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EXTENDING TAM FOR GENERATIVE AI - HOW TECHNOPHOBIA AND INSTITUTIONAL CONTEXT SHAPE AI ADOPTION AMONG EGYPTIAN ACADEMICS: A MIXED-METHODS LENS

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ABSTRACT

Aim/Purpose	This paper investigates how academics in Egyptian higher education adopt and engage with generative AI tools, addressing the limited understanding of faculty perceptions and the role of technophobia in influencing adoption.
Background	Existing research on generative AI adoption primarily focuses on a single tool (e.g., ChatGPT) and overlooks broader organizational and psychological factors. This study extends the Technology Acceptance Model (TAM) to include technophobia and organizational innovative culture, providing a comprehensive explanation of adoption behaviors in the Egyptian higher education context.
Methodology	A mixed-methods design was employed. Quantitative data were collected from 195 academics via a structured survey measuring TAM constructs, technophobia, and organizational culture. Qualitative data were obtained through semi-

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	structured interviews to capture experiences, perceived benefits, and concerns regarding generative AI tools.
Contribution	The study refines TAM by demonstrating that technophobia indirectly affects adoption through perceived usefulness and perceived ease of use, while organizational innovative culture does not moderate adoption relationships. It offers both theoretical insights and practical guidance for the responsible use of generative AI in higher education.
Findings	Perceived usefulness was the strongest predictor of adoption intention, whereas perceived ease of use was not significant. Technophobia reduced perceived usefulness and ease of use but did not directly affect adoption intention. Organizational innovative culture did not moderate relationships. Interviews highlighted efficiency benefits of generative AI alongside concerns about ethics, originality, and policy gaps.
Recommendations for Practitioners	Universities should establish clear policies for the use of generative AI in teaching, assessment, and research, and provide regular training and awareness programs to support responsible adoption. Institutions should encourage critical and purposeful use rather than dependence on generative AI.
Recommendations for Researchers	Future studies may expand TAM by including constructs such as trust, perceived risk, and institutional policy support, explore discipline-specific adoption patterns, and examine long-term impacts on teaching and learning.
Impact on Society	Generative AI has the potential to enhance academic productivity while raising ethical and integrity concerns. Balanced and responsible implementation can maintain the educational and social mission of universities.
Future Research	Further research should involve a wider range of institutions, consider moderators such as digital literacy and organizational readiness, and develop ethical and pedagogical frameworks for the constructive use of AI in higher education.

Keywords: generative AI, technology acceptance model, TAM, higher education, technophobia, organizational culture

INTRODUCTION

The turn of the millennium marked the beginning of a massive technological shift, centred on the rapid evolution of artificial intelligence. Today, AI is no longer a futuristic concept; it is a practical force reshaping sectors from factory floors to digital storefronts. The reach of AI extends beyond simple automation, offering the power to boost output, displace traditional roles, and fundamentally rewrite the rules of business ecosystems. This shift has compelled leadership teams to confront the generative AI (GenAI) era, weighing its operational advantages against the risks associated with such a disruptive tool (Hashmi & Bal, 2024).

The rapid advancement of artificial intelligence (AI) has reshaped multiple sectors, including higher education (Law, 2024). Among recent innovations, generative AI has gained particular attention for its ability to create original text, code, audio, images, and video by learning patterns from existing data (Feuerriegel et al., 2024). A growing number of tools, such as ChatGPT, Google Gemini, DeepL Write, Claude, Microsoft Copilot, Grammarly GO, and Canva AI, are now used in universities to support academic writing, content creation, coding tasks, data analysis, and administrative work.

Recent studies illustrate this trend. Zou and Huang (2023) found that doctoral students showed strong interest in using ChatGPT for academic writing, while Ghimire and Edwards (2024) reported that instructors generally hold positive attitudes toward generative AI tools, with perceived usefulness and ease of use acting as central drivers of acceptance. Similarly, Sharawy (2023) found broad agreement among educators regarding the inevitability of integrating AI into teaching and learning, especially through easily deployable tools such as chatbots. Despite these advantages, the adoption of generative AI in academic settings raises several concerns. (Guha et al., 2024).

As Cheng et al. (2025) note, such inaccuracies, along with incorrect citations and unreliable references, raise significant questions about the credibility and ethical use of academic writing. Further concerns relate to academic creativity and integrity. George et al. (2024) reported a notable decline in effort devoted to routine cognitive activities compared with eight years ago, suggesting a growing dependence on technology. This trend fuels worries that overreliance on generative AI may diminish originality, critical thinking, and sustain intellectual engagement.

Although interest in this domain is increasing, existing research remains limited in scope. Much of the literature focuses primarily on ChatGPT and relies heavily on the Technology Acceptance Model (TAM) (Al-kfairy, 2024; Zou & Huang, 2023). This narrow focus overlooks the broader ecosystem of generative AI tools used by academics and understates the potential influence of psychological and institutional barriers. In particular, technophobia (fear or anxiety associated with using advanced technologies) has received limited empirical attention, despite its relevance to the adoption of fast-evolving generative AI systems. Moreover, little research has examined how the organizational climate of universities influences the adoption process. These gaps are especially salient in developing countries such as Egypt, where institutional readiness varies, and digital transformation is still emerging.

Egypt's higher education system is among the oldest and largest in the Middle East and North Africa region, encompassing a diverse mix of public, private, and non-profit universities, as well as branch campuses of international institutions (Azoury & Habchi, 2023). The system is overseen by the Ministry of Higher Education and Scientific Research. Over the past decade, the sector has experienced notable expansion in the number of universities and higher education institutions, driven by growing societal demand for tertiary education and national policy initiatives aimed at diversifying educational pathways and aligning academic outcomes with labor market needs (Buckner, 2013). Concerning digital transformation, Egyptian universities have increasingly adopted e-learning platforms, learning management systems, and blended learning tools, particularly following the COVID-19 pandemic, which served as a critical catalyst for accelerating the integration of digital technologies into teaching and assessment practices.

Nevertheless, levels of digital readiness and the adoption of advanced technologies, such as GenAI, remain uneven across institutions due to variations in organizational resources, technological infrastructure, and the availability of institutional support and academic training. This heterogeneity renders the Egyptian higher education context especially suitable for examining the psychological and organizational factors influencing generative AI adoption, particularly considering the ongoing tension between innovation-driven ambitions and prevailing institutional and ethical challenges. Egyptian higher education provides a timely and relevant context for this investigation, given its growing interest in AI-driven educational reform and the absence of clear institutional guidelines governing the use of generative AI.

Accordingly, this study addresses the following research questions:

1. What is the current experience of academic staff in Egyptian higher education institutions with using generative AI tools in teaching and learning?
2. How does technophobia influence the acceptance and use of generative AI tools among academic staff in Egyptian universities?
3. To what extent does the organizational climate within Egyptian universities promote the adoption and effective use of generative AI tools in academic activities?

To address these questions, the study adopts a mixed-methods approach that integrates quantitative survey data with qualitative interview insights. This design offers a more comprehensive view of the factors shaping generative AI adoption, overcoming the limitations of relying on a single methodological perspective (Al-kfairy, 2024). While prior work, such as Jo (2024), has focused on student use of AI chatbots, the present study extends this line of inquiry by examining academics as a distinct and influential user group whose adoption decisions directly shape teaching, research, and institutional policy. This study contributes to the literature by examining the adoption of generative AI tools through an extended TAM framework that incorporates technophobia and organizational climate. Drawing on data from 295 academics across Egyptian universities, the study offers empirical insight into both psychological and institutional factors influencing adoption. The remainder of this paper is organized as follows: the next section presents the theoretical framework and hypotheses; this is followed by the methodology, results, discussion, and implications; and the paper concludes with recommendations and directions for future research.

THEORETICAL FRAMEWORK

This study employs the Technology Acceptance Model (TAM) as its core framework to examine generative AI adoption in higher education. To extend TAM, technophobia is incorporated as a barrier influencing perceptions of usefulness and ease of use, while organizational innovative culture is considered a contextual factor shaping academics' attitudes, intentions, and integration of generative AI tools.

GENERATIVE AI TOOLS IN THE ACADEMIC CONTEXT

Artificial intelligence has increasingly reshaped educational systems by supporting personalized learning, automating assessment, and improving instructional efficiency. AI in Education (AIED) has evolved since the 1970s toward adaptive and student-centred models (Joshi et al., 2021). Recently, generative AI (GenAI) has become one of the most influential developments, offering accessible, conversational, and content-producing capabilities (Hamerman et al., 2025). Generative AI models, including tools such as ChatGPT and Gemini, continue to influence higher education by supporting innovative teaching and assessment practices (Wang et al., 2024). A UK-based study found that more than 80% of respondents anticipated greater use of generative AI in academia, with almost half supporting curriculum integration (Arowosegbe et al., 2024).

Faculty members are increasingly deploying generative AI tools to support instructional tasks, although concerns remain regarding academic integrity and job security (Aad & Hardey, 2025). Wang et al. (2024) further demonstrated that most top U.S. universities adopt a cautious yet open stance toward generative AI integration in teaching and research. AI tutoring systems, such as Intelligent Tutoring Systems (ITS), foster personalized learning experiences tailored to each learner's needs (Joshi et al., 2021). However, despite these benefits, generative AI can also trigger technophobia, a psychological barrier that reduces willingness to use advanced tools in educational settings (Alquran et al., 2024; Khasawneh, 2018a, 2023).

