



Miscalibrated trust: How academic perceptions and misconceptions shape ChatGPT adoption in higher education

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ABSTRACT

The rapid diffusion of generative artificial intelligence (GenAI), particularly large language models such as ChatGPT, has reshaped academic workflows while raising questions about trust, misconceptions, and future expectations. This study examines an integrated framework grounded in the unified theory of acceptance and use of technology and the technology acceptance model to assess how foundational acceptance drivers, cognitive evaluations, misconceptions, and trust are associated with academics' forward-looking expectations of ChatGPT. Survey data from 252 academics in Malaysian public and private universities were analyzed using partial least squares structural equation modelling. Performance expectancy, effort expectancy, and facilitating conditions were positively associated with perceived ease of use (PEOU) or perceived usefulness (PU), while PEOU was positively associated with trust. Social influence was not significantly associated with PU. Two unexpected patterns were observed: PU was positively associated with misconceptions, and misconceptions were positively associated with trust. These cross-sectional associations suggest that functional appreciation can coexist with inflated capability beliefs and potentially miscalibrated trust, but they do not establish a causal mechanism of belief amplification. The Malaysian setting is analytically relevant because higher education institutions are expanding digitalization while national initiatives increasingly emphasize responsible AI governance, institutional capability, and digital skills. The findings highlight the importance of AI literacy, transparent institutional guidance, verification practices, and calibrated reliance when integrating GenAI into higher education.

Keywords: artificial intelligence, ChatGPT, academic perception, technology acceptance, structural equation modelling, higher education

INTRODUCTION

The rapid integration of sophisticated artificial intelligence (AI) technologies, particularly large language models such as ChatGPT, has profoundly reshaped various facets of academic contexts, prompting a significant shift in how higher education institutions approach knowledge generation, dissemination, and assessment (Ali et al., 2025; Shahzad et al., 2024). ChatGPT, developed by OpenAI, is designed to generate human-like text, facilitating tasks such as paraphrasing, translation, editing, summarization, lecture preparation, and even preliminary data analysis (Eka et al., 2025). Its adoption is expanding across academic settings, where it is used to streamline teaching and research activities (Bhullar et al., 2024; Shahzad et al., 2024). This study is contextualized within Malaysia's public and private higher education system. Malaysia's current policy environment increasingly links digitalization with responsible AI. The national guidelines on AI governance and ethics emphasize safe, transparent, accountable, and trustworthy AI, while the digitalization of higher education action plan 2025-2030 prioritizes digital leadership, skills development, institutional capability, and data infrastructure (Ministry of Science, Technology and Innovation Malaysia, 2024; Ministry of Higher Education Malaysia, 2025). This setting makes Malaysia analytically relevant because academics are adopting generative AI (GenAI) while universities are simultaneously developing governance, literacy, and support arrangements. Examining academics in this environment therefore provides contextual evidence on how technology acceptance, misconceptions, and trust are related during a period of rapid institutional digital transformation.

Despite the substantial opportunities to enhance educational experiences through personalized learning, streamlined administrative tasks, and improved student engagement, the pervasive use of ChatGPT has also sparked considerable debate about its impact on teaching and learning (Ali et al., 2024; Eka et al., 2025; Malik et al., 2025). Foremost among these concerns is the challenge to academic integrity, with questions arising around issues of plagiarism, authorship, and potential cognitive overreliance (Karkoulou et al., 2024). The varying perceptions and levels of trust among educators critically influence the effective implementation and utilization of such AI tools in pedagogical practices (Bhat et al., 2024; Bikanga Ada, 2024; Malik et al., 2025). Academics' willingness to integrate AI depends on their expectation of benefits versus their concerns (Viberg et al., 2024). Some academics recognize AI's potential for personalized learning and administrative efficiency, while others harbor concerns regarding data privacy, accuracy, and a lack of clarity about the technology's inner workings (Ali et al., 2025; Deric et al., 2025; Malik et al., 2025). Misconceptions regarding ChatGPT's capabilities can impede its practical adoption (Ali et al., 2025). Therefore, a thorough examination of academics' perceptions and trust in AI, specifically concerning ChatGPT, is crucial for identifying limitations and enabling adoption, informing policy, supporting professional development, and ensuring its effective and ethical integration into educational practices (Bhat et al., 2024; Deric et al., 2025; Malik et al., 2025). Understanding academics' perceptions also offers insights into how the gap between AI advancement and classroom realities can be bridged.

Literature Review

Research on GenAI adoption in higher education can be grouped into three related streams, but their findings do not always point in the same direction. The first stream applies technology acceptance perspectives and generally finds that performance expectancy (PE), effort expectancy (EE), facilitating conditions (FC), perceived usefulness (PU), and perceived ease of use (PEOU) are important correlates of adoption-related beliefs (Arbulú Ballesteros et al., 2024; Bhat et al., 2024; Foroughi et al., 2024; Shahzad et al., 2024; Subhani et al., 2025). However, contextual factors are less consistent. For example, social influence (SI) can be important in some higher education settings, whereas educators in other settings appear to rely more on personal evaluation than on social endorsement (Amin et al., 2024; Bhat et al., 2024). Evidence from Peruvian universities similarly indicates that the strength of unified theory of acceptance and use of technology (UTAUT)-related relationships depends on the educational and institutional setting (Arbulú Ballesteros et al., 2024). The second stream focuses on misconceptions and the quality of users' understanding. Studies warn that users may overestimate ChatGPT's autonomy, accuracy, or ability to replace human reasoning, particularly when fluent outputs are mistaken for reliable understanding (Ali et al., 2025; Bikanga Ada, 2024; Eka et al., 2025). Practical experience can help users recognize system limitations, yet

automation research also shows that successful or convenient system performance can encourage reliance on heuristics and overconfidence rather than complete calibration (Parasuraman & Riley, 1997; Skitka et al., 1999). The third stream examines trust. Trust is associated with perceived reliability, security, knowledge, prior experience, and perceived risk, but it is not automatically equivalent to accurate understanding (Amin et al., 2024; Balaskas et al., 2025; Deric et al., 2025; Viberg et al., 2024). Trust-calibration research specifically argues that appropriate reliance requires that trust correspond to a system's actual capabilities and limitations (Lee & See, 2004).

These streams create two unresolved tensions. First, greater PU may either improve belief calibration through experience or coexist with overgeneralized capability beliefs. Second, misconceptions may ultimately weaken stable trust when expectations are violated, but inflated beliefs may also coexist with high reported trust at a particular point in time. The reviewed studies generally examine acceptance, misconceptions, and trust separately or in various combinations, leaving limited evidence on how PU, misconceptions, trust, and forward-looking expectations are statistically related within a single academic framework. The inconsistency of contextual findings also underscores the importance of examining these relationships in Malaysia, where public and private institutions operate within a rapidly evolving digital and responsible AI policy environment. Accordingly, the present study tests the dominant calibration-based expectations while allowing the empirical results to reveal whether alternative association patterns emerge.

