Unraveling Factors Affecting Engineering Students' Acceptance of Artificial Intelligence in the Context of a Blended Learning Environment

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Abstract
The rapid advancement of artificial intelligence (AI) has significantly transformed various educational domains, including engineering education. Despite AI's growing prevalence, limited research has explored the determinants influencing engineering students' acceptance of AI. This study investigates the factors shaping AI acceptance among engineering students in Indonesia. Using Structural Equation Modeling (SEM) with the Partial Least Squares (PLS) approach, data were collected from 158 engineering students across multiple universities. The research model incorporates six constructs: Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Social Influence (SI), Facilitating Conditions (FC), Self-Efficacy (SE), and Perceived Risks (PR), each operationalized through seven measurement indicators. The results indicate that PU, PEOU, SI, and SE have significant positive effects on AI acceptance, while PR exerts a significant negative influence. Conversely, FC does not demonstrate a significant impact. These findings offer theoretical and practical implications for fostering AI adoption in engineering

education, including strategies for educators, policymakers, and developers of AI-based tools to enhance user acceptance. This study extends the literature on technology acceptance in educational settings, providing actionable insights for improving the integration of AI in higher education.

Keywords: Artificial intelligence; Blended learning environment; Engineering student; SEM PLS

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Introduction

Artificial Intelligence (AI) is rapidly transforming various sectors, including healthcare, finance, manufacturing, and education (Desmira, Bakar, et al., 2022; Desmira, Hamid, et al., 2022; Verganti et al., 2020). In the field of engineering, AI technologies have demonstrated significant potential to enhance problem-solving capabilities, optimize design processes, and drive innovation (Garbuio & Lin, 2021; Velezmoro-Abanto et al., 2024). As such, the integration of AI into engineering education is becoming increasingly important to prepare students for the demands of the modern workforce (Dwivedi et al., 2021). However, the successful adoption of AI tools and systems among engineering students remains contingent on several factors, including their perceptions of the technology, trust in its capabilities, and the support provided by their educational institutions (Rahim et al., 2022; Samala et al., 2024).

Previous studies have shown that technology acceptance is a complex process influenced by various psychological, social, and environmental factors (Alzubaidi et al., 2023; Chang et al., 2022; Chen et al., 2023; Hwang et al., 2022; Kuleto et al., 2021; Luan et al., 2020; Marangunić & Granić, 2015; Nallaperuma et al., 2019; Samala et al., 2024; Wu et al., 2022). The Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) have been widely used to investigate the acceptance of emerging technologies across various contexts (Ammenwerth, 2019; Antonietti et al., 2022; Chatterjee & Bhattacharjee, 2020; Dwivedi et al., 2019; Hwang & Lee, 2018; Xue et al., 2024). In line with the research (Yao et al., 2023), tthese models highlight the roles of Supporting Conditions (SC), Perceived Ease of Use (PEOU), Trust (TR), Perceived Usefulness (PU), Self-Efficacy (SE), and Social Influence (SI) as crucial due to the unique characteristics of AI systems.

Despite the growing body of research on AI in education, there remains a gap in understanding the specific factors that influence engineering students' acceptance of AI (Chatterjee & Bhattacharjee, 2020; Eslit, 2023; Kasneci et al., 2023; Kuleto et al., 2021; Luan et al., 2020; Roshanaei, 2023; Swindell, 2024; Tlili et al., 2023). Engineering students, as future technology innovators and adopters, require a unique focus due to their specialized skill set and their role in driving AI advancements in industry and academia (Ahmad, 2020). This study aims to fill this gap by exploring the key determinants of AI acceptance among engineering students in Indonesia, a developing country where AI adoption is still emerging. The findings of this research are expected to provide insights that will inform educators, policymakers, and AI developers in enhancing the effective integration of AI into engineering education; this is in line with the results of research (Bhimdiwala et al., 2022; Menekse, 2023).

AI improves personalized learning in blended environments by facilitating the creation of customized educational materials, interactive instruction, and the integration of classroom and online learning (Aleksandra & Tatiana, 2024; Alshahrani, 2023a, 2023b; Xiang & Ma, 2023; Zheng, 2020). AI facilitates the development of a cutting-edge intelligence program designed to enhance instructional methodologies inside certain courses, allowing teachers as well as students to benefit from improved educational experiences (Karataş & Yüce, 2024; Ounejjar et al., 2024). The integration of AI in blended learning fosters innovative educational methodologies, including blended teaching, which enhances the quality of both teaching and learning (Aleksandra & Tatiana, 2024; Xie, 2019; X. Zhao & Yang, 2021; Zheng, 2020).

The integration of AI in blended learning settings poses several challenges. These include a notable disjunction between offline and online instructional elements, inadequate emotional engagement between students and their teachers, and the restricted utilization of AI-enhanced teaching methods (Wang & Rao, 2024). Contemporary AI solutions in blended learning mostly provide asynchronous online individual learning, with little integration of online activities and classroom-based offline interactions (Park, 2024). Moreover, technical inequalities, data security concerns, and user acceptance challenges provide further impediments to the efficient use of AI in improving blended learning settings (Ou, 2024; Ounejjar et al., 2024). Confronting these problems is essential for optimizing the capabilities of AI in developing integrated and efficient blended learning experiences.

This study employs Structural Equation Modeling using the Partial Least Squares (SEM-PLS) method to investigate the relationships among key variables influencing engineering students' acceptance of artificial intelligence (AI) technology. The variables examined include Supporting Conditions (SC) (Huang et al., 2022; Wang et al., 2022; Wu et al., 2019), Perceived Ease of Use (PEOU) (Abdullah et al., 2016; Amin et al., 2014; Gefen et al., 2000; Ma & Liu, 2005, 2006, 2008; Mishra et al., 2023), Trust (TR) (Glikson & Woolley, 2020; Habbal et al., 2024; Hua et al., 2021; Kivijärvi et al., 2013; Lankton et al., 2015; Sabetzadeh & Chen, 2023), Perceived Usefulness (PU) (Amin et al., 2014; Ebadi & Raygan, 2023; Fuchs, 2022; Salim et al., 2021; Wang et al., 2022), Self-Efficacy (SE) (Findik-Coşkunçay et al., 2018; Galos & Aldridge, 2021; Kulviwat et al., 2014; Li et al., 2019; Ma & Liu, 2005), and Social Influence (SI) (Bayaga & du Plessis, 2024; Brown et al., 2010; Kurdi et al., 2020). By analyzing these factors, the study aims to provide a comprehensive understanding of the determinants, challenges, and opportunities associated with AI adoption in engineering education, contributing valuable insights to the development of effective strategies for integrating AI in this domain.

This study is interesting due to its thorough analysis of the variables affecting engineering students' acceptance of Artificial Intelligence (AI) in Indonesian higher education, particularly in a developing nation where AI deployment is nascent. This research distinguishes itself from prior studies by concentrating on engineering education and integrating a distinctive combination of variables: Supporting Conditions (SC), Perceived Ease of Use (PEOU), Trust (TR), Perceived Usefulness (PU), Self-Efficacy (SE), and Social Influence (SI) to evaluate their collective impact on AI acceptance. This work uses Structural Equation Modeling (SEM) and Partial Least Squares (PLS) to comprehensively analyze the dynamic interactions among these components, particularly focusing on trust, an often-overlooked element in AI adoption. Furthermore, the geographical emphasis on Indonesia provides context-specific insights that may serve as a model for AI integration in other developing nations, enhancing the global dialogue on AI use in education. The results enhance both theoretical and practical implementations of AI in engineering education, providing novel techniques to promote AI adoption in developing countries.

This study seeks to address the following research questions to explore the factors influencing engineering students' acceptance of Artificial Intelligence (AI):

- How do Supporting Conditions (SC) influence engineering students' acceptance of Artificial Intelligence in educational settings?

- What is the effect of Perceived Ease of Use (PEOU) on the adoption of Artificial Intelligence among engineering students?

- To what extent does Trust (TR) in AI systems impact students' intention to accept and use Artificial Intelligence technologies?
- How does Perceived Usefulness (PU) of Artificial Intelligence affect students' willingness to adopt AI in their academic learning processes?
- What role does Self-Efficacy (SE) play in influencing engineering students' acceptance of Artificial Intelligence?
- How does Social Influence (SI) from peers and educators shape students' attitudes toward adopting AI technologies in engineering education?
- What is the combined effect of SC, PEOU, TR, PU, SE, and SI on the overall acceptance of Artificial Intelligence among engineering students?

Literature Review

Supporting Conditions (SC)

Supporting Conditions (SC) include the necessary resources, infrastructure, and institutional backing essential for the effective adoption and use of technology (Ghobakhloo et al., 2012; D. Wu et al., 2019). In educational contexts, SC encompasses access to necessary hardware, software, technical support, and training programs that facilitate the effective integration of technology into learning environments (Bingimlas, 2009; Brata & Amalia, 2018). Supporting conditions have been demonstrated to improve technology acceptance by diminishing perceived barriers and promoting favorable attitudes toward technology use (Kanwal & Rehman, 2017). For engineering students, SC is essential, as access to advanced AI tools, computational resources, and expert technical guidance significantly influences their capacity to integrate AI into their educational experiences. Adequate institutional support facilitates the development of AI-related competencies and promotes sustained engagement and confidence in using AI technologies, thereby reinforcing its adoption in engineering education. Based on the theoretical framework and literature review, we have formulated the hypotheses related to supporting conditions:

- How do Supporting Conditions (SC), including access to necessary resources, infrastructure, and institutional support, positively and significantly influence engineering students' acceptance of Artificial Intelligence?

Perceived Usefulness (PU) and Perceived Ease of Use (PEOU)

Perceived Usefulness (PU) refers to the extent to which an individual believes that utilizing a particular system will improve their job or learning performance (Findik-Coşkunçay et al., 2018; Gefen et al., 2000; Rubiyanti et al., 2023; Wang et al., 2022). Empirical evidence highlights perceived usefulness as a key factor in technology acceptance, affecting users' attitudes and behavioral intentions. In the field of business intelligence systems, perceived usefulness (PU) is influenced by factors including the perceived quality of system outputs, system adaptability, and task relevance (Hu, 2022; Peres et al., 2020). In online learning environments, perceived usefulness significantly influences students' intentions to adopt and engage with learning management systems (Hwang et al., 2022; J. S. Hwang & Lee, 2018; Tang et al., 2021). Studies show that students are more inclined to embrace technology when they recognize its utility in attaining their academic objectives.