Cross-cultural research highlights significant variations in generative AI adoption and perceptions in higher education (HE) across different regions. Yusuf et al. (2024) examined generative AI use among 1,217 participants from 76 countries and found high awareness and engagement with generative AI tools for tasks such as information retrieval and text paraphrasing. Their results indicate that cultural dimensions strongly shape both perceived benefits and concerns, including ethical considerations and potential for academic dishonesty. Complementing this global perspective, Al-Zahrani and Alasmari (2025) focused on 508 participants across 259 institutions in the Middle East and North Africa (MENA) region, revealing disparities in generative AI adoption across economic groups and countries. While generative AI integration in high-income and middle-income institutions was relatively advanced, many institutions were still in early stages of implementing adaptive learning platforms and AI-enhanced research tools. Barriers such as financial constraints, infrastructure limitations, and unclear policies were particularly pronounced in low-income contexts.

Together, these studies underscore that cross-cultural, economic, and institutional factors significantly influence both the adoption and effective utilization of generative AI in higher education, highlighting the need for context-sensitive policies, faculty training, and strategic investments to promote equitable and responsible generative AI integration. In Egypt, digital transformation strategies, such as the Ministry of Higher Education's digital university initiative, have accelerated the use of generative AI tools in teaching and research. However, disparities in digital competence, uneven institutional infrastructure, and concerns over job displacement continue to influence academics' perceptions of generative AI. These structural and cultural conditions make Egypt an important and unique context for studying technophobia, TAM variables, and the adoption of generative AI tools.

The Technology Acceptance Model (TAM).

The Technology Acceptance Model (TAM) was developed by Davis et al. (1989) and was designed to examine the key drivers of computer adoption. Rooted in the Theory of Reasoned Action, TAM has grown into a recognized socio-technical framework that seeks to clarify how individuals come to accept and employ technology (Zou & Huang, 2023).

TAM includes multiple variables that explain individuals' intentions and actual use of technology, whether directly or indirectly, such as perceived ease of use, perceived usefulness, and attitudes toward technology (Schepers & Wetzels, 2007; Scherer et al., 2019). Perceived usefulness, as described by Davis (1989), refers to how strongly individuals believe that technology use will enhance their ability to perform tasks. In other words, if people find technology useful, they are more likely to use it. Perceived ease of use represents an additional determinant of intention to adopt a technology, which represents the degree to which people consider the technology easy to use and free from effort (Davis, 1989).

Thus, when technology is seen as both easy to use and useful, users are more motivated to use it (Park & Kim, 2023). The core constructs of the TAM are perceived ease of use (PEOU), perceived usefulness (PU) and behavioral intention (BI) demonstrate strong reliability and have been effectively applied within various contexts (King & He, 2006; Scherer et al., 2019), including the acceptance of e-learning within the student community at universities (Al Kurdi et al., 2020). To increase its applicability across diverse domains such as higher education, TAM has been extended over time to incorporate various external variables that may influence technology adoption.

These include factors that either facilitate or hinder acceptance, such as self-efficacy and technophobia (Dogruel et al., 2015) and organizational culture (Namouni, 2020). Such extensions open the door to a fuller understanding of users' attitudes and behaviors toward emerging technologies in specific contexts. These findings align with a growing body of recent studies that confirm that the core TAM constructs remain central to AI adoption in higher education (Rad et al., 2022). There have been multiple investigations over recent years have used the TAM model to examine AI-based instructional tools (Hazzan-Bishara et al., 2025; Liling & Aklani, 2023; Rahman et al., 2025). Therefore, this study's conceptual framework is grounded in the TAM, incorporating technophobia and organizational innovation as independent and moderating variables.

The Role of Technophobia in Shaping TAM Constructs for Generative AI Adoption

Technophobia is defined as fear or anxiety related to interacting with new technologies (Osiceanu, 2015). Technophobia has increasingly been recognized as a psychological barrier that negatively affects the acceptance of digital tools in educational settings. In this context, Jo (2024) described technophobia as a form of fear and anxiety that leads students to avoid engaging with unfamiliar technologies. Similarly, Khasawneh (2018a) defined technophobia as an irrational emotional response –

ranging from active avoidance behaviors (fear) to passive psychological discomfort (anxiety) – triggered by new technologies that disrupt familiar routines. Traditionally, technophobia research has largely centred on "computer phobia", a concept often used interchangeably with technophobia, given the central role of computers in both educational and professional environments (Khasawneh, 2018b). However, as educational technology continues to evolve, particularly with the rise of generative AI, there is an increasing demand to examine technophobia in relation to these advanced tools. Rehman et al. (2024), in their review of eighteen educational studies on technophobia, emphasize that anxiety toward technology can severely obstruct the learning process, making it one of the most critical barriers to adoption of technology. Zhao et al. (2025) also recommend adopting a mixed-methods approach (combining surveys and interviews) to enhance the understanding of how technophobia shapes the integration of generative AI within educational settings. Early research by Sinkovics et al. (2002) contributed to the development of a technophobia scale that expanded beyond computers to encompass a range of everyday technologies, including ATMs and fax machines. This broader approach provides a useful framework for contemporary studies.

Thus, the present study adopts technophobia measures from Sinkovics et al. (2002) and Nimrod (2018) to assess attitudes toward generative AI tools such as ChatGPT within academic contexts. These insights suggest that technophobia should be considered a key external determinant in the TAM, especially in higher education, where resistance to technology may undermine efforts to integrate innovative tools such as ChatGPT into teaching and research.

Organizational Innovative Climate and Its Influence on TAM Constructs for Generative AI in Higher Education

An innovative culture entails a combination of shared values and guiding principles that promote innovation within organizations. It cultivates creativity, openness to novel ideas, and flexibility in making decisions (Mohamad et al., 2020; Toaldo et al., 2013). Although Empaynado-Porto (2020) examined this construct within the scope of schools, the results are equally relevant to higher education, where similar cultural and structural factors influence the acceptance of emerging technologies. As an illustration, Mohamad et al. (2020) employed organizational innovative culture (OIC) as a moderating variable in their study and found that when institutions demonstrate a high level of innovative culture, it significantly enhances the implementation of innovative practices across the organization.

The Conceptual Model

Building on the extended Technology Acceptance Model (TAM), this study proposes a framework to explain academics' adoption of generative AI in higher education. The model incorporates technophobia as a negative psychological barrier influencing perceived ease of use and perceived usefulness, while organizational innovative climate is introduced as a contextual factor that facilitates or hinders adoption.

Technophobia and Behavioral Intention (BI)

Previous research has consistently demonstrated that technophobia, explained as fear or anxiety associated with new technologies, can negatively influence the acceptance and adoption of emerging digital tools. For example, Zhao et al. (2025) found that among business managers in China, technophobia significantly reduced their readiness to embrace generative AI, highlighting its role as a psychological barrier. Similarly, Jo (2024) examined technology adoption among university students and reported that technophobia had a detrimental impact on their intention to use generative AI tools such as ChatGPT. These findings suggest that fear or discomfort with technology can undermine the main components of the TAM, particularly perceived usefulness and behavioral intention. As such, further investigation is warranted into how technophobia influences the adoption of generative AI tools in the higher education sector, thereby reinforcing the hypothesis that technophobia negatively moderates TAM variables in this context.

H1: Technophobia negatively influences behavioral intention to use generative AI tools.

Technophobia and the TAM (Ease of Use, Usefulness)

Technology offers numerous advantages, such as flexibility, broad accessibility, convenience, cost-effective delivery, enhanced collaboration, and the ability to stay current with emerging trends across various platforms. However, despite these benefits, hesitation or fear of adopting new technologies, commonly referred to as technophobia, may serve as a major obstacle to acceptance. Technophobia may negatively impact key factors within the TAM, such as perceived usefulness and perceived ease of use, thereby hindering users' willingness to adopt new tools (Dogruel et al., 2015). This fear or anxiety can prevent individuals from fully recognizing the potential advantages of technology, limiting its broader adoption and integration (Rehman et al., 2024).

H2: Technophobia negatively influences perceived ease of use of generative AI tools.

H3: Technophobia negatively influences the perceived usefulness of generative AI tools.

Perceived ease of use, perceived usefulness, and behavioral intention to use generative AI tools.

Perceived ease of use contributes positively to users' perceptions of usefulness and their intention to use technology. For instance, Zou and Huang (2023) found that perceived ease of use significantly enhances students' perceived usefulness of ChatGPT for writing purposes. Similarly, Park and Kim (2023) emphasized that improving individuals' perceived ease of use is important, as it not only enhances perceived usefulness but also strengthens the intention to use digital mental healthcare tools. Their study highlighted that factors such as perceived usefulness and ease of use play important roles in explaining why people adopt specific digital health technologies. According to King and He (2006), perceived usefulness strongly influences whether individuals decide to use a technology, underscoring its critical role in technology acceptance. However, Zou and Huang (2023) also noted that, for doctoral students using ChatGPT, Behavioral intention was not significantly affected by either perceived usefulness or perceived ease of use, suggesting that further research is needed to investigate these relationships in diverse contexts, especially in academic settings.