Theoretical Framework

This study is grounded in an integrated theoretical framework drawing from the UTAUT and the technology acceptance model (TAM). Both models are widely recognized for explaining technology acceptance and belief formation in emerging technological contexts (Amin et al., 2024; Balaskas et al., 2025; Khan et al., 2025; Shahzad et al., 2024; Subhani et al., 2025). While TAM emphasizes users' cognitive evaluations of a system through PU and PEOU, UTAUT extends this perspective by incorporating PE, EE, SI, and FC as foundational determinants of technology-related beliefs (Venkatesh et al., 2003). In the integrated framework, UTAUT constructs represent institutional, social, and expectancy-based conditions that shape academics' initial evaluations of ChatGPT, while TAM constructs capture PEOU and PU as more proximal cognitive evaluations. The framework then incorporates misconceptions and trust as belief-calibration constructs that are particularly relevant to GenAI. This extension is grounded in trust-in-automation research rather than inferred solely from the empirical results. Lee and See (2004) argue that appropriate reliance depends on calibrating trust in an automated system's actual capabilities. Parasuraman and Riley (1997) similarly distinguish appropriate use from misuse and overreliance, while Skitka et al. (1999) show that automation can bias judgment when users defer excessively to automated outputs. Applied to ChatGPT, these perspectives imply two theoretically plausible processes. Under a calibration pathway, task-specific experience with a useful system should expose both strengths and limitations, reduce exaggerated capability beliefs, and support trust that is better aligned with observed performance. Under an amplification pathway, fluent and apparently successful outputs can serve as salient cues of competence, encouraging users to generalize beyond the tasks they have actually evaluated and to report high trust despite inaccurate beliefs about their capabilities. In this study, the terms usefulness-amplification and miscalibrated trust are therefore used only as theoretically grounded interpretive labels for possible patterns of association. They are not assumed to be established causal mechanisms. The hypotheses concerning PU and misconceptions, and misconceptions and trust, follow the dominant calibration logic in prior literature: useful experience is expected to reduce misconceptions, and inaccurate beliefs are expected to weaken stable trust when system limitations become evident. Trust, in turn, is expected to be positively associated with forward-looking expectations because confidence in present reliability can support more favorable beliefs about future academic use. This framework thus combines acceptance constructs with belief accuracy and trust calibration while retaining clear distinctions between hypothesized relationships. [Figure 1](#) shows the research framework.

Hypothesis Development

Performance expectancy

PE refers to the degree to which an academic believes that using ChatGPT enhances their academic productivity, task efficiency, and overall performance outcomes (Arbulú Ballesteros et al., 2024; Subhani et

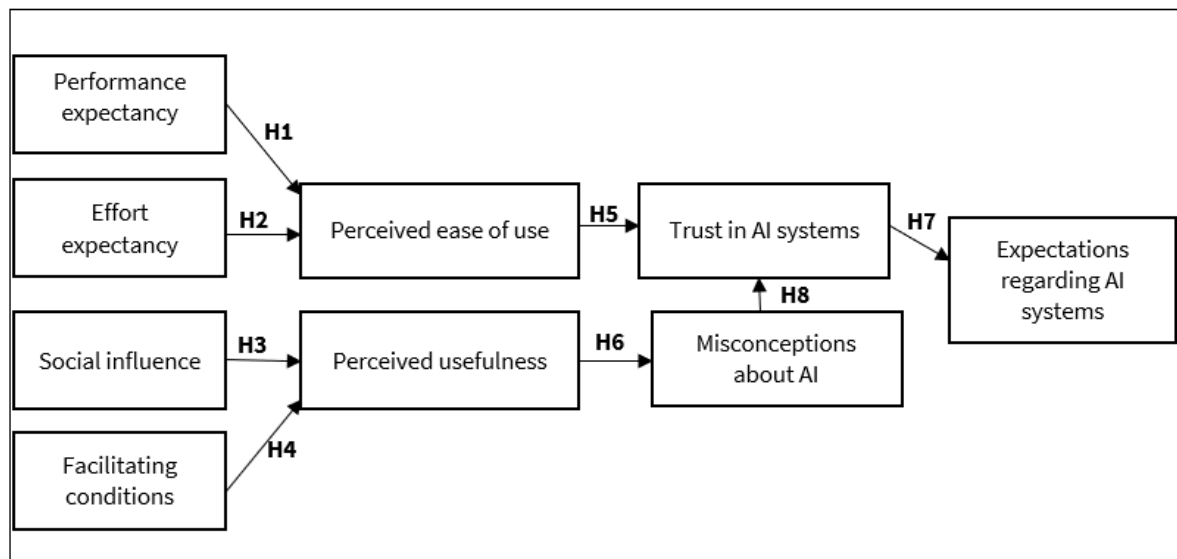


Figure 1. Research framework (developed by the authors)

al., 2025). PE captures outcome-oriented performance enhancements, such as improvements in productivity, efficiency, work quality, and overall academic performance. In the realm of information technology, PE has consistently been identified as a strong predictor of technology acceptance and use (Arbulú Ballesteros et al., 2024). Users who perceive technology as directly beneficial to their daily tasks are more inclined to adopt it (Arbulú Ballesteros et al., 2024; Bhat et al., 2024). For an AI system like ChatGPT, performance expectations encompass its capacity to comprehend and generate high-quality natural language output effectively (Ali et al., 2025). While traditional TAMs typically link these performance expectations directly to behavioral intention, GenAI introduces a unique cognitive dynamic. Emerging perspectives suggest a ‘motivational framing effect,’ where the anticipation of high academic rewards increases a user’s willingness to engage, thereby cognitively reducing the perceived complexity of the tool (Khan et al., 2025). In other words, when academics anticipate significant productivity benefits, this motivation shapes their evaluation of the system’s usability. Thus, it is hypothesized that:

H1. *PE for ChatGPT positively influences the PEOU among academics, specifically in relation to their experience with the tool.*

Effort expectancy

EE denotes the perceived ease of using a system. More specifically, EE refers to the degree to which an academic perceives that learning and operating ChatGPT requires minimal cognitive and technical effort (Khan et al., 2025; Subhani et al., 2025). It reflects anticipated ease of learning, becoming skillful, and operating the system with low mental effort. Technologies perceived as easy to use are more readily accepted and adopted by users (Arbulú Ballesteros et al., 2024; Bhat et al., 2024). In the context of ChatGPT, if academics find the system intuitive to operate and seamlessly integrate it into their academic responsibilities, their likelihood of adoption increases (Khan et al., 2025). Previous research highlights PEOU as a significant predictor of new technology adoption (Foroughi et al., 2024; Khan et al., 2025). Specifically, users who perceive minimal effort required for system interaction are more likely to accept and frequently utilise it (Foroughi et al., 2024). Although conversational AI interfaces may appear effortless due to their natural-language design, their academic use introduces distinct complexities. Generating scientifically accurate, critically reasoned, and academically rigorous outputs often requires advanced prompt engineering and careful fact checking (Bhullar et al., 2024). This hidden cognitive workload means that initial expectations of low effort do not necessarily translate into actual ease when performing complex scholarly tasks. To examine this dynamic, the following hypothesis is proposed:

H2. *EE for ChatGPT positively impacts academics’ perceptions of ease of use, specifically their experience with the tool.*