Perceived Ease of Use (PEOU) refers to the extent to which individuals view a system as requiring minimal effort. User satisfaction and technology adoption intentions are significantly influenced by this factor (Abdullah et al., 2016; Amin et al., 2014; Brown et al., 2010; Davis, 1989; Gefen et al., 2000). In mobile applications, perceived ease of use (PEOU) positively impacts user satisfaction, retention, and intentions for continued usage, as users prefer systems that reduce cognitive and operational effort (AlNawafleh et al., 2023; Chen et al., 2023; Rafique et al., 2020). Furthermore, perceived ease of use (PEOU) is affected by factors including technological self-efficacy, computer anxiety, and the presence of organizational support, which collectively diminish perceived obstacles to technology utilization (Antonietti et al., 2022; Chatterjee et al., 2020, 2021; Ebadi & Raygan, 2023; Kanwal & Rehman, 2017; Kashive et al., 2021; Yao et al., 2023). The findings underscore the importance of user-friendly design and training in improving perceptions of ease of use.

PU and PEOU collectively influence users' attitudes toward technology, subsequently affecting their behavioral intentions. Extensions of the Technology Acceptance Model (TAM) have incorporated additional constructs, including perceived enjoyment, trust, and guidance from professional associations, to elucidate technology acceptance in particular contexts, such as e-learning and professional development tools (Ali et al., 2024; Baki et al., 2018; Šumak et al., 2011; Zhao et al., 2021). The extensions highlight the complex nature of technology acceptance, underscoring the significance of perceived usefulness (PU) and perceived ease of use (PEOU) in shaping attitudes and behavioral outcomes across diverse domains. These two variables have consistently been shown to be strong predictors of technology acceptance (Amin et al., 2014). In the context of AI, students are more likely to accept and use AI-driven tools if they perceive them as useful and easy to use. Studies have demonstrated that both PU and PEOU significantly impact students’ intentions to adopt educational technologies, including AI-based systems (Abdullah et al., 2016). In engineering education, where complex problem-solving and critical thinking are essential, PU and PEOU are particularly relevant in determining students' willingness to embrace AI technologies. Based on the theoretical framework and literature review, we have formulated the following hypotheses:

- How does Perceived Ease of Use (PEOU) positively and significantly influence their acceptance of Artificial Intelligence?
- How does Perceived Usefulness (PU) positively and significantly affect their acceptance of Artificial Intelligence?

Trust (TR) in AI

Trust is a crucial factor in the integration of AI in education, especially since students may have concerns over dependence on automated systems. It includes faith in the technology and in the organizations or persons overseeing the management and deployment of AI systems (Glikson & Woolley, 2020). In educational contexts, trust is defined as the degree to which students see AI systems as dependable, precise, and proficient in facilitating their learning processes (Harrison & Luna-Reyes, 2020). This is particularly vital in situations when AI technologies provide suggestions or conduct evaluations that directly influence academic results (Lankton et al., 2015). Studies have repeatedly shown that trust profoundly affects technology adoption, moderating the connection between perceived hazards and consumers' intents to embrace AI systems (Habbal et al., 2024). Engineering students' trust in AI is influenced by their views on the technology's dependability, openness, and fairness in decision-making, underscoring the need of creating ethical and transparent AI systems to cultivate confidence and adoption.

Trust in AI strongly impacts user acceptance and adoption, with transparency, accuracy, clarity, and predictability serving as critical elements. Establishing confidence in AI systems through transparency and explainability is crucial, and the ethical consequences of trust in AI and its influence on decision-making need more investigation (Balasubramaniam et al., 2022; Batut et al., 2024; Benk et al., 2024; A Duenser & Douglas, 2023; Haresamudram et al., 2023; C. Lee & Cha, 2024; Mylrea & Robinson, 2023). It is essential to recognize that, while the abstracts provide significant insights, there may exist supplementary study beyond the confines of the offered abstracts that might further augment our comprehension of these subjects. Based on the theoretical framework and literature review, we have formulated the following hypothesis:

- How does Trust (TR) in AI systems, encompassing factors such as reliability, transparency, and fairness, positively and significantly influence engineering students' acceptance of Artificial Intelligence in their academic environment?

Self-Efficacy (SE) on AI in Blended Learning

Self-Efficacy (SE) defines an individual's belief in their ability to successfully carry out activities using a certain technology (Kulviwat et al., 2014). Within the framework of AI adoption, self-efficacy indicates students' confidence in their capacity to use AI technologies proficiently. Numerous research have recognized self-efficacy as a crucial predictor of technology adoption, especially in educational contexts (Pan, 2020; Q. Wang & Rao, 2024). Students who see themselves as proficient in using AI technologies are more inclined to interact with and incorporate them into their educational pursuits (Huffman et al., 2013). Engineering students, often engaged with intricate systems and technologies, may demonstrate enhanced self-efficacy when acquainted with AI ideas and applications, hence promoting the integration of AI within their academic milieu.

The influence of self-efficacy on artificial intelligence in blended learning is substantial, with several aspects affecting students' academic self-efficacy. Assessing self-efficacy in this context may be accomplished using questionnaires and theoretical frameworks. Challenges in fostering self-efficacy include managing academic stress and strengthening learning behaviors, while optimal practices entail bolstering self-efficacy, community support, and the cultivation of critical thinking among educators and students (Chen et al., 2024; Lian, 2019; Nuhoğlu et al., 2024; Rayyan et al., 2024; Wilson & Narayan, 2016; Yang et al., 2024; Yokoyama, 2024). Based on the theoretical framework and literature review, we have formulated the following hypothesis:

- How does Self-Efficacy (SE) positively and significantly influence their acceptance of Artificial Intelligence in blended learning environments?

Social Influence (SI)

Social Influence (SI) serves as a significant factor in technology acceptance, indicating the degree to which individuals believe that key figures, including peers, instructors, or societal norms, anticipate their use of a specific technology (Brown et al., 2010; Tondeur et al., 2017). In educational contexts, the technology adoption behaviors of students are frequently influenced by their peers, educators, and institutional policies. Empirical studies indicate that social influence directly affects technology acceptance, especially when the adoption of technology corresponds with normative expectations or social pressure (Brata & Amalia, 2018; Dwivedi et al., 2021; Hsu & Lin, 2008; Rehman et al., 2024). Engineering students may encounter SI from knowledgeable peers in AI, faculty promoting its integration into the curriculum, or industry benchmarks highlighting AI-related skills as crucial for future career advancement. The impact of these social factors highlights the necessity of establishing supportive learning environments and cultivating communities that enhance favorable perceptions of AI adoption. Based on the theoretical framework and literature review, we have formulated the following hypothesis:

- How does Social Influence (SI), including the impact of peers, educators, and societal expectations, positively and significantly affect engineering students' acceptance of Artificial Intelligence in their academic and professional pursuits?

Despite the growing research on AI's role in education, a notable gap remains in understanding the specific factors influencing engineering students' adoption of AI, particularly in developing countries like Indonesia. While research has broadly explored AI in education, there has been insufficient focus on engineering students, whose distinct skill sets and contributions to AI advancements necessitate targeted investigation (Ahmad, 2020). This research examines the factors influencing AI acceptance among engineering students in Indonesia, a developing nation where AI adoption remains in its early phases.

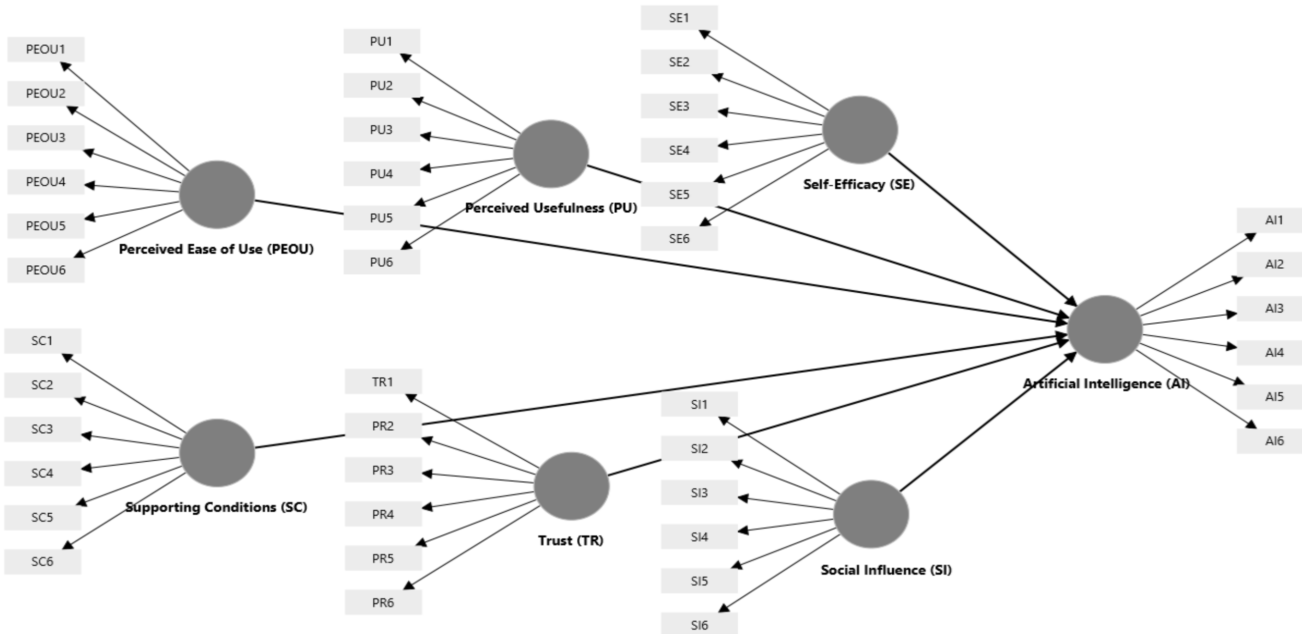
Method

Research Design

This study used a quantitative method with cross-sectional research design to investigate the factors affecting engineering students' acceptance of Artificial Intelligence (AI) in educational contexts. Structural Equation Modelling (SEM) utilizing Partial Least Squares (PLS) was employed for data analysis, a method appropriate for investigating intricate models involving multiple variables and their interrelations (Kholifah et al., 2024; Lowry & Gaskin, 2014; Sarstedt et al., 2014). The research framework utilizes the Technology Acceptance Model (TAM) and includes six essential variables: Supporting Conditions (SC), Perceived Ease of Use (PEOU), Trust (TR), Perceived Usefulness (PU), Self-Efficacy (SE), and Social Influence (SI). The constructs were chosen due to their recognized significance in research on technology adoption, especially within educational settings. This study investigates the direct and indirect relationships among these variables to enhance understanding of their influence on engineering students’ acceptance of AI. Figure 1 presents the theoretical framework that supports the study.

