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Exploring the Adoption of AI-Driven Adaptive Learning in Higher Education: A Multidimensional TAM Perspective

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Abstract

This study aims to explore the concept of AI-based adaptive learning in the context of higher education, particularly focusing on its acceptance among university lecturers. Employing a qualitative, conceptual review approach, the study relies entirely on secondary data through the analysis of relevant existing literature. The primary objective is to identify current trends, challenges, and the potential for implementing AI-driven adaptive learning systems, as well as to assess lecturers' acceptance and readiness towards such technologies. This study applies the Technology Acceptance Model (TAM) to examine acceptance. The findings suggest that although awareness of AI's capacity to personalize learning is increasing, the level of acceptance among lecturers remains influenced by factors such as technological literacy, institutional support, and perceived effectiveness. This study contributes towards policy formulation and the development of appropriate training to support the integration of AI in teaching and learning in universities.

Keywords: Adaptive Learning, Artificial Intelligence, Technology Acceptance, Tam Model, Higher Education

Introduction

Despite significant advancements in educational technology, many students in higher education institutions continue to face challenges in adapting to traditional learning approaches. Numerous studies have identified persistent issues such as low academic performance, limited student engagement, and dissatisfaction with learning experiences as pressing concerns within the academic community (Beck & Woolf, 2016). One technological innovation that offers the potential to address these challenges is the use of adaptive learning tools. These tools are designed to provide personalized learning experiences tailored to individual learners' needs and capabilities. However, their application remains relatively underexplored within the context of higher education. Adaptive learning technologies serve both functional and pedagogical roles, enhancing teaching and learning outcomes. (Johnson et al., 2016).

Recent literature has demonstrated growing interest in the integration of adaptive learning tools in tertiary education. For instance, Kerr and McCoy (2018) underscore the effectiveness of such tools in improving academic outcomes. Their study of various platforms adopted by higher education institutions revealed that adaptive tools not only facilitate the comprehension of complex concepts but also foster greater student engagement. Similarly, Fletcher and McKellar (2016) evaluated the efficacy of adaptive learning models, concluding that these approaches can significantly benefit students, particularly in diverse educational contexts. Their analysis indicated that students utilizing adaptive learning technologies tend to demonstrate improved academic performance and heightened motivation compared to those engaging with conventional instructional methods.

The *NMC Horizon Report: 2016 Higher Education Edition* (Johnson et al., 2016) further reinforces the relevance of adaptive learning by identifying it as a key trend in contemporary educational technology. The report highlights several institutional case studies that exemplify successful implementation, thereby affirming the transformative potential of these tools in enhancing the university learning experience. Despite their promise, the adoption of adaptive learning tools remains uneven, and several questions persist regarding their effective implementation. There is a critical need for further empirical research to explore the challenges, opportunities, and contextual strategies associated with their integration in higher education settings.

The purpose of this study is to investigate the acceptance and use of adaptive learning technologies among university lecturers that have integrated such tools into their teaching practices. By examining lecturers' perspectives and experiences, this research aims to contribute to a deeper understanding of the factors influencing the adoption of adaptive learning in higher education.

Literature Review

The Potential and Challenges of AI-Based Adaptive Learning in Higher Education

AI-based adaptive learning offers numerous benefits for students, educators, and institutions. It facilitates instruction that is tailored to the individual needs, preferences, and learning pace of each student. Adaptive learning platforms dynamically adjust content difficulty to support learning and provide supplementary resources that promote learner autonomy and mastery. Students are empowered to monitor their own progress, identify areas for improvement, and take greater responsibility for their learning through timely and targeted feedback.

Educators benefit from valuable insights into students' progress and performance, enabling early identification of struggling learners, more focused interventions, and the ability to tailor instructional strategies accordingly. Institutions, in turn, gain from improved student outcomes, increased engagement, and enhanced scalability in delivering education (Joshi, 2024). According to El Sabagh (2021), each student possesses a unique learning style and tends to engage with different types of instructional materials and activities. Therefore, The most effective learning environments adapt to individual learner needs. The development of high-quality, customized instructional materials and activities that align with students' learning styles can enhance participation and motivation.

