US JOURNAL OF NEW INSIGHTS IN TECH & EDUCATION

Vol 3, No. 2 · Article ID: USJNITE-2303 · Journal Homepage: www.edtechinsights.org

Designing Smart Learning Environments for Personalized Education: Investigating the Influence of Adaptive Technologies on Student Learning Experiences

MD Shahadat Hossain Shishir[1], Md Rasel Ul Alam [2], Md. Farhan Islam Alvi [3]

[1]*World University of Bangladesh, Dhaka, Bangladesh*

[2] *University of the Cumberlands, Kentucky, USA*

[3]*Jagannath University, Dhaka, Bangladesh*

**Corresponding author:* shahadatdaf20@gmail.com

Received: 20 July 2023; Revised: 20 September 2023; Accepted: 26 October 2023; Published: 12 November 2023

KEYWORDS

Smart learning
Personalized education
Adaptive learning
Learning analytics
Intelligent tutoring
Student engagement
Learner modelling
Artificial intelligence

Abstract

The rapid integration of artificial intelligence, learning analytics, intelligent tutoring, adaptive assessment, and connected learning technologies is reshaping higher education learning environments. However, the literature often treats smart learning environments, adaptive technologies, personalized learning, and student experience as separate research streams. This paper integrates these perspectives by identifying five recurring mechanisms: smart-environment infrastructure, learner modelling, adaptive content and assessment, feedback and visualization, and learner agency and self-regulation. The synthesis indicates that adaptive systems are most consistently associated with improved learning fit, engagement, self-regulation, and perceived usefulness when adaptation is timely, interpretable, and connected to meaningful learning tasks. However, technology alone does not guarantee better learning experiences; outcomes depend on how learner data inform pedagogical decisions, the degree of learner control, instructor involvement, and attention to privacy, transparency, and equity. Based on these findings, the paper proposes the Smart Personalized Learning Experience Framework (SPLEF), which models a pathway from smart-environment capabilities through adaptive technologies and personalization quality to learner processes and learning experience outcomes. The framework provides a design-oriented basis for advancing learner-centred, data-informed, adaptive, and ethically governed personalization in higher education.

1. Introduction

Technology-supported education is moving from delivery-oriented digital platforms toward environments that can observe learners, interpret learning data, and adjust instructional experiences. The shift matters because higher education increasingly serves learners who differ in prior knowledge, pace, motivation, disciplinary background, digital confidence, and preferred ways of interacting with learning resources. A smart learning environment (SLE) is therefore not simply a classroom with more technology; it is an ecosystem in which digital systems, learning spaces, data, and pedagogical processes are coordinated to support context-aware and learner-responsive learning. Foundational work on SLEs emphasizes this integration of intelligent technologies, learner information, feedback, and context-sensitive support (Peng et al., 2019; García-Tudela et al., 2021; Demir, 2021).

Personalized education extends this logic by asking how instruction can be systematically adapted to individual learners rather than merely offered in multiple formats. Tetzlaff et al. (2021) conceptualize personalization as dynamic adaptation of instructional conditions to changing learner states, while Shemshack and Spector (2020) show that the literature has used personalized, individualized, customized, and adaptive learning as overlapping but not identical terms. The distinction is important for design. Personalization is the educational objective; adaptive technologies are a mechanism through which that objective can be operationalized; and the smart learning environment provides the infrastructure and context through which adaptation occurs.

Empirical research supports the value of adaptive components but also reveals important conditions. Adaptive formative assessment can improve learning performance and engagement when question selection and memory support respond to learner knowledge (Yang et al., 2022). Personalized self-regulated online learning has produced stronger learning gains than conventional self-regulated online learning, while learner attitudes predict continued use (The use of a personalized learning approach..., 2022). Automated data-driven feedback can personalize pedagogical interventions in intelligent tutoring systems, reducing reliance on manually authored rules (Kochmar et al., 2022). Learning analytics dashboards can change online study behaviour, although effects on final performance are not guaranteed (Hellings & Haelermans, 2022). These findings imply that the educational value of adaptation depends on the chain linking data, algorithmic decisions, learner perception, and learning activity.

The student experience dimension is especially important. A system may be technically adaptive yet feel intrusive, confusing, overly prescriptive, or irrelevant to learners. Conversely, a relatively simple adaptive feature may produce a strong learning experience when it makes progress visible, provides actionable feedback, and allows learners to understand why a recommendation has been made. Work on open learner models and visualization shows that transparent representations of learner progress can support self-regulation and behavioural change (Ferreira et al., 2019; Sun et al., 2023). Studies of adaptive learning perceptions likewise suggest that university students distinguish between the existence of adaptive features and their usefulness for actual learning. In other words, “smartness” should be judged through the quality of the learning experience it enables, not only through the sophistication of the underlying algorithm.

This paper addresses that problem by integrating the literature on SLEs, adaptive technologies, learner modelling, learning analytics, artificial intelligence, self-regulation, and student experience. The paper makes three contributions. First, it provides a structured synthesis of 31 open-access studies published no later than 2023, with four studies from the US Journal of New Insights in Tech & Education included as part of the evidence base. Second, it identifies cross-study mechanisms that explain how adaptive technologies can influence personalized learning experiences. Third, it proposes the Smart Personalized Learning Experience Framework (SPLEF), a design-oriented framework linking environmental capabilities, adaptive technologies, personalization quality, learner processes, and experience outcomes.

