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# Students' intention to use artificial intelligence in business courses: an extended TAM approach in a developing economy

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**Introduction:** This study examines students' adoption of Artificial Intelligence (AI) in business education through an extended Technology Acceptance Model (TAM), positioning AI as an intelligent and adaptive socio-technical system rather than a conventional digital tool.
**Methods:** Drawing on data from 521 undergraduate business students in private universities in Cairo, Egypt, the study employs structural equation modelling to investigate the psychological, contextual, and cognitive factors of AI usage.
**Results:** Findings reveal that perceived usefulness and perceived ease of use remain central drivers of students' attitudes toward AI; however, AI-specific factors (including job relevance, self-efficacy, and perceived resource availability) significantly shape these perceptions. Notably, the results highlight the importance of contextual constraints in developing economies, where institutional support and access to technological resources play a critical role in facilitating AI adoption.
**Discussion:** By extending TAM to the context of AI-enabled learning, this study contributes to the literature by emphasizing the dual role of AI as both a technological tool and a cognitive partner in the learning process. The findings offer implications for the design of digitally enhanced curricula, particularly in emerging markets, and provide insights into how higher education institutions can better align with the demands of an AI-driven workforce.

KEYWORDS
**artificial intelligence, digital transformation, higher education, structural equation modelling, technology acceptance model**

## 1 Introduction

The integration of AI into the business field appears to be a dramatic change that is going to continue reshaping professional competence across industries. Regarding business intelligence, big data analysis, and data mining-based emerging trends, professionals across business disciplines must acquire advanced technological skills in addition to their traditional expertise, enabling professionals to improve their analytical skills and thus contribute significantly to organizational decision-making processes. However, how far this potential is realized will depend considerably on how well universities align their curricula with the requirements of the digital economy.

Over the past decades, universities have remained upfront in playing a critical role in preparing schools of business graduates with technical skills and the capability for problem-solving to resolve the challenges facing companies. The evolving demands of the business environment necessitate curriculum reforms that integrate AI tools to better equip students with the skills required to meet industry expectations and address real-world challenges (Qasim and Kharbat, 2020). Students' willingness to adopt AI depends on their technological readiness and the perceived usefulness of AI (Nouraldeen, 2023).

In business schools particularly, the rapid transformation of industry practices and the increasing demand for AI-related competencies require deeper investigation into the factors influencing students' acceptance of AI tools. Previous studies emphasized the importance of integrating AI technologies into higher education to enhance students' digital competencies and preparedness for labor market demands (Gaviria Rodríguez et al., 2025). Moreover, recent studies indicate a growing use of AI tools (Afzaal et al., 2025; Alismaiel et al., 2022; Gaviria Rodríguez et al., 2025; Lin et al., 2023); however, adoption remains uneven, and significant gaps persist in curriculum integration, ethical considerations, and evidence of learning outcomes. Students in business-related programs increasingly use AI for productivity enhancement, personalized learning, and language support, yet empirical evidence remains limited and is often concentrated in specific contexts (Almaraz-López et al., 2023; Zhou and Liu, 2024).

Despite extensive applications of the Technology Acceptance Model (TAM) in educational contexts (Davis, 1989; Venkatesh and Davis, 2000), prior studies have concentrated mainly on traditional TAM constructs, including perceived usefulness (PU) and perceived ease of use (PEU), without sufficiently incorporating psychological, contextual, and cognitive factors that may shape students' readiness to adopt AI technologies in academic settings (Afzaal et al., 2025; Gaviria Rodríguez et al., 2025). In particular, the roles of Job Relevance (JR), Self-Efficacy (SE), Perceived Resources (PR), and Anxiety (AX) remain fragmented, as most studies examine these constructs in isolation rather than as an integrated set of antecedents simultaneously influencing both PU and PEU (Afzaal et al., 2025; Castiblanco Jimenez et al., 2020; Gaviria Rodríguez et al., 2025; Gökçe Tekin, 2024; Tırpan and Bakırtaş, 2024).[1]

In addition, limited empirical work has examined how psychological barriers such as AX, together with resource-based facilitating conditions such as PR, interact with positive drivers like JR and SE to influence technology acceptance in academic settings (Hong et al., 2002; Venkatesh et al., 2003). This gap is particularly evident in contexts where emerging digital tools are reshaping teaching and learning processes, requiring a more comprehensive understanding of both enabling conditions and emotional inhibitors within a unified framework.

Therefore, this study addresses these gaps by proposing an integrated TAM extension that simultaneously examines JR, SE, PR, and AX as antecedents of PU and PEU, and investigates the mediating pathways through PU/PEU → ATT → BI within higher education settings. Hence, it will analyze how psychological factors (SE and AX) and contextual factors (PR and JR) impact cognitive beliefs about AI (PEU and PU), which consequently shape students' ATT and BI toward AI adoption.

This study contributes to the literature on AI adoption in higher education in several important ways. First, it extends the TAM by integrating contextual and psychological variables, including SE, JR, PR, and AX, alongside PEU, PU, thereby offering a more comprehensive understanding of AI adoption behavior among business students. Second, unlike prior studies that focused on isolated AI applications or general educational technologies, this research specifically investigates AI adoption within business schools, a context characterized by increasing industry demand for analytical, technological, and decision-making competencies. By doing so, the study provides empirical evidence on how AI technologies can support the development of students' analytical and technical skills required in modern business environments. Third, the study simultaneously examines both students' attitudes toward AI and their behavioral intention to use AI, providing a more integrated perspective on the mechanisms influencing AI acceptance in higher education. Using Structural Equation Modeling (SEM), the findings offer robust empirical validation for the proposed extended TAM framework and contribute theoretically and practically to the growing discourse on AI integration in business education curricula.

The rest of the study is organized as follows: Section 2 sets out the theoretical background and hypotheses development. Section 3 describes the research methodology, including sample selection, data collection, and measurement of variables, while Section 4 presents the results of the empirical analysis, and Section 5 presents the conclusion.

# 2 Literature review

## 2.1 Theoretical background

Previous studies have developed various models to better understand factors influencing the adoption of new technology. These models provide valuable insights into why individuals choose to adopt innovations (Shroff et al., 2011). Davis (1989) established the TAM, which is considered one of the most significant and widely used frameworks to explain and forecast technological acceptance in various contexts (Alfadda and Mahdi, 2021; Mailizar et al., 2021a).