Despite its promise, research on the impact of adaptive learning remains limited, as the implementation of such systems is still in its early stages (Weber, 2019). Nevertheless, several preliminary studies have demonstrated positive effects on student learning outcomes (Bailey, Vaduganathan, Henry, Laverdiere, & Pugliese, 2018), as well as reductions in course dropout rates (Daines, Troka, & Santiago, 2016). In a survey on the use of information and communication technologies in higher education, Green (2018) found that the majority of higher education leaders expressed a positive attitude toward adaptive learning and believed it holds significant potential to improve student achievement.

While interest in adaptive learning is growing in educational practice, widespread implementation remains limited. Previous studies have shown that higher education institutions face multiple barriers and challenges in adopting adaptive learning approaches. These challenges include technological, pedagogical, and administrative issues (Bailey et al., 2018; Johnson & Zone, 2018). Key technological challenges include managing real-time data (Zliobaite et al., 2012), integrating adaptive learning solutions into existing Learning Management Systems (LMS), and addressing the complexity and usability of adaptive systems (Dziuban et al., 2018).

Existing literature often discusses these challenges in isolation or through specific disciplinary or geographic lenses. It remains unclear which challenges require the most attention during the implementation process. Furthermore, much of the discourse has been dominated by perspectives from countries such as the United States, the United Kingdom, and Australia contexts in which adaptive learning has been more widely implemented.

Based on prior research, the integration of AI into teaching and learning has the potential to positively impact both instructors and students. Although implementation challenges persist, it is imperative to embrace technological progress while seeking to mitigate these challenges, focusing instead on the long-term benefits to teaching and learning. The research gap in this domain remains substantial, particularly concerning empirical studies on the implementation of AI-driven adaptive learning. Most existing research is still dominated by international scholars, indicating the need for broader, context-specific investigations in diverse educational settings.

The Technology Acceptance Model (TAM) and Its Relevance to the Adoption of AI-Based Adaptive Learning in Higher Education

The Technology Acceptance Model (TAM) has been widely utilized to explain users' acceptance and use of new technologies, particularly within the domains of information systems and educational technology (Lu, Yu, Liu, & Yao, 2003). First proposed by Davis (1989), TAM was developed to offer a parsimonious yet theoretically robust framework for understanding how users come to accept and engage with computer-based technologies. The model was derived from the Theory of Reasoned Action (TRA) (Ajzen & Fishbein, 1980), which posits that individual behaviour is determined by behavioural intentions shaped by attitudes and subjective norms.

TAM extends this theory by focusing specifically on the determinants of technology acceptance. It introduces two key constructs: **perceived usefulness (PU)** and **perceived ease of use (PEOU).** Perceived usefulness is defined as the degree to which a person believes that using a particular technology would enhance their performance, while perceived ease of use refers to the degree to which a person believes that using the technology would be free from effort (Davis, 1989). According to the model, these beliefs shape users' attitudes toward the technology, which in turn influence their behavioural intention to use it, and eventually, actual usage behaviour.

TAM describes a **three-stage acceptance process**: external variables such as system design features, prior experience, and user training affect users' cognitive evaluations (i.e., PU and PEOU). These cognitive evaluations then influence affective responses, particularly behavioural intention, which is the primary predictor of actual technology use (Davis, 1993). Over time, subsequent refinements of the model have emphasized that behavioural intention can be influenced both directly and indirectly by these cognitive factors. For instance, perceived ease of use has been found to indirectly influence behavioural intention through its effect on perceived usefulness.

Further elaboration of TAM by Davis (1993) suggested that behavioural intention and behaviour can also be substituted or complemented by the construct of **attitude toward behaviour**, which reflects an individual's overall affective evaluation of engaging in a specific behaviour. This perspective is consistent with Ajzen's (2011) later work on behavioural theories, which emphasizes the role of affective and evaluative processes in behavioural decision-making. The stronger the positive affective evaluation, the higher the likelihood of actual adoption and use of the technology. In this context, **perceived usefulness often has a direct effect on actual system usage**, which highlighting its importance in shaping behaviour, whereas perceived ease of use plays a supportive role by enhancing the perception of usefulness.

In educational settings, TAM has been instrumental in evaluating the adoption of new learning technologies. Its simplicity, predictive power, and adaptability to various technological contexts have made it one of the most widely applied models in education technology research. The development of TAM-based measurement instruments has addressed the previous lack of validated tools to assess users' subjective perceptions, offering both **theoretical insights and practical utility** (Araújo & Casais, 2020). These instruments have enabled researchers and practitioners to identify and understand the **cognitive and affective antecedents** that mediate users' acceptance of digital tools.

