Understanding Technology Adoption in Higher Education: A Conceptual Review of Generative Artificial Intelligence and the UTAUT Model

Professor (Dr.) KOH Kee Lee

Stanfort Academy (London Metropolitan University)

Abstract

The rapid emergence of Generative Artificial Intelligence (GenAI) has transformed higher education by introducing advanced tools capable of generating text, images, code, and other content. This study explores the adoption of GenAI in higher education through the lens of the Unified Theory of Acceptance and Use of Technology (UTAUT). It examines the key determinants influencing adoption—including performance expectancy, effort expectancy, social influence, and facilitating conditions—as well as extended constructs such as perceived risk, trust, and AI literacy. The findings indicate that students are generally more inclined to adopt GenAI due to its perceived academic benefits, ease of use, and social normalisation, whereas academic staff tend to adopt these technologies more cautiously owing to concerns about academic integrity, reliability, and institutional policies. Performance expectancy consistently emerges as the strongest predictor of adoption, while facilitating conditions and organisational support play a crucial role in sustaining usage, particularly among educators. The study further underscores the importance of institutional strategies—including AI literacy development, clear policy frameworks, and training initiatives—in promoting responsible and effective AI integration. Overall, this research contributes to a deeper understanding of behavioural intentions and usage patterns of GenAI in academic environments and offers practical implications for enhancing technology acceptance in higher education.

Keywords: Generative AI, UTAUT, higher education, technology adoption, behavioural intention, AI literacy, trust, perceived risk

1. Introduction

Generative Artificial Intelligence (GenAI) has rapidly emerged as one of the most transformative technologies of the twenty-first century. Tools such as ChatGPT, Gemini, Claude, Microsoft Copilot, and other large language models (LLMs) are increasingly being integrated into education, business, healthcare, and government operations (Dwivedi et al., 2023; Kasneci et al., 2023). In higher education, GenAI is reshaping how students learn, conduct research, write assignments, and engage with educational content (Baidoo-Anu & Ansah, 2023; Cotton et al., 2023). Similarly, educators are exploring how these technologies can enhance teaching, assessment, curriculum design, and administrative tasks, while simultaneously addressing concerns about academic integrity and ethical use (Kasneci et al., 2023; Tlili et al., 2023).

Despite the widespread availability of GenAI tools, adoption rates vary significantly across individuals and institutions. While some users enthusiastically embrace these technologies, others remain hesitant due to concerns about reliability, ethical use, privacy, and academic integrity (Dwivedi et al., 2023; Tlili et al., 2023). Consequently, researchers have increasingly examined the determinants of GenAI acceptance and usage through technology adoption frameworks such as the Unified Theory of Acceptance and Use of Technology (UTAUT), which highlights the roles of performance expectancy, effort expectancy, social influence, and facilitating conditions in shaping users' behavioural intentions and actual technology use (Venkatesh et al., 2003; Chiu, 2023).

Developed by Venkatesh et al. (2003), the UTAUT model provides a comprehensive explanation of why individuals choose to adopt or reject new technologies by integrating key constructs from several earlier technology acceptance theories. Recent studies have increasingly applied UTAUT and its extensions to examine the adoption of GenAI and artificial intelligence technologies in higher education and professional settings, demonstrating its continued relevance in explaining users' behavioural intentions and technology usage patterns (Chiu, 2023; Al-Emran, 2023; Al-Emran & Griffy-Brown, 2023; Dwivedi et al., 2023).

This article explores the relationship between GenAI and the UTAUT model, discussing how the model helps explain user acceptance, behavioural intention, and actual usage of AI technologies in higher education.

2. Literature Review

2.1 Understanding Generative Artificial Intelligence

Generative AI refers to computational techniques capable of generating new and meaningful content—including text, images, audio, and video—by learning patterns from large volumes of training data. Unlike traditional AI systems, which focus primarily on classification, prediction, or decision-making, GenAI produces novel outputs that resemble human-created content (Feuerriegel et al., 2023; Cao et al., 2023).

