



# Using General Attitudes towards Artificial Intelligence Scale (GAAIS) to Measure AI-Educational Technologies (AI-EdTech) Adoption

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## ABSTRACT

### BACKGROUND & CONTEXT

AI-driven educational technologies are increasingly embedded in higher education, yet their adoption remains uneven across regions and disciplines. AI adoption is accelerating but empirical evidence is limited in Malaysia, particularly among engineering students. It is important to understand these psychological and functional determinants to support responsible deployment of AI-EdTech.

### PURPOSE OR GOAL

This study examines how engineering students in Malaysian universities adopt AI-EdTech by combining the GAAIS with the TAM, and investigates how positive and negative perceptions shape judgments of usefulness and ease of use, and how these judgments translate into adoption. The study tests hypotheses that conceptualise GAAIS constructs as antecedents to TAM constructs, while also considering prior AI experience as a moderating influence.

### APPROACH OR METHODOLOGY

A quantitative survey of 160 engineering students captures attitudes using the GAAIS and adoption constructs using validated TAM constructs. Data were analysed using PLS-SEM, incorporating assessments of reliability, validity, common method bias, and model fit. Bootstrapping (5,000 resamples) and predictive relevance tests supported the evaluation of structural relationships.

### CONCLUSIONS

This conceptual paper reports no findings. The study suggests that the GAAIS significantly influences perceptions of usefulness and ease of use, which predict adoption. This study reveals psychological dispositions as key antecedents to TAM constructs in AI-EdTech adoption among engineering students. The study highlights the importance of integrating AI literacy, ethical awareness, and experiential learning within engineering education.

### KEYWORDS

GAAIS, TAM, AI-EdTech.

## Introduction

The global education technology (EdTech) market in 2021 demonstrated that digital innovation is being combined into education at an accelerated pace, with a market value of USD 254.8 billion (Ruci, 2024). Artificial intelligence (AI) has become a key enabler of this transformation, reshaping teaching practices through adaptive, personalised, and data-driven learning models. The AI in education segment reached USD 5.88 billion in 2024 and is projected to grow at a compound annual growth rate of 31.2% by 2030, reflecting its increasing role in institutional strategies (Grand View Research, 2025). Adoption patterns also show significant growth, with 82% of college students and 58% of secondary school students reporting AI usage (Ruci, 2024), while 66% of teachers have incorporated AI tools into pedagogy (Intel, 2025; Hamilton & Swanston, 2024). Despite these advances, overall digital penetration in education remains limited, as only 4% of the USD 6.6 trillion global education market is digitised (Grand View Research, 2025). This highlights both the untapped potential and the urgent need to integrate AI systematically to enhance scalability, equity, and learning outcomes.

Meta-analyses confirm that perceived ease of use and perceived usefulness are strong predictors of positive attitudes toward, and adoption of, AI technologies and AI-based applications in education (Şimşek et al., 2025; Taheri et al., 2025). In Malaysia, however, adoption of Artificial Intelligence Educational Technologies (AI-EdTech) depends not only on usefulness (practicality) and ease of use but also on positive and negative perceptions of these constructs, emphasising the need for a broader framework (Viberg et al., 2024). The Technology Acceptance Model (TAM), derived from the Theory of Reasoned Action (TRA), posits that behavioural intentions determine technology adoption, with motivational factors such as perceived ease of use (behavioural) and perceived usefulness (cognitive) such as playing a central role (Zuo et al., 2025). While prior research has emphasised their influence on adoption, Faiz et al. (2024) and Alshammari and Alkhwalidi (2025) have argued that user characteristics, organisational factors, and evolving digital environments also play important roles. Lee et al. (2025) and Prasetyo et al. (2025) have noted that reliance on perceived ease of use and perceived usefulness alone is insufficient to promote flexibility and inclusion.