In the context of **AI-based adaptive learning**, TAM provides a valuable framework for examining the factors that influence the acceptance and use of such systems among educators and students in higher education. Adaptive learning systems, powered by artificial intelligence, are designed to respond to learners' individual progress by personalizing content, pace, and feedback. However, the effectiveness of these technologies depends not only on their technical capabilities but also on the **extent to which users accept and trust the system.**

This study contends that the acceptance and implementation of AI-based adaptive learning tools is influenced by a complex **interplay** of variables, including users' technological proficiency, prior experience, institutional support, and attitudes toward innovation. For instance, a lecturer's belief in the usefulness of adaptive learning (e.g., its potential to improve student engagement and outcomes) and the perceived ease of use of the system (e.g., intuitive interface, seamless integration with LMS platforms) will play a crucial role in shaping their intention to incorporate it into their teaching. Similarly, **institutional policies and support systems** such as training programs, technical assistance, and incentives can act as external variables that significantly impact acceptance levels.

Moreover, the integration of TAM into studies on AI-based adaptive learning aligns with the growing recognition that technology adoption in education is not merely a technical issue but also a **behavioural and organizational challenge**. Understanding how educators perceive, evaluate, and engage with adaptive technologies is essential for informing implementation strategies, training, and policy development.

In summary, the Technology Acceptance Model offers a robust theoretical foundation for understanding the determinants of user acceptance of AI-driven adaptive learning technologies in higher education. Its constructs provide a valuable lens through which to analyse the cognitive, affective, and contextual factors that influence technology uptake. As institutions continue to invest in personalized, data-driven learning solutions, TAM remains a critical tool for ensuring that these innovations translate into meaningful pedagogical outcomes.

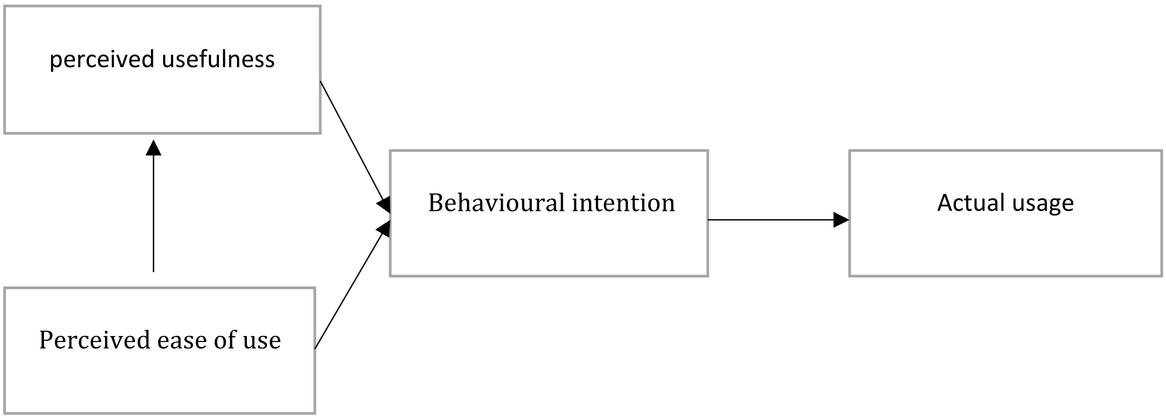

Figure 1: Technology Acceptance Model (TAM)
Source: Venkatesh et.al (2003); Davis et.al (1989)

Method

This study adopts a qualitative research design in the form of a conceptual review that focuses on the analysis of secondary data derived from existing literature. This approach is deemed appropriate as the study does not involve primary data collection through empirical methods but rather aims to understand and synthesize findings from previous research related to AI-based adaptive learning and its acceptance among university lecturers.

The conceptual review method is employed to gather, analyse, and interpret a range of scholarly works that are relevant to the phenomenon under investigation. The Technology Acceptance Model (TAM) is adopted as the underlying conceptual framework to examine the acceptance of adaptive learning technologies. TAM facilitates the exploration of key factors such as perceived usefulness and perceived ease of use, which are central to understanding technology adoption among educators.