Social influence

SI refers to the extent to which academics perceive that important others and the broader academic community encourage or support the use of ChatGPT. In an academic environment, recommendations from colleagues, peers, or superiors can significantly impact the adoption of AI technology (Arbulú Ballesteros et al., 2024; Diep & Dang, 2025). Studies reveal that SI can modulate perceptions of technology's usefulness and effectiveness (Diep & Dang, 2025). Furthermore, peer influence and academic authority are known to affect technology usage in academic settings (Chan & Hu, 2023; Diep & Dang, 2025). For instance, if a respected colleague endorses the use of ChatGPT, other academics are more likely to perceive the system as beneficial (Chan & Hu, 2023). However, it is important to contrast this with the highly autonomous nature of the academic profession, in which scholars may resist peer pressure and rely solely on personal evaluation (Karkoulis et al., 2024). To test which of these competing forces dominates in the context of GenAI, it is hypothesized that:

H3. *SI is positively associated with the PU of ChatGPT in academic settings.*

Facilitating conditions

FC refer to the extent to which organizational and technical resources are available to support the use of technology (Subhani et al., 2025; Venkatesh et al., 2003). Within academic environments, such enabling conditions include access to structured training, technical assistance, compatible digital infrastructure, and clear institutional guidelines governing AI usage. These resources reduce operational barriers and create a supportive ecosystem that encourages meaningful engagement with the system (Bhat et al., 2024). When adequate FC are in place, academics are better equipped to explore ChatGPT's capabilities, experiment with its features, and integrate it into task-specific academic activities such as idea generation, drafting, analysis, and problem-solving. This supportive context enhances users' ability to recognize the system's instrumental value rather than merely its performance outcomes. In other words, FC enable academics to experience and realize the functional benefits of ChatGPT in their academic processes. Prior research supports this reasoning. Studies indicate that robust infrastructure and accessible support mechanisms strengthen users' evaluations of a technology's practical utility (Arbulú Ballesteros et al., 2024; Bhat et al., 2024). When users have access to clear tutorials, responsive assistance, and compatible systems, they report greater PU because they can apply the technology to their specific tasks more effectively. In other words, GenAI tools like ChatGPT are highly accessible at the consumer level, some might argue that traditional institutional IT infrastructure is no longer a prerequisite for adoption. However, applying AI to rigorous academic tasks introduces complex ethical, pedagogical, and data security challenges. Emerging literature suggests that without explicit institutional guidelines and specialized training, academics may hesitate to fully integrate AI into core scholarly tasks, thereby failing to recognize its deeper utility (Subhani et al., 2025). Therefore, we argue that robust institutional FC remain a critical catalyst for academics to safely explore and realize the system's instrumental value. Based on this discussion, the hypothesis is:

H4. *FC positively affect the PU of ChatGPT among academics.*

Perceived ease of use

PEOU is a fundamental factor in technology acceptance and refers to the extent to which academics experience ChatGPT as clear, understandable, user-friendly, and effortless during interaction (Foroughi et al., 2024). When users perceive a system as easy to use, they are more inclined to adopt it (Foroughi et al., 2024; Khan et al., 2025). For ChatGPT, an intuitive interface, seamless navigation, and user-friendly features augment the probability that users will find the system both useful and reliable (Paradedda et al., 2025). Users who perceive the system as easy to use are more likely to trust and integrate it into their daily routines (Shahzad et al., 2024). Recent studies reinforce this finding, demonstrating that ease of use is a significant predictor of technology acceptance in AI systems as ChatGPT (Deric et al., 2025; Foroughi et al., 2024). Systems perceived as user-friendly tend to inspire greater trust and engagement, with users' perceptions of ease of use strongly linked to their trust in AI technologies (Deric et al., 2025; Shahzad et al., 2024). However, in the context of GenAI, the relationship between ease of use and trust presents a unique theoretical tension. Because ChatGPT functions as a 'black box' with obscured decision-making processes, a highly simplistic

interface could theoretically mask underlying algorithmic inaccuracies, potentially prompting skepticism among rigorous academics who demand methodological transparency. Despite this risk, recent empirical studies suggest that usability remains the primary gateway to cognitive confidence; an academic must first feel that the system is predictable and user-friendly before they can establish foundational trust in its technical reliability (Deric et al., 2025; Khan et al., 2025). In line with this perspective, we argue that seamless interaction is a prerequisite for trust formation. Based on this discussion, the hypothesis is

H5. *PEOU of ChatGPT is positively related to trust in AI systems (TAS) among academics.*

Perceived usefulness

PU refers to academics' evaluation of ChatGPT's task-specific instrumental value in activities such as academic decision-making, idea generation, problem-solving, and research support (Foroughi et al., 2024; Khan et al., 2025). In technology acceptance research, usefulness is generally assessed by evaluating whether a system helps users accomplish relevant tasks more effectively. Such task-specific evaluation can also provide information about the system's boundaries. When academics repeatedly compare ChatGPT outputs with disciplinary knowledge, source material, and scholarly quality requirements, practical experience should make discrepancies, factual errors, and limitations more visible. This exposure can replace speculative assumptions with evidence-based judgements, thereby improving belief calibration (Ali et al., 2025; Balaskas et al., 2025; Deric et al., 2025). A more informed understanding of what ChatGPT can and cannot do should reduce beliefs that it is error-free, possesses human-like understanding, can fully replace academic judgment, or can solve every academic problem. Trust-calibration research similarly suggests that experience can support more appropriate reliance when users evaluate automation against observed performance rather than surface fluency alone (Lee & See, 2004). Automation bias provides an important alternative possibility because successful system use may sometimes encourage overreliance or capability overgeneralization (Parasuraman & Riley, 1997; Skitka et al., 1999). Nevertheless, the dominant calibration logic predicts that, as academics recognize the practical usefulness of ChatGPT through informed use, misconceptions should decrease rather than increase. Hence, the hypothesis is that:

H6. *PU of ChatGPT is negatively associated with misconceptions about AI (MAI) systems among academics.*

Trust in AI systems

TAS refers to the extent to which academics perceive ChatGPT as reliable, secure, dependable, and capable of producing trustworthy academic outputs. In academic contexts, trust reduces uncertainty associated with GenAI tools and strengthens users' confidence in their consistent and secure performance (Amin et al., 2024; Deric et al., 2025; Foroughi et al., 2024; Gefen et al., 2003; Shahzad et al., 2024). When academics perceive ChatGPT as reliable and capable of handling academic information securely, they are more likely to develop confidence in the system's continued and responsible use within scholarly activities (Balaskas et al., 2025; Deric et al., 2025). While earlier adoption models often treat initial usage intention as the final outcome, this study uniquely positions 'forward-looking expectations' as the ultimate dependent variable. Therefore, the expectations regarding AI systems (EAS) refer to academics' forward-looking beliefs about the future role, impact, and pedagogical potential of ChatGPT and similar AI technologies in academia. This construct captures anticipated long-term significance, improvement, and transformation of academic work practices due to AI systems. We argue that trust functions as the vital cognitive bridge between present-day system evaluation and future-oriented belief formation. As trust in ChatGPT increases, uncertainty diminishes, enabling academics to form more stable and optimistic projections about the system's future integration into teaching, research, and academic decision-making processes. Prior research indicates that trust significantly influences users' attitudes and expectation formation toward AI technologies (Amin et al., 2024; Balaskas et al., 2025; Foroughi et al., 2024). When users perceive a system as reliable and secure, they are more inclined to believe that it will continue to evolve positively and contribute meaningfully to professional practices (Amin et al., 2024; Foroughi et al., 2024; Shahzad et al., 2024). In the context of higher education, trust therefore serves as a foundational belief that shapes academics' forward-looking evaluations of AI's institutional and transformative potential. Based on discussion, the hypothesis is:

H7. *TAS significantly enhances expectations about AI systems, specifically for ChatGPT in academic contexts.*

Misconceptions about AI

MAI are exaggerated or overgeneralized beliefs about ChatGPT's capabilities, including assumptions of error-free performance, human-like understanding, complete task autonomy, or universal problem-solving ability. These beliefs can create a mismatch between what users expect and what the system can reliably deliver. Trust-calibration theory proposes that appropriate trust should correspond with an automated system's demonstrated competence and limitations rather than with inflated expectations (Lee & See, 2004). In academic work, where factual accuracy, reasoning quality, source verification, and intellectual responsibility are important, encounters with factual inaccuracies, logical inconsistencies, or incomplete contextual understanding can make an expectation-reality gap especially salient (Ali et al., 2025; Deric et al., 2025). When exaggerated expectations are contradicted by observed limitations, perceived reliability and dependability can decline, thereby weakening stable trust (Amin et al., 2024; Bikanga Ada, 2024). Clear institutional guidance and AI literacy can support more realistic beliefs about capability and more appropriately calibrated reliance. Automation research recognizes that users can sometimes display excessive short-term confidence in systems that appear highly capable (Parasuraman & Riley, 1997; Skitka et al., 1999), but this possibility does not alter the dominant calibration-based expectation that inaccurate beliefs should be negatively related to stable trust. The hypothesis, therefore, tests the expected negative association:

H8. *Misconceptions about ChatGPT are negatively associated with TAS among academics.*

METHODOLOGY

This study adopted a quantitative research design using a deductive approach to test the proposed hypotheses derived from the integrated UTAUT and TAM framework. Cross-sectional data were collected through a structured questionnaire administered electronically. The unit of analysis was at the individual level, focusing on academicians working in higher education institutions. The target population comprised academicians from both public and private higher education institutions in Malaysia. Given the structural differences in funding models, governance systems, and institutional policies between public and private universities, both sectors were included to ensure broader generalizability of findings within the Malaysian higher education context.

The minimum required sample size was determined using G*Power software as in previous studies (Cheah et al., 2018; Foroughi et al., 2024; Lijie et al., 2024). An a priori power analysis was conducted with a statistical power of 0.80, an effect size of 0.15, a significance level of 0.05, and a maximum of two predictors pointing at a single endogenous construct. The analysis indicated a minimum required sample of 68 respondents. Although the minimum required sample was 68, a 500 questionnaires were distributed to account for potential non-response and to enhance statistical robustness. A stratified random sampling technique was employed to ensure balanced representation between public and private universities. The strata were defined based on institutional category (public versus private), as these sectors operate under different administrative and structural frameworks that may influence technology acceptance behavior. To maintain proportional balance, 250 questionnaires were distributed to academicians from public universities and 250 to those from private universities. A list of academicians was compiled from the Ministry of Higher Education database and official institutional websites. From these lists, respondents were randomly selected and invited via email to participate in the study. The questionnaire was distributed electronically. Participants were informed about the purpose of the study, the voluntary nature of participation, and their right to withdraw at any time without penalty. Informed consent was obtained electronically before respondents proceeded with the questionnaire. All responses were anonymized to ensure confidentiality and data protection. After four weeks, 272 responses were received, yielding a response rate of 54.4 percent. Following data screening, 20 incomplete questionnaires were excluded. The final usable sample consisted of 252 responses, exceeding the minimum required sample size.

Of the 252 valid responses, 44.4 percent were male and 55.6 percent were female. In terms of age distribution, 35.3 percent were aged between 18 and 25 years, 35.3 percent between 26 and 35 years, 20.2 percent between 36 and 44 years, and 9.2 percent were 45 years and above. The demographic profile of respondents indicates that 35.3 percent were aged between 18 and 25 years. While this may appear unusually

high for a sample described as academics, it reflects the institutional realities of Malaysian universities. In addition to degree-level programs, many universities also host certification, matriculation, and diploma courses, where lecturers are often younger and fall within this age range. This structural characteristic of the Malaysian higher education system helps explain the higher proportion of young academics in the sample. Regarding ethnicity, 31.7 percent were Malay, 24.2 percent Chinese, 23.8 percent Indian, and 20.3 percent from other ethnic backgrounds. In terms of educational attainment, 42.9 percent held a PhD, 16.2 percent held a master's degree, and 40.9 percent reported other qualifications. With respect to marital status, 57.6 percent were married, 35.7 percent were single, and 6.7 percent reported other statuses. Monthly income distribution showed that 4.0 percent earned between RM3000 and RM4000, 30.2 percent between RM4001 and RM6000, 33.3 percent between RM6001 and RM8000, and 32.5 percent above RM8000. In terms of institutional affiliation, 50.4 percent were from public universities and 49.6 percent from private universities. Regarding academic rank, 32.5 percent were lecturers, 30.2 percent were senior lecturers or assistant professors, 33.3 percent were associate professors, and 4.0 percent were professors.

Instrument Development and Validation

The questionnaire was designed to capture both demographic information and construct-related measures aligned with the proposed research framework. In addition to demographic data, respondents were asked about their experience with ChatGPT to contextualize their responses, as familiarity with the system may influence perceptions of usefulness, ease of use, trust, and expectations. Prior to full-scale data collection, the instrument was pre-tested with six academicians, comprising three from public universities and three from private universities. While the initial face-validity pre-test was limited to six experts, the construct validity of these historically established scales was rigorously confirmed through confirmatory composite analysis in PLS-SEM prior to structural testing. This process aimed to establish face validity and content validity. Based on their feedback, minor revisions were made to improve clarity, wording precision, and questionnaire layout. The final questionnaire consisted of two sections. The first section collected demographic information, while the second section measured the study constructs. All construct items were adapted from recent ChatGPT studies (Bhat et al., 2024; Bhullar et al., 2024; Chan & Hu, 2023; Zhao et al., 2024) and foundational technology acceptance literature (Davis, 1989; Venkatesh et al., 2003). These items were subsequently modified to reflect the academic context of ChatGPT usage, as summarized in [Table 1](#).