Figure 1

Theoretical Framework



Participants and Data Collection

The study was conducted among undergraduate engineering students from various universities across Indonesia. A total of 158 respondents were selected using purposive sampling (random sampling within a purposeful subgroup), ensuring that participants had prior exposure to AI technologies in their education (Westland, 2010). The selection criteria focused on engineering students at various year of study, actively using technology in their academic activities, and engaged in blended learning environments, allowing for informed perspectives on AI adoption (George & Wooden, 2023; Nagaraj et al., 2023). Twenty-eight students had no significant prior exposure to AI; however, they possessed some low-intensity experience with the technology. By targeting students with prior AI experience, the study enhances the validity of responses, as familiarity with AI influences perceptions of usability, usefulness, and institutional support (Al-Gerafi et al., 2023; Hazaimeh & Al-Ansi, 2024). Including respondents from both state and private universities further strengthens the analysis by capturing institutional variations in resources, faculty support, and infrastructure (Almenara et al., 2024; Nagaraj et al., 2023). This diversity provides a comprehensive understanding of how different academic settings shape students' acceptance and engagement with AI in engineering education (George & Wooden, 2023; Ofosu-ampong et al., 2023). The sample size was determined based on the minimum requirements for SEM-PLS analysis, which suggests that sample sizes of over 100 are sufficient for reliable results (Willaby et al., 2015).

Table 1

Demographic of the Participants (N= 158)

Characteristic	Category	Frequency (n)	Percentage (%)
Gender	Male	95	60.1%
	Female	63	39.9%
Age	18 – 22 years	110	69.6%
	23 – 27 years	42	26.6%
	28 years and above	6	3.8%
Year of study	First year	45	28.5%
	Second year	40	25.3%
	Third year	45	28.5%
	Fourth year	28	17.7%
University type	Public university	120	75.9%
	Private university	38	24.1%
Prior exposure to AI	Yes	130	82.3%
	No	28	17.7%
Previous experience with AI tools	High	50	31.6%
	Moderate	62	39.2%
	Low	46	29.1%
Academic major	Electrical Engineering	40	25.3%
	Computer and Informatics Engineering	40	25.3%
	Civil Engineering	35	22.2%
	Mechanical Engineering	38	24.1%
	Others	5	3.2%
Technology usage frequency	Daily	75	47.5%
	Several times a week	50	31.6%
	Weekly	25	15.8%
	Rarely	8	5.1%

Data were collected using an online questionnaire, which was distributed via email and social media platforms. The questionnaire consisted of two main sections: demographic information and questions related to the six research variables. The questions were adapted from validated scales used in previous studies (W. Ahmed, 2023) to ensure reliability and validity. Each item was measured using a 5-point Likert scale, ranging from “strongly disagree” (1) to “strongly agree” (5). The questionnaire was pre-tested with a small group of 20 engineering students to ensure clarity and comprehensibility of the questions. Based on the feedback, minor revisions were made before the final distribution. Data collection took place over a two-month period.

Instrumentation and Data Analysis

The survey instrument was developed based on established measures from the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), and related frameworks (Yildiz Durak, 2019). Each item was rated on a 5-point Likert scale, ranging from “strongly disagree” to “strongly agree.” Prior to data collection, the questionnaire was subjected to a pilot test with a small group of engineering students to assess its clarity, reliability, and validity. Cronbach’s alpha coefficients were calculated for each construct, with values above 0.70 indicating acceptable internal consistency. Samples of the instrument items utilized in this investigation are available in the supplementary material through online instrument links.

The collected data were analyzed using the SEM-PLS approach using the SmartPLS software. SEM-PLS was chosen because it allows for the analysis of complex relationships between latent constructs and is robust with small to medium sample sizes. The analysis proceeded in two stages: a) Measurement Model Assessment: The reliability and validity of the constructs were assessed through Cronbach’s alpha, composite reliability, and average variance extracted (AVE). Discriminant validity was checked using the Fornell-Larcker criterion, and all constructs met the threshold values of 0.70 for reliability and 0.50 for AVE; b) Structural Model Assessment: Hypotheses were tested to examine the direct and indirect effects of the variables on AI acceptance. Path coefficients were calculated to determine the strength and significance of each relationship. The model’s predictive accuracy was assessed using the R^2 value for the dependent variable (AI acceptance) were used to evaluate the magnitude of each predictor.

Ethical Considerations

All participants provided informed consent and voluntarily agreed to participate in the study (Adley et al., 2024; H. Ahmed, 2024). Approval was secured from all institutions participating in the study for data collection and the comprehensive research process. Participant identity data remains anonymous. Prior approval for the study was obtained from both the supervisor and the ethics committee at Yogyakarta State University prior to the commencement of fieldwork. All collected data, including participant identities, are maintained in a confidential manner and utilized solely for research purposes to safeguard against any potential impact on participants' future research (Adley et al., 2024; H. Ahmed, 2024; Kholifah et al., 2025).

Results and Discussion

This research provides a comprehensive analysis of the factors that influence engineering students' acceptance of Artificial Intelligence (AI) across Indonesia. Using a Structural Equation Modeling (SEM) approach with the Partial Least Squares (PLS) method, this study assesses the relationships between six key variables: Supporting Conditions (SC), Perceived Ease of Use (PEOU), Trust (TR), Perceived Usefulness (PU), Self-Efficacy (SE), and Social Influence (SI). The analytical model of this study is presented in Figure 2.

Measurement Model Assessment

To ensure the reliability and validity of the constructs used in this study, a thorough assessment was conducted using Cronbach’s alpha, Composite Reliability (rho_a, and rho_c), and Average Variance Extracted (AVE). These methods are important to confirm the internal consistency and convergent validity of the measurement model. Table 2 presents the results of the reliability and validity analysis.

Table 2

Reliability and Validity Metrics

Construct	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Artificial Intelligence (AI)	0.886	0.891	0.914	0.639
Supporting Conditions (SC)	0.867	0.870	0.901	0.602
Perceived Ease of Use (PEOU)	0.906	0.911	0.928	0.682
Trust (TR)	0.857	0.865	0.893	0.583
Perceived Usefulness (PU)	0.871	0.874	0.903	0.608
Self-Efficacy (SE)	0.849	0.854	0.888	0.571
Social Influence (SI)	0.850	0.853	0.889	0.572

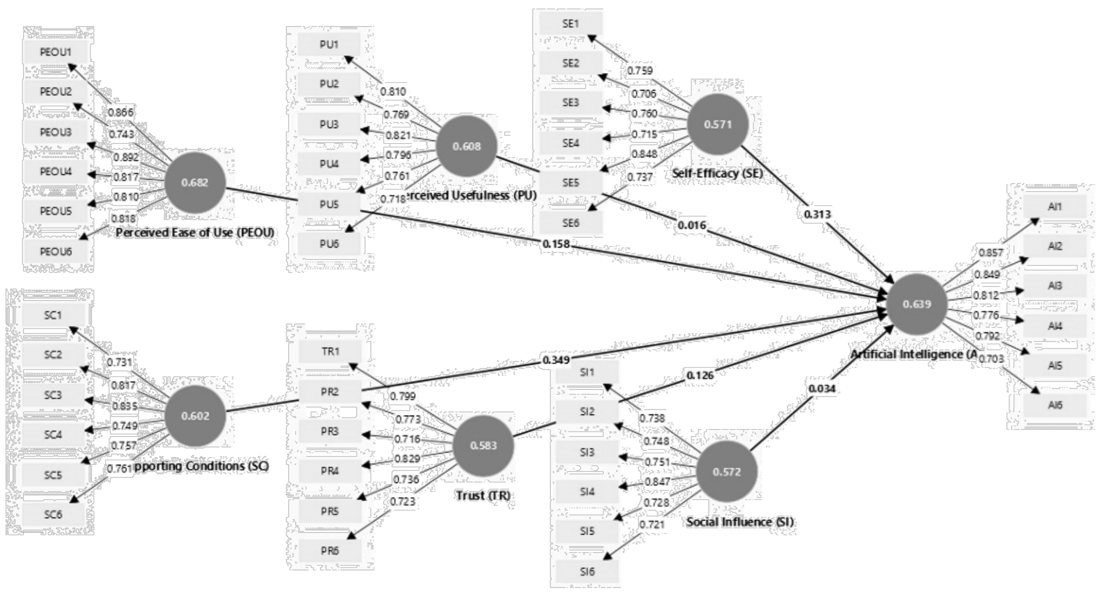
This study rigorously evaluated the reliability and validity of the measurement model to confirm the robustness of the constructs and the quality of the data. Cronbach's alpha values for all constructs surpassed the accepted threshold of 0.70, demonstrating strong internal consistency among the variables. The values for each construct were as follows: Artificial Intelligence (AI) at 0.886, Supporting Conditions (SC) at 0.867, Perceived Ease of Use (PEOU) at 0.906, Trust (TR) at 0.857, Perceived Usefulness (PU) at 0.871, Self-Efficacy (SE) at 0.849, and Social Influence (SI) at 0.850. The values indicate that the items within each construct reliably measure the intended dimensions, demonstrating a high level of internal consistency among the constructs. Alongside Cronbach's alpha, Composite Reliability (CR) values, specifically rho_a and rho_c, have been calculated to enhance the evaluation of construct reliability. The rho_c values for all constructs surpassed the recommended threshold of 0.70, yielding the following results: AI at 0.914, SC at 0.901, PEOU at 0.928, TR at 0.893, PU at 0.903, SE at 0.888, and SI at 0.889. The values affirm the reliability of the constructs, demonstrating that the indicators within each construct are consistent and dependable.