Then, Ajzen (1991) proposed the Theory of Planned Behavior (TPB) to explain how intentions to adopt technology are influenced by users' attitudes, subjective norms, and perceived behavioral control (Harper and Kim, 2018; Hung and Jeng, 2013). Likewise, the Unified Theory of Acceptance and Use of Technology (UTAUT) integrate aspects such as performance expectancy, effort expectancy, social influence, and facilitating conditions to specify a holistic explanation of technology adoption (Suliman et al., 2024).

TAM, grounded in the Theory of Reasoned Action, is one of the most widely used frameworks for understanding and predicting technology adoption behavior (Hsu, 2016; Mittal and

[1]For clarity, key constructs are referred to by their full names at first use (e.g., "perceived ease of use") and their acronyms (PEU) only thereafter; a comprehensive Table of Abbreviations is provided in Supplementary Appendix S3. Throughout the manuscript, full terms are reintroduced periodically to maintain readability and avoid abbreviation fatigue.

Alavi 2020), Proposed by Davis and Venkatesh (1996), TAM suggests that PU and PEU are the two primary factors influencing an individual's ATT toward technology, which subsequently affects BI and ultimately leads to actual technology use. PU refers to the extent to which an individual believes that using a particular technology enhances performance, whereas PEU reflects the degree to which the technology is perceived as easy to use with minimal effort. Due to its strong predictive capability and broad applicability across different contexts, TAM remains a fundamental framework for analyzing technology adoption and enhancing user acceptance (Scherer et al., 2019).

Building on these theoretical foundations, the present study adopts the TAM as the primary framework to examine business students' adoption of AI tools in higher education settings. In addition, the study incorporates selected constructs derived from TPB and UTAUT to provide a more comprehensive explanation of AI adoption behavior. Specifically, the study integrates JR, SE, PR, and AX as external antecedents influencing PU and PEU, which subsequently affect ATT and BI. By combining cognitive, contextual, and psychological factors within an extended TAM framework, this study aims to provide a deeper understanding of the factors shaping AI acceptance among business students.

## 2.2 Hypotheses development

### 2.2.1 Anxiety

Anxiety (AX), especially information and communication technology anxiety, has been one of the most widely researched issues in technology adoption. AX is a consequence of several variables, which in turn affect users' BI to accept new technology, according to TAM. A high level of AX can prevent students from adopting technology effectively. Technology-related anxieties, such as fears of misuse or concerns over data privacy, can have a significant influence on users' PEU and this ultimately impacts their learning experience (Sukhia et al., 2021), reduces the BI to use new technologies, as well as PU. Addressing the underlying causes of AX is critical to increasing the adoption of AI. This can be achieved by providing adequate training, support, and resources to instructors and students, fostering their confidence in using AI effectively (Abdullah et al., 2016; Hsu et al., 2009). Conversely, research indicates that AI-powered applications can considerably reduce students' exam AX and negative academic emotions while enhancing their positive academic experiences (Gao, 2024). Based on previous studies, we derive the following hypothesis:

> **H1:** Anxiety negatively affects students' perceived ease of use of AI tools in undergraduate business courses.

### 2.2.2 Self-efficacy

Self-efficacy (SE) relates to students' confidence in their abilities to successfully utilize new technologies (Moos and Azevedo, 2009). SE is a key element of PEU, affecting students' readiness to adopt AI in educational settings. Students who possess greater SE are more inclined to view new technology as easy to use, increasing their willingness to engage with it, positively affecting the PEU of new technologies, and enhancing their BI to use new technologies (Abdullah et al., 2016; Hai et al., 2022; Zhang et al., 2023). SE can also serve as a moderator between PEU, PU, and the BI to adopt AI. This suggests that students' confidence in their skills bridges the gap between technical design elements and their readiness to adopt AI. To successfully integrate AI into business education, it is critical to increase students' SE, through focused training and skill development programs, and creating a supportive learning environment (Osman et al., 2024). Educational systems should prioritize measures that increase students' SE, as this indirectly influences their ATT and BI to use new technologies in various educational settings (Basuony et al., 2021). Therefore, we hypothesize that

> **H2a:** Self-efficacy positively affects students' perceived ease of use of AI tools in undergraduate business courses.

> **H2b:** Self-efficacy positively influences the students' perceived usefulness of AI tools in undergraduate business courses.

### 2.2.3 Perceived resources

Perceived resources (PR) examine the individual's confidence in the availability of appropriate tools, support systems, and infrastructure necessary for effective use of information and communication technology (Lee, 2008; Oh et al., 2003). Access to educational resources significantly influences both learning outcomes and technology acceptance. Adequate resources, such as timely technical support, training programs, and easily accessible equipment, are vital to build users' confidence and competence in interacting with information systems, thereby improving PEU (Cheney and Dickson, 1982; Gable et al., 1991). In the context of AI adoption, studies show that organization's PR positively influences university students' BI to use AI in coursework, with PEU and PU acting as key mediators (Hoi et al., 2023). Therefore, when integrating AI into business courses, providing sufficient resources is likely to enhance students' ability and willingness to effectively engage with it. Based on previous studies, we hypothesize the following

> **H3a:** Perceived resources positively affect students' perceived ease of use of AI tools in undergraduate business courses.

> **H3b:** Perceived resources positively influence students' perceived usefulness of AI tools in undergraduate business courses.

### 2.2.4 Job relevance

Job relevance (JR) refers to an individual's perception of the extent to which technology is applicable to their job. Numerous studies highlight how students perceive the advantages of aligning AI with their academic and professional objectives (Tan et al., 2024). Students tend to use an application based on the degree to which they believe it will improve their job performance. This means that ATT towards using AI is shaped by how users perceive the usefulness of AI (Alfadda and Mahdi, 2021). Anjala (2024) found that using AI has a positive impact on job performance, indicating that JR may increase the PU of incorporating AI in education. This optimism stems from students' growing knowledge of how AI technologies could revolutionize their future careers, motivating educational institutions to modify their curricula to effectively incorporate these technologies. Based on this, we derive the following hypothesis:

> **H4:** Job relevance has a positive effect on students' perceived usefulness of AI tools in undergraduate business courses.

### 2.2.5 Perceived ease of use

Perceived ease of use (PEU) indicates the degree to which individuals believe that using technology involves minimal effort (Davis and Venkatesh, 1996). In the context of TAM, PEU plays a substantial role in determining users' perceptions of technology and their likelihood of adopting and continuing to use it. Studies show that students are more likely to continue using learning platforms that they perceive as easy to use (Mailizar et al., 2021b). Similarly, Osman et al. (2024) found that when AI tools are easy to use, students develop more positive ATT toward them, are more likely to have BI to use them, and ultimately adopt them.