Table 1. Research instruments

No	Main variable	Items	References
1	EE	Learning to use ChatGPT is easy for me. It is easy for me to become skillful at using ChatGPT. Interacting with ChatGPT does not require much mental effort. I find ChatGPT easy to operate.	Bhat et al. (2024), Davis (1989), Venkatesh et al. (2003)
2	EAS	I expect ChatGPT to play a significant role in my future academic work. I expect AI systems like ChatGPT to become essential in academia. I expect ChatGPT to continuously improve in supporting academic tasks. I expect AI systems to transform academic work practices. I have the resources necessary to use ChatGPT.	Bhullar et al. (2024), Gefen et al. (2003), Venkatesh et al. (2003)
3	FC	I have the knowledge necessary to use ChatGPT. ChatGPT is compatible with other systems I use. A specific person (or group) is available for assistance with ChatGPT difficulties.	Bhat et al. (2024), Venkatesh et al. (2003)
4	MAI	I believe ChatGPT can perform tasks without any errors. I think ChatGPT can fully replace human academic work. I assume ChatGPT can understand and generate text perfectly like a human. I believe ChatGPT can solve any academic problem.	Bhullar et al. (2024), Chan and Hu (2023)
5	PEOU	My interaction with ChatGPT is clear and understandable. I find it easy to get ChatGPT to do what I want it to do. ChatGPT responds in a user-friendly manner. Overall, using ChatGPT feels effortless.	Davis (1989), Gefen et al. (2003), Venkatesh et al. (2003), Zhao et al. (2024)
6	PU	ChatGPT is useful for supporting my academic decision-making. ChatGPT helps me generate ideas for academic work. ChatGPT supports problem-solving in my academic tasks. ChatGPT enhances the effectiveness of my academic processes.	Davis (1989), Gefen et al. (2003), Venkatesh et al. (2003), Zhao et al. (2024)

Table 1 (Continued).

No	Main variable	Items	References
7	PE	Using ChatGPT improves my academic productivity. Using ChatGPT enhances the quality of my academic work. ChatGPT enables me to accomplish academic tasks more efficiently. Using ChatGPT improves my overall academic performance.	Bhat et al. (2024), Davis (1989), Venkatesh et al. (2003)
8	SI	People who influence my behavior think that I should use ChatGPT. People who are important to me think that I should use ChatGPT. My colleagues support the use of ChatGPT. The academic community encourages the use of ChatGPT.	Bhat et al. (2024), Venkatesh et al. (2003)
9	TAS	I trust ChatGPT to perform my academic tasks reliably. I believe ChatGPT is secure in handling my data. I feel confident in ChatGPT's abilities. ChatGPT is trustworthy.	Amin et al. (2024), Gefen et al. (2003)

Adaptation involved contextualizing generic scale items; for example, references to “the system” were replaced with “ChatGPT,” and “work tasks” were specified as “academic decision-making and research”. All items were measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). This scale allowed respondents to provide structured evaluations of their perceptions regarding ChatGPT and related AI systems.

STATISTICAL ANALYSIS AND RESULTS

Common Method Variance

Common method variance (CMV) is a potential issue associated with collecting data through the survey method. Thus, we employed Harman single-factor and the variance inflation factor (VIF) to test the CMV issue. The Harman single factor shown that the first factor accounted for 31.51%, which is less than 50% of the total variance extracted suggested no CMV issue. To further validate this finding, we have checked the VIF was examined to test multicollinearity issues in this study. The analysis results in [Table 2](#) displayed that all the values of VIF of individual items and constructs are below the threshold of 5.0 (Liang & Shiao, 2018). These results reveal that multicollinearity did not significantly influence the study's findings. Consequently, the threat of CMV is non-existent in this study. Furthermore, while Harman's single-factor test and VIF assessments indicated no severe CMV, the reliance on cross-sectional, self-reported data means CMV cannot be entirely eliminated.

Structural Model Results

The structural equation model (SEM) of this research was developed using Smart PLS software. According to Liengaard et al. (2021), the partial least squares (PLS) method is suitable for constructing predictive and theoretical research models, making it the most appropriate option for this type of investigation. Compared to other SEM methods, PLS-SEM is reliable for intricate models with numerous constructs and indicators, even with smaller sample sizes (Hair et al., 2019). Additionally, it employs bootstrapping, a resampling technique that produces trustworthy outcomes even with smaller samples (Hair et al., 2019). The theoretical framework in the current study was articulated based on identifying factors that influence academics' beliefs in AI systems and trust, as presented in [Figure 1](#). This aligns with a past study by Hair et al. (2020), highlighting PLS's relevance for the current examination.

PLS-SEM has become popular, especially for its two-step approach to analyzing studies' data. The first stage assesses the measurement model's inter-item reliability, internal consistency, and convergent and discriminant validity. The second stage tests the hypotheses and determines the predictive power of the structural model. Therefore, it was a suitable analysis method for examining causal links between variables (Henseler et al., 2016). Composite reliability (CR) was calculated with the results illustrated in [Table 2](#) to ensure each construct's internal consistency. Moreover, [Table 2](#) also showed construct validity evaluation for each statement (item) measuring the variables, Cronbach's alpha coefficient results, and the average variance extracted (AVE) values to measure convergent validity, which is the extent to which the items in a construct

Table 2. Summary of the results of the assessments

Table 1. Summary of the results of the assessments						
Variables	Items	Loadings	Cronbach's alpha	CR	AVE	VIF
EAS	EAS1	0.815	0.808	0.873	0.633	1.854
	EAS2	0.796				1.914
	EAS3	0.799				1.680
	EAS4	0.772				1.631
EE	EE2	0.774	0.797	0.881	0.712	1.459
	EE3	0.883				1.972
	EE4	0.869				1.958
FC	FC1	0.899	0.696	0.867	0.766	1.399
	FC2	0.851				1.399
MAI	MAI1	0.899	0.776	0.899	0.817	1.671
	MAI2	0.909				1.671
PE	PE1	0.854	0.842	0.894	0.679	2.179
	PE2	0.861				2.231
	PE3	0.803				1.835
	PE4	0.776				1.574
PEOU	PEU1	0.727	0.739	0.853	0.660	1.250
	PEU3	0.843				1.772
	PEU4	0.861				1.844
PU	PU2	0.916	0.790	0.905	0.826	1.744
	PU3	0.902				1.744
SI	SI2	0.705	0.747	0.856	0.666	1.272
	SI3	0.857				1.786
	SI4	0.877				1.849
TAS	TAS1	0.816	0.821	0.882	0.652	1.812
	TAS2	0.840				1.933
	TAS3	0.808				1.782
	TAS4	0.764				1.489
Average scores					0.712	
AVE*R ²					0.379	
√AVE*R ² (GoF)					0.616	

Note. R² = 0.533

share a high variance (Shaked et al., 2020). The statistical software systems used for data analysis are SPSS 24 and Smart PLS 4.

Measurement Model

The study's measurement model was evaluated in several steps. First, inter-item reliability was measured through factor loadings with a threshold of 0.70 and above (Hair et al., 2020). The second step evaluated convergent validity through the AVE, which exceeded 0.50 (Hair et al., 2020). The third step assessed the CR scores above the threshold level of 0.70, which Hair et al. (2020) suggested, ensuring internal consistency reliability. As illustrated in [Table 2](#), the coefficients for CR exceeded the 0.70 threshold, indicating the reliability of the proposed model. Overall, the measurements in [Table 2](#) show the model's convergent validity, reflecting a strong alignment between the proposed constructs and the theoretical model.

Discriminant Validity

Discriminant validity in this study was evaluated using the Fornell-Larcker (1981) criterion and the heterotrait-monotrait (HTMT) ratio. According to Fornell and Larcker (1981), the AVE square root should exceed the correlations between any two variables within the model. As demonstrated in [Table 3](#), all the study's constructs met this criterion, establishing discriminant validity. The results exhibited in [Table 3](#) prove that the AVE values of the constructs exceeded the squared inter-construct correlations and Cronbach's alpha coefficients, indicating the legitimacy and validity of the measurement scale used in this study.