H4: Perceived ease of use has a positive effect on perceived usefulness of generative AI tools.

H5: Perceived ease of use positively influences behavioral intention to use generative AI tools.

H6: Perceived usefulness positively influences behavioral intention to use generative AI tools.

The mediation effect of (PEOU and PU)

Existing studies substantiate this mediation effect. For instance, Moslehpour et al. (2018) reported that both PU and PEOU mediated the association between personality traits and intentions to purchase online. Their findings highlight that for online platforms to appeal to users, they must offer intuitive, user-friendly interfaces along with reliable features such as simple ordering, fast delivery, responsive support, and transparent return policies. These elements enhance PU and PEOU, which ultimately boost user engagement. Similarly, Hussain et al. (2025) demonstrated that in the healthcare sector, PU and PEOU positively mediated the association between technology sophistication and nurses' intentions to use AI-powered medical applications. Their findings suggest that when technological systems are seen as both easy to use and beneficial to performance, professionals are more inclined to adopt them. A recent study of Hasan et al. (2023) highlights how students' technology orientations shape their acceptance of AI-powered chatbots in education. The study found that positive technology readiness factors, specifically Optimism and Innovativeness, significantly increased both PEOU and PU of chatbot tools. In contrast, the negative readiness factors of discomfort and insecurity showed inhibitory effects. Discomfort reduced PEOU, while insecurity not only lowered PEOU but also had a direct negative impact on PU. Together, these findings indicate that students who feel confident and enthusiastic about new technologies are more likely to view generative AI as useful and easy to use.

In contrast, those who experience anxiety, fear, or uncertainty toward technology evaluate these systems less favorably. Ardiyanti and Susilowati (2024) further confirmed that the relationship between digital competence and AI adoption is mediated by perceived usefulness, meaning that people with higher digital proficiency are more likely to adopt AI when they perceive it as useful. Building on these insights, the current study assumes that if academics perceive generative AI tools as convenient to use and beneficial for their teaching and research, their readiness to adopt and embed these tools in academic life will increase accordingly.

H7: TAM (PEOU and PU) mediates the relationship between technophobia and behavioral intention to use generative AI tools.

H7a: PEOU mediates the relationship between technophobia and behavioral intention to use generative AI tools.

H7b: PU mediates the relationship between technophobia and behavioral intention to use generative AI tools.

The Moderating Effect of Organizational Innovation

Previous studies have emphasized the vital role of organizational culture in shaping the adoption of technology. For instance, Ghasemtabar et al. (2019) reported that organizational culture strongly impacted technology acceptance among teachers in smart schools, thereby validating a conceptual model built on this premise. Similarly, Khasawneh (2018a) emphasized that the organizational environment, including its norms, support systems, and openness to innovation, can either exacerbate or alleviate technophobia and emotional resistance to technology. A supportive and innovative organizational climate not only reduces fear but also fosters readiness for change. Building on these insights, it is reasonable to propose that organizational innovation may strengthen the influence of TAM constructs (perceived usefulness and perceived ease of use) on individuals' behavioral intention to adopt generative AI systems in academic environments. Jo (2024) noted the need for future studies to examine institutional-level effects of AI adoption. In response, this study explores how organizational factors, such as the innovative climate, influence the strength of the relationship between TAM variables and behavioral intentions among academic staff.

H8: Organizational innovation positively moderates the relationship between TAM and behavioral intention to use generative AI tools.

H8a: Organizational innovation positively moderates the relationship between PEOU and behavioral intention to use generative AI tools.

H8b: Organizational innovation positively moderates the relationship between PU and behavioral intention to use generative AI tools.

Figure 1 presents the proposed conceptual model of the study, which serves as the basis for hypothesis development and empirical testing.

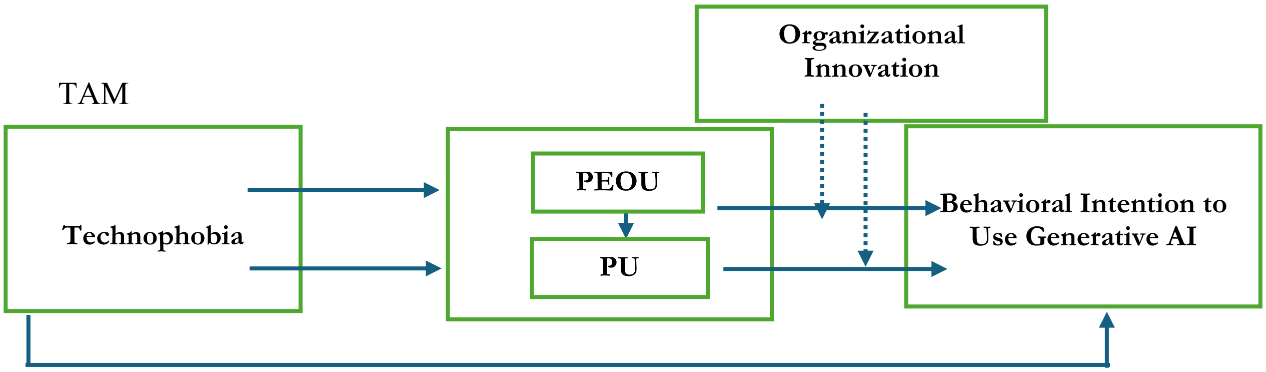

Figure 1. Conceptual model made by the authors

To synthesize prior studies, the literature review identified key research gaps relevant to the present study. Table 1 summarizes these gaps and illustrates their linkage to the study constructs and the development of the proposed hypotheses.

Table 1. Summary of literature gaps, constructs, and hypotheses development

Literature gap	Construct(s)	Justification	Linked hypotheses
Limited understanding of the negative psychological barriers (technophobia) to generative AI adoption in higher education in developing countries.	Technophobia	Technophobia generates fear/anxiety that reduces readiness to use generative AI tools (Jo, 2024; Zhao et al., 2025). It undermines TAM components (Dogruel et al., 2015; Khasawneh, 2018a).	H1: Technophobia to BI (negative)
Lack of empirical models integrating technophobia with TAM constructs for generative AI tools.	Technophobia, PEOU, PU	Technophobia reduces perceptions of ease and usefulness, weakening TAM paths (Rehman et al., 2024).	H2: Technophobia to PEOU (negative) H3: Technophobia to PU (negative)
Insufficient clarity regarding how PEOU and PU influence BI in the context of generative AI (some inconsistent findings noted in prior studies, such as Zou & Huang, 2023).	PEOU, PU, BI	TAM asserts that PEOU enhances PU and both shape intention (Davis, 1989; Park & Kim, 2023). Generative AI studies show mixed results requiring further research.	H4: PEOU to PU H5: PEOU to BI H6: PU to BI
Limited research on the mediation effects of TAM between psychological factors (e.g., technophobia) and the adoption of generative AI.	PEOU, PU as mediators	Studies show PEOU and PU mediate relationships between individual characteristics and technology adoption (Hussain et al., 2025; Moslehpour et al., 2018).	H7: PEOU + PU mediate. H7a: PEOU mediates. H7b: PU mediates
Lack of understanding of institutional-level influences (organizational innovative climate) on AI/TAM relationships.	Organizational Innovative Climate (OIC)	OIC enhances readiness for innovative technologies and reduces emotional resistance (Khasawneh, 2018a; Mohamad et al., 2020).	H8: OIC moderates TAM to BI H8a: OIC moderates PEOU to BI H8b: OIC moderates PU to BI

METHODOLOGY

This research employs an explanatory sequential design, blending quantitative and qualitative approaches, to examine how generative AI tools are accepted in academic settings and to analyze how technophobia affects the core elements of the TAM. Given that generative AI remains a relatively new phenomenon in higher education and that scholarly work on its adoption is still limited, this design offers a practical way to reveal emerging patterns, perceptions, and key drivers influencing its uptake. The mixed-methods approach integrates quantitative and qualitative data to gain a thorough understanding of the research problem. The quantitative phase was used first to test relationships among TAM constructs, technophobia, and behavioral intention across a broader sample. The subsequent qualitative phase was then conducted to explain, interpret, and deepen the understanding of the quantitative results. This echoes the current research aims, which are to provide a comprehensive view of the adoption process.

PHASE 1: QUANTITATIVE

Respondents were requested to participate in an online survey. The first section comprised 30 items measuring key constructs, which consisted of five multi-item scales ranging from 1 (strong disagreement) to 5 (strong agreement). Technophobia was assessed through 13 items adapted and modified from Sinkovics et al. (2002) and Nimrod (2018), for example, "I feel some anxiety when I approach generative AI tools in my academic activities." PU and PEOU in relation to generative AI use for academic tasks were assessed through nine items derived from Ibrahim et al. (2018), such as "Using generative AI-powered educational tools can help make my teaching or academic tasks more efficient. I find generative AI tools for teaching or academic tasks easy to use." Behavioral intention to use generative AI in academic contexts was captured with three items adapted from Venkatesh et al. (2012) and Jo (2024); for example, "I plan to continue using generative AI frequently in my academic work." Additionally, the innovative climate of the educational institution was assessed through five items adapted and modified from Mohamad et al. (2020); for example, "Our educational institution's (university's) culture allows people to be creative." The second section of the questionnaire gathered information on demographics, such as gender, age (generation), academic position, academic specialization, and type of educational institution, in addition to generative AI tools used, such as ChatGPT, Google Gemini, Microsoft Copilot, Claude, and others, which can assist people with academic tasks.