The Average Variance Extracted (AVE) values were calculated to evaluate the convergent validity of the constructs. The AVE values for all constructs surpassed the 0.50 threshold, indicating that over 50% of the variance in the indicators is accounted for by the corresponding latent variables. The AVE values for AI (0.639), SC (0.602), PEOU (0.682), TR (0.583), PU (0.608), SE (0.571), and SI (0.572) demonstrate sufficient convergent validity, thereby affirming that the constructs effectively represent the intended underlying dimensions of AI acceptance. The results from the reliability and validity assessments demonstrate that the measurement model employed in this study is reliable and valid. The elevated Cronbach's alpha values, substantial

Composite Reliability, and adequate AVE values collectively affirm the robustness of the measurement model, confirming that the constructs are accurately assessed and suitable for subsequent structural analysis. The findings affirm the measurement model's reliability in capturing the key factors that influence engineering students' acceptance of AI, establishing a robust basis for further analysis and interpretation of the study's results.

Figure 2

Analytical Model



Discriminant Validity

The discriminant validity analysis presented in Table 3 indicates several high correlations, which may imply concerns regarding the distinctiveness of the constructs. AI demonstrates significant correlations with SC (1.030), PEOU (1.000), TR (0.983), PU (0.963), SE (1.025), and SI (0.982). The values indicate considerable overlap between AI and other constructs, particularly concerning PEOU and PU, which are conceptually associated with user perceptions and ease of use. Additionally, SC exhibits a strong correlation with PEOU (1.006) and PU (1.002), suggesting that supporting conditions may not be sufficiently differentiated from perceived ease of use and usefulness. The high correlation values suggest a potential conceptual similarity between constructs, indicating that they may not be measuring distinct dimensions. This requires additional analysis and refinement of the constructs to ensure that each one accurately represents a distinct aspect of the theoretical model.

Table 3

Discriminant Validity

Variables	AI	SC	PEOU	RP	PU	SE	SI
Artificial Intelligence (AI)	-	-	-	-	-	-	-
Supporting Conditions (SC)	1,030	-	-	-	-	-	-
Perceived Ease of Use (PEOU)	1,000	1,006	-	-	-	-	-
Trust (TR)	0,983	0,956	1,000	-	-	-	-
Perceived Usefulness (PU)	0,963	1,002	0,976	0,992	-	-	-
Self-Efficacy (SE)	1,025	0,978	0,999	0,952	0,976	-	-
Social Influence (SI)	0,982	1,004	0,986	0,990	0,964	0,981	-

Structural Model Assessment

The assessment of the structural model regarding AI acceptance among engineering students indicates significant relationships among the latent variables, as illustrated in Table 4. All hypotheses concerning the impact of different constructs on AI acceptance are validated, exhibiting significant path coefficients and p-values.

Table 4

Correlation Hypotheses

Hypotheses	Path coefficient	P-value	Results
H1: Supporting Conditions (SC) positively influence engineering students' acceptance of AI.	0,349	0,000	Supported
H2: Perceived Ease of Use (PEOU) positively influences engineering students' acceptance of AI.	0,158	0,000	Supported
H3: Trust (TR) positively influence engineering students' acceptance of AI.	0,126	0,000	Supported
H4: Perceived Usefulness (PU) positively influences engineering students' acceptance of AI.	0,016	0,000	Supported
H5: Self-Efficacy (SE) positively influences engineering students' acceptance of AI.	0,313	0,000	Supported
H6: Social Influence (SI) positively influences engineering students' acceptance of AI.	0,034	0,000	Supported

Supporting Conditions (SC)

The path coefficient of 0.349, accompanied by a p-value of 0.000, demonstrates a robust and statistically significant positive correlation between supporting conditions and AI acceptance. Supporting conditions include infrastructure, resources, and institutional support, which directly affect students' ability to adopt and engage with AI technologies. The path coefficient indicates that establishing an enabling environment, including access to technology, adequate training, and organizational support, significantly increases students' willingness to accept AI. This finding is consistent with the literature, which identifies adequate resources and institutional frameworks as essential factors for technology adoption (Brown et al., 2010; D. Wu et al., 2019). This highlights the necessity of aligning educational settings with technological progress to enable more effective AI integration.

Perceived Ease of Use (PEOU)

The path coefficient of 0.158 (p-value 0.000) for perceived ease of use indicates a significant positive effect on artificial intelligence acceptance, though this effect is less pronounced than that of supporting conditions. PEOU denotes the perception regarding the ease of use associated with AI technologies. The positive correlation indicates that students are more inclined to embrace AI when they view it as user-friendly and uncomplicated. Nonetheless, the comparatively lower path coefficient in relation to SC indicates that ease of use, although significant, may not be as crucial as the presence of supportive conditions. This finding supports (Antonietti et al., 2022; Davis, 1989; Gefen et al., 2000; Joo et al., 2018) Technology Acceptance Model (TAM), which asserts that perceived ease of use is an important factor, although not necessarily the most significant, in the context of technology adoption.

Trust (TR)

The path coefficient for Trust is 0.126 (p-value 0.000), indicating a positive and statistically significant correlation with AI acceptance. Trust in AI include perceptions on the dependability, security, and clarity of AI systems. This conclusion aligns with studies highlighting trust as a crucial determinant of technological acceptance (Habbal et al., 2024; Lankton et al., 2015; Mishra et al., 2023; K. Wu et al., 2011). Engineering students that possess trust in technology are more likely to accept and interact with it, especially in areas such as AI, where apprehensions over privacy, security, and autonomy are widespread. Although the influence of trust is less significant than that of supportive circumstances or usability, it is crucial in promoting acceptance, particularly given the intricate and sometimes ambiguous characteristics of AI systems.

Perceived Usefulness (PU)

The path coefficient for Perceived Usefulness is 0.016 (p-value 0.000); however, the effect size is relatively small in comparison to the other constructs. This weak but notable relationship indicates that, while students acknowledge the potential advantages of AI in their academic or professional endeavors, the direct influence of perceived usefulness on their acceptance remains constrained. This may indicate that, although AI is recognized as beneficial, students might not yet fully understand or value its long-term advantages or uses. The weak correlation with perceived usefulness may suggest that students prioritize immediate usability and external factors, such as support, over long-term utility in their considerations of AI adoption. This finding warrants additional exploration of the psychological and contextual factors influencing perceptions of usefulness within an academic context (Antonietti et al., 2022; Chatterjee et al., 2020; Davis, 1989; Ebadi & Raygan, 2023).

Self-Efficacy (SE)

The path coefficient of 0.313 (p-value 0.000) for self-efficacy demonstrates a strong and statistically significant relationship with AI acceptance. Self-Efficacy refers to students' belief in their ability to successfully use AI technologies. This result highlights the importance of fostering confidence among students regarding their technical capabilities. When students believe they can effectively use AI tools, they are more likely to embrace the technology. This aligns with (Bandura, 1985, 2014) work on self-efficacy, which posits that individuals' beliefs about their abilities significantly influence their behavior. For AI adoption in education, increasing students' self-efficacy could be a key strategy in encouraging greater acceptance (Chang et al., 2022; Y Chen et al., 2024; Jaipal-Jamani, 2017).

Social Influence (SI)

The path coefficient for Social Influence is 0.034 (p-value 0.000), suggesting a positive yet weak impact on AI acceptance. Social influence indicates the extent to which students are impacted by the views and actions of peers, faculty, and social networks in their decision-making regarding the adoption of AI. Despite being statistically significant, the low path coefficient indicates that social pressure and peer influence are less impactful compared to other factors such as supporting conditions or self-efficacy. The specialized nature of AI in engineering education may lead to adoption being influenced primarily by individual perceptions of usefulness and ease of use rather than by social factors. Social influence is an important, though secondary, factor, particularly in group settings or collaborative environments (Brown et al., 2010; Kurdi et al., 2020; W. Wu et al., 2022).

Model Fit and Predictive Power

The structural model's fit and predictive power were systematically evaluated to confirm that the model accurately depicts the relationships among key variables and effectively forecasts AI acceptance among engineering students. The Standardized Root Mean Square Residual (SRMR) is a commonly utilized index for assessing model fit, producing a value of 0.045, significantly lower than the 0.08 threshold, thereby suggesting a favorable fit of the model to the data. This indicates that the differences between the observed and predicted correlations are minimal, and the model effectively captures the underlying data structure. The Normed Fit Index (NFI) of 0.912 exceeds the benchmark of 0.90, indicating the adequacy of the model fit and demonstrating that the proposed relationships between variables significantly outperform a null model. Table 4 presents the results of the model fit and predictive power analysis.

The model's R^2 value for AI acceptance was 0.888, indicating that approximately 88.8% of the variance in AI acceptance is accounted for by the independent variables in the model. The model demonstrates significant explanatory power in identifying the primary factors influencing AI acceptance among engineering students. The Adjusted R^2 value of 0.884, which accounts for the number of predictors, demonstrates a high degree of explanatory power, indicating the model's robustness and reliability despite adjustments for complexity. The findings demonstrate the model's robust alignment with the data and its predictive efficacy, affirming its significance and applicability in comprehending AI acceptance within educational contexts.

