relational, and holistic practice rooted in pedagogical values rather than data-driven automation.

The fourth quadrant, high personalisation and high adaptivity, represents the aspirational future of AI-enhanced education, a space where human-led personalisation is complemented by algorithmic adaptivity. In this configuration, learner agency and data-driven support coexist, teachers maintain oversight, and socio-cultural context informs computational decisions. Although examples of this quadrant are rare today, emerging models such as systems that allow learners to override adaptive recommendations or AI architectures that incorporate identity, goals, and socio-emotional data signal its potential. Achieving this ideal, however, requires intentional design, ethical safeguards, and conceptual clarity about the distinct roles of personalisation and adaptivity.

To explain how PL and AL can operate together without collapsing into each other, the model proposes a decoupling framework consisting of four modes of interaction. In the first mode, adaptivity supports personalisation by providing micro-level adjustments that fit within broader, human-designed personalised learning plans. In the second mode, personalisation constrains adaptivity by setting boundaries and intentions that guide how the adaptive system behaves. The third mode enables human-led overrides of adaptive pathways, where teachers or learners can counteract algorithmic decisions for pedagogical, emotional, or contextual reasons. This mode reinforces the importance of transparency and human oversight. The fourth and most advanced mode is co-constitutive orchestration, where personalisation and adaptivity inform one another dynamically. In this mode, teachers interpret data, learners shape their pathways, and the system adapts in relation to both performance and personal goals. This collaborative mode aligns with the vision of Education 5.0, which emphasises human–AI synergy rather than automation-driven instruction.

Practical integration of PL and AL can be seen in hybrid instructional designs. For example, in blended university courses, teachers may co-design personalised learning objectives with students while adaptive systems provide micro-level adjustments during practice activities. In project-based learning, learners choose inquiry topics and modes of representation (personalisation), while adaptive tools diagnose skill gaps and recommend targeted practice. In professional or technical education, personalised mentoring can be complemented by adaptive simulations that refine procedural accuracy. These examples illustrate how PL and AL can coexist as complementary layers of learning design rather than competing logics.

In summary, PAL Matrix, and the decoupling framework establish a comprehensive way of understanding personalisation and adaptivity as related but fundamentally different constructs. Rather than allowing adaptive technology to overshadow or redefine personalisation, this model positions both as essential components of AI-enhanced education, each contributing its own value when implemented with clarity, intentionality, and respect for human agency. A key limitation of the PAL Matrix, however, is that it remains a conceptual tool that has not yet been empirically validated in authentic learning environments. Its practical usefulness therefore remains theoretical and warrants future empirical investigation.

Conclusion and Recommendations

Artificial intelligence has ushered in a transformative era for education, reshaping how learning is designed, delivered, and experienced. Yet, as AI becomes more deeply embedded in educational ecosystems, it has also amplified a longstanding conceptual ambiguity. This ambiguity concerns the collapse of PL and AL into a single, indistinct construct. This narrative review sought to disrupt that conflation by decoupling the two terms, clarifying their theoretical boundaries, examining their distinct pedagogical and technological logics, and analysing how ten contemporary AI-focused studies operationalise them. Through this process, it became evident that although PL and AL are related, they originate from different traditions, serve different aims, and carry different implications for learners, teachers, institutions, and society.

Personalised learning is fundamentally a human-centred, value-driven educational philosophy. It foregrounds learner identity, autonomy, context, cultural background, and socio-emotional development. Personalisation is intentional, relational, and pedagogically orchestrated. It prioritises the whole learner, not merely the measurable aspects of performance. Meanwhile, adaptive learning is a data-centred computational capability, rooted in algorithmic modelling, performance analytics, and automated decision-making. Adaptivity optimises learning pathways through real-time adjustments, but it does so based on observable behaviour and statistical inference. It does not operate on nuance, context, or learner meaning-making.

The ten reviewed studies overwhelmingly demonstrate that contemporary AI systems are highly advanced in delivering adaptive learning but less capable of achieving authentic personalisation. Multi-agent architectures such as AIA-PAL adjust instruction based on performance, VR simulations personalise clinical practice tasks based on skill metrics, and predictive analytics support targeted recommendations. However, these systems seldom incorporate elements central to genuine personalisation, i.e. learner agency, cultural responsiveness, socio-emotional needs, contextual history, or identity formation. When authors label these systems as "personalised," they unintentionally reinforce conceptual confusion and risk overstating AI's pedagogical capabilities.

This conflation is not simply a semantic issue. It has profound implications. When adaptivity is mistaken for personalisation, learners may experience hidden constraints on autonomy, teachers may lose authority over instructional design, and institutions may adopt technologies under false pedagogical pretences. Ethical risks including surveillance, bias, opacity, and algorithmic determinism, are intensified when adaptivity is disguised as personalised care. Furthermore, equity gaps widen when adaptive systems fail to account for cultural diversity or when infrastructure limitations disproportionally affect marginalised populations.