GenAI has expanded rapidly across a wide range of applications, demonstrating its ability to produce human-like content across multiple formats. Prominent examples include ChatGPT for text generation, Gemini for multimodal content creation, GitHub Copilot for programming assistance, DALL·E for image generation, and Claude for research and document analysis. These tools are built on advanced machine learning architectures that enable them to generate contextually relevant outputs based on user prompts, making them highly versatile across professional and educational domains (GitHub, 2024; Ramesh et al., 2022; Anthropic, 2024).

In higher education, GenAI is increasingly adopted by students to support a variety of academic tasks, including brainstorming, summarising academic articles, translating languages, assisting with coding, supporting research, and drafting essays and reports. These applications highlight the role of GenAI as a cognitive support tool that enhances productivity and learning efficiency rather than replacing human intellectual effort (Kasneci et al., 2023; Zawacki-Richter et al., 2019).

Educators are also integrating GenAI into their teaching and administrative practices through lesson planning, content development, assessment design, administrative support, and the creation of personalised learning experiences. This integration reflects a broader shift toward AI-supported pedagogy, where educators leverage intelligent systems to improve instructional quality and efficiency (Holmes et al., 2019; Holmes & Miao, 2023).

The rapid growth and widespread adoption of GenAI have generated significant academic interest in the factors influencing their acceptance and use. Researchers are increasingly examining behavioural, technological, and organisational determinants that shape user adoption, particularly in educational contexts where GenAI is transforming traditional teaching and learning processes (Dwivedi et al., 2023).

Despite its numerous benefits, the adoption of GenAI in higher education has also raised significant concerns. A major issue relates to the accuracy and reliability of AI-generated content. GenAI systems are prone to producing fabricated or misleading information—commonly referred to as "hallucinations"—which may compromise the quality of academic work if users fail to verify outputs critically (Ji et al., 2023; Kasneci et al., 2023). Furthermore, excessive reliance on GenAI may weaken students' critical thinking, problem-solving, and independent learning abilities, as learners may become dependent on AI-generated solutions rather than engaging in deeper cognitive processes (Tlili et al., 2023).

Academic integrity represents another important challenge. The ability of GenAI tools to generate essays, reports, and assignments has intensified concerns about plagiarism, authorship, and the authenticity of student work. Educational institutions continue to face difficulties in developing effective policies and assessment strategies that balance innovation with ethical academic practices (Cotton et al., 2023; Dwivedi et al., 2023). Additionally, issues relating to data privacy, security, and intellectual property have emerged as users often provide sensitive information to AI platforms, creating potential risks regarding data misuse and ownership of generated content.

From an educational perspective, unequal access to advanced GenAI technologies may widen existing digital divides among students, particularly between those with differing levels of technological literacy and financial resources (Zawacki-Richter et al., 2019). Moreover, concerns have been raised about algorithmic bias embedded within training datasets, which may result in discriminatory or culturally biased outputs that influence learning experiences and decision-making processes (Bender et al., 2021). Consequently, while GenAI offers substantial opportunities for enhancing teaching and learning, its adoption must be accompanied by appropriate governance frameworks, ethical guidelines, and digital literacy initiatives to mitigate potential risks and ensure responsible use.

2.2 Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT) was developed by Venkatesh et al. (2003) to provide a comprehensive framework for explaining individuals' acceptance and use of information technologies. The model synthesised eight prominent theories and models of technology adoption, including the Technology Acceptance Model (TAM), the Theory of Planned Behaviour (TPB), and Innovation Diffusion Theory (IDT), among others. According to UTAUT, four key constructs influence an individual's intention to adopt and use a technology: (1) performance expectancy, (2) effort expectancy, (3) social influence, and (4) facilitating conditions. Performance expectancy refers to the degree to which an individual believes that using a technology will improve their performance; effort expectancy relates to perceived ease of use; social influence reflects the extent to which significant others encourage technology use; and facilitating conditions refer to the availability of organisational and technical resources that support adoption. Together, these constructs shape users' behavioural intentions, which subsequently influence their actual technology usage (Venkatesh et al., 2003).

Despite its widespread application and strong explanatory power, the UTAUT model has been subject to several criticisms. One major limitation is its complexity: the original framework incorporates multiple constructs, moderators, and relationships that can make empirical testing challenging and reduce its practical applicability across different contexts (Bagozzi, 2007). Critics argue that integrating numerous variables may yield a model that is theoretically comprehensive but difficult to operationalise effectively in real-world studies.