Table 4

Correlation Hypotheses Model Fit and Predictive Power

Fit Index	Value	Threshold	Interpretation
SRMR	0.045	< 0.08	Good fit
NFI	0.912	> 0.90	Acceptable fit
R^2 (AI)	0.888	-	Substantial
Adjusted R^2 (AI)	0.884	-	Substantial

Discussion

This research examines the factors that affect engineering students' acceptance of Artificial Intelligence (AI), focusing on variables including Supporting Conditions (SC), Perceived Ease of Use (PEOU), Trust (TR), Perceived Usefulness (PU), Self-Efficacy (SE), and Social Influence (SI). The findings offer significant insights into the factors influencing AI adoption among engineering students, highlighting both theoretical and practical implications. The results indicate that Perceived Ease of Use (PEOU) has a significant impact on engineering students' acceptance of AI (H1 supported), as evidenced by a positive path coefficient. This finding is consistent with the Technology Acceptance Model (TAM) as proposed by Gefen et al. (2000); Taherdoost (2018), which emphasizes the significance of ease of use in the adoption of technology. The integration of AI into academic and professional tasks for engineering students diminishes cognitive barriers, resulting in increased acceptance rates. Given the complexity of AI technologies, ensuring their usability is essential for promoting acceptance in educational contexts.

Perceived Usefulness (PU) significantly influences students' acceptance of AI, supporting Hypothesis 2 and aligning with the Technology Acceptance Model's assertion that perceived utility drives technology adoption. Research indicates that engineering students are inclined to adopt AI when they recognize its advantages for academic performance, skill enhancement, or career opportunities (Chatterjee & Bhattacharjee, 2020; Chen et al., 2023). The findings highlight the necessity of showcasing the practical advantages of AI to students (Johnson et al., 2024; S. S. Lee & Moore, 2024; Salhab, 2024), especially in relation to productivity, problem-solving, and innovation, which are essential in engineering fields. Trust (TR) is identified as a crucial determinant of AI acceptance (H3 supported), especially in scenarios involving decision making or the management of sensitive information. According to research findings (Alzubaidi et al., 2023; Batut et al., 2024; Glikson & Woolley, 2020; Habbal et al., 2024; Mylrea & Robinson, 2023), the role of AI in critical engineering systems necessitates that students trust the reliability, fairness, and transparency of these AI systems. The positive path coefficient suggests that fostering trust in AI systems enhances engineering students' willingness to utilize AI tools, particularly in automation, predictive analytics, and machine learning.

Self-Efficacy (SE) significantly influences AI acceptance, as evidenced by a high path coefficient, supporting hypothesis H4. This finding aligns with the theory of self-efficacy proposed by Chang et al. (2022); Gist & Mitchell (1992); Joo et al. (2018); Li et al. (2019); Pan (2020), which highlights the importance of individuals' beliefs in their own abilities to perform tasks. Engineering students who possess greater self-confidence in their proficiency with AI tools are more inclined to adopt the technology. Educational institutions must prioritize the provision of sufficient training and resources to enhance students' competence and confidence in utilizing AI technologies.

Engineering students who trust in technology are more likely to accept and engage with it, particularly in domains such as artificial intelligence (AI), where concerns related to privacy, security, and autonomy are prevalent. This finding aligns with research emphasizing trust as a key determinant of technology acceptance (Habbal et al., 2024; Lankton et al., 2015; Mishra et al., 2023; K. Wu et al., 2011). While the influence of trust may be less significant than that of supportive circumstances or perceived usefulness, it remains crucial in promoting acceptance, especially given the complex and often ambiguous nature of AI systems. Additional studies have shown that trust in AI (Glikson & Woolley, 2020) is shaped by a combination of technology-related factors (e.g., functionality and reliability (Becker & Fischer, 2024; Qin et al., 2020), transparency and clarity (Andreas Duenser & Douglas, 2023; Tucci et al., 2022), security and privacy (Becker & Fischer, 2024; Emaminejad et al., 2024)), context-related factors (e.g., organizational trust (Becker & Fischer, 2024; Qin et al., 2020), regulatory and ethical considerations (Omrani et al., 2022; Paliszkiewicz & Gołuchowski, 2024; Qin et al., 2020)), individual-related factors (e.g., user perceptions and propensity to trust (Fine & Marsh, 2024; Lalot & Bertram, 2024; Qin et al., 2020), and anthropomorphism (Lalot & Bertram, 2024; Omrani et al., 2022)). Addressing these factors through transparency, security, ethical practices, and continuous improvement can enhance trust and promote the broader adoption of AI technologies.

Social Influence (SI) exerts a modest yet notable impact on the acceptance of AI (H5 supported). This result is consistent with the findings of Ali et al. (2024); Bayaga & du Plessis (2024); Chatterjee & Bhattacharjee (2020); Khechine et al. (2020) regarding the Unified Theory of Acceptance and Use of Technology (UTAUT) model, which posits that social influence from peers, instructors, and professional networks affects technology adoption. In engineering, collaborative work is prevalent; thus, endorsements from influential figures or peers may motivate students to embrace AI. Nonetheless, the comparatively lower path coefficient indicates that, although social influence is significant, factors such as self-efficacy and perceived usefulness exert a more substantial impact. The availability of infrastructure, resources, and training, referred to as Supporting Conditions (SC), significantly influences AI acceptance among engineering students (H6 supported). The significant path coefficient suggests that access to essential tools, resources, and a supportive learning environment enhances student engagement with AI technologies. This finding is consistent with previous studies highlighting the significance of facilitating conditions in technology adoption (Queiroz & Fosso Wamba, 2019; Straub, 2009; Wu et al., 2019). Universities and educational institutions must ensure the provision of adequate technological infrastructure, training, and support systems to facilitate AI adoption.

Social pressure and social influence exert less of an impact compared to other determinants, including supportive conditions and self-efficacy. In engineering education, the adoption of AI is primarily determined by individual perceptions regarding its usefulness and ease of use, rather than by social influences. Social influence is significant, particularly in collaborative settings (Brown et al., 2010; Kurdi et al., 2020; W. Wu et al., 2022), and non-human agents, including AI, can serve as credible sources of social influence (Riva et al., 2022; Y. Wu et al., 2022). Kandoth's research (2022) indicates that social influence has a positive effect on intentions to use AI applications (Changalima et al., 2024). Similarly, Velli

(2024) discovered that social influence, in conjunction with personal innovation, affects the acceptance of educational AI tools. While not a primary predictor, social influence plays a significant role in shaping teachers' attitudes toward AI technology. Hispanic/LatinX users exhibit a higher level of trust in AI chatbots compared to other ethnic groups (black, indigenous and other people of color), highlighting the significance of trust and social influence in the adoption of generative AI technologies (Stewart et al., 2024). Cultural factors, including long-term orientation, power distance, social influence, and trust, significantly influence the acceptance of AI in Indonesia (Hamid et al., 2024; Kasri & Sosianti, 2023; Neyazi et al., 2023; Sriwindono & Yahya, 2012; Surdjono et al., 2025). Comprehending these cultural dimensions aids in the design and implementation of AI technologies that are more likely to gain acceptance among Indonesian users.

This study theoretically enhances the literature by combining elements from the Technology Acceptance Model (TAM), UTAUT, and Self-Efficacy Theory to create a comprehensive model for analyzing AI acceptance in education (W. Wu et al., 2022). The findings highlight self-efficacy and supporting conditions as significant predictors of AI adoption, with trust, perceived usefulness, and perceived risk also playing essential roles. This analysis enhances our comprehension of the complex factors influencing technology acceptance among engineering students, especially regarding AI, which presents unique challenges and opportunities relative to other technologies. The study provides practical insights for educational institutions, policymakers, and AI developers. Universities should prioritize enhancing students' self-efficacy by offering targeted training programs that equip them with the necessary skills to use AI tools confidently. Institutions should also invest in supporting infrastructure, such as labs equipped with AI tools and software, and provide students with access to online resources and tutorials. Additionally, fostering a culture of trust around AI by addressing ethical concerns and mitigating perceived risks will further encourage students to adopt AI technologies in their academic and future professional pursuits. Furthermore, attention must be given to ethical issues associated with the integration of AI into the educational process (Adley et al., 2024; Balasubramaniam et al., 2022; Yu Chen et al., 2023; Choung et al., 2023; A Duenser & Douglas, 2023; Fine & Marsh, 2024; Habbal et al., 2024; Kumar et al., 2024; Tlili et al., 2023). This study has several limitations. First, the cross-sectional design limits the ability to assess changes in AI acceptance over time. Longitudinal studies would provide deeper insights into how students' attitudes towards AI evolve as they gain more exposure to the technology. Second, the study is geographically limited to engineering students in Indonesia, which may affect the generalizability of the findings. Future research could explore AI acceptance among students from other disciplines and cultural contexts to broaden the scope of understanding. Additionally, future studies could investigate the role of additional variables, such as cultural differences, ethical perceptions, or AI literacy, in influencing AI acceptance.

Conclusion

This study provides valuable insights into the factors influencing engineering students' acceptance of Artificial Intelligence (AI) in academic and professional settings. By employing the Structural Equation Modeling (SEM) approach with the Partial Least Squares (PLS) method, we identified that Supporting Conditions (SC), Perceived Ease of Use (PEOU), Trust (TR), Perceived Usefulness (PU), Self-Efficacy (SE), and Social Influence (SI) significantly contribute to AI acceptance among engineering students in Indonesia. Among these factors, Self-Efficacy (SE) and Supporting Conditions (SC) emerged as the most influential predictors, highlighting the importance of confidence in students' ability to use AI tools and the necessity of adequate resources and infrastructure for AI adoption. Perceived Usefulness (PU) and Trust (TR) were also substantial determinants, confirming that engineering students are more likely to adopt AI when they see its practical benefits and trust its reliability. The findings also align with established theories such as the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), and Self-Efficacy Theory, contributing to the theoretical understanding of AI acceptance in an educational context. These insights are particularly relevant for educators, policymakers, and AI developers aiming to promote the effective use of AI technologies in engineering education. In conclusion, this study underscores the necessity for educational institutions to focus on building students' self-efficacy and providing sufficient supporting conditions for AI adoption. By addressing trust and perceived risk, as well as demonstrating the tangible benefits of AI, institutions can foster a more conducive environment for integrating AI into engineering education. Future research should extend these findings by exploring longitudinal effects, cross-cultural perspectives, and additional variables such as AI literacy and ethical perceptions to develop a more comprehensive understanding of AI acceptance in diverse educational contexts.