The remainder of the paper is organized as follows. Section 2 reviews the conceptual and empirical literature. Section 3 explains the structured review method. Section 4 presents the thematic synthesis. Section 5 develops SPLEF and its propositions. Section 6 translates the framework into design principles and an implementation roadmap. Section 7 discusses theoretical and practical implications, followed by limitations, future research, and conclusion.

2. Literature Review

2.1 Smart Learning Environments as the Context for Personalization

Peng et al. (2019) place personalized adaptive learning within a smart learning environment and argue that intelligent technologies make it possible to adjust instruction around learner characteristics and learning states. García-Tudela et al. (2021) similarly emphasize that an SLE needs an explicit conceptual structure linking technological capabilities to educational practice. Demir (2021) expands the perspective to a broader smart education framework, highlighting the role of interconnected information technologies in transforming educational processes. Benita et al. (2021) further Illustrate the ecosystem perspective through an IoT-based learning environment in STEM education, where data and connected devices support richer learning activities.

The literature therefore suggests four core environmental capabilities: connectivity and interoperability; data capture and learner modelling;

context awareness; and mechanisms for feedback and adaptation. Technology-enhanced assessment visualization adds a fifth capability: open representation of learner state. Ferreira et al. (2019) show how student models and visualization can support both learner self-regulation and teacher oversight. Together, these studies position the SLE as a coordination layer in which learner data are converted into pedagogical opportunities. The environment is "smart" when these components operate together around learning goals rather than simply because many devices or AI functions are present.

Figure 1. Smart learning environment architecture synthesized from the reviewed literature. The framework emphasizes that smart infrastructure becomes educationally meaningful only when learner data and adaptive intelligence are connected to a personalized learning experience.

2.2 Personalized Education and Adaptive Technologies

Shemshack and Spector (2020) demonstrate why terminology matters: personalized learning is frequently used as an umbrella concept that overlaps with adaptive learning, individualized instruction, and customized learning. Tetzlaff et al. (2021) provide a dynamic view in which personalization is responsive to changing learner characteristics and instructional conditions. This dynamic orientation is consistent with Bayounes et al. (2022), who argue that adaptive learning guidance should consider learner motivation and learning intentions rather than only performance indicators. Smyrnova-Trybulska et al. (2022) add a learner-perception perspective, showing that student opinions are an important part of understanding adaptive learning in university settings.

Adaptive technologies vary in how they make personalization operational. Adaptive assessment changes item selection in response to estimated knowledge; intelligent tutoring systems adapt hints, tasks, and feedback; recommendation systems select learning resources; learning analytics systems surface patterns and risk indicators; and open learner models show students representations of their own progress. Yang et al. (2022) Demonstrate the value of adaptive formative assessment by combining computerized adaptive testing with a learning memory cycle. Christodoulou and Angeli (2022) show how an adaptive educational environment can improve learning outcomes by tailoring scenarios to learner needs. Kochmar et al. (2022) demonstrate a machine-learning approach to generating personalized pedagogical interventions. Across these studies, personalization is strongest when adaptation is tied to a clear pedagogical mechanism and a measurable learning need.

Figure 2. Adaptive personalization cycle. The reviewed studies collectively point to a recurring loop in which systems observe learner signals, model learner state, adapt instruction, receive learner responses, and use reflection or feedback to update subsequent support.

2.3 Learning Analytics, Learner Modelling, and Feedback

Learning analytics provides a data layer for personalization. Ifenthaler and Yau (2020) show that analytics can support study success through monitoring, prediction, and intervention, while Blumenstein (2020) emphasizes that analytics are most valuable when aligned with learning design. Hellings and Haelermans (2022) provide experimental evidence that learner-facing analytics can improve behaviour in online study, although their study did not find a corresponding overall effect on final exam performance. This is an important caution: data visibility can change behaviour without automatically producing deeper learning, so analytics must be pedagogically integrated.

Predictive learning analytics can support early intervention and personalization. Pérez Sánchez et al. (2022) demonstrate that learning-platform features can be extracted and modelled to predict student performance. Fang et al. (2022) show how interaction patterns in an intelligent tutoring system can be clustered to reveal different learner behaviours, enabling more targeted pedagogical adaptation. Sun et al. (2023) connect open learner modelling and AI-enabled visualization with self-regulated learning strategies and behavioural patterns. These studies reinforce the idea that learner modelling should not be treated as a background technical component; it directly shapes the decisions students and instructors receive.

2.4 Artificial Intelligence, Smart Classrooms, and the Learner Experience

AI expands personalization beyond rule-based branching. Zawacki-Richter et al. (2019) identified a growing set of AI applications in higher education, including profiling and prediction, assessment and evaluation, adaptive systems, and intelligent tutoring. Chen et al. (2020) mapped the broader AI-in-education landscape and highlighted the diversity of technical and pedagogical applications. Hwang and Tu (2021) similarly show how AI-related techniques are being applied to learning and teaching processes, while Crompton and Burke (2023) confirm that AI in higher education encompasses a wide range of functions with different pedagogical implications.