Another criticism concerns the model's limited consideration of contextual and cultural factors. Because UTAUT was developed primarily within organisational settings, technology adoption behaviours may vary significantly across cultures, educational environments, and demographic groups. Consequently, the model may not fully capture the influence of contextual variables that shape users' perceptions and behaviours in diverse settings (Straub et al., 1997; Williams et al., 2015).

Furthermore, UTAUT has been criticised for emphasising utilitarian and rational decision-making while overlooking emotional, psychological, and affective factors that may influence technology adoption. Constructs such as trust, anxiety, perceived risk, enjoyment, and personal innovativeness have been shown to play important roles in determining users' willingness to adopt emerging technologies, yet these variables are not explicitly incorporated into the original UTAUT framework (Bagozzi, 2007; Venkatesh et al., 2012).

In the context of GenAI adoption, the original UTAUT model may also be insufficient to explain concerns relating to ethical use, algorithmic bias, privacy risks, transparency, and academic integrity. These issues have emerged as critical determinants of user acceptance of AI technologies, suggesting that additional constructs may be necessary to adequately explain adoption behaviour in contemporary AI-driven environments (Dwivedi et al., 2023). As a result, many recent studies have extended or modified the UTAUT framework by incorporating variables such as trust, perceived risk, AI literacy, and ethical concerns to better capture the complexities associated with GenAI adoption.

2.3 Performance Expectancy and Generative AI

Performance expectancy refers to the degree to which an individual believes that using a particular technology will enhance their job performance, learning effectiveness, or task outcomes (Venkatesh et al., 2003). In the context of GenAI, performance expectancy reflects users' perceptions that AI-powered tools can improve productivity, save time, enhance learning outcomes, increase the quality of work, and support problem-solving activities. When users perceive that GenAI can help them accomplish tasks more efficiently and effectively, they are more likely to adopt and use these technologies. Numerous studies have identified performance expectancy as one of the strongest predictors of GenAI adoption, particularly in educational settings (Dwivedi et al., 2023). For example, university students often perceive tools such as ChatGPT as valuable academic assistants for conducting literature reviews, generating ideas, preparing assignments, summarising complex concepts, and supporting examination revision.

Lecturers may similarly view GenAI as a means of reducing administrative workload, developing teaching materials, designing assessments, and enhancing curriculum delivery. Accordingly, the greater the perceived usefulness and performance benefits of GenAI, the stronger users' intention to adopt and integrate these technologies into their academic and professional activities (Kasneci et al., 2023; Venkatesh et al., 2003).

While performance expectancy is recognised as a key determinant of technology adoption, its role in GenAI usage is not without limitations. Users may sometimes overestimate the perceived benefits, as GenAI systems can generate inaccurate, incomplete, or fabricated information—commonly known as "hallucinations"—which may negatively affect decision-making and task quality if outputs are not adequately verified (Ji et al., 2023). Consequently, perceived performance improvements may not always correspond to actual performance gains.

In educational settings, concerns have also been raised that excessive reliance on GenAI may undermine the development of critical thinking, analytical reasoning, creativity, and independent learning skills. Students who depend heavily on AI-generated responses may become less engaged in deeper cognitive processes, potentially reducing the educational benefits associated with active learning and knowledge construction (Tlili et al., 2023; Cotton et al., 2023). Although GenAI may improve short-term task efficiency, its long-term impact on learning effectiveness remains a subject of ongoing debate.

Furthermore, performance expectancy may be shaped by unrealistic expectations about GenAI capabilities. Users often perceive AI systems as highly intelligent and authoritative, which can lead to overconfidence in the quality and accuracy of generated content. When actual performance fails to meet these expectations, users may experience dissatisfaction, reduced trust, and diminished intention to continue using the technology (Glikson & Woolley, 2020). This issue is particularly relevant in academic environments where accuracy, credibility, and evidence-based reasoning are essential.