Furthermore, the HTMT ratio is considered an additional test for discriminant validity. Values exceeding 0.90 indicate potential issues with discriminant validity (Lijie et al., 2024; Seow et al., 2025). All the HTMT values in [Table 3](#) are below the threshold of 0.9 in the ranged between 0.09 and 0.86, indicated that discriminant validity is fulfil. The hypothesized relationships between constructs in the structural model were tested using

Table 3. Discriminant validity

Variables	EE	EAS	FC	MAI	PEU	PU	PE	SI	TAS
Fornell-Larcker criterion									
EE	0.844								
EAS	0.578	0.800							
FC	0.447	0.429	0.875						
MAI	0.470	0.352	0.185	0.904					
PEOU	0.630	0.588	0.450	0.430	0.810				
PU	0.472	0.395	0.401	0.385	0.692	0.910			
PE	0.705	0.615	0.600	0.374	0.592	0.460	0.820		
SI	0.064	0.024	0.003	0.036	0.077	0.102	0.100	0.820	
TAS	0.524	0.437	0.199	0.682	0.528	0.434	0.395	0.004	0.807
HTMT0.9 criterion									
EE									
EAS	0.72								
FC	0.61	0.57							
MAI	0.60	0.44	0.24						
PEOU	0.82	0.77	0.62	0.57					
PU	0.60	0.49	0.54	0.49	0.69				
PE	0.86	0.75	0.78	0.46	0.75	0.56			
SI	0.10	0.11	0.05	0.09	0.12	0.13	0.14		
TAS	0.66	0.53	0.26	0.85	0.68	0.54	0.48	0.09	

Table 4. VIF, R², F² and Q²

Path	VIF	R ²	f ²	Q ²
PE → PEU	1.990		0.077	
EE → PEU	1.990	0.440	0.161	0.285
SI → PU	1.000		0.013	
FC → PU	1.000	0.171	0.194	0.135
PEU → TAS	1.227		0.145	
MAI → TAS	1.227	0.533	0.542	0.339
PU → MAI	1.000	0.149	0.175	0.119
TAS → EAS	1.000	0.191	0.236	0.113

SEM through PLS. Cheah et al. (2018) suggested a bootstrapping process with 5,000 iterations to determine the significance of the subconstruct weights and path coefficients. Although PLS does not possess the quality of providing comprehensive overall fit indicators, Tenenhaus et al. (2005) established the goodness-of-fit (GoF) index as a diagnostic guide. The GoF index for endogenous constructs is measured through the geometric mean of the average communality and the average R².

Hoffmann and Birnbrich (2012) proposed thresholds for assessing the GoF results: 0.1 = small, 0.25 = medium, and 0.36 = large. Based on the calculations in [Table 2](#), the model in this study achieved a GoF score of 0.616, signifying a strong and robust fit. Further, the model fit was evaluated using the standardized root mean square residual (SRMR). The SRMR value for the composite model was 0.06, which is below the recommended threshold of 0.08, indicating acceptable model fit. This step concludes the evaluation of the measurement model and GoF. After that, the proposed hypotheses in the structural model were examined, as illustrated in [Figure 2](#).

The R² value in [Table 4](#) and [Figure 2](#) reveals the degree to which the independent construct(s) effectively predict the connected construct. Based on the categories proposed by Cohen (1988), an R² value of 0.26 signifies a strong effect, 0.13 is a moderate effect, and 0.02 is a weak effect. The value of R² in this study is in the range of 0.533 to 0.149, indicating that the proposed variables substantially explain TAS and PEOU and moderately explain others. This R² value is considered adequate for the analysis. Furthermore, [Table 4](#) reported the predictor variables' effect size (f²) to evaluate the model's predictive validity (Peng & Lai, 2012). The results show acceptable effect sizes of all eight exogenous constructs, supporting the structural model's robustness. Finally, path coefficient analysis was performed to assess the strength and statistical significance of the relationships between independent and dependent variables within the structural model. As presented in [Table 5](#) and [Figure 2](#), all proposed hypotheses (**H1-H8**) demonstrated positive associations, with most achieving statistical significance at $p < .01$. However, **H3** yielded a p-value of 0.138, indicating non-significance.

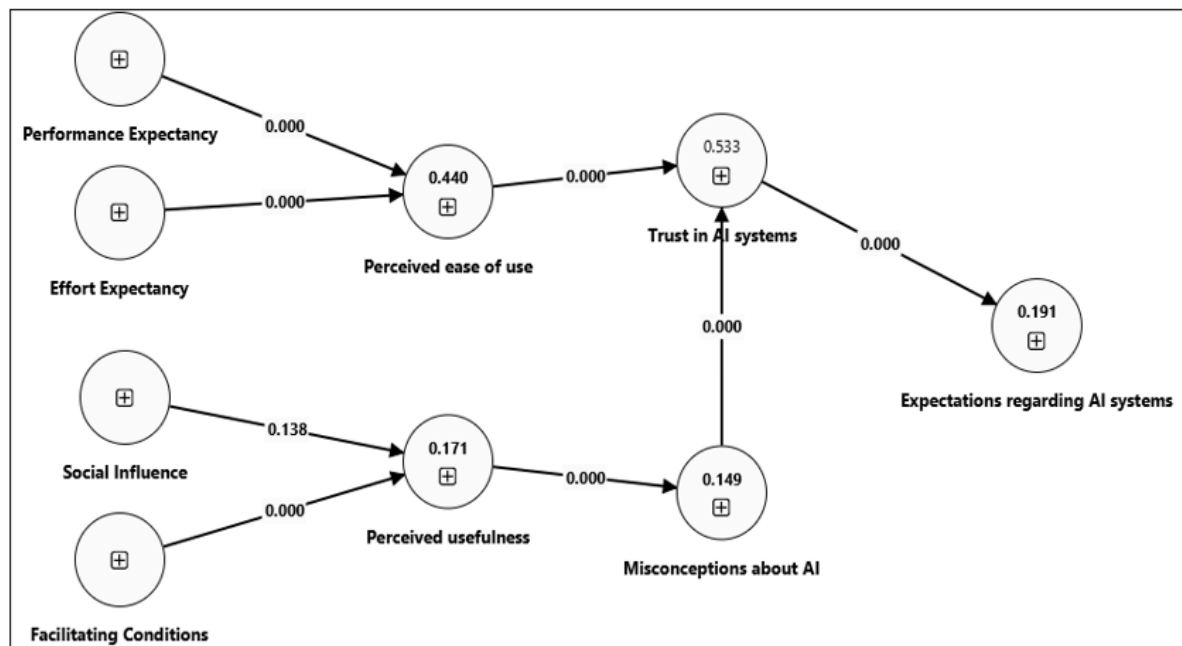


Figure 2. Results of structural model analysis (Smart PLS output)

Table 5. Results for path coefficient analysis

H	Path	Beta value	Standard error	t-value	p-values	LL	ULL	Decision
H1	PE → PEU	0.294	0.071	4.153	0.000	0.154	0.431	Supported
H2	EE → PEU	0.423	0.07	6.009	0.000	0.279	0.554	Supported
H3	SI → PU	0.103	0.069	1.483	0.138	-0.131	0.196	Not supported
H4	FC → PU	0.401	0.052	7.743	0.000	0.292	0.496	Supported
H5	PEU → TAS	0.288	0.045	6.346	0.000	0.196	0.374	Supported
H6	PU → MAI	0.385	0.056	6.902	0.000	0.272	0.489	Not supported
H7	TAS → EAS	0.437	0.053	8.312	0.000	0.320	0.531	Supported
H8	MAI → TAS	0.558	0.044	12.723	0.000	0.464	0.639	Not supported

Of the eight hypotheses tested, five (**H1**, **H2**, **H4**, **H5**, and **H7**) were supported, while three (**H3**, **H6**, and **H8**) were not. Notably, although **H6** and **H8** reached statistical significance, their directional effects diverged from the hypothesized relationships, thereby failing to support the proposed assumptions.