Dimitriadou and Lanitis (2023) add an important critical perspective. Smart classrooms can use AI and emerging technologies to automate assessment, support classroom management, and enrich teaching aids, but the implementation problem is not simply technological. The learning environment must remain usable, pedagogically relevant, and ethically governed. The same principle appears in the four USJNITE studies included in this review. Haider et al. (2021a) emphasize online engagement and digital equity; Haider et al. (2021b) review AI applications and their associated challenges; Haider et al. (2022a) illustrate how computer vision can support classroom engagement monitoring; and Haider et al. (2022b) examine generative AI as an emerging transformation opportunity alongside its risks. Together, these studies support a balanced interpretation: intelligent technology can extend the capacity of learning environments, but educational value depends on how it is embedded in learning design and governance.

2.5 Student Learning Experiences as the Outcome

Across the literature, learning experience emerges as a multidimensional outcome rather than a single attitude measure. The reviewed studies repeatedly refer to engagement, motivation, satisfaction, self-regulation, perceived usefulness, confidence, persistence, and learning gains. Gambo and Shakir (2021) identify self-regulated learning as a critical element of smart learning environments and highlight goal setting, help seeking, time management, and self-evaluation. The personalized self-regulated learning study (2022) found that attitude toward the learning environment was a strong predictor of continued use. Adaptive learning perceptions (Smyrnova-Trybulska et al., 2022) and technology-use experiences (Sage et al., 2021) likewise indicate that learner views should inform technology and environment design.

An important synthesis follows: personalization should be evaluated at two levels. The first is functional personalization—whether the system actually changes content, pace, assessment, or feedback based on learner information. The second is experiential personalization—whether learners perceive the resulting experience as relevant, controllable, understandable, and supportive of their learning goals. The second level helps explain why technically adaptive systems can have mixed effects: learners need to recognize value in the adaptation and retain enough agency to use it productively.

3. Review Method

This study uses a structured integrative literature-review design. The purpose is not to estimate a pooled effect size but to synthesize mechanisms that recur across research on smart learning environments, adaptive technologies, personalized education, learning analytics, and student learning experiences. The evidence base consists of 31 open-access studies published from 2019 through 2023. The set was assembled from the previously screened literature for this study and was supplemented with four US Journal of New Insights in Tech & Education papers selected by the author for direct thematic relevance. Studies published after 2023 were excluded from the formal evidence base in accordance with the study cutoff.

The analysis followed four stages: (1) topic and relevance screening; (2) extraction of each study's dominant technology, learning function, learner outcome, and implementation concern; (3) primary thematic coding; and (4) cross-study synthesis into design mechanisms and a conceptual framework. The primary thematic categories were smart-learning-environment foundations, personalization and adaptivity, learning analytics and learner modelling, AI/intelligent tutoring in higher education, and applied educational-technology studies from USJNITE. Because individual studies can address multiple themes, the categories are used as organizing roles rather than mutually exclusive methodological classes.

The review deliberately gives greater interpretive weight to studies that are empirical or systematic and that explain a mechanism connecting technology to learning. Conceptual and framework papers are used to define architecture and design principles, while empirical studies are used to identify observed or tested effects. This distinction prevents the framework from treating technical capability as equivalent to educational impact. Figures 7–11 are explicitly conceptual or schematic visualizations used to make the synthesis and propositions easier to inspect; they are not presented as new empirical results.

Figure 3. Structured review and framework-development workflow used in this study. The process was designed to separate evidence screening from interpretive framework construction

4. Findings and Cross-Study Synthesis

4.1 Evidence Distribution

The 31-study corpus is distributed across five primary thematic roles. Smart learning environment foundations constitute the largest infrastructure-oriented cluster, while personalization and adaptivity form the largest mechanism-oriented cluster. Learning analytics and learner modelling provide the data and decision layer, AI/ITS studies provide intelligent-intervention evidence, and the four USJNITE studies broaden the evidence to engagement, equity, classroom monitoring, and generative AI.

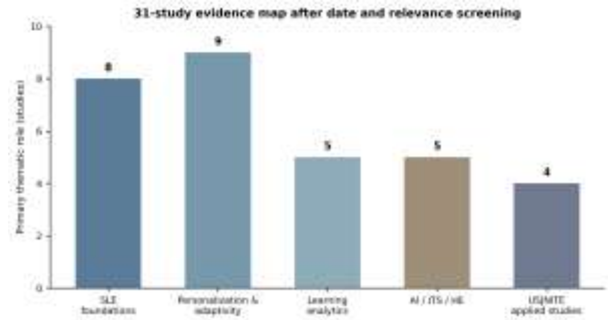

Figure 4. Primary thematic distribution of the 31-study evidence base. Categories were assigned according to the dominant contribution each study makes to the present synthesis

4.2 Mechanism 1: Learner Modelling Converts Data into Adaptation

A consistent mechanism across the evidence is the movement from raw learner signals to an interpretable learner state. Smart environments capture performance, behavioural, and contextual signals; learner models organize those signals; and adaptive engines use the resulting state to select subsequent actions. Peng et al. (2019), Ferreira et al. (2019), Fang et al. (2022), Pérez Sánchez et al. (2022), and Sun et al. (2023) each contribute different pieces of this process. The implication is that the quality of personalization is constrained by the quality, relevance, and interpretation of learner data. A system that collects more data is not necessarily more personalized if its learner model does not translate those data into pedagogically meaningful decisions.