Additionally, concerns about academic integrity and ethical use may offset the perceived performance benefits of GenAI. Although these tools can significantly reduce the time required to complete assignments and research tasks, their misuse may contribute to plagiarism, authorship disputes, and diminished academic authenticity (Dwivedi et al., 2023). Therefore, the relationship between performance expectancy and GenAI adoption may be more complex than the original UTAUT framework proposed, as users must balance perceived efficiency gains against potential educational, ethical, and quality-related risks.

2.4 Effort Expectancy and Generative AI

Effort expectancy refers to the degree of ease associated with using a technology and reflects users' perceptions of how simple and understandable a system is to operate (Venkatesh et al., 2003). In the context of GenAI, effort expectancy is particularly relevant because many AI platforms are designed with intuitive, user-friendly interfaces that require minimal technical expertise. Users can interact with GenAI systems through natural language prompts, enabling individuals with varying levels of digital literacy to access and utilise these technologies effectively. Factors influencing effort expectancy include ease of learning, user-friendly design, clarity of instructions, accessibility of AI tools, and the availability of training and support resources. Research has shown that individuals who perceive GenAI as easy to use are more likely to develop positive attitudes and stronger adoption intentions (Venkatesh et al., 2003). Conversely, users who perceive AI systems as complex or difficult to operate may be less inclined to engage with them. In higher education settings, institutions can enhance GenAI adoption by providing AI literacy programmes, training workshops, and practical guidance that improve users' confidence and competence. Such initiatives can reduce perceived effort and encourage greater acceptance and utilisation among students and educators (Kasneci et al., 2023; Holmes & Miao, 2023).

However, the influence of effort expectancy on adoption may not always be straightforward. Although many GenAI systems provide intuitive interfaces and natural language interactions, effective use often requires users to develop new competencies—including prompt engineering skills, critical evaluation of AI-generated outputs, and an understanding of AI limitations (Kasneci et al., 2023). As a result, users may initially underestimate the effort required to achieve high-quality and reliable outcomes.

Furthermore, the apparent simplicity of interacting with GenAI may create an illusion of competence, leading users to overestimate their ability to evaluate the accuracy and credibility of generated content. Although producing responses may appear effortless, verifying information, detecting errors, and assessing potential biases often require substantial cognitive effort and domain knowledge (Ji et al., 2023). Consequently, the perceived ease of use may mask the additional effort needed to ensure responsible and effective utilisation of GenAI.

Effort expectancy may also vary significantly across user groups. Individuals with limited digital literacy, inadequate technological experience, or insufficient AI knowledge may still perceive GenAI systems as complex and intimidating despite their user-friendly interfaces (Zawacki-Richter et al., 2019). In educational settings, disparities in technological skills and access to training resources may create unequal opportunities for effective AI adoption, potentially widening existing digital divides among students and educators.

Moreover, the rapid evolution of GenAI technologies requires users to continuously adapt to new features, updates, and emerging platforms. This ongoing learning process may increase perceived effort over time, particularly for educators who must integrate AI tools into teaching practices while simultaneously addressing ethical, pedagogical, and assessment-related concerns (Holmes et al., 2019; Dwivedi et al., 2023). Therefore, effort expectancy alone may not fully explain adoption behaviour, as users must also invest time and cognitive resources to develop AI literacy and ensure appropriate use of these technologies.

2.5 Social Influence and Generative AI

Social influence refers to the degree to which individuals perceive that important others believe they should use a particular technology (Venkatesh et al., 2003). In the context of GenAI adoption within higher education, social influence may stem from peers, lecturers, university administrators, professional communities, and industry expectations. As GenAI tools such as ChatGPT become increasingly integrated into academic and professional environments, their widespread use contributes to the normalisation of AI-assisted learning and work practices. When students observe classmates, lecturers, or colleagues actively using GenAI for tasks such as research, content creation, and problem-solving, they may feel encouraged to adopt these technologies themselves. Similarly, institutional support and positive recommendations from educators can strengthen users' perceptions of the value and legitimacy of GenAI. Empirical studies suggest that social influence plays a significant role in shaping students' intentions to use GenAI, although its impact may vary across user groups. While some studies report that social influence is a strong predictor of adoption behaviour, others find its effect less substantial than performance expectancy and perceived usefulness (Venkatesh et al., 2003). Nevertheless, institutional endorsement, peer acceptance, and professional expectations remain important drivers of positive attitudes toward GenAI in educational settings (Dwivedi et al., 2023; Kasneci et al., 2023).