Secondary data are obtained from various academic sources, including peer-reviewed journal articles, academic conference proceedings, technical reports, theses, dissertations, and relevant scholarly books. The selection of literature is guided by criteria such as topical relevance, academic credibility, and recency, with emphasis placed on works published within the last ten years to ensure contemporary relevance.

Content analysis is employed to identify major themes, patterns, and key findings across the selected literature. Particular attention is given to studies that discuss the implementation of AI in adaptive learning environments, the perceptions and readiness of lecturers to engage with such technologies, and the influencing factors as outlined in the TAM framework. Through this analytical process, the study aims to provide a comprehensive overview of the current landscape and to identify gaps in the literature that may inform future research directions.

Findings

Perceived Usefulness (PU) and Its Influence on Lecturers' Acceptance

Perceived Usefulness (PU) is widely recognised as a foundational element in the Technology Acceptance Model (TAM), initially proposed by Davis (1989). It is defined as the extent to which an individual believes that using a particular technology will improve their job performance. In the context of higher education, particularly regarding AI-based adaptive learning technologies, PU plays a pivotal role in shaping lecturers' attitudes toward adoption and sustained use.

In academic settings, where instructional efficacy and student outcomes are paramount, lecturers are more likely to adopt technological innovations when they perceive these tools as directly contributing to their teaching effectiveness and efficiency. AI-based adaptive learning systems offer numerous advantages that align closely with these expectations. They can tailor learning experiences to individual student needs, track progress in real-time, and provide data-driven insights that help educators refine their teaching strategies.

Research has consistently supported the critical role of PU in this domain. For instance, Mulaudzi and Hamilton (2025) demonstrated that lecturers who recognize the advantages of AI in customizing educational experiences and fostering greater student engagement are significantly more likely to incorporate these technologies into their pedagogical practices. Their study indicated that the perception of AI as a tool that enhances student interaction and personalizes content delivery contributes to a stronger willingness to adopt it.

Similarly, Negi et al. (2025) found that lecturers' belief in the effectiveness of AI to support e-learning environments is positively associated with their acceptance of such systems. Their findings suggest that when educators perceive AI tools as instrumental in overcoming traditional limitations of digital learning such as limited feedback, lack of personalization, or student disengagement they become more open to using them as integral components of their instructional repertoire.

Beyond conventional e-learning platforms, the application of AI in educational settings has evolved to include advanced technologies such as AI-driven robots and intelligent tutoring systems. According to Cao et al. (2021), these tools not only augment the teaching process but also introduce dynamic and interactive elements that transform traditional classrooms into more engaging and adaptive environments. AI-powered systems can simulate human-like interactions, offer personalized support, and even automate routine teaching tasks, thereby freeing up lecturers to focus on higher-order instructional activities.

Huang et al. (2021) further emphasize that the integration of AI in education can enhance students' cognitive development, critical thinking, and problem-solving skills. When lecturers observe tangible improvements in student learning outcomes as a result of AI interventions, their perception of usefulness is reinforced, fostering greater acceptance of the technology. Therefore, to encourage broader adoption of AI-based adaptive learning tools among lecturers, it is essential to clearly communicate and demonstrate their practical benefits. Evidence of enhanced teaching efficiency, improved student performance, and reduced administrative burden can significantly influence PU. Institutions should also provide adequate support, training, and real-world case studies that showcase successful implementations. In sum, PU is not just a theoretical construct; it is a real, experience-based perception that can make or break the integration of emerging technologies in educational contexts.

Perceived Ease of Use (PEOU) and Its Impact on Adoption

Perceived Ease of Use (PEOU) is another fundamental construct in the Technology Acceptance Model (TAM) introduced by Davis (1989). It is defined as the degree to which an individual believes that using a particular technology or system will be free of physical and mental effort. In the context of AI-based adaptive learning systems, PEOU is crucial because it directly influences lecturers' willingness to adopt and consistently use these technologies in their teaching practice.

Lecturers, often managing multiple responsibilities including course preparation, research, and student mentoring, tend to favour technologies that do not add unnecessary complexity or cognitive load to their workflow. If a system is perceived as difficult to learn or operate, it creates resistance, regardless of its potential benefits. Cheng (2012) emphasized that when AI tools are intuitive, user-friendly, and straightforward to navigate, lecturers feel more confident and motivated to integrate these technologies into their instructional methods. Conversely, if the technology demands extensive technical expertise or requires complicated procedures, lecturers may become frustrated or overwhelmed, leading to lower adoption rates.