Data collection and sampling

A purposive snowball sampling method was employed to collect data from academics in Egypt, as this approach is suitable for targeting a specific population with relevant expertise while also reaching additional participants through peer referrals (Etikan et al., 2015; Naderifar et al., 2017; Ting et al., 2025). The survey was created via Google Forms and shared across several channels, including social media platforms, such as Facebook, LinkedIn, and WhatsApp, as well as direct messages sent specifically to academics. Additionally, a QR code was generated and shared to offer participants a convenient way to access and complete the survey. To broaden the reach, participants were encouraged to forward the survey link or QR code to their academic colleagues, ensuring that responses were obtained exclusively from the target group while maximizing participation through peer networks (Palinkas et al., 2015). The survey was voluntary, and participants were notified that their responses would be utilized for research purposes. No identifying information was collected, ensuring anonymity and confidentiality.

Although the conventional 10-times guideline recommends a minimum participant count of 40 for the present model, based on having four predictors for the most complex construct (Barclay et al., 1995), more recent simulation research indicates that this heuristic can be substantially biased. Wagner and Grimm (2023) empirically tested the 10-times rule against larger multiples up to 60 times and demonstrated that the 10-times criterion underestimates the necessary sample size for robust estimation. Their findings recommend that researchers adopt at least a 30-times multiple to ensure sufficient statistical power and minimize bias. Following this updated guideline, a minimum of 120 responses would be required for this study.

Analytical procedures

With 195 valid responses, the sample size exceeded both traditional and more stringent thresholds for PLS-SEM, meeting current best practice standards. The analysis was carried out using SmartPLS 4.0 (Ringle et al., 2024). We selected PLS-SEM due to its suitability for prediction-oriented research, its robustness with moderate sample sizes, and its ability to accommodate interaction terms and complex models. The PLS-SEM algorithm was employed to assess the measurement model by examining reliability (Cronbach's alpha and composite reliability), convergent validity (AVE), and discriminant validity (HTMT ratio and the Fornell-Larcker test). Subsequently, bootstrapping with 5,000 sub-samples was used to estimate path coefficients and assess the hypotheses proposed in the study. Table 2 shows the demographic profiles of the participants who participated voluntarily in this study.

Table 2. The demographic profiles

Aspects	Frequency	%
Gender:		
Male	53	27.2%
Female	142	72.8%
Age and generation type:		
20 to 28 (GenZ)	68	34.8%
29 to 44 (GenY)	91	46.6%
45 to 60 (GenX)	32	16.4%
61 to 79 (Baby Boomers)	4	2.1%
Academic Position:		
MSc - Demonstrator – Teaching assistant	75	38.5%
PhD - Assistant Lecturer.	63	32.3%
Assistant Professor	31	15.9%
Associate Professor	9	4.6%
Professor	17%	8.7%
Specialization:		
Business and Economics	44	22.56
Health Sciences	64	32.82
Engineering	28	14.36
Computer Science and Information Technology	8	4.1
Natural sciences	25	12.82
Arts and Design	8	4.1
Humanities (e.g., History, Literature, Philosophy)	9	4.61
Social science disciplines (such as Sociology, Psychology, and Political Science)	6	3.07
Other	3	1.53
Type of educational Institution:		
Public (governmental) university	105	53.8
Public university with a special nature	58	29.74
Private university	19	9.74

Aspects	Frequency	%
National university	4	2.05
International university	9	4.61

Most participants were women and primarily from younger or mid-career age groups, with early-career academics making up the largest share. Health sciences and business were the most common fields, and the majority worked in public universities, with a few from private or international institutions.

PHASE 2: QUALITATIVE

To explore academics' views and worries surrounding the utilization of generative AI tools in higher education, this study conducted thematic, semi-structured interviews with a varied group of academics from different disciplines and academic ranks. This interview format combined a set of pre-defined themes and guiding questions to keep each discussion focused yet flexible enough for participants to share their personal perspectives in depth (Saunders et al., 2009). Open-ended questions were chosen because this method allows researchers to obtain comprehensive and nuanced information that cannot be captured through observation alone (Plano Clark & Creswell, 2015).

The interview questions were derived directly from the research objectives of the study and included prompts such as:

- Are you familiar with generative AI tools? What was your experience with them?
- How do you feel about using generative AI tools in your academic work?
- What concerns or fears do you have about using generative AI in higher education?
- Is there a policy or guideline for generative AI use at your institution, and if not, do you believe one is necessary?

All interviews were conducted one-on-one and in person, which encouraged open dialogue and provided the researcher with the opportunity to raise follow-up questions and clarify meanings as needed, resulting in rich and unbiased data (Plano Clark & Creswell, 2015; Saunders et al., 2009). Ethical approval for this study was waived; however, all participants were fully informed about the study's aims and procedures, and voluntary consent was obtained for their participation and the audio recording of the interviews. Therefore, respondents were clearly briefed on the aims of the research and provided consent for both the discussion and audio recording, ensuring ethical practices were maintained throughout the study.

Interview protocol and data gathering.

The research employed a convenience sampling technique to recruit the most readily available participants (Saunders et al., 2009). All interview respondents were notified about the study's aims before the interview began and gave explicit consent to participate and to have the discussions audio recorded. Their identities were anonymized in the transcripts via pseudonymization, and recordings were stored in a secure location to protect confidentiality. The interview phase concluded with seven participants due to time and resource constraints, by which point responses had begun to converge around common themes. This indicated that further interviews were unlikely to yield substantially new insights. The sample size was therefore considered sufficient for the study's purpose as an initial exploration of generative AI tools adoption within Egyptian higher education, while acknowledging that the findings do not encompass the entire spectrum of viewpoints. Data saturation was reached after seven interviews, as responses converged around common themes and additional interviews were unlikely to yield substantially new insights. Table 3 presents participant information and the length of the interviews.

Table 3. Participant information and the length of the interviews

Participant	Duration of the interview	Specialization
Professor 1 (Female)	8 minutes	Business -Accounting
Professor 2 (Male)	6 minutes	Engineering
Assistant Professor 1 (Female)	13 minutes	Business -Accounting
Assistant Professor 2 (Female)	9 minutes	Business -Human Resources
Assistant lecture 1(Female)	8 minutes	Business – Human Resources
Assistant lecture 2(Female)	6 minutes	Business -Accounting
Teaching assistant (Female)	6 minutes	Medicine

RESULTS

This section presents the findings obtained through the mixed-methods approach employed in this study. Quantitative data were collected and analyzed from the survey to capture broad patterns and relationships among the variables of interest. Complementing this, qualitative insights were gathered through interviews, which provide a richer understanding of participants' perspectives and experiences. Together, these findings offer a comprehensive view, combining statistical evidence with contextual explanations to strengthen the overall interpretation of the research outcomes.

SURVEY DATA ANALYSIS AND FINDINGS

All variables' variance inflation factors (VIF) range from 1 to 3.326, which falls within acceptable limits and indicates that multicollinearity is not a concern (Hair et al., 2011). Following Kock (2015), these full collinearity VIF values also imply that common method variance (CMV) is improbable as a significant issue, despite the use of a single questionnaire for data collection. After confirming that multicollinearity and common method variance were not problematic, the evaluation process started with the measurement model and proceeded to the structural model.

Measurement model

Before assessing the significance of the structural model's relationships, the reliability and validity of the measurement model must first be established (Fornell & Larcker, 1981). Firstly, checking the factor loading and deleting all the variables that have a loading less than 0.7, all demonstrate statistical significance ($p < 0.001$) and surpass 0.7, which is deemed acceptable (Hair et al., 2010).

The evaluation of reliability was carried out using Cronbach's alpha and composite reliability (CR). As presented in Table 2, each construct obtained Cronbach's alpha values higher than the suggested cutoff of 0.70 (Hair et al., 2021), supporting the reliability of the measurement items. Similarly, the CR values for all variables are more than the accepted cutoff of 0.70 (Hair et al., 2017), further demonstrating strong internal consistency and measurement reliability. The findings demonstrate that the indicators consistently reflect their underlying constructs. In addition, the AVE (Average Variance Extracted) was analyzed to evaluate convergent validity. Table 4 shows that all AVE values surpass the 0.50 benchmark suggested by Fornell and Larcker (1981), providing additional evidence of adequate convergent validity. After assessing the outer loadings (CR) and (AVE), it can be confirmed that convergent validity is established. This indicates that the measurement indicators consistently and accurately capture the intended constructs, as advised by Hair et al. (2014).

Table 4. Reliability and convergent validity

Constructs	Cronbach's alpha	Composite reliability	Average variance extracted (AVE)
Behavioral Intention to Use Generative AI	0.894	0.934	0.825
Perceived Ease of Use	0.707	0.836	0.630
Perceived Usefulness	0.833	0.882	0.600
Technophobia	0.773	0.851	0.589
Organization's Innovative Culture	0.873	0.904	0.654

Discriminant validity was assessed using the Heterotrait-Monotrait (HTMT) ratio and the Fornell-Larcker criterion. HTMT serves as a robust measure of discriminant validity by evaluating the correlations among pairs of constructs. As shown in Table 5, all HTMT measures are below the recommended cutoff of 0.90, indicating satisfactory discriminant validity in line with the guidelines of Fassott et al. (2016).