Although relevant in explaining technology adoption, the role of social influence in GenAI uptake has several limitations. One key concern is that social pressure may lead to compliance-driven adoption rather than genuine acceptance, where individuals use GenAI because it is socially expected rather than because they perceive it as beneficial (Venkatesh et al., 2003). This form of adoption may result in superficial engagement, limited critical evaluation, and inconsistent or inappropriate use of the technology.

In educational contexts, strong peer or institutional pressure to use GenAI may also contribute to conformity and dependency behaviours, where students adopt AI tools without fully understanding their limitations or ethical implications. This increases the risk of over-reliance on AI-generated outputs, potentially undermining independent learning, originality, and academic integrity (Cotton et al., 2023). Social influence may therefore inadvertently encourage usage that prioritises convenience over deep learning.

Moreover, the influence of peers and educators may not always be constructive. If influential users promote uncritical or excessive reliance on GenAI, this may normalise practices such as direct content generation for assignments, raising concerns about plagiarism, authorship, and authenticity in academic work (Dwivedi et al., 2023). This highlights that social influence can operate as a double-edged factor, shaping both appropriate and inappropriate adoption behaviours depending on the prevailing academic culture.

Another limitation is that social influence tends to diminish over time as users gain experience with technology. As individuals become more familiar with digital tools, their adoption decisions are increasingly driven by personal beliefs—such as perceived usefulness and ease of use—rather than external opinions (Venkatesh et al., 2003; Williams et al., 2015). Therefore, in the context of GenAI—where users often experiment independently—social influence may have a weaker or shorter-lived effect compared to other UTAUT constructs.

Additionally, social influence may vary significantly across cultural and institutional contexts. In more individualistic learning environments, students may rely less on peer or authority opinions when adopting new technologies, whereas in collectivist contexts, social expectations may exert stronger pressure (Straub et al., 1997). This variability suggests that the predictive power of social influence is not universal and may depend heavily on contextual and cultural conditions.

2.6 Facilitating Conditions and Generative AI

Facilitating conditions refer to the extent to which individuals believe that organisational and technical infrastructure is available to support the use of a particular technology (Venkatesh et al., 2003). In the context of GenAI, facilitating conditions include reliable internet access, availability of AI software, technical support services, training opportunities, and clear institutional policies governing acceptable use. When universities provide structured guidance and accessible resources for GenAI use, they create an enabling environment that encourages both students and educators to adopt these technologies. Conversely, uncertainty regarding policies, ethical boundaries, or a lack of technical support may discourage engagement with AI tools and limit their integration into academic practices. Research indicates that facilitating conditions positively influence both behavioural intention and actual usage of GenAI, particularly in higher education settings where institutional readiness plays a critical role in technology adoption (Venkatesh et al., 2003; Dwivedi et al., 2023). This factor is especially significant for academic staff, who often require formal institutional approval, training, and support before incorporating new technologies into teaching, assessment, and curriculum design (Kasneci et al., 2023; Holmes & Miao, 2023).

Despite their importance, facilitating conditions alone do not guarantee successful GenAI adoption. Even when institutions provide adequate infrastructure, training, and policy guidance, users may still face practical barriers such as unclear ethical frameworks, rapidly evolving tool capabilities, and inconsistent institutional enforcement, which can create uncertainty and hinder effective use (Dwivedi et al., 2023). In some cases, overly restrictive or ambiguous institutional policies may discourage experimentation and limit meaningful engagement with GenAI in teaching and learning contexts. Furthermore, disparities in access to high-quality devices, subscriptions, or advanced AI features can persist even within well-resourced institutions, leading to unequal adoption outcomes among students and staff (Zawacki-Richter et al., 2019). Therefore, facilitating conditions alone may be insufficient to ensure sustained or equitable GenAI usage without addressing broader issues of governance, digital inequality, and user confidence.