Moreover, previous literature has reported a positive relationship between PEU and students' BI to use AI, primarily mediated through their ATT toward AI rather than PU (Wu et al., 2024). Accordingly, to encourage students' adoption of AI, universities should simplify AI interfaces and enhance students' technological readiness. These considerations could have significant implications on designing curricula and developing policies aimed at effectively integrating AI into business education. Universities can address these issues by promoting AI integration, empowering both students and faculty, revamping learning methods, and establishing ethical guidelines for responsible AI use (Kanont et al., 2024). Based on these insights, we hypothesize the following

> **H5a:** Perceived ease of use has positively influenced students' attitudes toward using AI in the undergraduate business curriculum.

> **H5b:** Perceived ease of use has a positive effect on the students' perceived usefulness of AI in the undergraduate business curriculum.

### 2.2.6 Perceived usefulness

Perceived usefulness (PU) discusses the belief that using a certain technology will improve one's performance or learning experience (Davis and Venkatesh, 1996). According to TAM, PU has a significant impact on users' BI. Previous studies have identified that PU has a significant influence on the use of instructional technologies (Akour et al., 2022; Al-Adwan et al., 2021; Al-Rahmi et al., 2022). PU has a positive effect on students' ATT, BI, and actual use of AI-based systems (Osman et al., 2024). Some studies have suggested that PU does not adequately explain or significantly predict ATT toward AI and the BI to use it (Wu et al., 2024), contradicting the assumptions of TAM. As students engage with AI-powered technologies that provide personalized and efficient learning opportunities, they are expected to perceive them as valuable and beneficial. Therefore, we hypothesize the following

> **H6a:** Perceived usefulness positively influences students' attitude toward using AI in the undergraduate business curriculum.

> **H6b:** Perceived usefulness positively influences students' behavioral intention to use AI in the undergraduate business curriculum.

### 2.2.7 Behavioral intention and attitude toward usage

TAM states that behavioral intention (BI) is primarily influenced by PU and ATT toward usage. When individuals perceive technology as useful and easy to use, they accept it (Harper and Kim, 2018). Moreover, ATT toward AI meaningfully and positively forecasts the BI to use it (Wu et al., 2024). Numerous studies in higher education have shown that students' perceptions play a crucial role in their BI to adopt AI for enhancing their productivity, performance, and SE more effectively (Baca and Zhushi, 2025). ATT towards AI is influenced by specific variables like awareness and knowledge of AI, trust in AI technology, exposure to AI, BI to use AI, and personal experience with AI (Bati et al., 2024). Consequently, awareness and confidence in AI are among the major factors that significantly impact ATT and BI regarding AI adoption. In the context of students' ATT toward AI-based systems, the effects on their learning motives concerning goal attainment and subjective standards were negligible (Li, 2023). Consistently, studies have indicated that a positive ATT significantly influences BI, as users who perceive a system as favorable are more likely to adopt and continue using it. Based on these insights, we hypothesize the following

> **H7:** Students' attitude toward using AI integration in undergraduate business curricula positively influences their behavioral intention to adopt it.

## 3 Research methodology

### 3.1 Research model

To test the hypotheses of this study, we used SEM, facilitated by Smart PLS 4.1. This method was chosen because of its capability to analyze complex associations between latent and observed variables analysis. Also, it indicates the direct and indirect impact of several factors that are vital in our study. Given the complication of AI integration, which contains several interconnected variables, such as student self-efficacy (SE), anxiety (AX), perceived resources (PR), job relevance (JR), and their effect on the perceived ease of use (PEU), perceived usefulness (PU), attitudes (ATT), and behavioral intention (BI) to use, SEM allows to model this complex interaction holistically rather than testing them in isolation by leveraging the smart PLS 4.1. Figure 1 displays the conceptual framework of our study.

## 3.2 Population frame and sample

The participants of this study are undergraduate students from schools of business at universities in Cairo, Egypt. The key informants of our sample are selected from private universities in Cairo. These students (key informants) represent diverse majors within the schools of business, including Accounting, Finance, Marketing, Management, Information Technology Systems, and Economics. The population of this study consists of 18 private universities in Cairo that have schools of business (See Supplementary Appendix S1).

## 3.3 Data collection

In this study, the questionnaire was selected as a suitable measurement method to collect data. The questionnaire was designed to be answered on Google Doc and was sent to the respondents via email. Data collection took place from the academic calendar Spring 2024 and Fall 2024. A total of 521 responses were received out of 1,250, with a response rate of 41.76%, which consists of 264 (50.67%) female students and 257 (49.33%) male students. Table 2 shows the sociodemographic data that includes gender, major, academic level, AI applications, willingness to pay for AI applications, and time spent on AI applications per day.

## 3.4 Questionnaire design

We employed a self-reporting approach based on prior literature (Davis, 1989; Holden and Rada, 2011; Zhang et al., 2008), allowing participants to express their opinions and attitudes about integrating AI into the undergraduate curriculum within the courses of the schools of business by responding to a structured set of questions. These questions were closed-ended and utilized a predetermined Likert scale for interval measurement. The questionnaire was organized into two main sections: the first section gathered sociodemographic data, while the second explored factors influencing AI adoption in business education (see Supplementary Appendix S2).

Pre-testing focused on establishing the content validity of the survey instrument, followed by its refinement through a pilot study. Initially, discussions on integrating AI into business education curricula were conducted with academics and AI professionals. Their recommendations were incorporated to improve the relevance, clarity, and content validity of the questionnaire. Subsequently, the revised questionnaire was distributed to 20 randomly selected academics and professionals for independent review and pilot testing. Six completed questionnaires were received and evaluated. The respondents provided individual feedback on the clarity, relevance, wording, and overall structure of the survey items. Their responses were analyzed primarily to assess item comprehensibility, readability, and the overall flow of the questionnaire. Based on this feedback, minor revisions were made to improve the wording of several items and enhance the clarity of the survey instructions. No substantial modifications to the constructs or measurement scales were required, as the pilot participants generally agreed that the questionnaire was clear, relevant, and appropriate for the target population.

Furthermore, informed consent was obtained from all participants before they completed the questionnaire. To ensure confidentiality, the data was anonymized and securely maintained in line with data protection regulations. Access to the information was limited to the research team, and the reported findings were presented in aggregate form to preserve individual privacy.