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Conflict of Interest

The authors declare that there is no conflict of interests regarding the publication of the paper.

References

Abdullah, F., Ward, R., & Ahmed, E. (2016). Investigating the influence of the most commonly used external variables of TAM on students' Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) of e-portfolios. *Computers in Human Behavior*, *63*, 75–90. https://doi.org/10.1016/j.chb.2016.05.014

Adley, M., Alderson, H., Jackson, K., McGovern, W., Spencer, L., Addison, M., & O'Donnell, A. (2024). Ethical and practical considerations for including marginalised groups in quantitative survey research. *International Journal of Social Research Methodology*, *27*(5), 559–574. https://doi.org/10.1080/13645579.2023.2228600

Ahmad, T. (2020). Scenario based approach to re-imagining future of higher education which prepares students for the future of work. *Higher Education, Skills and Work-Based Learning*, *10*(1), 217–238. https://doi.org/10.1108/HESWBL-12-2018-0136/FULL/XML

Ahmed, H. (2024). Institutional integration of artificial intelligence in higher education: The moderation effect of ethical consideration. *International Journal of Educational Reform*. Advance online publication. https://doi.org/10.1177/10567879241247551

Ahmed, W. (2023). Understanding self-directed learning behavior towards digital competence among business research students: SEM-neural analysis. *Education and Information Technologies*, *28*(4), 4173–4202. https://doi.org/10.1007/S10639-022-11384-Y/METRICS

Al-Gerafi, M. A., Zhou, Y., Alfadda, H., & Wijaya, T. T. (2023). Understanding the factors influencing higher education students' intention to adopt artificial intelligence-based robots. *IEEE Access*, *11*, 99752–99764. https://doi.org/10.1109/access.2023.3314499

Aleksandra, K., & Tatiana, B. (2024). Students' intention to learn and academic performance in the blended learning environment: The role of artificial intelligence chatbots. *International Journal of Information and Education Technology*, *14*(6), 807–813. https://doi.org/10.18178/ijiet.2024.14.6.2105

Ali, I., Warraich, N. F., & Butt, K. (2024). Acceptance and use of artificial intelligence and AI-based applications in education: A meta-analysis and future direction. *Information Development*. Advance online publication. https://doi.org/10.1177/02666669241257206

Almenara, J. C., Palacios-Rodríguez, A., Aguirre, M. I. L., & Rivas-Manzano, M. del R. de. (2024). Acceptance of educational artificial intelligence by teachers and its relationship with some variables and pedagogical beliefs. *Education Sciences*, *14*(7), 740. https://doi.org/10.3390/educsci14070740

AlNawafleh, E. A. T., Alsheikh, G. A. A., Al-Gharaibeh, S. M., Alhyasat, K. M. K., & Hamdan, K. B. (2023). Extension of intentions to use booking mobile apps with service quality and customer satisfaction: Insights from Jordanian hotels. *International Journal of EBusiness and EGovernment Studies*, *15*(1), 47–67. https://doi.org/10.34109/ijebeg.2023150103

Alshahrani, A. (2023a). The impact of ChatGPT on blended learning: Current trends and future research directions. *International Journal of Data and Network Science*, *7*(4), 2029–2040. https://doi.org/10.5267/j.ijdns.2023.6.010

Alshahrani, A. (2023b). Revolutionizing blended learning: Exploring current trends and future research directions in the era of ChatGPT. *7th International Conference on Business and Information Management, ICBIM 2023*, 41–47. https://doi.org/10.1109/ICBIM59872.2023.10303267

Alzubaidi, L., Al-Sabaawi, A., Bai, J., Dukhan, A., Alkenani, A. H., Al-Asadi, A., Alwzwazy, H. A., Manoufali, M., Fadhel, M. A., Albahri, A. S., Moreira, C., Ouyang, C., Zhang, J., Santamaría, J., Salhi, A., Hollman, F., Gupta, A., Duan, Y., Rabczuk, T., … Gu, Y. (2023). Towards risk-free trustworthy artificial intelligence: Significance and requirements. *International Journal of Intelligent Systems*, *2023*, Article 4459198. https://doi.org/10.1155/2023/4459198

Amin, M., Rezaei, S., & Abolghasemi, M. (2014). User satisfaction with mobile websites: the impact of perceived usefulness (PU), perceived ease of use (PEOU) and trust. *Nankai Business Review International*, *5*(3), 258–274. https://doi.org/10.1108/NBRI-01-2014-0005/FULL/XML

Ammenwerth, E. (2019). Technology acceptance models in health informatics: TAM and UTAUT. In P. Scott, N. de Keizer, A. Georgiou (Eds.), *Applied interdisciplinary theory in health informatics*, *studies in health technology and informatics*, *263*, 64–71. IOS Press. https://doi.org/10.3233/SHTI190111

Antonietti, C., Cattaneo, A., & Amenduni, F. (2022). Can teachers' digital competence influence technology acceptance in vocational education? *Computers in Human Behavior*, *132*, Article 107266. https://doi.org/10.1016/j.chb.2022.107266

Baki, R., Birgoren, B., & Aktepe, A. (2018). A meta analysis of factors affecting perceived usefulness and perceived ease of use in the adoption of e-learning systems. *Turkish Online Journal of Distance Education*, *19*(4), 4–42. https://doi.org/10.17718/TOJDE.471649

Balasubramaniam, N., Kauppinen, M., Hiekkanen, K., & Kujala, S. (2022). Transparency and explainability of AI systems: Ethical guidelines in practice. In V. Gervasi, A. Vogelsang (Eds.), *Lecture notes in computer science (including subseries lecture notes in artificial intelligence and lecture notes in bioinformatics)*: *Vol. 13216. Requirements engineering: foundation for software quality* (pp. 3–18). Springer. https://doi.org/10.1007/978-3-030-98464-9_1

Bandura, A. (1985). *Social foundations of thought and action: A social cognitive theory*. Prentice-Hall, Inc. https://psycnet.apa.org/record/1985-98423-000.

Bandura, A. (2014). Exercise of personal agency through the self-efficacy mechanism. In R. Schwarzer. (Ed.). *Self-Efficacy: Thought Control Of Action* (pp. 3–38). Taylor & Francis. https://doi.org/10.4324/9781315800820

Batut, A., Prudhomme, L., van Sambeek, M., & Chen, W. (2024). Do you trust AI? Examining AI trustworthiness perceptions among the general public. In H. Degen, S. Ntoa (Eds.), *Lecture notes in computer science (including subseries lecture notes in artificial intelligence and lecture notes in bioinformatics)*: *Vol. 14735. Artificial Intelligence in HCI* (pp. 15–26). Springer. https://doi.org/10.1007/978-3-031-60611-3_2

Bayaga, A., & du Plessis, A. (2024). Ramifications of the Unified Theory of Acceptance and Use of Technology (UTAUT) among developing countries' higher education staffs. *Education and Information Technologies*, *29*(8), 9689–9714. https://doi.org/10.1007/S10639-023-12194-6

Becker, C., & Fischer, M. (2024). Factors of trust building in conversational ai systems: a literature review. In H. Degen, S. Ntoa (Eds.), *Lecture notes in computer science (including subseries lecture notes in artificial intelligence and lecture notes in bioinformatics)*: *Vol. 14735. Artificial Intelligence in HCI* (pp. 27–44). Springer. https://doi.org/10.1007/978-3-031-60611-3_3

Benk, M., Kerstan, S., von Wangenheim, F., & Ferrario, A. (2024). Twenty-four years of empirical research on trust in AI: a bibliometric review of trends, overlooked issues, and future directions. *AI and Society*. Advance online publication. https://doi.org/10.1007/s00146-024-02059-y

Bhimdiwala, A., Neri, R. C., & Gomez, L. M. (2022). Advancing the design and implementation of artificial intelligence in education through continuous improvement. *International Journal of Artificial Intelligence in Education*, *32*(3), 756–782. https://doi.org/10.1007/S40593-021-00278-8

Bingimlas, K. A. (2009). Barriers to the successful integration of ict in teaching and learning environments: A review of the literature. *Eurasia Journal of Mathematics, Science and Technology Education*, *5*(3), 235–245. https://doi.org/10.12973/EJMSTE/75275

Brata, A. H., & Amalia, F. (2018). Impact analysis of social influence factor on using free blogs as learning media for driving teaching motivational factor. *ACM International Conference Proceeding Series*, 29–33. https://doi.org/10.1145/3233347.3233360

Brown, S., Dennis, A., & Venkatesh, V. (2010). Predicting collaboration technology use: integrating technology adoption and collaboration research. *Journal of Management Information Systems*, *27*(2), 9–54. https://doi.org/10.2753/MIS0742-1222270201

Chang, C. Y., Hwang, G. J., & Gau, M. L. (2022). Promoting students' learning achievement and self-efficacy: A mobile chatbot approach for nursing training. *British Journal of Educational Technology*, *53*(1), 171–188. https://doi.org/10.1111/BJET.13158

Changalima, I. A., Amani, D., & Ismail, I. J. (2024). Social influence and information quality on Generative AI use among business students. *The International Journal of Management Education*, *22*(3), 101063. https://doi.org/10.1016/J.IJME.2024.101063

Chatterjee, S., & Bhattacharjee, K. K. (2020). Adoption of artificial intelligence in higher education: a quantitative analysis using structural equation modelling. *Education and*

Information Technologies, *25*(5), 3443–3463. https://doi.org/10.1007/S10639-020-10159-7

Chatterjee, S., Nguyen, B., Ghosh, S. K., Bhattacharjee, K. K., & Chaudhuri, S. (2020). Adoption of artificial intelligence integrated CRM system: an empirical study of Indian organizations. *Bottom Line*, *33*(4), 359–375. https://doi.org/10.1108/BL-08-2020-0057