4.3 Mechanism 2: Adaptation Works Best When It Changes the Learning Task

The strongest empirical examples alter what the learner actually does: they select questions, change learning paths, tailor feedback, recommend resources, or provide differentiated support. Yang et al. (2022) adapt formative assessment around knowledge and retention; Kochmar et al. (2022) generate personalized interventions; Christodoulou and Angeli (2022) tailor learning scenarios; and the personalized self-regulated learning study (2022) changes learning paths and materials. This evidence suggests that personalization is more meaningful when it modifies instructional action rather than only displaying personalized analytics.

4.4 Mechanism 3: Feedback Is the Bridge Between Adaptation and Experience

Adaptive decisions become part of the student experience through feedback. Visualization, open learner models, dashboards, and system-generated explanations help learners interpret the system's view of their progress. Ferreira et al. (2019) show how assessment visualization can support study behaviour, while Sun et al. (2023) connect AI-enabled visualization to self-regulation. The review therefore treats feedback quality as a central design variable: feedback should be timely, specific, actionable, and comprehensible, and where possible it should explain why a recommendation or adjustment occurred.

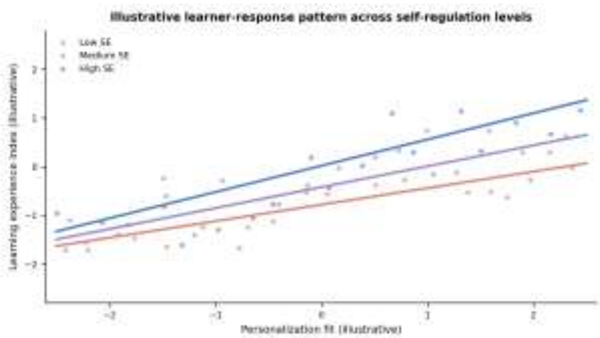

Figure 5. Illustrative relationship chart styled to visualize how higher personalization fit could be experienced differently across low-, medium-, and high-self-regulation learners. The plotted points and lines are schematic only and do not represent empirical estimates.

4.5 Mechanism 4: Learner Agency Moderates the Value of Adaptation

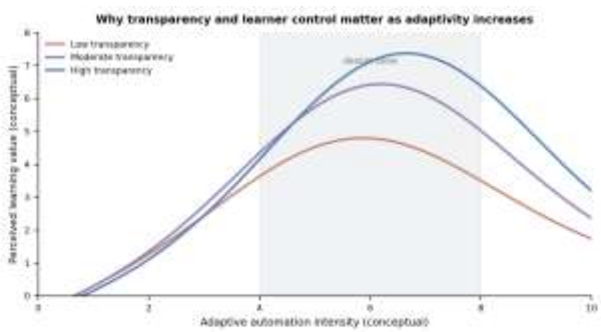

Figure 6. Conceptual adaptation-agency chart. The figure illustrates the review's proposition that increasing automation does not guarantee greater learning value unless transparency and learner control remain strong. The curves are conceptual, not empirical.

The reviewed literature repeatedly implies that personalization should not become automated prescription. Motivation-sensitive adaptation (Bayounes et al., 2022), self-regulation research (Gambo & Shakir, 2021), student opinions of adaptive learning (Smyrnova-Trybulska et al., 2022), and learner-facing analytics (Hellings & Haelermans, 2022) all point toward the importance of learner participation. Students should be able to inspect progress, understand options, override inappropriate recommendations where feasible, and contribute preferences or goals. Agency is therefore treated as a mechanism that converts adaptive capability into meaningful engagement rather than as a cosmetic user-interface feature.

4.6 Mechanism 5: Governance Shapes Trust, Equity, and Sustainability

AI and smart-classroom research also highlights limits that cannot be solved by better algorithms alone. The four USJNITE papers emphasize digital equity, AI opportunities and challenges, automated monitoring, and generative-AI risks (Haider et al., 2021a, 2021b, 2022a, 2022b). Dimitriadou and Lanitis (2023) similarly identify implementation and emerging-technology challenges in smart classrooms. The synthesis indicates that privacy, explainability, bias monitoring, data minimization, and instructor oversight are not external compliance issues; they affect whether students trust and use personalized systems. Governance is therefore included as a condition surrounding the full SPLEF pathway rather than as a post-implementation audit.

Table 1. Core evidence clusters and design signals

Evidence cluster	Representative studies	Design signal
SLE foundations	Peng et al. (2019); García-Tudela et al. (2021); Demir (2021); Benita et al. (2021)	Integrate infrastructure, context, data, and pedagogy.
Personalization & adaptivity	Shemshack & Spector (2020); Tetzlaff et al. (2021); Bayounes et al. (2022); Yang et al. (2022)	Adapt learning tasks, pathways, and support to learner state.
Analytics & learner modelling	Ifenthaler & Yau (2020); Hellings & Haelermans (2022); Pérez Sánchez et al. (2022); Sun et al. (2023)	Translate learner data into interpretable, actionable signals.
AI / ITS / HE	Zawacki-Richter et al. (2019); Chen et al. (2020); Kochmar et al. (2022); Crompton & Burke (2023)	Use AI to augment, not replace, pedagogical decision making.
USJNITE applied studies	Haider et al. (2021a, 2021b, 2022a, 2022b)	Balance engagement, equity, monitoring, opportunity, and risk.