The challenge of complexity in AI systems is well-documented. Ifinedo (2017) pointed out that the sophistication and intricacy of AI technologies can pose significant barriers, particularly for lecturers who have limited experience with advanced digital tools or insufficient access to ongoing technical support. This barrier is compounded in institutions where resources for professional development and training are scarce. Without adequate training, even potentially valuable AI systems can be underutilized or rejected outright, as lecturers prioritize tools that minimize their workload and cognitive strain.

Supporting this view, recent research by Negi et al. (2025) highlighted the direct impact of perceived ease of use on instructors' attitudes toward e-learning platforms enhanced with AI functionalities. Their study found a strong positive correlation between the perceived simplicity of the platform's interface and the lecturers' intention to adopt and use it. When the systems are designed with clear navigation, minimal steps to perform key tasks, and responsive interfaces, lecturers report a more favourable user experience, which translates into higher acceptance rates.

Moreover, the importance of PEOU extends beyond initial adoption to long-term usage. Even when lecturers recognize the usefulness of AI tools, sustained engagement depends on the continued ease of use. Features such as seamless integration with existing educational technologies (e.g., Learning Management Systems), responsive customer support, and accessible troubleshooting resources all contribute to maintaining positive perceptions of ease.

Therefore, it is imperative that developers of AI-based adaptive learning technologies prioritize user-cantered design principles. This includes employing intuitive interfaces, minimizing unnecessary technical jargon, and ensuring that essential functions are easily accessible. In parallel, educational institutions must invest in comprehensive training programs, workshops, and ongoing technical assistance to empower lecturers. Such support helps build digital literacy and confidence, thereby reducing apprehension and resistance. Overall, perceived ease of use is a critical determinant in lecturers' adoption of AI-based adaptive learning systems. By making these tools straightforward and providing sufficient training and support, stakeholders can significantly improve lecturers' acceptance and successful integration of AI into their educational practices, ultimately enhancing both teaching and learning experiences.

Attitude toward Use (ATU) and Behavioural Intention to Use (BIU)

Attitude Toward Use (ATU) and Behavioural Intention to Use (BIU) are pivotal constructs within the Technology Acceptance Model (TAM), representing how lecturers emotionally and cognitively evaluate adaptive learning technologies and how these evaluations shape their intent to implement such tools in university teaching. ATU captures lecturers' positive or negative feelings about using AI-driven adaptive learning systems, while BIU reflects their planned commitment to incorporate these systems into their instructional practices (Davis, 1989).

In the context of universities, where adaptive learning systems are designed to personalize education by tailoring content, pacing, and assessments to individual student needs, lecturers' attitudes play a vital role. University educators are tasked with not only delivering content but also facilitating diverse student learning pathways. When lecturers perceive adaptive learning technologies as aligned with their pedagogical goals helping them to meet varied student needs more effectively they tend to develop a more positive attitude toward these tools.

Tarhini et al. (2017) demonstrated that lecturers' attitudes toward adaptive learning are influenced by their prior experiences with digital educational tools, their understanding of how AI can enhance student learning, and the level of institutional support provided. Lecturers who have had positive encounters with educational technology are generally more confident and optimistic about adopting AI-based adaptive learning platforms. Moreover, when university leadership actively supports implementation through training, resources, and encouragement lecturers feel more motivated to engage with these systems.

The role of ATU is particularly significant because it directly influences lecturers' Behavioural Intention to Use (BIU) adaptive learning technologies. For example, Negi et al. (2025) found that instructors who hold favourable attitudes toward AI enhanced e-learning systems are more inclined to incorporate them into their courses. This behavioural intention is crucial in the university setting, where adoption is not simply about initial use but ongoing integration that can transform instructional practices.

Positive attitudes toward adaptive learning systems often emerge when lecturers observe tangible benefits, such as improved student engagement, personalized feedback, and data-driven insights into learner progress. These benefits help lecturers feel that the technology supports their teaching effectiveness rather than complicates it. On the other hand, if lecturers harbour doubts about the relevance or reliability of adaptive learning platforms, or if they fear that AI might undermine their professional autonomy, their attitudes and consequently their behavioural intentions may be negative.