Table 5. Heterotrait-monotrait ratio (HTMT) – Matrix

Construct	Behavioral intention to use Generative AI	Perceived Ease of use	Perceived usefulness	Technophobia	Organization's innovative culture	Organization's innovative culture x perceived ease of use	Organization's innovative culture x technophobia	Organization's innovative culture x perceived effectiveness
Behavioral intention to use generative AI								
Perceived ease of use	0.558							
Perceived usefulness	0.665	0.754						
Technophobia	0.345	0.593	0.483					
Organization's innovative culture	0.143	0.404	0.235	0.186				
Organization's innovative culture x perceived ease of use	0.181	0.160	0.224	0.059	0.159			
Organization's innovative culture x technophobia	0.182	0.115	0.132	0.083	0.055	0.620		
Organization's innovative culture x perceived usefulness	0.074	0.096	0.083	0.035	0.037	0.552	0.528	

In addition, the Fornell-Larcker criterion was employed as an additional test, revealing that the square root of the AVE for each construct surpassed its correlations with the remaining constructs, as detailed in Table 6. This outcome confirms that the constructs are distinct from one another, providing further evidence of discriminant validity (Fornell & Larcker, 1981; Henseler et al., 2015). Together, these findings validate the constructs' reliability and confirm that the measures are valid for assessing the structural model.

Table 6. Fornell-Larcker criterion

Construct	Behavioral intention to use Generative AI	Perceived ease of use	Perceived usefulness	Techno-phobia	Organization's innovative culture
Behavioral intention to use Generative AI	0.908				
Perceived ease of use	0.447	0.793			
Perceived usefulness	0.586	0.586	0.775		
Technophobia	-0.302	-0.451	-0.410	0.768	
Organization's innovative culture	0.141	0.322	0.212	-0.144	0.809

The structural model

The structural model assesses the degree to which the proposed research framework aligns with the data. (Schreiber et al., 2006). Partial Least Squares (PLS) was used to assess the overall fit of the structural model. Two key fit indices were examined: the Normed Fit Index (NFI)and the Standardized Root Mean Square Residual (SRMR) (Hair et al., 2019). The SRMR, which measures the variance between observed and expected correlations, was found to be 0.071, falling below the accepted standard of 0.08 (Hu & Bentler, 1999), providing a good fit. Similarly, the NFI, which reflects how well the proposed model improves fit compared to a baseline model, was 0.755, which is considered acceptable by Schermelleh-Engel et al. (2003) since it is closer to 1. Together, these results confirm that the model demonstrates adequate alignment with the data and can be used for further structural analysis. Regarding inner model assessment, the coefficient of determination (R^2) indicates that the proposed model demonstrates satisfactory explanatory power for the key endogenous constructs. Specifically, the predictors explain 38.9% of the variance in behavioral intention to use generative AI (adjusted $R^2 = 0.366$), reflecting a moderate level of explanatory strength that is consistent with prior technology adoption studies examining emerging and complex digital innovations.

In addition, the model accounts for 20.4% of the variance in Perceived Ease of Use (adjusted $R^2 = 0.200$), suggesting that ease perceptions are influenced by additional factors beyond those captured in the current framework. By contrast, Perceived Effectiveness exhibits stronger explanatory power, with an R^2 of 0.370 (adjusted $R^2 = 0.364$), indicating that the included antecedents play a substantial role in shaping users' evaluations of the effectiveness of generative AI systems. Taken together, these results confirm that the model is adequately specified and capable of explaining meaningful variance in both cognitive perceptions and behavioral intentions related to the adoption of generative AI. Furthermore, the effect size analysis (f^2) provides additional insight into the relative contribution of each exogenous construct. The results indicate that Perceived Effectiveness exerts a large effect on behavioral intention to use generative AI ($f^2 = 0.252$), highlighting its central role in shaping users' adoption intentions. In comparison, Perceived Ease of Use shows only a small effect on behavioral intention ($f^2 = 0.014$), suggesting that ease considerations play a secondary role once effectiveness perceptions are established. Technophobia demonstrates a negligible direct effect on behavioral intention ($f^2 = 0.002$), although it exhibits a substantial effect on Perceived Ease of Use ($f^2 = 0.256$) and a small effect on Perceived Effectiveness ($f^2 = 0.042$), indicating its indirect influence through key cognitive perceptions.

With respect to contextual factors, organizational innovative culture shows a negligible direct impact ($f^2 = 0.001$), while its interaction terms with perceived ease of use, technophobia, and perceived effectiveness yield only small to negligible moderating effects (f^2 values ranging from 0.001 to 0.009). Collectively, these findings suggest that individual cognitive evaluations, particularly perceived effectiveness, dominate the explanatory structure of generative AI adoption, whereas organizational-level moderators exert a more limited incremental influence. Predictive relevance (Q^2) evaluates how accurately the model can predict the values of endogenous constructs. In this study, Q^2 was assessed using the PLS Predict algorithm proposed by Shmueli et al. (2016). The Q^2 value for behavioral intention to use generative AI tools was reported to be 0.084, which is exceeding zero, indicating that the model demonstrates predictive relevance for this construct. By reviewing both the R^2 and Q^2 values, the predictive capability of the research model was evaluated, as these indicators reflect the predictive relevance and the model's explanatory power (Nguyen et al., 2023). Tables 7, 8 and 9 show the findings of testing the proposed hypotheses, including both direct and indirect paths and moderating effects using SmartPLS 4.0 with 5,000 bootstrap subsamples (Ringle et al., 2024). Direct effects assessment at Table 7 showed that Technophobia did not have a significant impact on behavioral intention to use generative AI (H_1: $\beta = -0.037$, $p = 0.583$). However, it showed a significant negative impact on both PEOU (H_2: $\beta = -0.451$, $p = 0.000$) and PU (H_3: $\beta = -0.182$, $p = 0.006$). PEOU was found to significantly impact PU. (H_4: $\beta = 0.504$, $p = 0.000$) but did not significantly affect behavioral intention to use generative AI (H_5: $\beta = 0.126$, $p = 0.176$). Finally, PU showed a statistically significant positive impact on behavioral intention to use generative AI (H_6: $\beta = 0.497$, $p = 0.000$).

Table 7. Direct effect

Aspects	Original sample (O)	T statistics (|O/STDEV|)	P values	Hypotheses
Technophobia -> Behavioral Intention to Use Generative AI	-0.037	0.549	0.583	H_1: not supported
Technophobia -> Perceived Ease of Use	-0.451	8.845	0.000	H_2: supported
Technophobia -> Perceived Usefulness	-0.182	2.764	0.006	H_3: supported
Perceived Ease of Use -> Perceived usefulness	0.504	9.717	0.000	H_4: supported
Perceived Ease of Use -> Behavioral Intention to Use Generative AI	0.126	1.354	0.176	H_5: not supported
Perceived Usefulness -> Behavioral Intention to Use Generative AI	0.497	5.911	0.000	H_6: supported

Table 8 shows the mediation effects. The mediating effect of PEOU on the relationship between Technophobia and Behavioral Intention was not significant (H_7a: $\beta = -0.057$, $p = 0.190$). However, the indirect effect through PU was significant (H_7b: $\beta = -0.091$, $p = 0.016$), validating the presence of partial mediation. This suggests that Technophobia reduces PU, which subsequently reduces individuals' intention to employ generative AI tools. (Baron & Kenny, 1986). Table 9 illustrates the findings of the moderating effects analysis.

Table 8. Mediation effect (indirect effect)

Aspects	Original sample (O)	T statistics (|O/STDEV|)	P values	Hypotheses
Technophobia -> Perceived Ease of Use -> Behavioral Intention to Use Generative AI	-0.057	1.312	0.190	H_7a: not supported
Technophobia -> Perceived Usefulness -> Behavioral Intention to Use Generative AI	-0.091	2.415	0.016	H_7b: supported

Table 9. Moderating effect

Aspects	Original sample (O)	T statistics (|O/STDEV|)	P values	Hypotheses
Organization's innovative culture x Perceived Ease of Use -> Behavioral Intention to Use Generative AI	-0.072	0.624	0.533	H_8a: not supported
Organization's innovative culture x Perceived Usefulness -> Behavioral Intention to Use Generative AI	0.023	0.251	0.802	H_8b: not supported

Findings suggest that the interplay between organizational innovative culture and PEOU was not a significant predictor of behavioral intention to adopt generative AI (H_8a: $\beta = -0.072$, $p = 0.533$). Similarly, the interaction between an organization's innovative culture and perceived usefulness was not significant (H_8b: $\beta = 0.023$, $p = 0.802$). These outcomes recommend that an organizational innovative culture does not exert a significant moderating impact on the effects of Perceived Ease of Use or Perceived usefulness on the intention to use generative AI tools. Figure 2 effectively illustrates the proposed PLS-SEM model examining how TAM and organizational innovative climate collectively shape academics' behavioral intentions to adopt generative AI tools.