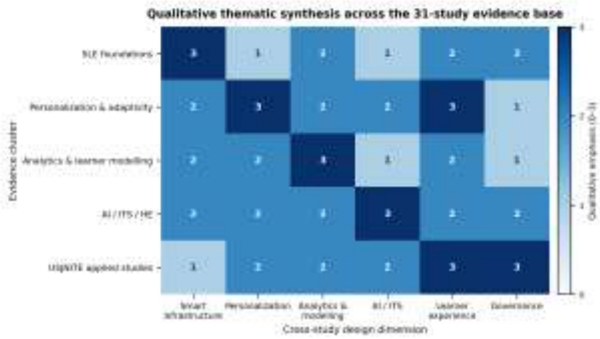

Figure 7. Qualitative thematic synthesis matrix showing where the reviewed evidence is most concentrated across smart infrastructure, personalization, analytics, AI/ITS, learner experience, and governance. Values represent qualitative coding emphasis for synthesis purposes, not effect sizes.

5. Smart Personalized Learning Experience Framework (SPLEF)

The evidence synthesis supports a framework in which adaptive technologies are not the endpoint. They are the middle layer connecting smart-environment capabilities to learner experience. SPLEF proposes a five-part pathway: (1) SLE capabilities provide the data, connectivity, and context; (2) adaptive technologies transform learner information into instructional adjustments; (3) personalization quality captures whether those adjustments are relevant, timely, transparent, and controllable; (4) learner processes describe the cognitive and motivational response, including self-regulation and engagement; and (5) learning experience represents proximal outcomes such as satisfaction, perceived effectiveness, confidence, and sustained participation.

Figure 8. Smart Personalized Learning Experience Framework (SPLEF). The model integrates infrastructure, adaptive intelligence, personalization quality, learner processes, and student experience while surrounding the pathway with governance conditions.

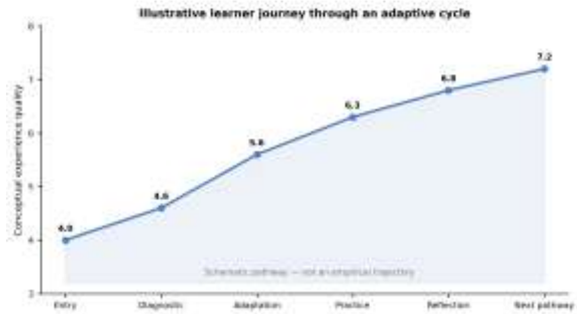

Figure 9. Illustrative learner journey through an adaptive cycle, showing how diagnostic information, adaptive support, practice, reflection, and the next learning pathway can form a continuous experience. The trajectory is schematic rather than empirical.

5.1 Framework Constructs

- SLE capabilities: connectivity, interoperability, context awareness, learner-data capture, visualization, and system integration.
- Adaptive technology quality: learner-model accuracy, adaptive content selection, assessment adaptivity, recommendation relevance, feedback specificity, and adaptation timeliness.
- Personalization quality: perceived fit to learner needs, relevance to current goals, transparency of recommendations, pacing appropriateness, and learner control.
- Learner processes: self-regulation, autonomy, motivation, persistence, cognitive engagement, and strategic help seeking.
- Learning experience outcomes: engagement, satisfaction, perceived learning effectiveness, confidence, continued-use intention, and perceived learning gains.
- Governance conditions: privacy, equity, explainability, accessibility, responsible monitoring, instructor scaffolding, and institutional policy.

5.2 Propositions

P1. Stronger smart-learning-environment capabilities enable more effective adaptive personalization because they increase the availability and integration of relevant learner information.

P2. Higher-quality learner modelling and adaptive decision making improve personalization quality by increasing the fit and timeliness of content, assessment, and feedback.

P3. Personalization quality positively influences learner self-regulation and engagement because learners can more easily connect learning activities with their needs and goals.

P4. Learner agency and transparency strengthen the relationship between adaptive technology quality and learning experience; adaptation that is opaque or overly prescriptive is less likely to be experienced as supportive.

P5. Engagement, self-regulation, and perceived usefulness function as proximal pathways through which personalized experiences contribute to perceived learning effectiveness and sustained participation.

P6. Privacy, equity, explainability, and instructor scaffolding condition the sustainability of personalized learning by shaping trust, accessibility, and appropriate use of adaptive recommendations.

Table 2. SPLEF constructs and suggested indicators

Construct	Suggested indicators	Illustrative evidence base
Adaptive technology quality	accuracy; feedback specificity; adaptivity; pacing; recommendation relevance	Peng et al.; Kochmar et al.; Yang et al.
Personalization quality	relevance; fit; transparency; learner control; goal alignment	Shemshack & Spector; Tetzlaff et al.; Smyrnova-Trybulska et al.
Learner process	self-regulation; autonomy; motivation; persistence; cognitive engagement	Gambo & Shakir; Bayounes et al.; Sun et al.
Learning experience	engagement; satisfaction; confidence; perceived effectiveness; continued use	Hellings & Haelermans; Haider et al.; Christodoulou & Angeli
Governance	privacy; equity; explainability; instructor oversight; accessibility	Dimitriadou & Lanitis; Haider et al.; Crompton & Burke

6. Design Principles for Smart Personalized Learning

6.1 Design for Pedagogical Adaptation, Not Algorithmic Novelty

The literature suggests that institutions should begin with instructional problems before selecting adaptive technologies. Adaptive assessment, learner models, recommendations, and feedback are useful because they alter a learning task or support a learning decision. Therefore, design teams should define the learning objective, identify the decision that needs to adapt, specify the learner signal required, and only then select the algorithmic approach. This sequence reduces the risk of deploying technically sophisticated systems that do not improve the learning task.