Although Technology Acceptance Model (TAM) remains a valuable framework, it has limitations. Critics contend that it oversimplifies adoption processes by neglecting contextual, psychological, and social dimensions (Lee et al., 2025). Some argue for combining TAM with complementary theories, while others point out that it fails to capture diverse user motivations (Wang et al., 2025). Iyer and Bright (2024) and Lee et al. (2025) have also called for a paradigm shift, advocating the inclusion of psychological and social perspectives. While TAM cannot fully account for the complexity of AI-driven adoption, it remains foundational for framing such investigations (Song et al., 2025). Empirical findings further highlight these details, such as perceived ease of use has been negatively correlated with AI chatbot adoption, while perceived usefulness among college students showed no significant relationship (Awal & Haque, 2024). Other research points to mediation effects; for instance, Liu and Ma (2024) found that perceived ease of use did not directly predict English learners' attitudes but influenced them indirectly through perceived usefulness, consistent with TAM. Extending this line of inquiry, Song et al. (2025) build a multi-level structural model that expands TAM by combining perceived variables, top management support, and organisational performance indicators, empirically validating their mediating roles in shaping AI adoption and its impact on decision-making efficiency and technological depth.

Turning to attitudes, it is important to recognise that attitudes toward AI are multifaceted and context-dependent, differing from traditional attitude constructs. Schepman and Rodway (2020) introduced the General Attitudes toward Artificial Intelligence Scale (GAAIS) to account for contextual factors such as user characteristics, societal influences, cultural contexts, specific AI attributes, and application-specific conditions. Stein et al. (2024) further noted that while the simplicity of GAAIS facilitates large-scale data collection, it limits analytical depth in capturing cultural diversity and the complexities of AI. Nevertheless, its broad applicability makes it highly

effective in research settings that emphasise accessibility and efficiency, enabling insights into ease of use and perceived usefulness.

Accordingly, this study incorporates GAAIS as a fundamental psychological construct that shapes how users initially perceive and evaluate AI-EdTech. The framework recognises that individuals' pre-existing dispositions toward AI as a general concept strongly influence their judgments about specific AI-EdTech tools in Malaysia. Despite the global growth of AI in education, the literature on AI-EdTech adoption remains scarce. A systematic review of Scopus revealed only 10 publications between 2022 and 2025, with none addressing the Malaysian context; instead, most of these studies were concentrated in the United Kingdom (4 studies). Similarly, a search in Emerald Insight yielded 60 results related to AI-EdTech, yet none focused specifically on Malaysia. SpringerLink produced only one relevant publication, which likewise did not examine Malaysian students. The searches employed keywords such as "adoption," "adopting," "AI-EdTech," "Artificial Intelligence Educational Technology," and "Malaysia." These findings show that localised empirical research remains limited, particularly investigations that combine traditional adoption models such as TAM with contemporary attitudinal measures like GAAIS. This gap emphasises the need for integrative approaches capable of capturing both cognitive and affective dimensions of adoption in higher education, particularly among engineering students in Malaysian universities.

## Literature Review

### Theoretical Foundation

Attitudinal research provides valuable insights into individual and collective decision-making, particularly regarding technology adoption. Previous research has examined attitudes towards AI from the perspectives of anxiety, personality, trust, and demographics (Schepman & Rodway, 2020; Schepman & Rodway, 2022; Kaya et al., 2024; Keung & So, 2025). Gender differences are evident, with females generally expressing fewer positive views (Gnambs et al., 2025). Evidence regarding younger age groups is mixed, although younger individuals are generally reported as more positive (Hoffman et al., 2024). Higher levels of education are also associated with more positive attitudes (Stöhr et al., 2024; Wang et al., 2024a).

A systematic review of AI adoption further revealed that effort expectancy, performance expectancy, and perceived usefulness are strong predictors of behavioural intention and adoption (Wang et al., 2024a; Guo & Erdenebold, 2025), while trust and general attitudes remain key determinants of adoption and acceptance (Kelly et al., 2023). Complementary research highlights the influence of technological factors (e.g., relative advantage, complexity, and usability) as well as psychological factors (e.g., achievement expectations, confidence, and intrinsic motivation) (Bond et al., 2024) in adoption decisions (Al-kfairy, 2024).