DISCUSSION

This study examined how foundational acceptance drivers, cognitive evaluations, misconceptions, and trust interact to shape academics' expectations of ChatGPT. Rather than merely confirming traditional relationships, the findings reveal a complex process of belief formation. Several relationships are consistent with TAM and UTAUT expectations, whereas **H3**, **H6**, and **H8** require closer contextual and theoretical interpretation. The discussion therefore focuses on why these unexpected patterns may have appeared, how they compare with findings from other higher education settings, and which theoretical perspectives can plausibly account for them without treating the observed paths as direct proof of underlying psychological processes.

PE was positively associated with PEOU, supporting **H1**. Academics who reported stronger expectations that ChatGPT could enhance their productivity and academic performance also tended to perceive the system as easier to use. This pattern is consistent with technology acceptance research, which shows that expected performance benefits are associated with favorable evaluations of GenAI (Arbulú Ballesteros et al., 2024; Bhat et al., 2024). When academics anticipate meaningful benefits from ChatGPT, they may be more motivated to engage with the system, learn its features, and become familiar with its interface. However, because the study is cross-sectional, the finding should be interpreted as an association rather than evidence that PE directly causes PEOU.

EE demonstrated an even stronger positive association with PEOU, supporting **H2**. This is consistent with earlier research showing that technologies expected to require less cognitive and technical effort are generally perceived as more usable (Foroughi et al., 2024; Khan et al., 2025). The finding suggests that academics who expect ChatGPT to be relatively easy to learn and use also tend to find the system clear and manageable. This relationship is particularly plausible for conversational AI because natural-language interfaces lower many of the technical barriers associated with conventional digital systems. Nevertheless, academically rigorous use may still require substantial effort in prompting, verification, source checking, and critical evaluation.

FC were positively associated with PU, supporting **H4**. In the Malaysian setting, this finding is particularly relevant because current higher education digitalization policy emphasizes digital skills, leadership, infrastructure, and institutional capability (Ministry of Higher Education Malaysia, 2025). The result should not be interpreted as evidence that institutional support directly causes usefulness perceptions. Rather, respondents reporting stronger FC also tended to report greater instrumental value from ChatGPT. This suggests that access to training, technical assistance, appropriate infrastructure, and institutional guidance may be associated with more favorable evaluations of GenAI.

SI, however, was not significantly associated with PU, and **H3** was therefore not supported. This result differs from evidence in some contexts where SI has been reported as an important adoption-related factor, but it is closer to findings indicating weaker social-group influence among educators in other settings (Amin et al., 2024; Bhat et al., 2024). Evidence from Peruvian universities and cross-country teacher research similarly demonstrates that technology acceptance and trust relationships can vary across institutional and cultural settings (Arbulú Ballesteros et al., 2024; Viberg et al., 2024).

One plausible explanation is that academic work involves substantial professional autonomy and disciplinary judgement. Academics may therefore evaluate ChatGPT primarily through personal experience with tasks rather than uniform peer expectations. Malaysia's combination of public and private institutions, different academic disciplines, and evolving university-level AI policies may further reduce the consistency of normative pressure. Thus, the non-significant relationship may represent a contextual boundary condition of SI rather than evidence that social factors are universally unimportant.

The positive association between PU and misconceptions was contrary to **H6**. Rather than concluding that usefulness causes misconceptions, the finding indicates that respondents who rated ChatGPT as more useful also tended to hold stronger inflated capability beliefs. This unexpected result deserves careful interpretation.

Automation-bias research provides one possible explanation. When an automated system repeatedly provides fluent, convenient, or apparently successful outputs, users may rely on salient performance cues and generalize beyond the tasks they have actually verified (Parasuraman & Riley, 1997; Skitka et al., 1999). In GenAI, linguistic fluency can make system competence appear broader than it actually is. Users may therefore recognize genuine task-level utility while simultaneously developing exaggerated assumptions regarding accuracy, autonomy, or human-like understanding.

This creates a possible pattern of usefulness amplification in which task-specific value and inaccurate global beliefs coexist. However, this interpretation remains provisional. The cross-sectional design cannot determine whether PU preceded misconceptions, whether misconceptions influenced usefulness ratings, or whether both were affected by another factor such as AI literacy, experience, frequency of use, or disciplinary background. Consequently, the term usefulness-amplification is used as a descriptive interpretation of the observed association and not as evidence of an established causal mechanism.

PEOU was positively associated with TAS, supporting **H5**. Respondents who perceived ChatGPT as clearer and easier to use also tended to report greater trust. This finding is broadly consistent with previous technology acceptance studies that link usability to confidence and trust (Deric et al., 2025; Shahzad et al., 2024). Ease of interaction may reduce uncertainty during system use, but ease of use should not be treated as evidence that an AI system is necessarily accurate or reliable.

The positive association between misconceptions and trust was also the opposite of that hypothesized in **H8**. Trust-calibration theory argues that appropriate reliance requires that trust correspond to actual system capability (Lee & See, 2004). The present finding should therefore not be interpreted as proof that misconceptions generate trust. A more cautious interpretation is that some respondents simultaneously

reported inflated beliefs concerning ChatGPT's capabilities and high levels of confidence in the system. This configuration is consistent with a potential miscalibrated-trust pattern at the time of measurement.

Research on GenAI indicates that trust can be associated with user experience, proficiency, AI understanding, cultural context, and perceived system performance (Deric et al., 2025; Viberg et al., 2024). Trust may therefore reflect a mixture of knowledge, experience, contextual norms, and perceived performance rather than a purely rational assessment of system capability. Individuals who have not yet encountered significant system failures may report strong trust even when their underlying capability beliefs are inaccurate. Future longitudinal research is required to determine whether such confidence persists when users encounter errors or limitations.

TAS was positively associated with forward-looking expectations, supporting **H7**. This result is consistent with research linking trust with more favorable acceptance and future-use beliefs (Amin et al., 2024; Balaskas et al., 2025; Shahzad et al., 2024). Academics who reported greater confidence in ChatGPT also tended to express stronger expectations regarding the future role of AI in academic work. Nevertheless, because the data are cross-sectional, the association does not establish that trust temporally causes more optimistic expectations.