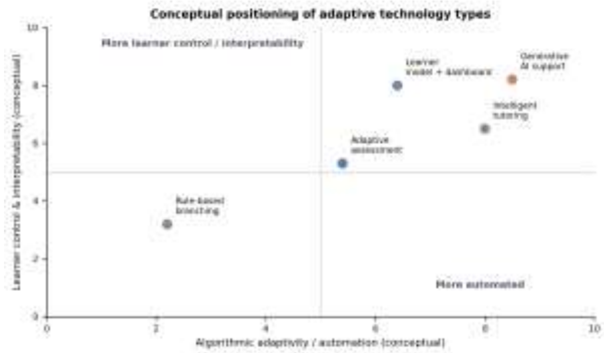

Figure 10. Conceptual positioning of technology types along two design dimensions: algorithmic adaptivity/automation and learner control/interpretability. The placement is a synthesis aid rather than an empirical ranking.

6.2 Make Adaptation Visible and Interpretable

Learner-facing visualization is a recurring strength in the literature. When students can see progress, predicted status, or reasons for recommendations, they can use the information for self-regulation rather than simply receiving automated decisions. Open learner models and analytics dashboards are therefore valuable not only as monitoring tools but also as pedagogical interfaces. Explanations should use accessible language, show actionable next steps, and avoid presenting predictions as fixed judgments.

6.3 Preserve Learner Agency

Personalization should include configurable boundaries. Students should have opportunities to set goals, express preferences, review recommendations, and override or question an adaptation when appropriate. This is especially important in higher education, where the educational objective includes developing independent learning capacity. A system that always decides for the student may optimize short-term task completion while weakening the development of self-regulation.

6.4 Keep Teachers in the Loop

Adaptive systems should augment instructors rather than make pedagogical decisions invisible. Analytics and learner models can help instructors identify patterns, but teachers need contextual information to decide whether an intervention is appropriate. The reviewed literature supports a division of labour in which systems monitor, model, recommend, and personalize while instructors interpret, scaffold, motivate, and exercise professional judgment.

6.5 Treat Equity and Privacy as Design Variables

Personalization can reproduce inequity when systems rely on incomplete or biased data, require devices or connectivity that some learners cannot access, or infer motivation and ability from behaviour without context. The evidence from digital-equity discussions and AI-in-education reviews suggests that institutions should monitor differential access, prediction error, recommendation quality, and unintended consequences across learner groups. Privacy safeguards should follow data minimization and purpose limitation, with meaningful communication about what data are collected and how they affect learning experiences.

Figure 11. Implementation roadmap for institutions moving from technology adoption to sustainable personalized learning. Evaluation is continuous and includes both learner experience and governance indicators.

7. Discussion

The central finding of this synthesis is that adaptive technology influences student learning experiences through an intermediate chain rather than through direct technological exposure. Smart learning environments provide the infrastructure, learner modelling makes student state actionable, adaptive technologies modify instruction, and personalization quality determines whether those modifications are experienced as relevant and supportive. Learner processes then convert the experience into engagement, self-regulation, persistence, and perceived learning effectiveness. This structure reconciles apparently mixed findings in the literature: adaptive technologies can be effective, but effectiveness is mediated by design quality and learner response.

The framework also extends conventional discussions of personalized learning by separating functional adaptivity from experiential personalization. A platform can change content based on learner performance and still provide a poor learning experience if the recommendations are opaque, poorly timed, or disconnected from learner goals. Conversely, even a moderate level of adaptivity can be valuable if the learner sees why the adjustment occurred and can use it to regulate learning. This distinction suggests that future empirical studies should measure both system-level adaptation and student-level perceptions rather than treating “adaptive learning use” as a single variable.

The inclusion of the four USJNITE studies strengthens the contextual breadth of the synthesis. The 2021 technology-enhanced learning review links digital learning technologies with student engagement and digital equity; the 2021 AI review places AI applications within broader opportunities and challenges; the 2022 computer-vision study illustrates automated monitoring for classroom engagement; and the 2022 generative-AI review highlights transformative possibilities alongside risks. These studies suggest that smart personalized environments will increasingly combine multiple forms of intelligence—analytics, computer vision, recommender logic, language models, and adaptive assessment. The challenge is to integrate them into a coherent pedagogical system rather than assemble disconnected AI features.

The framework also has implications for research design. The literature includes systematic reviews, conceptual models, quasi-experiments, randomized experiments, learner-log analyses, and predictive modelling. No single method captures the full phenomenon. Future studies should therefore use mixed-method or multimodal designs in which system telemetry, learner perceptions, learning outcomes, and instructor observations are analysed together. Longitudinal designs are particularly important because personalization is inherently dynamic: an intervention may be useful at one point in a course and unnecessary or counterproductive at another.