To foster strong positive attitudes and robust behavioural intentions among university lecturers, institutions must adopt a multifaceted approach. This includes providing clear evidence of the pedagogical advantages of adaptive learning, creating opportunities for lecturers to experience these benefits first-hand, and offering continuous support through professional development and technical assistance. Building communities of practice where lecturers can share successes and challenges also helps normalize adaptive learning technology use, reducing apprehension and increasing enthusiasm. In summary within the university context, Attitude Toward Use and Behavioural Intention to Use are critical in determining whether lecturers embrace AI-based adaptive learning systems. Positive attitudes shaped by relevant experience, perceived pedagogical alignment, and institutional support lead to stronger behavioural intentions, ultimately promoting the successful adoption and sustained integration of adaptive learning technologies into higher education teaching and learning.

External Factors Influencing TAM Constructs in the Adoption of AI-Based Adaptive Learning in Universities

While the Technology Acceptance Model (TAM) provides a robust theoretical framework to understand lecturers' acceptance of AI-based adaptive learning systems, it is essential to recognize that external factors beyond the core TAM constructs Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude Toward Use (ATU), and Behavioural Intention to Use (BIU) also exert significant influence. In the university context, these external variables encompass institutional support mechanisms, ethical considerations surrounding AI, and the digital readiness of both lecturers and the institution itself.

One of the most critical external factors is institutional support. As noted by Teo (2011) and Venkatesh and Bala (2008), access to comprehensive training programs, encouragement from university leadership, and the availability of technical assistance are crucial in building lecturers' confidence and motivation to embrace AI technologies. When universities invest in continuous professional development opportunities that familiarize lecturers with AI-driven adaptive learning systems, they lower perceived barriers related to complexity and uncertainty. Administrative encouragement—such as recognizing and rewarding innovation in teaching also fosters a positive culture around technology adoption. Conversely, where such support structures are absent or insufficient, even adaptive learning tools that lecturers perceive as useful and easy to use may fail to achieve meaningful integration.

In addition to institutional factors, ethical concerns have emerged as significant external influences on lecturers' acceptance of AI in education. Studies by Luckin et al. (2016) and Selwyn (2019) highlight issues related to data privacy, transparency, academic autonomy, and the broader pedagogical impact of AI systems. For example, lecturers may worry about the collection and use of sensitive student data, fearing breaches of confidentiality or misuse of information. There may also be concerns that reliance on AI could undermine lecturers' professional judgment, reducing their control over curriculum design and instructional decisions. These ethical considerations, while not explicitly captured within the traditional TAM framework, act as moderating variables that can influence how TAM constructs translate into actual acceptance behaviour. A lecturer might recognize an AI system's usefulness and ease of use yet resist adoption due to fears of surveillance, loss of autonomy, or unintended consequences on teaching quality.

Another crucial external factor is the overall digital readiness of the university and its lecturers. This encompasses the availability of necessary technological infrastructure, the institution's strategic vision for digital transformation, and the digital literacy levels among faculty members. Institutions that have developed robust IT environments, foster a culture of innovation, and promote ongoing digital skills development tend to experience higher acceptance rates of advanced technologies such as AI-based adaptive learning systems.

Taken together, these external factors underscore the importance of adopting a holistic perspective when examining lecturers' acceptance of AI in higher education. Successful implementation of adaptive learning technologies requires more than just addressing perceived usefulness and ease of use; it demands that universities proactively manage ethical concerns, provide sustained institutional support, and enhance digital readiness. By integrating these contextual elements with the TAM constructs, stakeholders can better understand and address the complex interplay of influences that shape lecturers' adoption behaviours.

Recognizing and addressing external factors such as institutional support, ethical considerations, and digital readiness is vital to fostering an environment conducive to the acceptance and effective use of AI-based adaptive learning tools by university lecturers. This comprehensive approach not only supports technology adoption but also ensures that these innovations are implemented responsibly and sustainably within academic settings.

Disciplinary Variations in Acceptance Levels of AI-Based Adaptive Learning Systems

Disciplinary differences among university lecturers significantly influence their acceptance and use of AI-based adaptive learning technologies. Research consistently shows that acceptance rates vary notably across academic disciplines, reflecting diverse experiences with technology, pedagogical traditions, and cultural norms within faculties. For example, faculty members in Science, Technology, Engineering, and Mathematics (STEM) fields typically exhibit higher levels of acceptance compared to their counterparts in the humanities and social sciences (Zhu et al., 2020).