## 3.5 Measurement of variables

The questionnaire was designed to collect data on the factors influencing AI adoption in business education. The instrument comprised 42 measurement items representing eight constructs. The classification of these constructs into exogenous and endogenous variables was based on the theoretical structure of the extended Technology Acceptance Model (TAM) and the hypothesized causal relationships among the study constructs. Specifically, self-efficacy (SE), anxiety (AX), job relevance (JR), and perceived resources (PR) were specified as exogenous variables because they represent antecedent factors that influence users' perceptions and acceptance of AI and are not predicted by any other construct in the proposed model. In contrast, perceived ease of use (PEU), perceived usefulness (PU), attitude toward AI usage (ATT), and behavioral intention (BI) were classified as endogenous variables because they are influenced by one or more constructs in the model and serve as mediating or outcome variables in the AI adoption process. A five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree) was used to measure all constructs. The Kaiser–Meyer–Olkin (KMO) measure confirmed sampling adequacy with a value of 0.911, while Bartlett's test of sphericity was statistically significant at the 1% level ($\chi^2 = 2{,}799.342$), indicating the suitability of the data for factor analysis. A summary of the study variables is presented in Table 1.

# 4 Data analysis

## 4.1 Descriptive analysis

Panel (A) of Table 2, females students represent 50.67% of the sample, while Males students account for 49.33%, demonstrating a balanced gender representation. Panel (B) shows that the highest

TABLE 1 Exogenous and endogenous variables.

| Panel A: Endogenous Variables | | |
|---|---|---|
| Variables | Indicators | Definition |
| PEU | PEU1 – PEU5 | The level to which an individual believes that using AI technology will require little or no effort [4]. |
| PU | PU1 – PU6 | The extent to which an individual believes that using AI technology will improve their job performance[4]. |
| ATT | ATT1 – ATT6 | An individual's assessment of a technology or a particular behavior related to its use [43]. |
| Outcome variable: | | |
| BI | BI1 – BI4 | An individual's intention to use a tool of AI technology [44]. |
| **Panel B: Exogenous variables** | | |
| AX | AX1 – AX5 | Reflects users' emotional responses, such as fear or nervousness, which may hinder technology adoption and acceptance [45]. |
| SE | SE1 – SE4 | The belief in one's capability to successfully finish a task using AI technology [42]. |
| JR | JR1 – JR4 | Reflects the extent to which individuals think that using technology is applicable to their job tasks, thereby impacting their adoption intention [31]. |
| PR | PR1 – PR8 | Reflects users' assessment of the availability of time, effort, and support needed to effectively adopt and utilize the technology [24]. |

percentage was 34% for the Accounting major students, this concentration in business disciplines aligns with trends observed in contemporary higher education enrollment patterns. Panel (C) shows that the highest percentage of the respondents are in the second year 35.51% or 31.29% in the final year of study 31.29%. Panel (D) shows that a high percentage of respondents, 65.07%, indicated that they are not willing to pay. Panel (E) shows that the use of AI applications was clearly dominated by non-daily use 45.49%.

## 4.2 Reliability and validity

Table 3 reports a strong reliability and validity assessment of the constructs used in this study. Cronbach's alpha values are all

TABLE 3 Reliability and validity measures.

| Variables | Cronbach's alpha | Composite reliability | Average variance extracted |
|---|---|---|---|
| AX | 0.807 | 0.864 | 0.562 |
| ATT | 0.907 | 0.928 | 0.683 |
| PEU | 0.847 | 0.891 | 0.621 |
| JR | 0.892 | 0.925 | 0.755 |
| PR | 0.780 | 0.844 | 0.476 |
| PU | 0.884 | 0.912 | 0.632 |
| SE | 0.863 | 0.907 | 0.710 |
| BI | 0.882 | 0.918 | 0.738 |

TABLE 2 Descriptive analysis.

| Description | N | Percentage | Description | N | Percentage |
|---|---|---|---|---|---|
| **Panel (A) Gender** | | | **Panel (C) Academic Level** | | |
| Female | 264 | 50.67% | Freshman (1st year) | 87 | 16.70% |
| Male | 257 | 49.33% | Sophomore (2nd year) | 185 | 35.51% |
| **Total** | **521** | **100%** | Junior (3rd year) | 86 | 16.51% |
| | | | Senior/Graduating Senior (4th year) | 163 | 31.29% |
| **Panel (B) Major** | | | **Total** | **521** | **100%** |
| Accounting | 178 | 34.16% | **Panel (D) Willingness to Pay for AI Applications** | | |
| Finance | 75 | 14.40% | No | 339 | 65.07% |
| Management or Business Administration | 81 | 15.55% | Yes | 182 | 34.93% |
| Marketing | 47 | 9.02% | **Total** | **521** | **100%** |
| Economics | 25 | 4.80% | **Panel (E) Time Spent on AI Applications (Daily)** | | |
| Information Technology Systems | 11 | 2.11% | Less than 1 h | 137 | 26.30% |
| Others | 104 | 19.96% | 1–2 h | 101 | 19.39% |
| **Total** | **521** | **100%** | 3–5 h | 29 | 5.57% |
| | | | More than 5 h | 17 | 3.26% |
| | | | Do not use daily | 237 | 45.49% |
| | | | **Total** | **521** | **100%** |

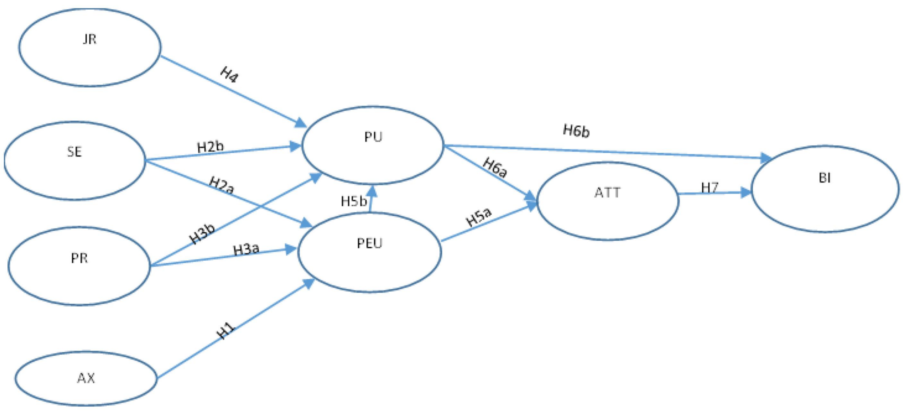


FIGURE 1
Conceptual framework.