8. Theoretical and Practical Implications

8.1 Theoretical Implications

The paper contributes an integrative model that connects SLE theory, personalized education, adaptive technology, learning analytics, self-regulated learning, and AI in higher education. Rather than treating these as parallel literatures, SPLEF specifies how they fit together as layers of one learning system. The framework also introduces personalization quality as an intermediate construct between adaptive technology and learner experience, highlighting the importance of relevance, transparency, timeliness, and control.

8.2 Practical Implications

For institutions, the framework suggests a phased approach: diagnose learner needs, instrument the environment, deploy targeted adaptive functions, strengthen learner and instructor control, and evaluate both outcomes and governance conditions. For instructional designers, the recommendation is to define the adaptation decision before selecting the technology. For platform developers, the priority is interpretable adaptation, actionable feedback, and flexible learner control. For instructors, analytics should be positioned as decision support rather than automated judgment.

9. Limitations and Future Research

This study is an integrative review rather than a meta-analysis, so it does not estimate a single pooled effect of adaptive technologies. The 31-paper corpus was purposefully assembled around topical relevance and open access, which may exclude relevant studies behind paywalls or studies using different terminology. The thematic counts shown in Figure 4 are organizing devices rather than estimates of the size or quality of the underlying evidence.

The framework should also be empirically validated. A useful next step is to operationalize SPLEF as a multi-construct survey and learner-telemetry model, then test it with PLS-SEM or covariance-based SEM using real student data. Longitudinal studies should examine how personalization quality changes over time and whether learner agency, prior knowledge, digital literacy, and instructor scaffolding moderate effects. Experimental comparisons between transparent versus opaque adaptive systems would be especially valuable for testing the role of explainability and trust.

Finally, future research should examine the equity dimension directly. Smart environments can personalize access and support, but they can also reproduce existing differences if data quality, device access, language support, or algorithmic performance vary across groups. Cross-institutional and cross-cultural studies are needed to determine which elements of SPLEF are broadly transferable and which must be locally calibrated.

10. Conclusion

Smart learning environments create the conditions for personalized education, but adaptive technologies alone do not determine the quality of the resulting learning experience. The 31 open-access studies reviewed in this paper converge on a more nuanced pathway: learning environments capture and organize learner information; adaptive technologies use that information to modify learning tasks; personalization quality determines whether those modifications fit learner needs and goals; and learner processes convert the experience into engagement, self-regulation, persistence, and perceived learning effectiveness. The proposed Smart Personalized Learning Experience Framework brings these mechanisms together and positions governance, transparency, equity, and instructor scaffolding as conditions for sustainable implementation. The framework can guide future empirical research and practical design work aimed at moving higher education from technology adoption toward learner-centred, adaptive, and ethically governed smart learning environments.

References

Bayounes, W., Bayoudh Saâdi, I., & Kinshuk. (2022). Adaptive learning: Toward an intentional model for learning process guidance based on learner's motivation. Smart Learning Environments, 9, 33. https://doi.org/10.1186/s40561-022-00215-9

Benita, F., Virupaksha, D., Wilhelm, E., & Tunçer, B. (2021). A smart learning ecosystem design for delivering Data-driven Thinking in STEM education. Smart Learning Environments, 8, 11. https://doi.org/10.1186/s40561-021-00153-y

Blumenstein, M. (2020). Synergies of learning analytics and learning design: A systematic review of student outcomes. Journal of Learning Analytics, 7(3), 13–32. https://doi.org/10.18608/jla.2020.73.3

Chen, X., Xie, H., & Hwang, G.-J. (2020). A multi-perspective study on artificial intelligence in education: Grants, conferences, journals, software tools, and research topics. Computers and Education: Artificial Intelligence, 1, 100005.

Christodoulou, A. C., & Angeli, C. (2022). Adaptive learning techniques for a personalized educational software in developing teachers' technological pedagogical content knowledge. Frontiers in Education, 7, 789397. https://doi.org/10.3389/feduc.2022.789397

Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: The state of the field. International Journal of Educational Technology in Higher Education, 20, 22. https://doi.org/10.1186/s41239-023-00392-8

Del Olmo-Muñoz, J., González-Calero, J. A., Diago, P. D., et al. (2023). Intelligent tutoring systems for word problem solving in COVID-19 days: Could they have been (part of) the solution? ZDM–Mathematics Education, 55, 35–48. https://doi.org/10.1007/s11858-022-01396-w

Demir, K. A. (2021). Smart education framework. Smart Learning Environments, 8, 29. https://doi.org/10.1186/s40561-021-00170-x

Dimitriadou, E., & Lanitis, A. (2023). A critical evaluation, challenges, and future perspectives of using artificial intelligence and emerging technologies in smart classrooms. Smart Learning Environments, 10, 12. https://doi.org/10.1186/s40561-023-00231-3

Fang, Y., Lippert, A., Cai, Z., Chen, S., Frijters, J. C., Greenberg, D., & Graesser, A. C. (2022). Patterns of adults with low literacy skills interacting with an intelligent tutoring system. International Journal of Artificial Intelligence in Education, 32, 297–322. https://doi.org/10.1007/s40593-021-00266-y

Ferreira, H., de Oliveira, G. P., Araújo, R., Dorça, F., & Cattelan, R. (2019). Technology-enhanced assessment visualization for smart learning environments. Smart Learning Environments, 6, 14. https://doi.org/10.1186/s40561-019-0096-z