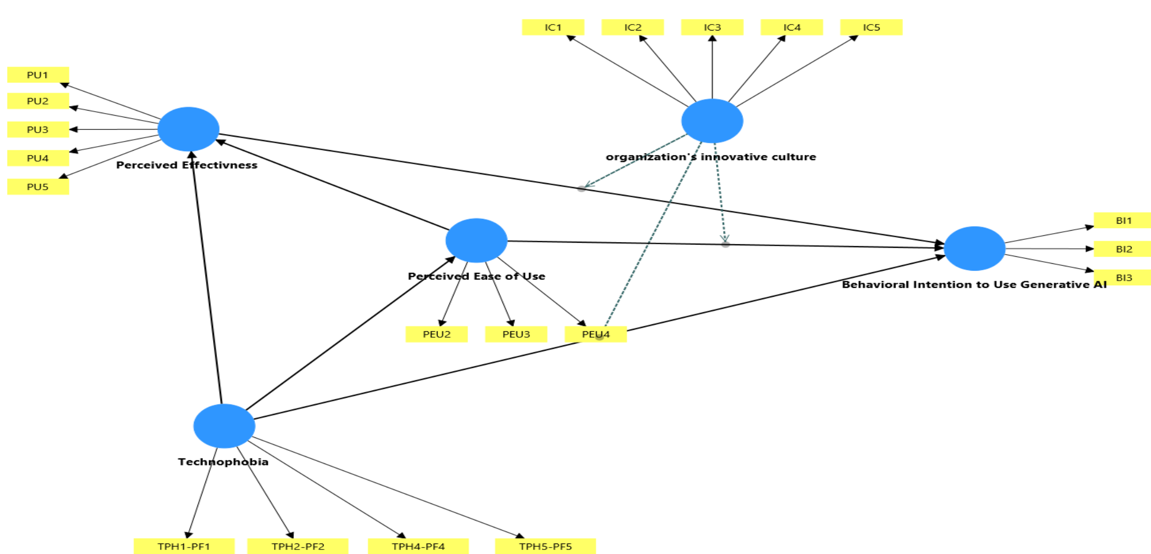

Figure 2. Structure figure (extracted from Smart PLS)

In brief, the quantitative phase highlighted the factors most closely linked to the willingness to use generative AI, including the significant role of perceived usefulness and its relationship with technophobia. To better understand the underlying reasons and contextual nuances behind these patterns, we turned to in-depth interviews with academic staff. The insights from this qualitative phase are presented in the following section.

INTERVIEW DATA ANALYSIS AND FINDINGS.

By using NVivo to collect the codes and themes for thematic analysis, the study generated the following themes from the responses of interviewees and based on the research questions (Braun & Clarke, 2006)

Theme 1: Experience with generative AI tools

Overall Positive Experience. Overall, the academics described their experience with generative AI tools as positive. For example, one professor explained, "Overall, the experience was not bad. I think when it comes to generative AI tools, we should focus on taking advantage of their benefits" (Professor 1). Similarly, a teaching assistant rated their experience as "about 7 out of 10" (Teaching Assistant 2). Another participant added, "I can't imagine my life without them" (Teaching Assistant 1). These comments show that participants generally perceive generative AI tools as valuable and supportive in their academic work.

Time-saving. A key benefit mentioned by nearly all participants was time-saving. As one teaching assistant noted, "I think it has a positive side – mainly in saving time." Another academic highlighted how generative AI tools help locate and summarize information quickly: "It can do great paraphrasing, summarizing, or help you understand something faster by providing quick links or pointing you to the latest version of a book – much quicker than searching multiple websites yourself" (Assistant Professor 1). Likewise, a professor stated, "Of course, it would definitely make many tasks in our work faster and more efficient" (Professor 2). Support for Writing and Editing Participants also highlighted that generative AI tools are helpful for text improvement and generating teaching materials. For instance, one academic explained that Grammarly can "enhance text, make it sound more emotional, or more academic" (Teaching Assistant 1). They also noted that AI can help faculty members create quizzes: "Faculty may use AI for things like generating MCQs from a document – it scans the text, suggests titles, and creates questions, which the teacher can then review. It is not doing anything groundbreaking …" (Teaching Assistant 1). Brainstorming and Generating Ideas. Finally, several participants described generative AI tools as useful for brainstorming and idea generation. As one assistant lecturer commented, "Gen generative AI tool opens up ideas or gives me suggestions" (Assistant Lecturer 2). Another professor agreed, "One benefit is that they can help improve wording a bit. They can also help with brainstorming" (Professor 1). "I use ChatGPT to understand what students do because they use it in their assignments" (Assistant Professor 2).

Inaccurate information and misleading. Despite the many advantages, participants also described clear drawbacks that can affect the reliability of generative AI tools. A major concern is that AI sometimes provides inaccurate or misleading information. As one teaching assistant explained, "For example, Grammarly often restructures sentences so much that it can completely change the meaning. Also, sometimes ChatGPT gives me incorrect references or content that is just meant to please me rather than being accurate (Assistant Lecturer 1). Another shared, "So, I asked the AI which textbook would be better for this purpose. But the choice it suggested for the database was really odd. Gemini gave me an answer like, 'No, you won't find free access to this,' while in reality, there was free access, like with Odoo, for example. So, it can give inaccurate information and sometimes steer you toward more commercial options" (Assistant Professor 1).

Double-checking efforts. Because of these inaccuracies, academics often need to double-check AI outputs, which can increase their workload rather than reduce it. One participant stated, "Usually, faculty don't rely heavily on AI because they know it can provide inaccurate information, so they double-check" (Assistant Lecturer 1). Another said, "So now I always double-check it, which feels like double effort" (Assistant Lecturer 2). They also warned that failing to verify AI-generated content can cause problems, especially under time pressure: "Unfortunately, sometimes we're under tight deadlines and don't have time to verify everything properly, which can lead to problems" (Assistant Lecturer 1).

Overall, the qualitative findings suggest that academics generally value generative AI for its practical advantages, particularly its ability to save time, support writing, and stimulate ideas. These positive experiences are consistent with the quantitative results showing that perceived usefulness has a strong and significant influence on the intention to use generative AI (H_6). However, participants also highlighted issues such as inaccurate outputs and the need for constant verification, which can undermine the perceived ease of use. This is consistent with quantitative findings indicating that perceived ease of use had no significant effect on behavioral intention (H_5), suggesting that even when academics recognize the benefits of generative AI tools, practical challenges and doubts about reliability may still limit their willingness to fully integrate such tools into their work.

Theme 2: Feeling and fears.

When asked about their overall feelings towards using generative AI in an academic context, most participants reported generally positive attitudes, although some concerns were noted. For example, one assistant lecturer stated, "I would say positive, because in the end, it's still helpful. But you must double-check its output; you cannot trust it 100%" (Assistant Lecturer 2), while another added, "I feel they provide strong support, despite their downsides" (Assistant Lecturer 1). However, some participants described mixed feelings.

One assistant professor explained, "I have mixed feelings. Sometimes I am afraid of it, and sometimes I like their answers, but sometimes they are stupid tools and still ask, "What do you mean by this?" (Assistant Professor 2). Feelings about generative AI also appeared to evolve with experience and familiarity: as one professor noted, "It depends on how they are used. At first, when someone uses any software without knowing much about it, they feel hesitant or cautious. But once they become familiar with it and learn what to do and what not to do, things get better" (Professor 1). While most participants described generally positive experiences with generative AI, several conveyed mixed emotions, balancing appreciation for its benefits with lingering concerns. These accounts of early hesitation, unease, and cautious engagement mirror the patterns of technophobia identified in the survey phase. Quantitative findings showed that such apprehension was associated with lower perceptions of ease of use and effectiveness, while the qualitative insights reveal how these feelings emerge in practice – from initial anxiety and skepticism to gradual comfort as familiarity grows. Despite this progression, traces of reluctance persisted for some, suggesting that technophobic tendencies may endure even with increased exposure.

Theme 3: Ethical concerns in the academic context

When asked about their concerns and fears regarding the use of generative AI tools, participants highlighted several important ethical issues. A recurring worry was that increasing reliance on AI as a supportive tool might lead to its replacing more critical academic effort. As one assistant professor stated, "The biggest issue is that as reliance on these supportive tools grows, they can turn into main tools" (Assistant Professor 1). Also, "Overreliance on generative AI tools may hinder critical thinking and reduce the motivation to learn, provided by Teaching Assistant 1. Participants expressed particular concern about the misuse of AI at the academic research level. One assistant professor explained, "In research, the risk is even bigger. Overusing AI without consulting real research is a disaster. For example, if you ask it to organize your references, it can mess them up badly. It might create fake DOIs or mix citation styles" (Assistant Professor 1). Another participant emphasized that it is "completely unethical to ask AI to write a research paper for you, for example. And it is usually obvious when this happens – that's where the ethical concerns show up" (Professor 1). Similarly, a professor noted their worry about postgraduate students misusing AI: “That worries me. Another issue is postgraduate students – I have noticed many users of generative AI randomly writing research articles or theses, which is a serious concern” (Professor 2).