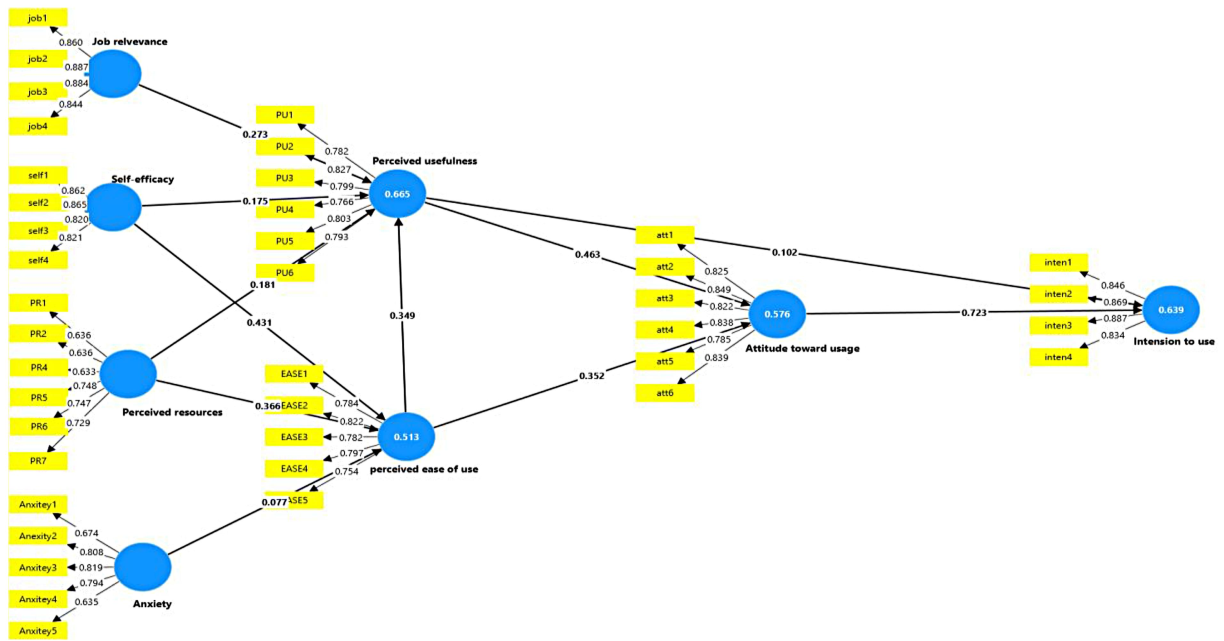


FIGURE 2
Path analysis.

well above the threshold of 0.7, indicating a very good internal consistency measure at a variable level (Hair et al., 2010). Composite reliability is an internal consistency better than Cronbach's alpha in that it does consider the different factors loadings each item has with one another. The average variance extracted is used to assess convergent validity, which is the degree to which a construct correlates with other measures of the same construct. A threshold of 0.5 is commonly used to indicate adequate convergent validity (Fornell and Larcker, 1981). Most variables meet this criterion, confirming adequate convergent validity, except for perceived resources (0.476), which falls slightly below, but this value was after deleting two statements which have the lowest loading values (statement 3 and statement 8).

## 4.3 Structure equation modelling

Figure 2 shows the SEM result, highlighting the relationships among key technology acceptance constructs and their indicators. The figure shows the latent constructs for JR, SE, PR, and AX as exogenous. It displays the mediating roles of PU and PEU, paths logically leading from the exogenous variables through the mediators to the dependent variable, BI.

Table 4 presents the fit indices for both the saturated model and estimated model. By using comparison between the estimated and the saturated model, the goodness-of-fit test examines the SEM against several fit indices. The Standardized Root Mean Square Residual (SRMR) values of 0.059 for the saturated model and 0.082 for the estimated model are in the range of the acceptable level (0.08), hence there is an appropriate fit (Hair et al., 2010). The SRMR for the projected model is rather higher, thus the fit of the estimated model is rather worse than that of the saturated model. This conforms with the results of this study, in which the projected model fits rather than perfectly.

The projected model (2,938.103) and saturated model (2,737.803) of Chi-square statistics indicate higher values in the estimated model, indicating less fitness. But chi-square is sample size sensitive (Hair et al., 2010). It is thus not the only indicator of the models' fit. Showing good, but not a perfect fit, the Normed Fit Index (NFI) values for both saturated and estimated models respectively are below the essential cut-off of 0.90. This is consistent with the results of the research showing that although the model is good, it might be improved.

Greater differences in the estimated model (d_ULS = 6.011 and d_G = 1.028) than in the saturated model (d_ULS = 3.193 and d_G = 0.907) indicate Unweighted Least Squares Discrepancy (d_ULS) and Geodesic Discrepancy (d_G) respectively. This indicates that the projected model fits less than the saturated model. Though the estimated model shows a fair match based on SRMR, the higher Chi-square, lower NFI, and greater d_ULS and d_G (Fornell and Larcker, 1981).

### 4.3.1 Direct effect of structure equation model

Table 5 summarizes the results shown in Figure 2, indicating that all hypothesized paths are significant at $p < 0.05$. AX has a positive and significant impact on PEU at 5% significance level.

TABLE 4 Goodness of fit.

| Model fit statistics | Saturated model | Estimated model |
|---|---|---|
| SRMR | 0.059 | 0.082 |
| d_ULS | 3.193 | 6.011 |
| d_G | 0.907 | 1.028 |
| Chi-square | 2,737.803 | 2,938.103 |
| NFI | 0.806 | 0.791 |

This finding contradicts with the generally expected negative relation (Hsu et al., 2009; Sukhia et al., 2021) and calls for further examination of context-specific factors that may affect such a relationship. One possible explanation is that AX surrounding AI technologies does not necessarily discourage engagement; rather, it may stimulate students to invest extra effort in learning and understanding AI tools due to concerns about their academic and future professional relevance. As students become more familiar with these technologies through repeated use, they may perceive them as easier to operate. Moreover, the extensive integration of AI applications into educational activities may reduce the inhibiting effects traditionally associated with technology anxiety. Consequently, anxiety in this context may coexist with increased exploration and learning, leading to higher perceptions of ease of use. This finding suggests that the role of anxiety in AI adoption may be more nuanced than previously assumed and may depend on the specific educational and technological context.