Overall, the findings demonstrate that favorable functional evaluations of ChatGPT can coexist with inaccurate beliefs about its capabilities and high reported trust. In Malaysia, this pattern has practical relevance because institutional digitalization is occurring alongside national emphasis on responsible, transparent, accountable, and trustworthy AI governance (Ministry of Science, Technology and Innovation Malaysia, 2024). Wider availability of GenAI should therefore be accompanied by AI literacy, verification practices, privacy and data guidance, and clear expectations concerning human oversight. The labels "usefulness-amplification" and "potentially miscalibrated trust" are used to organize and interpret these unexpected associations. They should not be understood as claims that this cross-sectional study has established causal psychological mechanisms. Longitudinal, experimental, and cross-country research is needed to determine the temporal ordering and boundary conditions of these patterns.

Implications of the Study

Theoretical implications

The findings provide evidence that established TAM and UTAUT constructs remain relevant when GenAI acceptance is considered together with belief accuracy and trust calibration. PE, EE, FC, PEOU, and trust showed the expected associations within the model, whereas the relationships involving misconceptions did not follow the hypothesized calibration pathway. The positive association between PU and misconceptions, together with the positive association between misconceptions and trust, indicates that functional value, inaccurate capability beliefs, and trust can coexist within the same respondent profile. This pattern supports the relevance of considering trust-calibration and automation-bias perspectives alongside conventional acceptance models (Lee & See, 2004; Parasuraman & Riley, 1997; Skitka et al., 1999). It does not, however, establish a causal belief-amplification mechanism. The non-significant social-influence relationship also indicates that UTAUT relationships may be context-sensitive. Findings from diverse educational and national settings suggest that normative influence and trust vary across institutional, professional, and cultural conditions (Amin et al., 2024; Arbulú Ballesteros et al., 2024; Bhat et al., 2024; Viberg et al., 2024). Within the Malaysian sample, professional autonomy, institutional diversity, and an evolving responsible AI policy environment may represent relevant contextual conditions for future testing. Overall, the model provides evidence of how acceptance constructs, misconceptions, trust, and forward-looking expectations are statistically related within a single higher education framework, while identifying association patterns that require stronger longitudinal and experimental verification.

Practical implications

The findings have practical relevance for university leaders and policymakers seeking responsible integration of GenAI. In Malaysia, these recommendations align with the digitalization of higher education action plan 2025-2030 and the national guidelines on AI governance and ethics, both of which emphasize institutional capability, skills development, governance, and responsible use (Ministry of Higher Education

Malaysia, 2025; Ministry of Science, Technology and Innovation Malaysia, 2024). Because FC were positively associated with PU, universities should combine access to ChatGPT with structured training, technical assistance, clear institutional rules, and discipline-specific examples of appropriate use. This is an association rather than evidence that support alone will cause effective adoption, but it indicates that respondents who perceived stronger institutional support also recognized greater practical value. The positive association between PEOU and trust further indicates that usability and clear onboarding matter. At the same time, ease and fluency should not be treated as evidence of accuracy. Training should therefore require verification of factual claims and sources, clarify privacy and data-handling expectations, and reinforce human responsibility for academic judgement.

The unexpected positive associations involving misconceptions are especially important for AI literacy. Institutions should explicitly distinguish linguistic fluency from factual reliability, demonstrate common failure modes, and train users to recognize fabricated information, incomplete reasoning, inaccurate citations, and task boundaries. Such measures can support calibrated reliance rather than either uncritical confidence or blanket rejection of AI. The weak social-influence relationship also suggests that universities may benefit more from evidence-based demonstrations and transparent guidance than from simple peer endorsement. Academics should be shown how GenAI performs on authentic teaching and research tasks, where it adds value, and where independent checking remains necessary. These recommendations are risk-informed responses to the observed associations and should not be interpreted as causal guarantees, given that the study used cross-sectional self-reported data.

Limitations and Future Research Suggestions

This study is subject to several limitations that provide opportunities for future research. First, data were collected exclusively from academics in Malaysia, which limits the generalizability of the findings to other higher education systems. Countries differ in governance arrangements, AI regulations, institutional practices, funding structures, technological infrastructure, and cultural conditions. Malaysia's position as an emerging economy also shapes the environment within which academics interact with GenAI. Comparative cross-country research and multi-group analyses across different regulatory and cultural environments could provide stronger evidence regarding the extent to which institutional context shapes AI acceptance, misconceptions, and trust. Second, the cross-sectional and self-reported research design limits causal interpretation. Structural path coefficients in this study indicate statistical associations measured at one point in time and cannot establish temporal ordering. Accordingly, usefulness-amplification and potential miscalibrated trust is treated as provisional interpretations of unexpected association patterns rather than proven psychological mechanisms. Longitudinal or experimental designs are required to determine whether changes in PU precede changes in misconceptions and whether misconceptions subsequently alter trust.

Third, the age distribution limits the representativeness of the sample because 35.3 percent of respondents were between 18 and 25 years old, which is unusually high for a sample of academics. This profile may overrepresent younger participants and limits generalization to the broader Malaysian academic workforce. Future research should consider age and academic-rank quotas or stratified sampling, provide more detailed eligibility screening, and examine whether the structural relationships differ across age and career-stage groups. Another limitation concerns the rapid evolution of GenAI tools. The capabilities of systems such as ChatGPT have advanced substantially across successive versions. These changes may influence users' perceptions and experiences. The present study did not identify the specific ChatGPT version used by each respondent. The absence of version-specific information should therefore be considered when interpreting and generalizing the findings. Future studies should record the model version, type of access, frequency of use, and principal use cases.

The model also does not explicitly examine potential moderating variables such as AI literacy, prior technological expertise, academic discipline, usage intensity, or ethical orientation. Science, technology, engineering and mathematics, social sciences, business, humanities, and professional disciplines may display different patterns of technology use and trust. Future research could examine whether the relationships between PU and misconceptions, or between misconceptions and trust, vary according to levels of AI knowledge, academic discipline, or prior experience. Such analyses would help clarify the conditions under which usefulness-amplification patterns and trust miscalibration may occur.

Overall, future research should continue refining TAMs in the context of intelligent and autonomous systems while recognizing that GenAI introduces cognitive complexities beyond conventional adoption questions. Longitudinal, experimental, multi-country, and multi-group research will be particularly valuable for determining whether the unexpected associations observed in this study persist over time and across different institutional contexts.

CONCLUSION

This study examined how technology acceptance constructs, misconceptions, trust, and forward-looking expectations are related in a sample of academics from Malaysian public and private universities. The findings support several established acceptance relationships, including associations involving PE, EE, FC, PEOU, and trust. The unexpected positive associations between PU and misconceptions, and between misconceptions and trust, indicate that functional appreciation can coexist with inflated capability beliefs and high reported confidence. These patterns are consistent with the possibility of trust miscalibration, but the cross-sectional design does not establish a causal mechanism or temporal sequence. In Malaysia's rapidly digitalizing higher education environment, where national policy increasingly emphasizes responsible AI governance and digital capability, the findings underline the importance of combining access to GenAI with AI literacy, verification, transparent institutional guidance, data governance, and human oversight. Future longitudinal, experimental, and cross-country studies should determine whether the observed patterns persist over time and under different cultural, disciplinary, and regulatory conditions. Such research would provide stronger evidence on when functional appreciation of GenAI leads to appropriately calibrated reliance and when it may coexist with excessive or inaccurate confidence.

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