Chatterjee, S., Rana, N. P., Dwivedi, Y. K., & Baabdullah, A. M. (2021). Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model. *Technological Forecasting and Social Change*, *170*, Article 120880. https://doi.org/10.1016/J.TECHFORE.2021.120880

Chen, C.-C., Liu, C.-C., Chiu, T.-H., Lee, Y.-W., & Wu, K.-C. (2023). Role of perceived ease of use for augmented reality app designed to help children navigate smart libraries. *International Journal of Human-Computer Interaction*, *39*(13), 2606–2623. https://doi.org/10.1080/10447318.2022.2082017

Chen, Y, Li, C., Cao, L., & Liu, S. (2024). The effects of self-efficacy, academic stress, and learning behaviors on self-regulated learning in blended learning among middle school students. *Education and Information Technologies, 29,* 24087–24110. https://doi.org/10.1007/s10639-024-12821-w

Chen, Yu, Jensen, S., Albert, L. J., Gupta, S., & Lee, T. (2023). Artificial Intelligence (AI) student assistants in the classroom: Designing chatbots to support student success. *Information Systems Frontiers*, *25*(1), 161–182. https://doi.org/10.1007/S10796-022-10291-4

Choung, H., David, P., & Ross, A. (2023). Trust and ethics in AI. *AI and Society*, *38*(2), 733–745. https://doi.org/10.1007/S00146-022-01473-4

Christopher Westland, J. (2010). Lower bounds on sample size in structural equation modeling. *Electronic Commerce Research and Applications*, *9*(6), 476–487. https://doi.org/10.1016/J.ELERAP.2010.07.003

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly: Management Information Systems*, *13*(3), 319–339. https://doi.org/10.2307/249008

Desmira, Bakar, N. A., Hashim, M. R., Wiryadinata, R., & Hamid, M. A. (2022). Laboratory prediction energy control system based on artificial intelligence network. *Bulletin of Electrical Engineering and Informatics*, *11*(3), 1280–1288. https://doi.org/10.11591/EEI.V11I3.1821

Desmira, D., Hamid, M. A., Bakar, N. A., Nurtanto, M., & Sunardi, S. (2022). A smart traffic light using a microcontroller based on the fuzzy logic. *IAES International Journal of Artificial Intelligence*, *11*(3), 809–818. https://doi.org/10.11591/ijai.v11.i3.

Duenser, A, & Douglas, D. M. (2023). Whom to trust, how and why: Untangling artificial intelligence ethics principles, trustworthiness, and trust. *IEEE Intelligent Systems*, *38*(6), 19–26. https://doi.org/10.1109/MIS.2023.3322586

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., … Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, *57*, Article 101994. https://doi.org/10.1016/J.IJINFOMGT.2019.08.002

Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., & Williams, M. D. (2019). Re-examining the Unified Theory of Acceptance and Use of Technology (UTAUT): Towards a revised theoretical model. *Information Systems Frontiers*, *21*(3), 719–734. https://doi.org/10.1007/S10796-017-9774-Y

Ebadi, S., & Raygan, A. (2023). Investigating the facilitating conditions, perceived ease of use and usefulness of mobile-assisted language learning. *Smart Learning Environments*, *10*(1), 1–15. https://doi.org/10.1186/S40561-023-00250-0

El-Sofany, H.F. & El-Haggar, N. (2020). The effectiveness of using mobile learning techniques to improve learning outcomes in higher education. *International Journal of Interactive Mobile Technologies, 14*(8), 4-18. https://doi.org/10.3991/ijim.v14i08.13125

Emaminejad, N., Kath, L., & Akhavian, R. (2024). Assessing trust in construction AI-powered collaborative robots using structural equation modeling. *Journal of Computing in Civil Engineering*, *38*(3), Article 04024011. https://doi.org/10.1061/JCCEE5.CPENG-5660

Eslit, E. R. (2023). Blending boundaries in the new normal: Leveraging technology, AI and global perspectives in modern education. *Journal of Learning and Educational Policy*, *4(1)*, 8–18. https://doi.org/10.55529/jlep.41.8.18

Findik-Coşkunçay, D., Alkiş, N., & Özkan-Yildirim, S. (2018). A structural model for students' adoption of learning management systems: An empirical investigation in the higher education context. *Educational Technology & Society*, *21(2)*, 13–27. https://drive.google.com/file/d/1-KuZ-RQy9nmiN2tGYZc7r23K853GjQOR/view

Fine, A., & Marsh, S. (2024). Judicial leadership matters (yet again): The association between judge and public trust for artificial intelligence in courts. *Discover Artificial Intelligence*, *4*, Article 44. https://doi.org/10.1007/S44163-024-00142-3

Fuchs, K. (2022). An interview study to explore the perceived usefulness of in-house training programs in tourism and hospitality education. *Heliyon*, *8*(12), Article e12547. https://doi.org/10.1016/j.heliyon.2022.e12547

Galos, S., & Aldridge, J. M. (2021). Relationships between learning environments and self-efficacy in primary schools and differing perceptions of at-risk students. *Learning Environments Research*, *24*(2), 253–268. https://doi.org/10.1007/s10984-020-09323-0

Garbuio, M., & Lin, N. (2021). Innovative idea generation in problem finding: Abductive reasoning, cognitive impediments, and the promise of artificial intelligence. *Journal of Product Innovation Management*, *38*(6), 701–725. https://doi.org/10.1111/JPIM.12602

Gefen, D., Straub, D. W., & Straub Mack Robinson, D. J. (2000). The relative importance of perceived ease of use in IS adoption: A study of e-commerce adoption. *Journal of the Association for Information Systems*, *1*(1), Article 8. https://doi.org/10.17705/1jais.00008

George, B., & Wooden, O. S. (2023). Managing the strategic transformation of higher education through artificial intelligence. *Administrative Sciences*, *13*(9), Article 196. https://doi.org/10.3390/admsci13090196

Ghobakhloo, M., Hong, T. S., Sabouri, M. S., & Zulkifli, N. (2012). Strategies for successful information technology adoption in small and medium-sized enterprises. *Information, 3*(1), 36–67. https://doi.org/10.3390/INFO3010036

Gist, M. E., & Mitchell, T. R. (1992). Self-efficacy: A theoretical analysis of its determinants and malleability. *The Academy of Management Review, 17*(2), 183–211. https://doi.org/10.2307/258770

Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals*, *14*(2), 627–660. https://doi.org/10.5465/ANNALS.2018.0057

Habbal, A., Ali, M. K., & Abuzaraida, M. A. (2024). Artificial Intelligence Trust, Risk and Security Management (AI TRiSM): Frameworks, applications, challenges and future research directions. *Expert Systems with Applications*, *240*, Article 122442. https://doi.org/10.1016/J.ESWA.2023.122442

Hamid, M. A., Nurtanto, M., Desmira, D., Setiawan, D., Hakiki, M., & Fadli, R. (2024). Technological support to foster students' learning experience in electrical measurement class: A mobile learning-based hypermedia approach. *2024 International Conference on TVET Excellence and Development, ICTeD 2024*, 177–182. https://doi.org/10.1109/ICTED62334.2024.10844631

Haresamudram, K., Larsson, S., & Heintz, F. (2023). Three levels of AI transparency. *Computer*, *56*(2), 93–100. https://doi.org/10.1109/MC.2022.3213181

Harrison, T. M., & Luna-Reyes, L. F. (2020). Cultivating trustworthy artificial intelligence in digital government. *Social Science Computer Review, 40*(2), 494–511. https://doi.org/10.1177/0894439320980122

Hazaimeh, M., & Al-Ansi, A. M. (2024). Model of AI acceptance in higher education: Arguing teaching staff and students perspectives. *International Journal of Information and Learning Technology*, *41*(4), 371–393. https://doi.org/10.1108/ijilt-01-2024-0005

Hsu, C. L., & Lin, J. C. C. (2008). Acceptance of blog usage: The roles of technology acceptance, social influence and knowledge sharing motivation. *Information & Management*, *45*(1), 65–74. https://doi.org/10.1016/J.IM.2007.11.001

Hu, Y. (2022). Application of artificial intelligence technology and blockchain technology in vocational education. *ICBDE '22: Proceedings of the 5th International Conference on Big Data and Education,* 15–21. https://doi.org/10.1145/3524383.3524400

Hua, C., Cole, S., & Xu, N. (2021). Rethinking trust in tourism apps: the moderating effect of age. *Journal of Hospitality and Tourism Technology*, *12*(3), 548–562. https://doi.org/10.1108/JHTT-01-2020-0013

Huang, F., Teo, T., & Scherer, R. (2022). Investigating the antecedents of university students' perceived ease of using the Internet for learning. *Interactive Learning Environments*, *30*(6), 1060–1076. https://doi.org/10.1080/10494820.2019.1710540

Huffman, A. H., Whetten, J., & Huffman, W. H. (2013). Using technology in higher education: The influence of gender roles on technology self-efficacy. *Computers in Human Behavior*, *29*(4), 1779–1786. https://doi.org/10.1016/J.CHB.2013.02.012

Hwang, G. J., Tu, Y. F., & Tang, K. Y. (2022). AI in online-learning research: Visualizing and interpreting the journal publications from 1997 to 2019. *International Review of Research in Open and Distance Learning*, *23*(1), 104–130. https://doi.org/10.19173/IRRODL.V23I1.6319

Hwang, J. S., & Lee, H. J. (2018). A meta-analysis of advanced UTAUT variables in the ICT industry: An analysis of published papers in Korean journals. *International Journal of Innovative Computing, Information and Control*, *14*(2), 757–766. http://www.ijicic.org/ijicic-140227.pdf

Jaipal-Jamani, K. (2017). Effect of robotics on elementary preservice teachers' self-efficacy, science learning, and computational thinking. *Journal of Science Education and Technology*, *26*(2), 175–192. https://doi.org/10.1007/s10956-016-9663-z

Johnson, N., Seaman, J., & Seaman, J. (2024). The anticipated impact of artificial intelligence on US higher education: A national study. *Online Learning*, *28*(3), 9–33. https://doi.org/10.24059/OLJ.V28I3.4646

Joo, Y. J., Park, S., & Lim, E. (2018). Factors influencing preservice teachers' intention to use technology: TPACK, teacher self-efficacy, and technology acceptance model. *Educational Technology and Society*, *21*(3), 48–59. https://drive.google.com/file/d/1eJTooAlLhS_Dafxktrxjo9wu6Gk48ILP/view

Kandoth, S., & Shekhar, S. K. (2022). Social influence and intention to use AI: The role of personal innovativeness and perceived trust using the parallel mediation model.

