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The Transformation of Personalized Teaching Materials Usage in Higher Education: A Critical Literature Review

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Abstract: Personalized teaching materials are an innovation in answering the diversity of student characteristics in higher education. However, its implementation still faces challenges. This study aims to analyse the trends and identify research gaps of personalized teaching materials usages. The method used is a critical literature review of articles from internationally reputable databases. The results of the study show two main findings: (1) there is a transformation in the use of personalized teaching materials in three phases such as: technical and standardization phase; the dynamic pedagogical and adaptive integration phase, and the artificial intelligence and holistic welfare phase; (2) There are four main research gaps such as: inconsistencies in measurement methodology, obstacles to contextual implementation, conceptual ambiguity of personal needs, and limited lecturer readiness. The most valuable finding from review that the use of PTM where the implementation no longer lies in the "what" is learned but in the "how" the system is intelligently able to empathize with the cognitive and emotional state of learners to create a truly meaningful instructional experience. These are theoretical contribution in clarifying the evolution of the concept of PTM as well as practical contributions to the development of adaptive learning designs in higher education.

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Introducation

21st century education is characterized by demands for an adaptive and student-centered learning model. Conceptually, Personalized Learning refers to the process of adjusting the material, pace, and learning path based on the individual characteristics of the student, such as learning style, interests, and prior knowledge (Tudor et al., 2025). Artificial Intelligence (AI) and Industrial Revolution 4.0 have further accelerated the implementation of this approach even faster and made them an important part of the implementation of Education 4.0 (Castro et al., 2024). This development marks a fundamental paradigm shift from conventional e-learning to a more adaptive and personalized approach (Joshi & Vaidya,

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2013) and is supported by adaptive learning platforms and new computer technologies (Isaeva et al., 2025). The integration of Semantic Web technology plays a crucial role in enabling the provision of precise content according to the needs of learners in a virtual environment (Wen et al., 2012)

Simply put, Personalized Learning is the idea that by adapting teaching materials, we can effectively address students' personal needs—from learning styles, interests, prior knowledge, to social-emotional needs. Ideally, personalization should be understood as a dynamic process that systematically adapts instruction based on learner characteristics that change during and in interaction with the instructional process (Tetzlaff et al., 2021). Therefore, successful personalization requires repeated measurement of learner characteristics to make appropriate adaptations at specific times.

Technically, the personal learning system in higher education has its own complexity. This system must consider an in-depth content structure, logical order of learning materials, and *learning readiness support* to ensure its effectiveness for students (Chen, 2008; Zhong, 2022). This process must also always be based on appropriate and context-sensitive pedagogical strategies to produce a solid learning experience (O'Keeffe et al., 2006). The emerging pedagogical approach is called "*Personalized Adaptive Learning*," based on four core elements: 1) individual characteristics, 2) individual performance, 3) personal development, and 4) adaptive adjustment (Peng et al., 2019). Several studies have indicated that a personalization approach can improve engagement and autonomy and lead to better academic outcomes (Liu & Yuan, 2024; Tudor et al., 2025).

The use of PTM in higher education is urged to answer the needs of education that can be easily accessed, flexible hours, and the heterogeneity of students' academic backgrounds. In this condition, higher education institutions must maintain retention rates and ensure academic success in the midst of an increasingly diverse student population. This is what makes PTM not just an additional feature but an essential pedagogical strategy to bridge students' initial knowledge gaps and facilitate deep self-directed learning (du Plooy et al., 2024). The findings outlined above provide a positive perspective on personalized learning in general, but literature studies conducted by educational technology experts show that there are variations in terminology used to describe personalization (Shemshack & Spector, 2020). In addition, the implementation of personalization is described with various dimensions in technology-based learning (Nandigam et al., 2014). The existence of variations in terminology and the implementation with various dimensions can cause invalid information about PTM in higher education. This literature study is expected to provide an overview of PTM in higher education. The findings of this critical literature review are expected give a direction of the development of PTM in higher education.