Moreover, SE has a positive significant direct effect on PEU at 1%, consistent with previous studies (Abdullah et al., 2016; Hai et al., 2022; Zhang et al., 2023). SE has a positive significant effect on PU at 1%, consistent with (Hsu et al., 2009).

PR has a significant positive influence on PEU at 1%, in line with previous research (Cheney and Dickson, 1982; Gable et al., 1991; Lee et al., 2025). Furthermore, PR has a positive significant influence on PU at 1%, highlighting the need for adequate support and infrastructure in introducing AI to academic curricula, a finding that is consistent with previous research (Ajzen, 1991). JR which showed to lead to PU at 1%, in line with (Goodhue and Thompson, 1995).

The PEU has a direct significant positive influence on the ATT of the students at 1%. When students view AI tools as easy and straightforward to use, they are more likely to develop a positive ATT toward them (Osman et al., 2024). Moreover, PU has a positive direct significant influence on the ATT at 1%. This finding further supports the cognitive instrumental view, in which users access technology from an instrumental perspective, looking primarily at its PU and PEU (Akour et al., 2022; Al-Adwan et al., 2021; Al-Rahmi et al., 2022). In addition, PEU has a direct influence on PU at 1%, that further supports the TAM

TABLE 5 Results of the path analysis.

| Hypothesized Path | Original sample (O) | Sample means (M) | Standard deviation (STDEV) | T statistics (\|O/STDEV\|) | *P* values |
|---|---|---|---|---|---|
| AX -> PEU | 0.077 | 0.080 | 0.036 | 2.127 | 0.033 |
| ATT -> BI | 0.723 | 0.724 | 0.035 | 20.892 | 0.000 |
| PEU -> ATT | 0.352 | 0.351 | 0.045 | 7.864 | 0.000 |
| PEU -> PU | 0.349 | 0.348 | 0.045 | 7.696 | 0.000 |
| JR -> PU | 0.273 | 0.274 | 0.053 | 5.122 | 0.000 |
| PR -> PEU | 0.366 | 0.367 | 0.040 | 9.229 | 0.000 |
| PR -> PU | 0.181 | 0.182 | 0.040 | 4.560 | 0.000 |
| PU -> ATT | 0.463 | 0.465 | 0.043 | 10.694 | 0.000 |
| PU -> BI | 0.102 | 0.101 | 0.037 | 2.719 | 0.007 |
| SE -> PEU | 0.431 | 0.429 | 0.044 | 9.887 | 0.000 |
| SE -> PU | 0.175 | 0.173 | 0.053 | 3.284 | 0.001 |

TABLE 6 Total indirect effects and path coefficients.

| Indirect relations | Original sample (O) | Sample mean (M) | Standard deviation (STDEV) | T statistics (\|O/ STDEV\|) | *P* values |
|---|---|---|---|---|---|
| AX -> ATT | 0.03 | 0.031 | 0.019 | 1.584 | 0.113 |
| AX -> BI | 0.023 | 0.025 | 0.015 | 1.576 | 0.115 |
| AX -> PU | 0.02 | 0.021 | 0.013 | 1.505 | 0.132 |
| JR -> ATT | 0.127 | 0.129 | 0.03 | 4.282 | 0.000 |
| JR -> BI | 0.12 | 0.121 | 0.027 | 4.375 | 0.000 |
| PEU -> ATT | 0.161 | 0.161 | 0.025 | 6.506 | 0.000 |
| PEU -> BI | 0.407 | 0.406 | 0.032 | 12.747 | 0.000 |
| PR -> ATT | 0.28 | 0.28 | 0.026 | 10.762 | 0.000 |
| PR -> BI | 0.234 | 0.234 | 0.022 | 10.61 | 0.000 |
| PR -> PU | 0.135 | 0.135 | 0.023 | 5.758 | 0.000 |
| PU -> BI | 0.335 | 0.336 | 0.033 | 10.295 | 0.000 |
| SE-> ATT | 0.299 | 0.297 | 0.039 | 7.746 | 0.000 |
| SE -> BI | 0.249 | 0.247 | 0.035 | 7.091 | 0.000 |
| SE-> PU | 0.148 | 0.146 | 0.024 | 6.134 | 0.000 |

framework identifying ease of use as a key element of both PU and ATT. This ease of use leads to a sense of confidence, reduces the tendency to resist using AI technologies, and improves the feeling that these technologies are relevant to academic and future professional work. The result is consistent with (Wu et al., 2024). The effects of PU were both direct and indirect on BI via ATT, supporting a partial mediation structure. Such a nuanced pattern extends traditional TAM by highlighting complex pathways through which PU influence adoption decisions. The finding is in line with previous research (Akour et al., 2022; Al-Adwan et al., 2021; Al-Rahmi et al., 2022; Osman et al., 2024).

The strongest relationship in the model is between ATT and BI at 1%. These finding highlights user ATT as an important factor in mediating BI towards technology adoption. This finding is supported by both TAM (Davis, 1989) and Theory of Planned Behavior (Ajzen, 1991). The current empirical results support that the positive ATT of the end-users directly fosters the diffusion process (Bati et al., 2024; Wu et al., 2024; Zhang et al., 2023). The multiple significant paths leading to PU stress its importance as a critical mediator. This structural representation also corresponds to the statistical results in that it captures both direct and indirect effects, thus supporting the hypothesized theoretical framework through its integration of measurement and structural relationships.

The results of this study confirmed all the proposed hypotheses, with the exception of Hypothesis 1, which was rejected based on empirical evidence.

### 4.3.2 Indirect effect of structure equation model

Table 6 presents the path coefficients and analysis of total indirect effects validate significant and non-significant relationships between variables in the extended TAM framework. AX is not significantly related to ATT, BI, and PU ($p > 0.05$), suggesting that its effect on AI adoption is not significant. Conversely, some of the paths are statistically significant ($p = 0.000$). ATT and BI are both influenced significantly by JR, as hypothesized by Task-Technology Fit theory (Goodhue and Thompson, 1995). PEU influences ATT significantly and, alongside PU, influences BI significantly, as assumed in the TAM (Davis, 1989). In line with Resource-Based Theory, PR has a significant impact on ATT, BI, PU and institutional support; so, training, infrastructure, and resources help adopt AI (Barney, 1991). As TAM framework suggests, PU has a significant impact on BI. Moreover, SE implies that students' confidence in using AI increases their acceptance and perceived value since it has great effects on ATT, BI, and PU (Jokisch et al., 2020).