Personality traits have also emerged as potential predictors of attitudes toward AI. Studies using the GAAIS (Schepman & Rodway, 2020; Schepman & Rodway, 2022) show that introverts hold more positive views of AI, whereas extraverts are associated with stronger negative affect. Park and Woo (2022) further categorised attitudes into four dimensions by considering affective components (e.g., positive and negative emotions) and cognitive components (e.g., functional and social). Kaya et al. (2024) found that extraversion was weakly correlated with both GAAIS subscales, but not a significant predictor of either. Findings on neuroticism indicate stronger negative orientations, while openness correlates positively with functionality but loses explanatory power once proximal predictors are considered (Schepman & Rodway, 2022). These results highlight the importance role of personality in shaping positive and negative perceptual responses toward AI.

Attitudes toward AI are often difficult to capture due to media portrayals and limited public understanding of how AI functions in everyday applications. In many cases, individuals may not realise they are engaging with AI-driven systems, complicating measurement (Aquilino et al., 2025). Consequently, factors shaping AI-related perceptions vary depending on whether the focus is on general attitudes, usability, or acceptance. This emphasises the importance of

conceptual clarity in future investigations. In this respect, the GAAIS provides a powerful psychological perspective, capturing psychological constructs such as emotions, perceptions, and inclinations toward AI. It has been widely used in social psychology to examine the impact of personality traits and trust on technology adoption (Kaya et al., 2024; Cicero et al., 2025; Sacco et al., 2025). When combined with adoption models such as the TAM, the GAAIS provides deeper explanatory power by linking distal psychological dispositions to core concepts such as perceived usefulness and perceived ease of use. Furthermore, research on fundamental psychological needs such as autonomy, competence, and relatedness suggest that these factors (Wang et al., 2024b), as distal antecedents, indirectly shape the TAM constructs and ultimately influence adoption behaviour. While empirical research linking these needs to AI remains limited, emerging findings suggest that aligning AI systems with needs enhances attitudes, engagement, and satisfaction.

Drawing from these theoretical foundations, this study proposes a combined framework positioning the GAAIS as a psychological construct influencing perceived usefulness and perceived ease of use (TAM constructs), which in turn predict the adoption of AI-EdTech among engineering students in Malaysian universities. This perspective is particularly relevant given the accelerating adoption of AI-EdTech in the Malaysian education sector. By positioning the GAAIS as the fundamental psychological framework shaping initial attitudes and linking it to behavioural intentions through the TAM constructs, the model incorporates both psychological dispositions and functional evaluations. This provides a more comprehensive explanation of adoption behaviour and emphasises how initial attitudes toward AI broadly influence specific evaluations of AI-EdTech applications in learning environments.

### **Proposed Framework**

This study enhances the explanatory power of the TAM by combining it into the broader model of the GAAIS. The GAAIS captures underlying positive perceptions (i.e., measuring favourable attitudes such as the perception of opportunities) and negative perceptions (i.e., worries and negative emotions such as discomfort or fear) that shape these evaluations, while the TAM emphasises functional evaluations of technology through perceived ease of use and perceived usefulness (Schepman & Rodway, 2020; Schepman & Rodway, 2022). In this integrated model, optimism and appreciation for AI's potential strengthen perceptions of usefulness and ease of use, whereas ethical concerns, distrust, perceived risks weaken these perceptions. Thus, the GAAIS acts as an antecedent layer directly influencing the TAM constructs, creating a complementary framework that encompasses both cognitive-functional and affective dimensions of AI-EdTech adoption. This theoretical synthesis not only overcomes the limitations of each model but also provides a more comprehensive explanation of how individuals adopt AI-EdTech.