This research has novelty in two main aspects. First, this study identifies the transformation of PTM usage in three phases of development over the past two decades. Second, this study offers an integrated review of research gaps, covering methodological, conceptual, contextual, and lecturer readiness aspects, which have not been comprehensively studied in previous studies.

Research Method

This study uses the critical literature review method. Literature reviews are generally divided into two types, namely traditional and systematic (Grant et al., 2009; Jesson et al., 2011). This study falls under the category of traditional reviews that are flexible in nature

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and are used to analyze contemporary educational phenomena (Salim et al., 2024). This type of review differs from the systematic type in that it does not have a specific methodological approach but is more flexible, reviewing (Grant et al., 2009; Kulviwat et al., 2004). The critical literature review is used because it is exploratory & conceptual from one dimension and homogeneous, namely, PTM in higher education. On the other hand, systematic types are used when the variables being reviewed are not homogeneous and are multidimensional (Grant et al., 2009; Jesson et al., 2011). Usually, the findings of the critical literature review are followed by a systematic literature review with a broader purpose.

The four databases used in the critical literature review are from internationally reputable literature sources, namely Scopus, Web of Science, Google Scholar, and IEEE Xplore, as well as accredited national journals over the last 20 years. The keywords used in the search were "personalized learning materials" AND "adaptive learning," "instructional materials" AND "higher education," as well as "personalized learning" AND "learning readiness." The selection process is carried out in three stages. The first stage (Identification) generated 245 articles relevant to the keyword. The second stage (screening) is carried out by selecting titles and abstracts based on inclusion criteria: (1) published in the period 2006–2025, (2) focusing on learning materials in higher education, and (3) written in English or Indonesian. This stage screens the literature into 85 articles. The third stage (Eligibility) involves a *full-text review* to ensure the quality of the methodology and the relevance of the findings to the research gaps. As a result, a total of 54 main articles were selected for further analysis (Table 1). Data were analyzed using *content analysis techniques,* which were grouped into 3 main themes, namely, author (year of publication), research focus, main findings, and identified gaps (Table 2).

Table 1. Data-driven Reference Distribution (N= 54)

Database Name	Number of Articles	Percentage (%)
Scopus (Includes Q1, Q2, Q3)	25	36.2%
Web of Science (WoS)	21	39.3%
IEEE Xplore	3	6.0%
Google Scholar	4	6.8%
ERIC	1	1.7%

Result and Discussion
Result

A total of 54 main articles and aspects analyzed are shown in Table 2 as follows:

Table 2. Summary of the Main Literature based on research focus, key findings and gaps identified on the use of Personalized Teaching Materials in higher education

No	Author (Year)	Research Focus	Key Findings	Identified Gaps
1	(Tong & Ren, 2025)	Integration of deep knowledge tracing and cognitive load estimation using neural architecture.	Combining knowledge tracking with cognitive load improved learning efficiency by 24.6% and reduced student frustration.	These algorithms are very complex and require high computing power for real-time implementation in large classes.