### 4.3.3 The specific indirect relations

The analysis of indirect relationships, as presented in Table 7, revealed PU as an important mediating variable in predicting BI to use AI in business education. PEU, PU, and ATT towards usage were found to be key predictors. There were some statistically significant indirect effects ($p < 0.05$).

There was an indirect statistically significant effect (0.137, $p = 0.000$) from ATT towards usage to PR with PEU acting as the mediator. Consequently, the availability of resources increases the perception of how usable the AI tools are for the students and therefore their ATT. This is in line with Resource-Based Theory (Barney, 1991).The moderating relationship between PEU and BI to use, moderated through ATT toward usage, also provides a significant indirect influence (0.255, $p = 0.000$). This result is supported by TAM (Davis, 1989). PU demonstrated a significant indirect effect on BI via ATT (0.335, $p = 0.000$). A notable indirect effect (0.150, $p = 0.000$) was identified between SE and ATT towards use, with PEU serving as a mediator. The resources that affected PU acted through PEU (0.135, $p = 0.000$), implying a major role of institutional

TABLE 7 The specific indirect relations.

| Indirect Path | Original sample (O) | *P* values |
|---|---|---|
| PR -> PU -> BI | 0.018 | 0.019 |
| AX -> PEU -> PU | 0.020 | 0.132 |
| PR -> PEU -> ATT | 0.137 | 0.000 |
| JR -> PU -> ATT | 0.127 | 0.000 |
| JR -> PU -> BI | 0.028 | 0.017 |
| SE -> PU -> ATT | 0.080 | 0.003 |
| PEU -> ATT -> BI | 0.255 | 0.000 |
| SE -> PU -> BI | 0.018 | 0.059 |
| SE -> PEU -> ATT | 0.150 | 0.000 |
| PR -> PEU -> PU | 0.135 | 0.000 |
| PU -> ATT -> BI | 0.335 | 0.000 |
| PR -> PEU -> PU -> ATT -> BI | 0.045 | 0.000 |
| SE-> PEU -> PU | 0.148 | 0.000 |
| PEU -> PU -> ATT -> BI | 0.117 | 0.000 |
| SE -> PU -> ATT -> BI | 0.058 | 0.003 |
| PR -> PEU -> PU -> BI | 0.014 | 0.012 |
| PR -> PEU -> PU -> ATT | 0.063 | 0.000 |
| AX -> PEU -> PU -> ATT -> BI | 0.007 | 0.141 |
| SE-> PEU -> PU -> ATT | 0.069 | 0.000 |
| AX -> PEU -> ATT -> BI | 0.015 | 0.116 |
| SE -> PEU -> PU -> BI | 0.015 | 0.015 |
| PR -> PU -> ATT -> BI | 0.058 | 0.000 |
| AX -> PEU -> PU -> ATT | 0.009 | 0.142 |
| PR -> PEU -> ATT -> BI | 0.099 | 0.000 |
| AX -> PEU -> PU -> BI | 0.002 | 0.223 |
| SE -> PEU -> ATT -> BI | 0.108 | 0.000 |
| JR -> PU -> ATT -> BI | 0.092 | 0.000 |
| SE -> PEU -> PU -> ATT -> BI | 0.050 | 0.000 |
| AX -> PEU -> ATT | 0.020 | 0.114 |
| PEU -> PU -> ATT | 0.161 | 0.000 |
| PEU -> PU -> BI | 0.035 | 0.010 |
| PR -> PU -> ATT | 0.081 | 0.000 |

support in establishing the utility that students perceive from the use of AI.

The other indirect effects were not so strong but indeed valid. PR were associated with the intention to use through PU; SE was correlated with ATT toward using mediated by PU; and PEU was correlated with BI to mediated by PU. Conversely, some indirect routes were statistically non-significant. In particular, the paths of AX, i.e., AX → PEU → PU (0.020, $p = 0.132$), AX → PEU → ATT towards usage → BI (0.015, $p = 0.116$), and AX → PEU → PU → BI (0.002, $p = 0.223$), were insignificant. These results indicate that AX is not a good predictor of AI adoption based on PEU or PU in this situation, in line with this study's general result that the effect of AX is overcome by other factors like resource availability and training interventions

Xue et al.'s (2026). meta-analysis of 27 studies from a variety of national settings similarly identified ATT, PU, and PEU as the dominant predictors of BI. However, it also revealed that these pathways are not consistent across contexts: core TAM pathways were significantly stronger in high-uncertainty-avoidance cultures, where users are thought to examine a new technology's dependability and usability more closely before deciding whether to adopt it. This cross-cultural trend suggests that cultural orientation is a crucial border condition for TAM-based models and provides a reasonable explanation for why concern regarding AI registers differently across research, including this one. The idea that PR cannot be assumed to function uniformly across national contexts is further supported by Chauhan et al.'s (2023) meta-analysis of information technology diffusion in organizations, which found that characteristics conceptually related to compatibility and resource fit exert a stronger pull on adoption-related outcomes in developing economies than in developed ones. Ueno et al.'s (2024) review of metaverse adoption in higher education, in particular, warns that institutional infrastructure and lecturer readiness often determine whether positive attitudes translate into actual technology use, rather than student perceptions alone.

# 5 Conclusion

This study examines the effect of integrating AI into the undergraduate curricula of schools of business. The results provide strong evidence of perceived usefulness (PU), perceived ease of use (PEU), perceived resources (PR), and job relevance (JR) influencing technology adoption. Theoretically, the results are based on appropriate concepts in theories relating to information systems and organizational behavior.

The findings of this study revealed that self-efficacy (SE) positively affects both PEU and PU of AI. Additionally, PR positively impacts both PEU and PU of AI in undergraduate business courses. Furthermore, JR positively influences the PU of AI in business courses. Moreover, PEU and PU positively influence students' attitudes (ATT) toward using AI in the undergraduate business curriculum. PEU was found to have a positive effect on PU. Additionally, PU positively influences students' Behavioral intention (BI) to use AI, and students' ATT toward AI integration positively influences their BI to use it. This study validates the extended TAM by pinpointing ATT, PEU and PU as the key drivers of BI. SE, PR, and JR emerge as important antecedents that drive these constructs, while the role of anxiety (AX) and its relation to PEU present areas for further investigation. These findings lead to a deeper understanding of the drivers of technology acceptance, with some useful implications for both theoretical refinement and practical implementation strategies.