This framework aligns with the TAM, which posits that adoption is influenced by perceived usefulness and perceived ease of use. While previous research has extensively examined the relationship between these constructs and the adoption for various AI technologies (Al-kfairy, 2024; Ali et al., 2024; Liu & Ma, 2024), it has primarily focused on direct effects, often overlooking attitudinal antecedents that shape such perceptions. To address this gap, this study positions the GAAIS as distal psychological dispositions influencing perceived usefulness and perceived ease of use, which in turn shape adoption outcomes (e.g., the adoption of AI-EdTech). By integrating psychological dispositions with functional determinants, the framework offers a more comprehensive explanation of adoption behaviour among engineering students in Malaysian universities, illustrating how underlying attitudes towards AI translate into specific evaluations of usefulness and ease of use, ultimately driving adoption.

This framework is consistent with the TAM, which argues that these relationships are mediated by perceived usefulness and perceived ease of use. The TAM is widely considered one of the most applied models to explain AI technology adoption (Al-kfairy, 2024; Ali et al., 2024; Naseri & Abdullah, 2024). Research has extensively investigated the relationship between perceived ease of use, perceived usefulness, and adoption of various AI technologies, including AI-

EdTech, humanoid robots, and AI-powered chatbots (Arora et al., 2025; Kleine et al., 2025). However, existing research has primarily examined direct relationships, often overlooking how positive and negative perceptions of AI shape these evaluations (Yao et al., 2023; Anh, 2024; Peng & Robinson-Tay, 2025; Wei et al., 2025). To address this gap, this study positions the GAAIS as capturing the underlying psychological dispositions that shape perceptions of usefulness and ease of use, which subsequently act as mediators linking these dispositions to the adoption of AI-EdTech. This approach captures not only the functional determinants of adoption but also the broader psychological dispositions that drive or inhibit engineering students' engagement with AI in educational contexts.

In addition to the antecedents captured by the GAAIS, this study incorporates prior experience with AI as a moderator of the TAM pathway. Prior experience with AI shapes users' cognitive frameworks toward new technologies; for example, individuals familiar with AI are more likely to perceive AI-enabled applications (e.g., AI-EdTech, chatbots and humanoid robots) as both easy to use and useful, thereby strengthening the TAM constructs' predictive power for adoption (Alshamy et al., 2025; Nazaretsky et al., 2025). Conversely, limited or negative prior experience with AI may weaken this relationship, as users may retain scepticism, concerns about usability, or reduced trust (Harrasi et al., 2025). Incorporating this moderating effect into the GAAIS-TAM framework offers a more detailed explanation of adoption behaviour, illustrating how prior experience with AI can amplify or weaken the effects of perceived ease of use and usefulness. This addition not only situates adoption behaviour within users' cumulative experiences but also enhances the explanatory depth of the model by bridging positive and negative perceptions towards AI, with cognitive evaluations, and adoption outcomes into a unified framework.