No	Author (Year)	Research Focus	Key Findings	Identified Gaps
2	(Tuo et al., 2025)	Development and validation of instruments to measure personalized learning in smart classrooms.	Successfully validated the instrument with parameters: teacher guidance, technological support, and student agency as the main indicators.	The instrument is validated in the specific context of the smart classroom; Its reliability in traditional learning environments has not been tested.
3	(Q. Yang & Liang, 2025)	A personalized learning path recommendation system based on the Large Language Model (LLM).	LLMs are capable of processing unstructured behavioral data to provide highly adaptive learning path recommendations.	The existence of the potential for AI "hallucinations" in providing references to material that may not be academically valid.
4	(Semerikov et al., 2025)	The effect of Moodle's course design on the student sub-population	Personalization through different course structures significantly helps students with low initial knowledge levels	It has not explored how social interactions between sub-populations affect the effectiveness of such personalization.
5	(Kiran et al., 2025)	Technology-assisted personalized learning in Southeast Asia.	Digital tools increase interaction, but depend on the pedagogical readiness of lecturers.	Lack of a uniform frame-work for regional contexts with variations in infrastructure.
6	(Isaeva et al., 2025)	The effectiveness of adaptive platforms and new computer tech.	AI significantly improves accessibility and learning outcomes in higher edu.	The challenge of digital divide has not been fully resolved on a large scale.
7	(Jantakun et al., 2025)	Scientific analysis of personal learning research (2020-2024).	Publication growth is consistent with the dominance of output from China and the United States.	The need for more research contributions from developing countries for the balance of the context.
8	(Li, 2025)	Personalized learning path using Decision Tree (CART) algorithm	The CART method significantly improves students' grade point average and learning satisfaction.	The focus is still limited to entrepreneurship education; need testing on other domains.
9	(Jitpaisarnwattana, 2025)	The Effect of Personal Learning Plan (PLP) on Presentation Ability in MOOCs.	PLP improves language and presentation skills and fosters a positive attitude.	The improvement in pronunciation is not as significant as other aspects of competence.
10	(Lagos-castillo, 2025)	Mapping of personalized learning solutions in Intelligent classrooms.	Technology enables large-scale personalization through the integration of pedagogy and AI.	The lack of a framework that connects technology with emotional well-being.
11	(Nuci, 2025)	The Cloud eLearning paradigm uses AI techniques.	Cloud technology accelerates the automation of dynamic and scalable learning path creation.	Infrastructure dependency often ignores the variation in the technical readiness of each institution.
12	(Panwale & Vijayakumar, 2025)	Evaluation of AI (Google Gemini) interventions in distance education.	Personalization through AI improves MBA students' persuasive communication skills.	Need empirical evidence on long-term impacts on deep knowledge retention.
13	(C. Yu, 2025)	Development of need-based EAP material models for engineering education.	This model integrates vocabulary selection and multimodal tools to improve the efficacy of learning.	There is a need for further research on how contextual factors mediate teacher assessment practices.
14	(Duan et al., 2025)	Recommended learning resources through the Advanced Knowledge Graph.	Knowledge Graph improves the accuracy of learning resource recommendations for students.	The complexity of the algorithm makes it difficult to implement it in conventional LMS systems.
15	(Wang et	The use of Machine	The implementation of the	The main focus is still on the

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No	Author (Year)	Research Focus	Key Findings	Identified Gaps
	al., 2008)	Learning to adapt content based on learning styles.	classification algorithm significantly increased the average score of students.	results of cognitive scores, ignoring the affective aspect.
16	(Simon & Zeng, 2024)	Teachers' perspectives on adaptive learning technologies.	Teachers see technology as an aid, but feel they have lost pedagogical control.	The gap between the technical design of adaptive systems and the needs of teacher autonomy.
17	(du Plooy et al., 2024)	Scoping review of the characteristics of adaptive learning in higher education.	The success of personalization relies heavily on the integration of strong learning analytics.	Lack of consistency in defining student "engagement".
18	(Abu-rasheed et al., 20223)	Survey contextual indicators for adaptive recommendations.	Context (location, time, emotion) is crucial for the accuracy of learning recommendations.	There is a disconnect between the technical perspective (algorithm) and the pedagogical perspective.
19	(Area-Moreira et al., 2023)	Digital transformation of instructional materials in schools.	The transition to digital materials is changing the role of teachers and the way families engage in learning.	There is still a strong reliance on commercial platforms rather than open source (OER).
20	(Zhong, 2022)	A systematic review of the design elements of personalized learning in higher education.	Research interest is increasing but the maturity of implementation is still low in support of learning readiness.	Lack of understanding of comprehensive implementation in higher education.
21	(Fariani et al., 2022)	Systematic Literature Review personalized learning	The characteristics and level of knowledge of the learner are the most common compo-nents of personalization.	Lack of integration of social learning theory in digital models.
22	(Troussas et al., 2021)	Smart material delivery using instructional design modeling.	Advanced instructional design improves the effectiveness of human-computer interaction.	Lack of attention to cognitive load when material is delivered automatically.
23	(Elshani, 2021)	Generation of personal learning pathways based on genetic algorithms.	Genetic algorithms produce more effective learning paths than free search.	Lack of evaluation regarding emotional satisfaction towards the automatic pathway.
24	(Zhang et al., 2020)	Research synthesis of the implementation of personal learning (2006-2019).	Identify the role of technology and contextual factors as key themes.	Few studies have focused on consistent operational definitions.
25	(Walkington & Bernacki, 2020)	Assessment of personal learning research: Definition and future direction.	Emphasizing the alignment of learning theory (SRL) with personalization technology design.	Many studies focus only on tools without a strong theoretical foundation for education.
26	(Tetzlaff et al., 2021)	Development of a dynamic framework for personalized education.	Personalization is successful if learner characteristics are measured repeatedly throughout the process.	Dynamic measurement requires a heavy administrative burden on teachers.
27	(Plass & Pawar, 2020)	Taxonomy of adaptivity for learning.	Provides a structure to differentiate system control adaptivity vs learner control.	The taxonomy is still theo-retical and requires practical guidance for developers.
28	(Alamri et al., 2020)	Personalization as a motivational approach in online higher education.	Personalization supports the need for autonomy and competence (Self-Determination Theory).	The influence of social factors in personalization has not been widely explored.
29	(Bishop et al., 2020)	The role of teachers in a personal learning environment.	Teachers act as empowerers, scouts, scaffolders, and assessors.	There is a role strain due to the demands of drastic change.