This disparity can largely be attributed to several factors intrinsic to different disciplines. STEM lecturers often have greater familiarity and comfort with data-driven tools, computational methods, and algorithmic processes, which are integral components of AI systems. Their regular engagement with quantitative data and digital resources means they are more likely to perceive AI-based adaptive learning technologies as natural extensions of their existing teaching practices. Moreover, STEM education frequently emphasizes skills such as problem-solving and personalized learning paths, which AI adaptive systems are designed to enhance, further increasing perceived usefulness and willingness to adopt these technologies.

Conversely, lecturers in the humanities and social sciences may face unique challenges that affect their acceptance levels. These disciplines often prioritize interpretive, critical thinking, and discursive pedagogies that are less directly aligned with the structured, algorithm-driven approaches employed by many AI learning tools. Humanities faculty might also have concerns about the reductionist nature of adaptive learning technologies, fearing that AI could oversimplify complex intellectual processes or undermine the rich, dialogical aspects of their teaching. Additionally, differences in digital literacy, access to training tailored to discipline-specific needs, and perceptions about the relevance of AI tools to their subject matter contribute to lower acceptance rates in these fields. Understanding these disciplinary variations is essential for universities aiming to implement AI-based adaptive learning systems effectively. A one-size-fits-all approach to technology adoption risks alienating certain faculties and limiting overall institutional uptake. Instead, universities should develop targeted strategies that acknowledge and address the distinct needs, concerns, and pedagogical contexts of different academic disciplines.

For STEM lecturers, this may involve providing advanced workshops on integrating AI tools with subject-specific content, showcasing case studies that highlight successful applications in science and engineering education, and facilitating peer collaboration on technology-enhanced teaching innovations. For humanities and social science faculty, tailored support might focus on demonstrating how adaptive learning systems can complement critical thinking exercises, foster student reflection, and enhance personalized feedback without compromising academic rigor. Furthermore, institutions should consider fostering interdisciplinary dialogues around AI adoption, encouraging faculties to share perspectives and co-create adaptive learning solutions that respect diverse pedagogical values. By doing so, universities can build a more inclusive culture of technology acceptance that leverages the strengths of each discipline while addressing potential apprehensions. Disciplinary variations in lecturers' acceptance of AI-based adaptive learning systems reflect underlying differences in digital literacy, pedagogical norms, and perceived relevance. Recognizing and responding to these variations through customized, discipline-sensitive strategies is critical for promoting broader adoption and maximizing the transformative potential of AI technologies in higher education.

Conclusion

In conclusion, the acceptance of AI-based adaptive learning systems among university lecturers is influenced by a complex interplay of factors rooted in the Technology Acceptance Model Perceived Usefulness, Perceived Ease of Use, Attitude Toward Use, and Behavioural Intention to Use alongside critical external variables such as institutional support, ethical considerations, and digital readiness. Lecturers' disciplinary backgrounds further shape their acceptance levels, with STEM faculty generally more receptive due to greater familiarity with data-driven technologies compared to their humanities and social science counterparts. To foster widespread and sustained adoption, universities must adopt a holistic, tailored approach that addresses technical usability, demonstrates practical benefits, and supports lecturers through targeted training and resources. Additionally, acknowledging ethical concerns and promoting an inclusive culture of innovation are essential. By understanding and responding to these multifaceted factors, higher education institutions can effectively integrate AI-based adaptive learning, enhancing personalized teaching and learning experiences and ultimately contributing to improved educational outcomes.

This study makes a significant contribution to the discourse on educational technology by extending the Technology Acceptance Model (TAM) framework to the context of AI-based adaptive learning in higher education. By incorporating external variables such as institutional support, ethical considerations, and digital readiness, the research provides a more holistic understanding of lecturers' acceptance of adaptive learning tools. Moreover, the study highlights the importance of disciplinary perspectives in shaping adoption attitudes, offering nuanced insights for policy-makers and educational leaders. These findings are instrumental for guiding the development of targeted strategies, training programs, and supportive infrastructures that can enhance the effective and equitable integration of AI technologies in university teaching practices. Ultimately, this study paves the way for more context-specific, empirically grounded investigations in future research, especially within diverse cultural and institutional settings.

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