However, some participants felt that the risk at the research level is partly mitigated because journals and institutions increasingly check for AI-generated content. As one assistant professor explained, “As for research, I do not think it’s as big a threat because wherever you submit your research, they usually check if you used AI or not. So, you can’t really rely on it completely – there are always people reviewing your work. So, I think it poses less of a threat to research but has a bigger impact on teaching” (Assistant Professor 1). Participants expressed stronger concerns at the undergraduate level. Many emphasized that students often rely on generative AI tools without critical awareness or verification, accepting outputs at face value. As one assistant professor explained, “But at the undergraduate level, students often take AI output at face value and think it’s always correct.” (Assistant Professor 1). An assistant lecturer added, “The problem is that a lot of students rely on it completely. They might skip class or feel they don’t need college because they can just use ChatGPT. Now, students do entire projects with ChatGPT – they put in the project topic, take whatever it gives them, and believe it without checking or doing any real work themselves” (Assistant Lecturer 2). A major ethical concern raised by academics is the use of generative AI as a tool for cheating. One assistant professor summarized this issue clearly: “The main concern is that students use it to cheat on their assignments, which has become a common practice among undergraduate students” (Assistant Professor 2). In sum, ethical risks were a shared concern among nearly all participants, with strong emphasis on potential misuse by students and the possibility of undermining academic integrity.

Theme 4: Policies and guidelines for using generative AI in higher education.

Due to increasing concerns about the potential misuse and negative impacts of generative AI tools in higher education, some universities have begun developing policies to guide and limit their use (Xiao et al., 2023). However, the participants in this study emphasized that raising awareness and building understanding are equally, if not more, important than imposing strict rules at this stage. One assistant lecturer highlighted this point, stating, “At this stage, raising awareness is more important than having strict policies. It’s better to educate students rather than just punish them if they use AI for assignments. Instructors expect that students might use it and plan accordingly” (Assistant Lecturer 1). Similarly, an assistant professor noted, “It is important to first teach undergraduate students how to use it responsibly and explain the associated concerns before allowing them to use it for their assignments” (Assistant Professor 2).

Despite the growing need for clear guidance, all participants confirmed that, at present, their institutions do not have any formal or documented policies specifically addressing the use of generative AI tools. For example, one professor stated, “As an official policy, no. I know there are copyright agreements and ethics documents for postgraduates when they’re doing interviews or similar activities – but for generative AI tools specifically, I don’t think there’s a formal document” (Professor 1). A teaching assistant from another university echoed this, explaining, “My university doesn’t have guidelines for using AI at the moment, but they are working on it” (Teaching Assistant 1). Another professor agreed, “No, I don’t think there is a documented policy. And I don’t think our university or any other university in Egypt has set clear rules or regulations for using generative AI tools yet” (Professor 2).

When asked how such policies should be designed, several participants suggested clear and practical steps. One professor outlined key elements that an effective policy should include: “We shouldn’t use these tools without understanding their scope and risks. In my view, if I were to design such a policy, it should include: An introduction to research and teaching ethics in general. Clear objectives of the guideline or policy. Specific dos and don’ts, explained clearly to everyone. Practical examples of what is acceptable and what is not. Regular updates are written in simple language so that students can easily understand them. Periodic orientation sessions or workshops, because AI keeps evolving with new versions” (Professor 1). Others highlighted the need to define clear limits for acceptable use. As one assistant lecturer suggested, "The most important thing is that the policy should define a certain percentage for using generative AI – whether in teaching or research. You shouldn't rely 100% on it for research or teaching. Not every aspect of teaching should depend on generative AI. So maybe we could standardize it – like set a maximum usage of 10% or 20%" (Assistant Lecturer 2). Similarly, another participant stressed that guidelines must clearly explain when using AI is acceptable and when it crosses a line: "So if we have guidelines, they should be detailed – specifying to what extent using AI counts as 'using AI,' not just for trivial tasks like summarizing" (Assistant Professor 1). Several participants also emphasized that the institution's IT team should play an active role in developing and managing these policies, given that generative AI tools are technological products that require proper understanding and oversight. As one professor explained, "It should be used by people who can apply it properly – maybe not necessarily experts, since we don't have many true AI experts in our community, but at least trained users who can use it correctly" (Professor 2)

Finally, participants agreed that comprehensive guidelines should include clear instructions for students, robust anti-plagiarism measures, and regular orientation for both staff and students. One assistant professor summarized this need, stating, "There should be clear guidelines outlining what students should and should not do when using generative AI. Universities should also implement programs to check for plagiarism and provide orientation sessions for academic staff on how to use generative AI responsibly and address related concerns" (Assistant Professor 2)

DISCUSSION

The current study aimed to investigate the integration and use of generative AI tools in the academic context by integrating a quantitative examination of technophobia and key Technology Acceptance Model (TAM) constructs with a qualitative exploration of academics' experiences, feelings, and concerns. By combining both approaches, this study offers a deeper understanding of how generative AI is perceived and used in the academic context, and of the factors that encourage or inhibit its acceptance among university staff.

INTERPRETATION OF QUANTITATIVE FINDINGS

Regarding H_1, the quantitative results demonstrated that technophobia was not a significant direct predictor of behavioral intention to use generative AI. This suggests that although some academics reported anxiety or discomfort with new technologies, such fear alone did not prevent them from intending to use generative AI tools in their academic duties. One way to make sense of this finding is to consider that academics may view the practical gains offered by generative AI, such as saving time or sparking ideas, as more important than their initial discomfort with technology. In this case, the perceived value of the tools to have outweighed any anxiety, which helps explain why fear alone did not prevent them from using AI. However, this finding diverges from some previous research. For example, Jo (2024) reported that technophobia negatively influenced students' behavioral intention to use AI chatbots in higher education. Similarly, Zhao et al. (2025) reported a statistically significant negative link between technophobia and managers' intention to use generative AI. These differences may indicate that the role of technophobia is context-dependent; in the current study, the professional responsibilities and perceived benefits for academics may reduce the weight of technophobia as a direct barrier to intention.

The H_2 and H_3 are supported, which indicates that the findings show that technophobia substantially reduces both POUE and PE of generative AI tools. This reveals that individuals who feel more anxious or fearful about technology are inclined to regard these tools as more complicated and less capable of delivering useful outcomes. This finding aligns with Khasawneh (2018a), who found that technophobia negatively affects ease-of-use and usefulness perceptions, which act as critical factors in predicting technology acceptance.

Regarding H_4, which is supported and consistent with the central premise of TAM, suggests that if users find a technology easy to use, they are more inclined to consider it useful and effective for accomplishing tasks. This outcome is consistent with Saif et al. (2024), who showed that students' perceptions of the ease of using ChatGPT significantly enhanced their belief in the tool's usefulness for academic work. For H_5, the association between perceived ease of use and the intention to use generative AI was not supported, suggesting that although academics generally view these tools as easy to use, this perception alone is insufficient to drive their intention to adopt them. This result corresponds to Ibrahim et al. (2018), who similarly showed that ease of use does not always translate directly into higher adoption intention. By contrast, H_6 was supported, with perceived usefulness showing a strong and positive influence on intention. This aligns with Na et al. (2022) and indicates that PU has a more significant influence than ease of use in the academic context. However, the findings of Jain and Raghuram (2024), who reported no significant effect of usefulness, point to the fact that usefulness alone may not always translate into adoption. One possible explanation is that usefulness can only exert a positive influence when other contextual concerns, particularly technophobia, ethical doubt, or policy uncertainty, are sufficiently addressed.

The mediation tests showed partial support for H_7: PU, but not PEOU, mediated the relationship between technophobia and intention. This indicates that technophobia reduces intention primarily by diminishing perceived usefulness. This supports earlier work by Makmor et al. (2019) and Ardiyanti and Susilowati (2024), highlighting the centrality of usefulness evaluations in shaping AI adoption. Finally, H_8 was not supported; organizational innovation culture did not moderate the relationship between TAM constructs. The non-significant moderating effect of organizational innovation culture may be explained by a gap between symbolic culture and enacted practice. As Schein (1990) notes, cultural values influence behavior only when translated into visible structures, routines, and guidance. Although universities often portray themselves as innovation-oriented, institutional rigidity, risk aversion, and regulatory uncertainty meant that such values were not operationalized into formal generative AI policies, training, or support mechanisms. Interview data reinforced this interpretation: staff reported an absence of institutional direction, relying instead on peer discussions or personal judgment. In this context, "innovation culture" remains largely rhetorical rather than actionable, which reduces its capacity to shape how TAM constructs translate into behavioral intention. Accordingly, the null moderating effect may reflect an implementation gap rather than the irrelevance of culture alone (Cao et al., 2025)

Interpretation of Qualitative Findings

The qualitative study sets out to explore academics' detailed experiences, concerns, and perspectives regarding the utilization of generative AI tools in higher education systems. Overall, the interviews confirmed that respondents generally perceive generative AI tools as helpful, particularly for saving time and supporting routine tasks. This reinforces the quantitative finding that perceived effectiveness strongly influences intention to use these tools. This outcome corresponds to Sharawy (2023). However, participants also expressed significant concerns, especially regarding the accuracy and reliability of AI-generated content, in addition to ethical issues such as student misuse and potential cheating. These concerns help explain why technophobia reduces PU and PEOU in the quantitative model. Furthermore, the interviews highlighted that while many academics acknowledge the benefits of generative AI, they remain cautious about over-reliance and stress the need for human oversight. These findings are consistent with Duong et al. (2023) and Saif et al. (2024). Such concerns are justified, given that generative AI can still produce inaccurate or biased content and may make it harder to verify the genuineness of student work. This underscores the importance of developing assessment approaches that promote reasoning skills and information appraisal (Reina Marín et al., 2025).