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No	Author (Year)	Research Focus	Key Findings	Identified Gaps
30	(Cavanagh et al., 2020)	Design framework for adaptive learning in higher education.	Identify five key design features to guide adaptive course development.	There is a lack of practical guidance for scalability at the university level.
31	(Garrett et al., 2020)	Personalize higher education mathematics with technology.	Technology increases engage-ment on difficult subjects through content personalization.	Difficulty balancing student autonomy with a rigid curriculum.
32	(Mchugh et al., 2020)	Analysis of personal learning themes using NLP.	NLP uncovers complex themes in school interviews that are often overlooked.	The gap between formal policy and real practice in the classroom.
33	(Xie et al., 2019)	A systematic review of adaptive learning trends (2007-2017).	Personal learning remains an interesting topic with a focus on various support parameters.	The need for mapping long-term affective learning outcomes.
34	(Peng et al., 2019)	Personal adaptive learning in a smart learning environment.	Proposes four pillars: charac-teristics, performance, deve-lopment, and adaptive adjustment.	The pedagogical readiness of teachers to interact with intelligent systems is still low.
35	(Tang et al., 2018)	Reinforcement learning approach to recommendation systems.	The algorithm is able to learn from the failure of recommen-dations to improve the next path.	Requires big datasets that are difficult to obtain in small institutions.
36	(Yi et al., 2017)	Personalized learning model through knowledge visualization.	Knowledge visualization has proven to be more effective than conventional methods.	There is a need for a me-thod that is more widely accepted by the various characteristics of the learner.
37	(Fitzgerald et al., 2017)	Personalization dimen-sion in Technology-Enhanced Learning.	Propose a framework for the analysis and creation of personalized TELs.	Often fails due to the ambiguity of concepts between the system and the role of the instructor.
38	(Laksitowening et al., 2017)	The Triple-Factor approach in e-learning personalization.	The combination of Learning Style, Knowledge, and Competence improves the accuracy of the system.	The implementation of standards-based education is still considered too rigid.
39	(Penuel & Johnson, 2016)	A critical review of empirical evidence of personalized learning.	Found that claims of effec-tiveness are often exaggerated without strict control.	It is difficult to separate the impact of technology from the quality of teacher teaching.
40	(Benhamdi et al., 2016)	Personalized recom-mendation system based on memory capacity.	Considering the capacity of learners' memory increases information retention.	Algorithms are difficult to apply to non-textual learning content.
41	(Scanion et al., 2015)	Evidence-based improvements to technology-based defenses.	System improvements must be based on user interaction data for efficiency.	Log data is often too technical for instructional designers to interpret.
42	(Nandigam et al., 2014)	A personalized learning paradigm for educators.	Success depends on the right combination of teaching methods and technology.	There is often an overlap of terms between personalization and individualization.
43	(Y. C. Yang et al., 2014)	Critical thinking-based adaptive English literacy instruction on Moodle	The use of Moodle significantly improves critical thinking and literacy skills.	The challenge of integrating high-level thinking skills is consistent.
44	(Joshi & Vaidya, 2013)	The paradigm-ma shift from conventional e-learning to personal	Transition to a more flexible and synchronous adaptive hypermedia system	Most systems are still reactive, not proactively predicting needs.
45	(Leight et al., 2013)	Web-based learning portfolio system.	Digital portfolios effectively document developments	High administrative burden for lecturers in managing