Gambo, Y., & Shakir, M. Z. (2021). Review on self-regulated learning in smart learning environment. Smart Learning Environments, 8, 12. https://doi.org/10.1186/s40561-021-00157-8

García-Tudela, P. A., Prendes-Espinosa, P., & Solano-Fernández, I. M. (2021). Smart learning environments: A basic research towards the definition of a practical model. Smart Learning Environments, 8, 9. https://doi.org/10.1186/s40561-021-00155-w

Haider, K., Alam, M. R. U., & Albi, A. I. (2022). Generative artificial intelligence on the threshold of educational transformation: A systematic review of language model applications, opportunities, and risks in education (2010–2021). US Journal of New Insights in Tech & Education, 2(1). https://www.edtechinsights.org/article/db76e935-3fbb-45a2-95e7-9b52faf995fa

Haider, K., Alam, M. R. U., & Mariz, O. A. (2021). Artificial intelligence in education: A systematic review and bibliometric topic modeling analysis of applications, challenges, and future directions. US Journal of New Insights in Tech & Education, 1(1). https://www.edtechinsights.org/article/913c99a5-a5c3-4128-8bc2-6035715e07c0

Haider, K., Chowdhury, S. H., & Alam, M. R. U. (2022). AI-based CCTV attendance systems in educational institutions: A computer vision and deep learning case study on automated monitoring for classroom engagement. US Journal of New Insights in Tech & Education, 2(1). https://www.edtechinsights.org/article/c26bb81e-5f1b-4bf5-89fd-3ff23cb214f7

Haider, K., Hasan, S., & Alam, M. R. U. (2021). Technology-enhanced learning in the COVID-19 era: A systematic review of online education platforms, student engagement, and digital equity. US Journal of New Insights in Tech & Education, 1(1). https://www.edtechinsights.org/article/929fcc41-94c1-49eb-9c13-d8de8b206f0c

Hellings, J., & Haelermans, C. (2022). The effect of providing learning analytics on student behaviour and performance in programming: A randomised controlled experiment. Higher Education, 83(1), 1–18. https://doi.org/10.1007/s10734-020-00560-z

Hwang, G.-J., & Tu, Y.-F. (2021). Roles and research trends of artificial intelligence in mathematics education: A bibliometric mapping analysis and systematic review. Mathematics, 9(6), 584.

Ifenthaler, D., & Yau, J. Y.-K. (2020). Utilising learning analytics to support study success in higher education: A systematic review. Educational Technology Research and Development, 68, 1961–1990. https://doi.org/10.1007/s11423-020-09788-z

Kochmar, E., Vu, D. D., Belfer, R., Gupta, V., Serban, I. V., & Pineau, J. (2022). Automated data-driven generation of personalized pedagogical interventions in intelligent tutoring systems. International Journal of Artificial Intelligence in Education, 32, 323–349. https://doi.org/10.1007/s40593-021-00267-x

Peng, H., Ma, S., & Spector, J. M. (2019). Personalized adaptive learning: An emerging pedagogical approach enabled by a smart learning environment. Smart Learning Environments, 6, 9. https://doi.org/10.1186/s40561-019-0089-y

Pérez Sánchez, C. J., Calle-Alonso, F., & Vega-Rodríguez, M. A. (2022). Learning analytics to predict students' performance: A case study of a neurodidactics-based collaborative learning platform. Education and Information Technologies, 27, 12913–12938. https://doi.org/10.1007/s10639-022-11128-y

Sage, K., Jackson, S., Fox, E., & Mauer, L. (2021). The virtual COVID-19 classroom: Surveying outcomes, individual differences, and technology use in college students. Smart Learning Environments, 8, 27. https://doi.org/10.1186/s40561-021-00174-7

Shemshack, A., & Spector, J. M. (2020). A systematic literature review of personalized learning terms. Smart Learning Environments, 7, 33. https://doi.org/10.1186/s40561-020-00140-9

Smyrnova-Trybulska, E., Morze, N., & Varchenko-Trotsenko, L. (2022). Adaptive learning in university students' opinions: Cross-border research. Education and Information Technologies, 27, 6787–6818. https://doi.org/10.1007/s10639-021-10830-7

Sun, J. C. Y., Tsai, H. E., & Cheng, W. K. R. (2023). Effects of integrating an open learner model with AI-enabled visualization on students' self-regulation strategies usage and behavioral patterns in an online research ethics course. Computers and Education: Artificial Intelligence, 4, 100120. https://doi.org/10.1016/j.caeai.2022.100120

Tetzlaff, L., Schmiedek, F., & Brod, G. (2021). Developing personalized education: A dynamic framework. Educational Psychology Review, 33, 863–882. https://doi.org/10.1007/s10648-020-09570-w

The use of a personalized learning approach to implementing self-regulated online learning. (2022). Computers and Education: Artificial Intelligence, 3, 100086. https://doi.org/10.1016/j.caeai.2022.100086

Yang, A. C. M., Flanagan, B., & Ogata, H. (2022). Adaptive formative assessment system based on computerized adaptive testing and the learning memory cycle for personalized learning. Computers and Education: Artificial Intelligence, 3, 100104. https://doi.org/10.1016/j.caeai.2022.100104

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education—Where are the educators? International Journal of Educational Technology in Higher Education, 16, 39. https://doi.org/10.1186/s41239-019-0171-0