The theoretical and practical implications of this study are significant when compared with past systematic reviews and meta-analyses in the field of educational technology. Theoretically, extending the TAM Model to Artificial Intelligence in education is critical because when compared to previous systematic reviews and meta-analyses on Artificial intelligence in education research. First, it validates the extended TAM, highlighting the effects of exogenous variables — JR, AX, SE, and PR — on the endogenous variables PEU, PU, and students' ATT, as well as their BI to adopt AI. Second, the study contributes to the literature by integrating cognitive, contextual, and psychological Factors within a unified TAM framework, providing a more comprehensive understanding of AI adoption dynamics in higher education settings, particularly among business students. Third, the study examines the mediating pathways through PEU and PU toward ATT and BI, offering deeper insights into the mechanisms through which students develop intentions to adopt AI technologies. This study offers a comprehensive framework for understanding the complex dynamics of AI adoption in educational settings. AI's distinct features adaptive computational functioning and autonomous decision-making fundamentally redefine the relative importance of perceived acceptance factors in comparison to traditional technologies (Xue et al., 2026).

Recent meta analytic evidence demonstrates that the TAM pathways linking Attitude to Intention and Perceived Usefulness to Intention exhibit markedly stronger effect sizes within the AI education than those documented in prior meta-analyses addressing general educational technology or mobile learning., suggesting that AI's capacity for real-time personalization amplifies the influence of core cognitive beliefs when adopting new technologies (Xue et al., 2026).

Furthermore, the integration of individual differences, such as computer SE and PEU provides a more robust theoretical foundation, as these factors have been proven to directly influence psychological, contextual, and cognitive factors and BI in the related digital learning environments (Hsia et al., 2014). Practically, the findings suggest that stakeholders should adopt holistic implementation strategies that account for cultural dimensions; for instance, in high uncertainty avoidance cultures where TAM pathways are more robust, emphasizing perceived ease of use and reliability is particularly effective (Xue et al., 2026). Within higher and business education specifically, utilizing emerging technologies for immersive and interactive learning experiences promotes deeper understanding, engagement, and motivation, thereby directly addressing the high demand for functional utility identified in recent research (Ueno et al., 2024).

The findings also identify key drivers of AI adoption, including PEU, JR, PR, PU, and SE, offering valuable implications for educators, universities, and policymakers seeking to enhance students' AI readiness and digital competencies. In addition, the findings suggest that anxiety has a comparatively weaker influence on AI adoption, highlighting the importance of training, institutional support, and resource availability in reducing psychological barriers and encouraging acceptance.

Some limitations that may limit the generalizability of our results must be acknowledged. This study is exploratory in nature, using a judgmental sample taken from private universities in Cairo, Egypt. There are many differences between the public and private universities in Egypt, regarding the integration of artificial intelligence (AI) into the educational process. Private universities have substantial financial resources that enable them to purchase paid licenses for AI-powered software and Learning Management Systems (LMS), in addition to establish advanced computer labs. The availability of these financial resources enables private universities to allocate regular budgets for capacity-building programs for faculty members on how to integrate AI tools into curricula and student assessment. Furthermore, the lower student density in these universities allows for smoother delivery of personalized learning experiences. They also offer greater internet stability for smaller groups, preventing connection interruptions while using interactive AI tools. In contrast, public universities rely more heavily on limited government funding. Also, these universities face ongoing challenges due to their very large student populations. Thus, in most cases, there are not enough resources to acquire advanced LMS or computer labs to meet the needs of such large numbers, and many students may be unable to use AI applications in their learning due to this limitation. Although public universities have highly qualified faculty members, a challenge lies in the inadequacy of ongoing training programs on modern AI tools and the reliance on traditional methods. These differences directly impact how and effectively AI tools are employed in teaching and academic research.

Consequently, the generalizability of our results to public universities and other different geographical regions may be limited. To enhance the external validity of the results, future research could expand the sample to comprise public universities in Egypt or in other countries with different social and cultural backgrounds. Moreover, this study did not consider the potential variations in AI acceptance and use across different economic, social, and cultural environments. Comparative studies between developed and developing countries on AI acceptance and usage intention are suggested to expand the terrain of knowledge and explore the differences in AI adoption and acceptance. Additionally, this study relied solely on self-reported data collected using a questionnaire. While being one of the most frequently used methods in the social sciences, questionnaires may lead to some sort of common method bias (CMB). CMB may arise when both the independent and dependent variables are measured using the same response method within one questionnaire and variables are collected from the respondents at the same point in time. In this study, responses were collected anonymously, and participation was voluntary to minimize evaluation concern and social desirability pressure. Using objective data sources alongside survey instruments would substantially enhance the validity and generalizability of findings. Future research may consider including some objective measures besides self-reported data. For example, to offer evidence related to AI adoption that is free from response bias, metadata data such as assignment submission can be collected from the universities learning management system. Furthermore, system usage logs could capture actual frequency and duration of students' use of AI tools as objective evidence of engagement, in addition to the results related to students' perceived usage obtained from the questionnaire. Moreover, observational data collected in classroom or experimental settings could also support self-reported patterns of using AI in the educational process. Furthermore, this study utilized a cross-sectional design, which only partially captures a few relationship variables' dynamic and interactive behavior. Longitudinal studies investigate the direction and strength of these interactions might be investigated in further studies to capture inside-individual changes.

## Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

## Ethics statement

The study was approved by the Institutional Review Board of American University in Cairo with Case# 2023-2024-120. Informed consent was obtained from all participants, and their privacy rights were strictly observed. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

## Author contributions

RE: Conceptualization, Data curation, Formal analysis, Resources, Visualization, Writing – original draft. AE: Data curation, Funding acquisition, Investigation, Project administration, Supervision, Writing – review & editing. MF: Data curation, Formal analysis, Resources, Validation, Writing – original draft. ME-D: Formal analysis, Methodology, Software, Validation, Visualization, Writing – review & editing. MB: Conceptualization, Data curation, Formal analysis, Methodology, Project administration, Supervision, Writing – review & editing.

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## Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

## Generative AI statement

The author(s) declared that generative AI was used in the creation of this manuscript. ChatGPT 4o was used in the writing process to improve the readability and language of the manuscript. After using this tool, the authors reviewed and edited the content as needed and took full responsibility for the content of the published article.

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## Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/feduc.2026.1893741/full#supplementary-material.

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