2.7 Behavioural Intention and Actual Use

According to UTAUT, behavioural intention is the most immediate determinant of actual technology usage, acting as the direct precursor to user behaviour (Venkatesh et al., 2003). In this framework, individuals are more likely to develop a strong intention to use GenAI when they perceive the technology as useful, easy to use, socially encouraged, and supported by adequate organisational and technical infrastructure. These combined perceptions shape users' willingness to engage with AI tools and influence their readiness to integrate them into academic and professional tasks. Behavioural intention subsequently translates into actual usage behaviour, meaning that stronger intentions lead to more frequent and sustained use of the technology over time. Recent research confirms that behavioural intention is a significant predictor of both the frequency and intensity of GenAI use among students and educators, particularly in higher education environments where tools such as ChatGPT are increasingly adopted for learning, teaching, and research support (Dwivedi et al., 2023; Kasneci et al., 2023; Venkatesh et al., 2003).

However, the relationship between behavioural intention and actual usage is not always consistent or direct. A well-documented limitation of intention-based models such as UTAUT is the presence of the "intention–behaviour gap," where strong intentions do not necessarily translate into actual or sustained technology use due to situational constraints, habits, or competing priorities (Bagozzi, 2007; Sheeran, 2002). In the context of GenAI, users may express positive intentions driven by perceived usefulness or social trends, yet their actual usage may remain limited because of concerns about accuracy, ethical implications, or institutional restrictions (Dwivedi et al., 2023). Moreover, rapid changes in AI tools and user fatigue with constantly evolving systems may further weaken the stability of behavioural intention over time. This suggests that behavioural intention alone may be insufficient to fully explain GenAI usage behaviour without considering contextual, ethical, and habitual factors.

2.8 Extending UTAUT for Generative AI

Although UTAUT provides a strong foundational framework for explaining technology adoption, researchers have increasingly argued that additional constructs are required to fully understand GenAI adoption in contemporary contexts (Venkatesh et al., 2003; Dwivedi et al., 2023). One important extension is perceived risk, which refers to users' concerns about privacy, data security, misinformation, bias, and potential academic misconduct associated with GenAI use.

Such concerns may negatively influence adoption intentions, as users may hesitate to rely on AI-generated outputs if they question their accuracy, reliability, or ethical implications (Dwivedi et al., 2023).

Another critical factor is trust, which has emerged as a central determinant of AI acceptance. Users are more likely to adopt GenAI when they trust the technology itself, the accuracy of its outputs, and the organisations providing AI services. Trust has also been found to moderate the relationship between performance expectancy and behavioural intention, thereby playing an important role in technology adoption decisions (Lee & See, 2004). In addition, AI literacy has become an increasingly important construct in understanding GenAI adoption. AI literacy refers to users' knowledge and understanding of AI capabilities, limitations, and appropriate usage. Individuals with higher levels of AI literacy tend to demonstrate greater confidence, more effective usage patterns, and stronger behavioural intentions to adopt GenAI tools. Consequently, educational institutions are increasingly emphasising AI literacy development as a prerequisite for responsible and effective adoption of GenAI in teaching, learning, and research environments (Long & Magerko, 2020; Holmes & Miao, 2023).

While extending UTAUT with constructs such as perceived risk, trust, and AI literacy enhances explanatory power, these additions also introduce conceptual overlap and measurement challenges. For instance, perceived risk and trust are often empirically interrelated, making it difficult to distinguish their independent effects on behavioural intention clearly (Gefen et al., 2003; McKnight et al., 2011). Similarly, expanding the model with multiple context-specific variables may reduce its parsimony—originally a key strength of UTAUT—and can lead to model complexity and inconsistent findings across studies (Bagozzi, 2007). Additionally, AI literacy as a construct may be unevenly defined and measured across studies, limiting comparability and generalisability, particularly in rapidly evolving technological environments (Long & Magerko, 2020). Furthermore, in the context of GenAI, users may report high trust or literacy without necessarily demonstrating accurate understanding or responsible usage, raising concerns about self-reported bias in adoption research (Dwivedi et al., 2023). Therefore, while these extensions improve contextual relevance, they also risk reducing theoretical clarity and empirical consistency in explaining GenAI adoption behaviour.