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No	Author (Year)	Research Focus	Key Findings	Identified Gaps
			authentically.	portfolios.
46	(Wen et al., 2012)	Provision of personal content through Semantic Web.	Semantic Web supports a more individualized and decentralized learning model	Complexity in building infra-structure that is easy to manage by non-technical teachers
47	(Xiaoyan & Ping, 2011)	XML-based personal learning system and Web Mining	XML allows for flexible data structures to map students' knowledge profiles	The gap in the user interface (UI/UX) is still complex for the average person
48	(W. Yu et al., 2010)	Web-based assessment and personal learning system	The integration of daily materials and assessments accelerates the identification of learning difficulties	The focus of the research is still on the technical side, not on the psychological experience of students
49	(Wang et al., 2008)	Individuation of web courses based on CELTS standards.	Content standardization makes it easy to exchange resources between platforms.	Standardization often hinders lecturers' creativity in designing unique material.
50	(Wang et al., 2008)	Automated generating system for web-based individual teaching.	Automated systems are able to provide instant feedback based on psychological theory.	The system is rigid and less capable of handling qualitative discussions.
51	(Chen, 2008)	Personal learning path based on difficulty level and ability.	Adjusting the difficulty of the material prevents excessive cognitive load	Have not taken into account the dynamic changes in student interests during the learning process.
52	(Waldeck, 2007)	Students' perceptions of personal education.	Students are more motivated when instructors care about their individual needs.	Personalization is often misunderstood simply as an "ease," not a "challenge."
53	(Teo & Gay, 2007)	A knowledge-based model for e-learning personalization.	Propose a model to make the use of personalization explicit.	The model is too technical and difficult for non-IT educators to adapt.
54	(O'Keeffe et al., 2006)	Context-sensitive personal learning experience *just-in-time*.	The use of standard metadata (SCORM) improves the efficiency of content assembly.	It is difficult to maintain a pedagogical quality when the content is assembled automatically by machines.

Table 2 indicates 2 important things, such as the following: First, there is a transformation in PTM usage in higher education which can be categorized into three phases as illustrated in Figure 1.

Figure 1. Diagram Transformation of Personalized Teaching Materials usage in higher education in the last 20 years

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Phase 1 Technical and Standardization (2006–2015) where the research focus is on the development of technical infrastructure and intelligent navigation systems. Phase 2 Dynamic Pedagogical and Adaptive Integration (2016–2020), there was a change where research shifted from system sophistication to alignment of technology design with formal learning theory. Phase 3: Artificial Intelligence and Holistic Well-being (2021–2025) where there was a massive integration of advanced artificial intelligence.

Second, Table 2 indicates that there is a gap in the research findings that show the variation of aspects studied about PTM in higher education. This gap can be used as a clue that there are still many aspects that have not been researched in detail or there are still many unknowns from the impact of the use of PTM on higher education.