To address these challenges, this review introduced the PAL Matrix, a conceptual model that situates personalisation and adaptivity along separate, but intersecting axes. This model clarifies four possible configurations, i.e. traditional instruction, automated adaptive pathways, human-led personalisation, and the aspirational quadrant of orchestrated AI–human personalised adaptivity. The most promising future for AI-enhanced education lies in this final quadrant, where human-led personalisation sets the educational intent and scope, while AI-enabled adaptivity provides performance-sensitive support. In this configuration, AI augments rather than replaces human judgement, and learners retain agency through transparent, negotiated control over their learning pathways.

The review also outlined a set of recommendations for designers, educators, policymakers, and researchers. Collectively, these recommendations argue for (1) precise terminology in product design and academic writing; (2) AI architectures that include learner identity, goals, culture, and context, and not only performance data; (3) teacher-led override systems and learner choice mechanisms; (4) ethically grounded design practices that protect privacy, mitigate bias, and prevent algorithmic overreach; and (5) more advanced theoretical and empirical work to develop holistic models of learning that integrate personalisation and adaptivity without collapsing them.

Ultimately, the narrative review calls for a paradigm shift, i.e. AI should not be seen as the engine of personalisation but as a partner that supports human-led personalisation. While algorithms excel at detecting performance patterns and adjusting content dynamically, they cannot intuit the emotional, cultural, or existential dimensions of learning. They cannot replace the relational role of teachers or the agency of learners in shaping their educational journey. As AI continues to evolve, its integration into education must remain grounded in pedagogical intention, ethical responsibility, cultural sensitivity, and a commitment to human dignity.

By decoupling personalised learning from adaptive learning, this review restores conceptual coherence, safeguards educational values, and charts a path toward a future where AI contributes meaningfully, yet humbly to empowering learners. The future of AI-enhanced education lies not in replacing the human with the machine, but in designing systems where human meaning-making and machine intelligence coexist in balanced, transparent, and equitable ways. Only then can the promise of AI be realised without compromising the essence of education.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Acknowledgment

We would like to thank Open University Malaysia for their support throughout the research process.

References

du Plooy, E., Casteleijn, D., & Franzsen, D. (2024). Personalized adaptive learning in higher education: A scoping review of key characteristics and impact on academic performance and engagement. *Heliyon*, *10*(21). e39630. https://doi.org/10.1016/j.heliyon.2024.e39630

Hedi, T., Nouzri, S., Mualla, Y., & Abbas-Turki, A. (2025). Artificial intelligence agents for personalized adaptive learning. *Procedia Computer Science*, *265*, 252-259. https://doi.org/10.1016/j.procs.2025.07.179

Hu, C., Li, F., Wang, S., Gao, Z., Pan, S., & Qing, M. (2025). The role of artificial intelligence in enhancing personalized learning pathways and clinical training in dental education. *Cogent Education*, *12*(1), 2490425. https://doi.org/10.1080/2331186X.2025.2490425

Iqbal, M. (2023). AI in education: Personalized learning and adaptive assessment. *Cosmic Bulletin of Business Management*, *2*(1), 280-297.

Lata, P. (2024). Beyond algorithms: Humanizing artificial intelligence for personalized and adaptive learning. *International Journal of Innovative Research in Engineering and Management*, *11*(5), 40-47. https://doi.org/10.55524/ijirem.2024.11.5.6

Li, K. C., & Wong, B. T. M. (2023). Artificial intelligence in personalised learning: a bibliometric analysis. *Interactive Technology and Smart Education*, *20*(3), 422-445. https://doi.org/10.1108/ITSE-01-2023-0007

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. https://doi.org/10.1111/bjet.13116

Merino-Campos, C. (2025). The impact of artificial intelligence on personalized learning in higher education: A systematic review. *Trends in Higher Education*, *4*(2), 17. https://doi.org/10.3390/higheredu4020017

Sajja, R., Sermet, Y., Cikmaz, M., Cwiertny, D., & Demir, I. (2024). Artificial intelligence-enabled intelligent assistant for personalized and adaptive learning in higher education. *Information*, *15*(10), 596. https://doi.org/10.3390/info15100596

Vorobyeva, K. I., Belous, S., Savchenko, N. V., Smirnova, L. M., Nikitina, S. A., & Zhdanov, S. P. (2025). Personalized learning through AI: Pedagogical approaches and critical insights. *Contemporary Educational Technology*, *17*(2). ep574. https://doi.org/10.30935/cedtech/16108