2.9 Generative AI Adoption in Higher Education

Higher education has emerged as one of the most dynamic contexts for GenAI adoption, with numerous recent studies applying UTAUT to explain usage patterns among students and academic staff (Venkatesh et al., 2003; Dwivedi et al., 2023). Among students, research consistently shows high levels of perceived usefulness, positive attitudes toward AI tools, strong behavioural intentions, and frequent use of GenAI for academic support activities such as writing assistance, summarisation, idea generation, and revision. Performance expectancy is repeatedly identified as the strongest predictor of adoption, indicating that students are primarily motivated by the perceived academic benefits and efficiency gains offered by tools such as ChatGPT (Kasneci et al., 2023).

In contrast, academic staff tend to adopt GenAI more cautiously due to concerns about academic integrity, the reliability and accuracy of AI-generated outputs, institutional policies, and broader ethical implications. While educators recognise the potential of GenAI to support teaching, research, and administrative tasks, their adoption decisions are often shaped by organisational constraints and governance structures. As a result, facilitating conditions and institutional support play a more significant role in influencing lecturers' adoption behaviour compared to students, underscoring the importance of policy clarity, training, and technical infrastructure in encouraging responsible use among faculty members (Dwivedi et al., 2023; Holmes & Miao, 2023; Venkatesh et al., 2003).

3. Implications for Universities

Universities aiming to promote responsible GenAI adoption should strategically strengthen the core dimensions of UTAUT—namely performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003; Dwivedi et al., 2023). To enhance performance expectancy, institutions should actively demonstrate the educational benefits of GenAI, share successful implementation case studies, and integrate AI tools into teaching and learning practices to highlight their academic value. Improving effort expectancy requires universities to provide user-friendly AI platforms, conduct training workshops, and develop accessible support resources that build users' confidence and competence.

In addition, strengthening social influence can be achieved by encouraging faculty champions to lead adoption efforts, promoting peer learning communities, and highlighting positive role models who effectively use GenAI in academic contexts. Facilitating conditions should be reinforced through the development of clear institutional policies on AI use, the provision of robust technical infrastructure, and the establishment of ethical guidelines to ensure safe and responsible engagement with AI tools. Collectively, these initiatives can significantly enhance user acceptance, reduce uncertainty, and foster responsible and effective use of GenAI across higher education institutions (Holmes & Miao, 2023; Kasneci et al., 2023).

4. Conclusion

Generative Artificial Intelligence is transforming higher education by providing powerful tools that support learning, teaching, research, and administration. However, successful implementation depends not only on technological capabilities but also on user acceptance.

The UTAUT model offers a valuable framework for understanding why individuals adopt GenAI technologies. Performance expectancy, effort expectancy, social influence, and facilitating conditions collectively shape behavioural intention and actual usage. Among these factors, performance expectancy consistently emerges as the strongest predictor of adoption, highlighting the centrality of perceived usefulness. At the same time, emerging constructs such as trust, perceived risk, and AI literacy are becoming increasingly relevant in the context of GenAI.

As universities continue integrating AI technologies into educational environments, applying the UTAUT framework can help policymakers, educators, and researchers design strategies that promote responsible, ethical, and effective adoption. Understanding the factors that drive acceptance will be essential for maximising the benefits of GenAI while minimising its risks.

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About the Author

Professor (Dr.) KOH Kee Lee is an academic leader and industry-experienced educator with more than 30 years of experience across higher education, IT solutions, paints and coatings, and battery manufacturing. He currently serves as Dean at Stanfort Academy (London Metropolitan University's external degree partner in Singapore), Professor of Practice at Wuhan Business University, and Emeritus Professor at STADA. He holds a Doctor of Business Administration (DBA) from PPA Business School (France), with a dissertation examining leadership styles and organisational culture in China (DKM Group), as well as multiple master's degrees from Australia and the United Kingdom. His research on leadership and organisational culture has been published in peer-reviewed journals, including The International Journal of Professional Management (2024) and International Journal of Public Sector Performance Management (2020). Professor Koh's teaching expertise spans marketing, strategic management, leadership, organisational behaviour, business strategy, and international business. He is also a trained and certified organisation transformist with ATD, USA.

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