All participants drew attention to the absence of explicit institutional guidance on how generative AI should be used in academic settings. Rather than calling for bans, most argued that what is urgently needed are awareness-raising efforts and practical guidelines that help educators and students use these tools responsibly. This observation echoes the findings of Ghimire and Edwards (2024), whose interviews with early adopters showed that staff are already integrating AI into their teaching and are looking for clearer policy direction. Similarly, Jain and Raghuram (2024) stress that user-centred and carefully regulated implementation of generative AI is essential if it is to improve the standard of educational services. In this regard, the current lack of AI-specific regulations in higher education represents more than a policy gap; it risks creating uncertainty around ethical, pedagogical, and technical boundaries, reinforcing the need for comprehensive frameworks (Reina Marín et al., 2025). Taken together, these insights suggest that higher education institutions should not only ensure the availability of generative AI tools but also develop comprehensive policies, offer training workshops, and engage IT teams in guiding best practices. Such steps can help maximize the benefits of AI while mitigating ethical risks and misuse among students.

The qualitative findings from the interviews provide valuable depth to understanding the ways academic staff in Egyptian higher education view and apply generative AI tools, directly addressing the study's three research questions. We can conclude the following: First, regarding their current experience (Q1), academics described generative AI as a supportive tool that offers tangible benefits, notably in saving time, paraphrasing, and brainstorming ideas. However, they consistently emphasized that although AI can simplify specific tasks, it cannot substitute for human judgment, and its outputs often require careful verification due to concerns about inaccuracies and misleading information. This reinforces the quantitative finding that perceived effectiveness, more than ease of use alone, is crucial for driving intention to adopt generative AI.

For the second question, the interviews shed light on the role of technophobia, revealing that initial anxiety or skepticism about generative AI's reliability and ethical use is common, especially when first experimenting with these tools. Yet many participants reported that hands-on practice and comparing multiple generative AI tools helped them gradually overcome their fears, clarifying why technophobia significantly lowers PEOU and PU but does not necessarily eliminate the intention to use AI altogether.

Regarding the third question, the data highlighted a notable gap between the presence of an 'innovative' organizational culture and its practical effect on staff behavior. Most participants reported an absence of formal guidelines or institutional policies governing AI use, leaving academics to navigate its application individually and inconsistently. This observation aligns with the quantitative result that an innovative climate did not moderate key TAM relationships, implying that a supportive culture alone is insufficient without concrete rules, practical training, and institutional oversight.

Integration of Findings

Table 10 summarizes the quantitative and qualitative findings, providing an integrated interpretation of the key relationships investigated in the study.

Table 10. Integration of quantitative results and qualitative insights

Relationship	Quantitative results	Qualitative insights	Integrated interpretation
Technophobia to behavioral intention to use generative AI	Not significant	Academics remain willing to use generative AI despite initial anxiety due to perceived benefits.	Technophobia does not directly reduce intention when usefulness is evident.
Technophobia to PEOU	Significant	Trust issues and fear of misuse make generative AI seem difficult to use.	Anxiety increases perceived complexity, lowering ease of use.

Relationship	Quantitative results	Qualitative insights	Integrated interpretation
Technophobia to PU	Significant	Accuracy, bias, and ethical concerns reduce trust in generative AI outputs.	Technophobia undermines perceived usefulness by reducing confidence in outputs.
PEOU to PU	Significant	Familiarity through practice increases recognition of generative AI benefits.	Greater ease of use enhances perceived usefulness.
PEOU to behavioral intention to use generative AI	Not significant	Ease of use alone is insufficient; value matters more.	Usefulness, not simplicity, drives intention.
PU to Behavioral Intention to use generative AI	Significant	Generative AI is valued for saving time and supporting tasks.	Confirms PU as the main driver of intention.
Technophobia to PEOU to Behavioral Intention (Mediation)	Not supported	Users may intend to adopt generative AI despite usability concerns.	Difficulty does not block intention when benefits are clear.
Technophobia to PU to Behavioral Intention (Mediation)	Supported	Fear reduces perceived usefulness, lowering intention.	Usefulness mediates the effect of technophobia on intention.
Innovative Culture × TAM Relationships	Not supported	Lack of formal policies and training limits practical impact.	Culture alone cannot substitute for clear guidelines and governance.

Theoretical Implications

This study contributes to theory by showing how technophobia and organizational climate relate to the classic TAM about generative AI in higher education (Davis et al., 1989; Jo, 2024; Khasawneh, 2018a). Quantitative results confirmed that technophobia lowers how easy and effective academics find generative AI tools but does not directly prevent them from wanting to use them, showing that usefulness matters more than ease alone. This deepens TAM by highlighting indirect effects. Additionally, qualitative findings reveal that even when academics feel cautious at first, they become more confident once they gain experience and see practical benefits. Finally, the non-significant role of organizational culture shows that clear guidelines and personal attitudes may be more important than a general innovative environment. Integrating qualitative insights to refine adoption theory. For example, qualitative findings indicate that trust-building, ethical concerns, and hands-on exposure play important roles in shaping adoption, expanding TAM's explanatory coverage. Together, this study enriches TAM by adding real-world fears, practical trust-building, and the need for clear institutional support.

Practical Implications

The findings point to several urgent actions for universities aiming to adopt generative AI in a responsible way. To begin with, institutions need to move beyond informal practices and put in place clear, written policies that specify which kinds of generative AI use are appropriate for teaching, research, and assessment. In addition, regular training sessions and awareness activities should be offered to both staff and students to ensure the benefits and limitations of these tools are fully understood. Working closely with IT units will also be essential to ensure that academics receive the technical assistance required for using generative AI tools properly and securely. Rather than prohibiting generative AI outright, universities should focus on developing digital literacy and critical thinking to help users integrate generative AI as an aid rather than a substitute for academic work. Finally, it is important that the growing commercial promotion of generative AI tools in the education sector aligns with institutional guidance, so that marketing does not encourage blind or inappropriate use but instead supports responsible engagement.

CONCLUSION

This study examined the adoption of generative AI tools among academics in higher education by integrating technophobia and organizational innovation culture into the Technology Acceptance Model (TAM). The findings demonstrated that while technophobia does not directly reduce intention to use generative AI, it significantly diminishes perceived usefulness and perceived ease of use, which, in turn, shape adoption decisions. Perceived usefulness emerged as the strongest predictor of intention, underscoring the practical value academics attach to generative AI in their daily work. Importantly, the study advances TAM by showing that technophobia operates as an emotional antecedent that indirectly influences behavioral intention through cognitive evaluations, rather than through direct pathways. In doing so, the study offers empirical support for extending TAM to include affective barriers. Additionally, the non-significant role of organizational innovation culture reveals that contextual factors exert limited influence when institutional policies and practices are not formally established, highlighting the need to differentiate between abstract culture and actionable support structures.

The qualitative findings deepened these insights by demonstrating how academics balance the benefits of generative AI with concerns related to accuracy, ethics, and student misuse. Participants emphasized the absence of formal institutional guidance and expressed a need for clearer policies, training, and support. Taken together, these findings address the research questions by illustrating how academics perceive generative AI, how technophobia shapes these perceptions, and why organizational culture has not yet translated into meaningful behavioral influence. Studying contributes both theoretically and practically. Theoretically, it refines TAM by incorporating emotional and contextual elements that explain variance in generative AI acceptance within higher education.

Practically, it underscores the need for universities to implement clear policies, build staff capacity, and embed generative AI literacy within institutional frameworks to encourage responsible adoption. Unlike most prior TAM-based studies, which have primarily examined students, technology professionals, or higher-education users in Western contexts, this research focuses on academics in Egyptian higher education, thereby extending knowledge of technology adoption to a Global context characterized by regulatory uncertainty and evolving institutional readiness. Second, the study specifically addresses the adoption of generative AI tools, rather than conventional educational technologies, highlighting a new class of disruptive technologies that directly affect academic practice.

While the study makes important contributions, several limitations remain. The quantitative sample was limited to academics from selected Egyptian universities, which could limit the applicability of the findings in different cultural or institutional settings. Similarly, the qualitative interviews were undertaken with a limited, convenience-based sample, potentially overlooking diverse perspectives. Additionally, the survey employed a non-probability sampling approach, which means that the participants may not fully represent the broader population of academic staff. It is possible, for example, that individuals with a stronger interest in technology were more willing to complete the survey, which may have led to slightly more positive perceptions of generative AI than would be observed in a truly random sample.

Subsequent research should extend this study to include larger and more diverse participant groups, as well as different academic disciplines and student populations. Longitudinal studies could also examine how perceptions and usage patterns evolve as generative AI tools become more integrated into everyday academic practices. Future research could elaborate on the qualitative results by incorporating additional variables, such as trust in AI, perceived risk, and institutional policy support, which participants repeatedly mentioned but are not yet widely included in acceptance models. It may also be useful to examine how generative AI adoption affects educational outcomes, such as teaching effectiveness or student learning, as the present study focused only on intention and perception. Additionally, future work could explore other moderating variables, such as individual digital literacy levels or institutional readiness, to reach a more detailed understanding of the determinants of generative AI usage in higher education.

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