Discussion

The transformation of the use of PTM shows a shift from a technology-based approach to a more holistic approach. The focus is no longer only on the content but also on how the system is able to respond to the cognitive and emotional state of the learner. The shifting can be divided into 3 phases as described below:

Phase 1 Technical and Standardization Phase (2006–2015). This phase focuses on technical infrastructure and intelligent navigation systems. This era emphasizes content standardization using protocols such as SCORM (Sharable Content Object Reference Model) and CELTS to ensure interoperability between platforms (O'Keeffe et al., 2006; Wang et al., 2008). XML-based technology (imsmanifest.xml) and web mining are the main instruments in mapping students' knowledge profiles in a structured manner (Xiaoyan & Ping, 2011) (Xiaoyan & Ping, 2011; W. Yu et al., 2010). Here, PTM is limited to adjusting the order of content based on user interaction log data.

Dynamic Pedagogical and Adaptive Integration Phase (2016–2020). This period shifted towards the alignment of technological design with formal learning theory. Examples: the importance of self-regulated learning in personalization design (Walkington & Bernacki, 2020); the use of more complex algorithms, such as reinforcement learning (Tang et al., 2018); and dynamic frameworks that allow systems to measure learner characteristics repeatedly throughout the process, not just at the beginning of the session (Tetzlaff et al., 2021). The role of teachers is redefined as facilitators or scaffolders in an adaptive digital ecosystem (Bishop et al., 2020).

Artificial Intelligence and Holistic Well-Being Phase (2021–2025). The most important examples in this phase are Large Language Models (LLMs), knowledge graphs, and neural architectures (Tong & Ren, 2025; Q. Yang & Liang, 2025). In contrast to the previous phase, which paid attention to cognitive efficiency and the accuracy of material recommendations, this phase takes into account the affective aspects and emotional well-being of the learner. Example: Innovations such as real-time estimation of cognitive load and reduction of student frustration are new indicators of success (Tong & Ren, 2025). In addition, personalization is now more proactive with AI's ability to process unstructured behavioral data to create highly personalized and humanistic learning paths.

The results of this review provide important information that there has been a shift in direction the use of PTM where the implementation no longer lies in the "what" is learned (content) but in the "how" the system is intelligently able to empathize with the cognitive and emotional state of learners to create a truly meaningful instructional experience. These findings make a theoretical contribution in clarifying the evolution of the concept of PTM as well as practical contributions to the development of adaptive learning designs in higher education.

In general, this literature review shows that PTM can effectively address students' personal needs and have positive impacts on academic performance and student engagement (du Plooy et al., 2024; Garrett et al., 2020; Tudor et al., 2025; Y. C. Yang et al., 2014; Yi et al., 2017). A systematic review over a decade (2007-2017) showed consistent positive trends in learners' learning achievement and affection when adaptive technology was applied (Xie et al., 2019). The positive impact of using PTM can also be seen in aspects of student involvement, motivation, and autonomy. Adjusting the material to the student profile has a positive impact on intrinsic motivation, engagement, and most importantly, increased student autonomy in a blended learning environment (Liu & Yuan, 2024). However, it was found that research gaps in PTM can be grouped into 4 gaps such as in measuring effectiveness and long-term empirical evidence, implementation and contextual barriers, conceptual clarity about "personal needs," and educator support and readiness.

The gap in effectiveness measurement lies in the inconsistency of measurement methodology. Personalization should be viewed as a dynamic framework that requires adaptation based on repeatedly measured data (Tetzlaff et al., 2021), but this is the reason why researchers failed to adopt this dynamic framework in their experimental designs. Technically, many personal learning systems also ignore the compatibility between learners' abilities and the difficulty level of courseware, as well as the problem of concept continuity in the curriculum sequence (Chen, 2008). The lack of a standardized evaluation framework capable of capturing these learning dynamics makes it difficult to make comparisons.

Complexity in higher education demands more than adaptive content, content structure, and material sequence, but also learning readiness support. Learning readiness such as prerequisite materials presented on time is still rarely measured in isolation (Zhong, 2022). The importance of an integrated assessment system in real-time is also still neglected even though in a web-based assessment system it is very crucial to evaluate student learning outcomes and lecturers' instructional practices accurately (W. Yu et al., 2010). This gap requires the development of a systematic taxonomy of adaptivity (Plass & Pawar, 2020) and comprehensive measurement models such as the three-factor approach (Laksitowening et al., 2017).