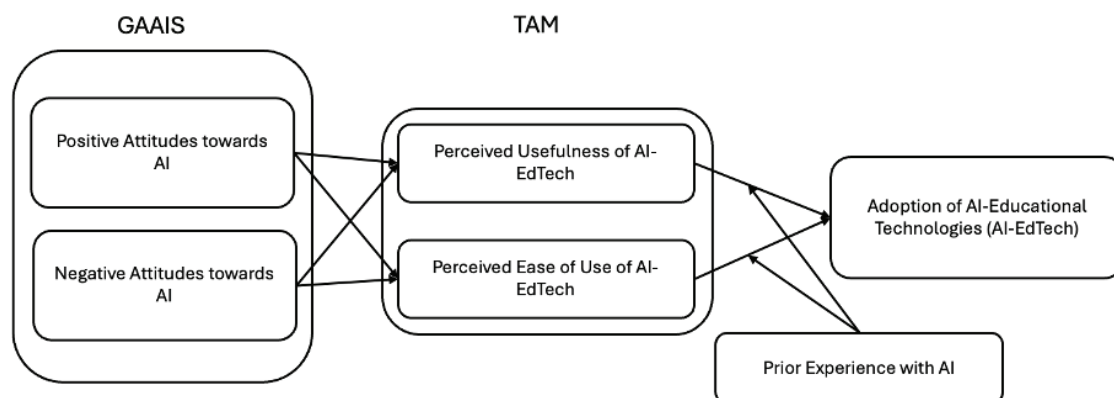


**Figure 1: Proposed Framework**

## Hypotheses

- H1: Positive attitudes toward AI positively influence perceived usefulness of AI-EdTech.
- H2: Positive attitudes toward AI positively influence perceived ease of use of AI-EdTech.
- H3: Negative attitudes toward AI negatively influence perceived usefulness of AI-EdTech.
- H4: Negative attitudes toward AI negatively influence perceived ease of use of AI-EdTech.
- H5: Perceived usefulness of AI-EdTech positively influence adoption of AI-EdTech.
- H6: Perceived ease of use of AI-EdTech positively influence adoption of AI-EdTech.
- H7: Perceived usefulness of AI-EdTech mediates the relationship between positive attitudes toward AI and adoption of AI-EdTech.
- H8: Perceived ease of use of AI-EdTech mediates the relationship between positive attitudes toward AI and adoption of AI-EdTech.
- H9: Perceived usefulness of AI-EdTech mediates the relationship between negative attitudes toward AI and adoption of AI-EdTech.

- H10: Perceived ease of use of AI-EdTech mediates the relationship between negative attitudes toward AI and adoption of AI-EdTech.
- H11: Prior experience with AI positively moderates the relationship between perceived usefulness of AI-EdTech and adoption of AI-EdTech.
- H12: Prior experience with AI positively moderates the relationship between perceived ease of use of AI-EdTech and adoption of AI-EdTech.

## Methodology

The study adopts a quantitative design involving engineering students in Malaysian universities, where positive and negative perceptions of AI are assessed using the GAAIS, and adoption constructs are derived from the TAM. Data will be collected via a structured questionnaire administered to 160 respondents, with sample size determined through G\*Power (version 3.1.9.7), and analysed using PLS-SEM. The measurement model will be validated through convergent validity (e.g., factor loadings  $>0.70$ , Average Variance Extracted (AVE)  $>0.50$ , and composite reliability (CR)  $>0.70$ ) and discriminant validity (e.g., Fornell–Larcker criterion and HTMT ratio, with thresholds  $<0.85$  or  $0.90$ ) (Asiri et al., 2024; Ballesteros et al., 2025). Common method bias will be mitigated using procedural remedies and statistically examined through Harman’s single-factor test and full collinearity Variance Inflation Factor (VIF) ( $VIF <3.3$ ) (Howard et al., 2024). Structural relationships will be analysed using PLS-SEM with a bootstrapping procedure of 5,000 resamples, employing bias-corrected and accelerated (BCa) 95% confidence intervals for inference (Gilling et al., 2025). Model fit will be assessed using Standardised Root Mean Square Residual (SRMR) ( $<0.08$ ) (Ozaki et al., 2025) and Normed Fit Index (NFI) ( $>0.90$ ) (Pei et al., 2025), while predictive relevance will be confirmed via Stone–Geisser’s  $Q^2$  ( $>0$ ) (Li et al., 2025).

## Conclusion

This paper advances the discussion on AI adoption in education by combining the GAAIS with the TAM into a framework. This is to assess adoption among engineering students in Malaysian universities, thereby bridging the gaps overlooked by traditional models. The framework highlights the role of positive and negative perceptions in shaping perceptions of usefulness and ease of use, offering a more comprehensive explanation of adoption behaviour. Other than that, this framework carries significant practical implications, for instance, it guides curriculum design by embedding AI literacy and ethics, supports faculty training to build teaching confidence, as well as guides EdTech developers in creating student-centred and trustworthy platforms. In conclusion, these insights not only provide a foundation for the responsible incorporation of AI into higher education but also offer inspiration and direction for future research, institutional practice, and policy innovations.

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### **Acknowledgements**

The authors acknowledge the Fundamental Research Grants Scheme (FRGS), grant number FRGS/1/2024/SS01/UTM/02/4 - R.J130000.7829.5F725 funded by the Ministry of Higher Education (MOHE) Malaysia, and part of this research is supported by UTMFR, grant number 23H26, Universiti Teknologi Malaysia.

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