Although proven to improve engagement and learning outcomes, implementation in higher education still faces significant challenges, especially related to infrastructure gaps, digital literacy, and lecturer readiness (Sigalla & Kimario, 2025). These findings reinforce the gap in research that is predominant in developed countries, where infrastructure has been built well. In the Indonesian context, this challenge is increasingly complex due to the inequality of access to technology between regions. Therefore, the development of PTM must consider aspects of accessibility, cultural context, and collaborative learning integration. The implementation of PTM nationally risks widening the gap in education quality if it is not accompanied by an equal improvement in lecturers' digital literacy.

At the university, implementation challenges are systemic (Cavanagh et al., 2020) highlight that the lack of a clear design framework and pedagogical approach from the practitioner's perspective is a major obstacle to the adoption of adaptive technologies in higher education. Although technology enables just-in-time learning experiences, successful implementation depends on the application of appropriate pedagogical strategies and sensitivity to the context of the learning environment (O'Keeffe et al., 2006). These challenges are reinforced by the problem of integrating adaptive learning platforms with

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existing Learning Management Systems and new technologies (Isaeva et al., 2025). This condition demonstrates the need for a deeper understanding of how lecturers and students actually experience and manage these changes (Mchugh et al., 2020).

The are several meaning conceptual about "personal needs." This gap can lead to widespread terminological confusion in this area (Shemshack & Spector, 2020) and further complicate efforts to standardize the concept of "personal needs." There is a need for greater conceptual clarity regarding the different dimensions of personalization that can be applied in the learning environment (Nandigam et al., 2014). The paradigm shift from conventional e-learning to Adaptive Educational Hypermedia Systems (AEHS) demands that personalization be based on a model that explicitly incorporates learning styles, cognitive traits, and behavioral models (Joshi & Vaidya, 2013). Additionally, a deeper understanding of the elements of Personalized Adaptive Learning (Peng et al., 2019) can provide a stronger framework for identifying holistic needs. support and readiness of lecturers Research on classroom customization explicitly identifies lecturer readiness as a key indicator and significant challenge that is closely related to the availability of resources and digital literacy (Sigalla & Kimario, 2025). The role of lecturers has shifted fundamentally, including the roles of empowerers, scouts, scaffolders, and assessors. This shift necessitates the need for training for lecturers to avoid role conflicts (Bishop et al., 2020).

The application of advanced models based on AI and the semantic web requires critical adjustment to the sociogeographical and technical realities in Indonesia. The first challenge is infrastructure digital inequality (cities, villages, remote areas). Global trends have shifted towards neural architectures and LLMs that require high cloud computing (Tong & Ren, 2025; Q. Yang & Liang, 2025). Indonesia still faces fundamental challenges in the form of inequality in digital infrastructure, such as access to unstable bandwidth. Therefore, Indonesia cannot fully adopt a heavy cloud-based model but must consider the development of personal content that is "data-light" or can be accessed offline-to-online. Personalization in the Indonesian context should not only be interpreted as the sophistication of algorithms but also the accessibility of fair materials in big cities and in remote areas.

Second: Digital literacy and lecturers' readiness as adaptive facilitators. A literature review identified a gap regarding the role of lecturers as adaptive facilitators (Bishop et al., 2020), where there was role strain of lecturers switching to digital facilitators. The shift in the role of lecturers requires a massive increase in digital pedagogy competencies. Indonesian's lecturer needs a structured training program.

Conclusion

This literature review produced two findings, namely: 1) There was a transformation in the use of PTM in three phases of development, and the implementation was not optimal due to methodological, contextual, conceptual, and lecturer readiness gaps.

Recommendation

Further research needs to be directed at longitudinal studies to measure the long-term impact of PTM on student retention, learning engagement, and academic outcomes. In addition, the development of dynamic measurement models, real-time assessment systems, and instruments to measure lecturer readiness is needed.

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