Forum Scientiae Oeconomia, *10*(3), 131-150. https://doi.org/10.23762/FSO_VOL10_NO3_7

Kanwal, F., & Rehman, M. (2017). Factors affecting e-learning adoption in developing countries-empirical evidence from Pakistan's higher education sector. *IEEE Access*, *5*, 10968–10978. https://doi.org/10.1109/ACCESS.2017.2714379

Karataş, F., & Yüce, E. (2024). AI and the future of teaching: Preservice teachers' reflections on the use of artificial intelligence in open and distributed learning. *International Review of Research in Open and Distributed Learning*, *25*(3 Special Issue), 304–325. https://doi.org/10.19173/irrodl.v25i3.7785

Kashive, N., Powale, L., & Kashive, K. (2021). Understanding user perception toward artificial intelligence (AI) enabled e-learning. *International Journal of Information and Learning Technology*, *38*(1), 1–19. https://doi.org/10.1108/IJILT-05-2020-0090

Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., … Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences*, *103*. Article 102274. https://doi.org/10.1016/j.lindif.2023.102274

Kasri, R. A., & Sosianti, M. W. (2023). Determinants of the intention to pay zakat online: the case of Indonesia. *Journal of Islamic Monetary Economics and Finance*, *9*(2), 275–294. https://doi.org/10.21098/JIMF.V9I2.1664

Khechine, H., Raymond, B., & Augier, M. (2020). The adoption of a social learning system: Intrinsic value in the UTAUT model. *British Journal of Educational Technology*, *51*(6), 2306–2325. https://doi.org/10.1111/BJET.12905

Kholifah, N., Nurtanto, M., Kassymova, G. K., Subakti, H., & Hamid, M. A. (2024). Evidence of positive influence: soft skills competence and organizational culture on innovative work behavior. *Journal of Education and Learning (EduLearn)*, *18*(4), 1158–1165. https://doi.org/10.11591/EDULEARN.V18I4.21018

Kholifah, N., Nurtanto, M., Mutohhari, F., Hamid, M. A., Mutiara, I., Setiawan, D., & Saputro, I. N. (2025). Factors influencing student career choice in vocational education in Indonesia: A mediating effect of self-efficacy. *Social Sciences & Humanities Open*, *11*, Article 101369. https://doi.org/10.1016/J.SSAHO.2025.101369

Kivijärvi, H., Leppänen, A., & Hallikainen, P. (2013). Technology trust: From antecedents to perceived performance effects. *Proceedings of the Annual Hawaii International Conference on System Sciences*, 4586–4595. https://doi.org/10.1109/HICSS.2013.510

Kuleto, V., Ilić, M., Dumangiu, M., Ranković, M., Martins, O. M. D., Păun, D., & Mihoreanu, L. (2021). Exploring opportunities and challenges of artificial intelligence and machine learning in higher education institutions. *Sustainability*, *13*(18), Article 10424. https://doi.org/10.3390/SU131810424

Kulviwat, S., Bruner, G. C., & Neelankavil, J. P. (2014). Self-efficacy as an antecedent of cognition and affect in technology acceptance. *Journal of Consumer Marketing*, *31*(3), 190–199. https://doi.org/10.1108/JCM-10-2013-0727

Kumar, S., Gunn, A., Rose, R., Pollard, R., Johnson, M., & Ritzhaupt, A. D. (2024). The role of instructional designers in the integration of generative artificial intelligence in online and blended learning in higher education. *Online Learning*, *28*(3), 207–231. https://doi.org/10.24059/OLJ.V28I3.4501

Lalot, F., & Bertram, A. M. (2024). When the bot walks the talk: investigating the foundations of trust in an Artificial Intelligence (AI) Chatbot. *Journal of Experimental Psychology: General*, *154*(2), 533–551. https://doi.org/10.1037/XGE0001696

Lankton, N. K., Harrison Mcknight, D., & Tripp, J. (2015). Technology, humanness, and trust: Rethinking trust in technology. *Journal of the Association for Information Systems*, *16*(10), Article 1. https://doi.org/10.17705/1jais.00411

Lee, C., & Cha, K. (2024). Toward the dynamic relationship between AI transparency and trust in AI: A case study on ChatGPT. *International Journal of Human-Computer Interaction,* 1-18. https://doi.org/10.1080/10447318.2024.2405266

Lee, S. S., & Moore, R. L. (2024). Harnessing Generative AI (GenAI) for automated feedback in higher education: A systematic review. *Online Learning*, *28*(3), 82–104. https://doi.org/10.24059/OLJ.V28I3.4593

Li, Y., Garza, V., Keicher, A., & Popov, V. (2019). Predicting high school teacher use of technology: Pedagogical beliefs, technological beliefs and attitudes, and teacher training. *Technology, Knowledge and Learning*, *24*(3), 501–518. https://doi.org/10.1007/s10758-018-9355-2

Lian, J. (2019). Investigating Chinese university EFL learners' self-efficacy in a blended learning environment. *International Conference on Computers in Education,* 650–655. https://doi.org/10.58459/icce.2019.639

Lowry, P. B., & Gaskin, J. (2014). Partial least squares (PLS) structural equation modeling (SEM) for building and testing behavioral causal theory: When to choose it and how to use it. *IEEE Transactions on Professional Communication*, *57*(2), 123–146. https://doi.org/10.1109/TPC.2014.2312452

Luan, H., Geczy, P., Lai, H., Gobert, J., Yang, S. J. H., Ogata, H., Baltes, J., Guerra, R., Li, P., & Tsai, C. C. (2020). Challenges and future directions of big data and artificial intelligence in education. *Frontiers in Psychology*, *11*, Article 580820. https://doi.org/10.3389/FPSYG.2020.580820

Ma, Q., & Liu, L. (2005). The role of internet self-efficacy in the acceptance of web-based electronic medical records. *Journal of Organizational and End User Computing*, *17*(1), 38–57. https://doi.org/10.4018/joeuc.2005010103

Marangunić, N., & Granić, A. (2015). Technology acceptance model: A literature review from 1986 to 2013. *Universal Access in the Information Society*, *14*(1), 81–95. https://doi.org/10.1007/S10209-014-0348-1

Menekse, M. (2023). Envisioning the future of learning and teaching engineering in the artificial intelligence era: Opportunities and challenges. *Journal of Engineering Education*, *112*(3), 578. https://doi.org/10.1002/JEE.20539

Mishra, A., Shukla, A., Rana, N. P., Currie, W. L., & Dwivedi, Y. K. (2023). Re-examining post-acceptance model of information systems continuance: A revised theoretical model using MASEM approach. *International Journal of Information Management*, *68*, Article 102571. https://doi.org/10.1016/J.IJINFOMGT.2022.102571

Mohd Rahim, N. I., A. Iahad, N., Yusof, A. F., & A. Al-Sharafi, M. (2022). AI-based chatbots adoption model for higher-education institutions: A hybrid PLS-SEM-neural network modelling approach. *Sustainability, 14*(19), Article 12726. https://doi.org/10.3390/SU141912726

Mylrea, M., & Robinson, N. (2023). Artificial Intelligence (AI) trust framework and maturity model: Applying an entropy lens to improve security, privacy, and ethical AI. *Entropy*, *25*(10), Article 1429. https://doi.org/10.3390/e25101429

Nagaraj, B. K., Kalaivani, A., Begum, R. S., Akila, S., Sachdev, H. K., & Kumar, N. S. (2023). The emerging role of artificial intelligence in STEM higher education: A critical review. *International Research Journal of Multidisciplinary Technovation*, *5*(5), 1–19. https://doi.org/10.54392/irjmt2351

Nallaperuma, D., Nawaratne, R., Bandaragoda, T., Adikari, A., Nguyen, S., Kempitiya, T., De Silva, D., Alahakoon, D., & Pothuhera, D. (2019). Online incremental machine learning platform for big data-driven smart traffic management. *IEEE Transactions on Intelligent Transportation Systems*, *20*(12), 4679–4690. https://doi.org/10.1109/TITS.2019.2924883

Neyazi, T. A., Khai Ee, T., Nadaf, A., & Schroeder, R. (2023). The effect of information seeking behaviour on trust in AI in Asia: The moderating role of misinformation concern. *New Media and Society*, *27*(4), 2414-2433. https://doi.org/10.1177/14614448231212804

Nuhoğlu, H., Şahin Sarkin, D. B., & Aşiroğlu, S. (2024). Digital transformation in science education: Teachers' self-efficacy of distance learning and blended learning experiences. *Participatory Educational Research*, *11*(3), 126–145. https://doi.org/10.17275/per.24.38.11.3

Ofosu-ampong, K., Acheampong, B., & Kevor, M. (2023). Acceptance of artificial intelligence (ChatGPT) in education: Trust, innovativeness and psychological need of students. *Information and Knowledge Management*, *13*(4), 37–47. https://doi.org/10.7176/ikm/13-4-03

Omrani, N., Rivieccio, G., Fiore, U., Schiavone, F., & Agreda, S. G. (2022). To trust or not to trust? An assessment of trust in AI-based systems: Concerns, ethics and contexts.

Technological Forecasting and Social Change, *181*, Article 121763. https://doi.org/10.1016/J.TECHFORE.2022.121763

Ou, Y. (2024). Strategies for applying BOPPPS model supported by intelligent algorithms in blended teaching of college English. *Applied Mathematics and Nonlinear Sciences*, *9*(1), 1-18. https://doi.org/10.2478/amns-2024-1719

Ounejjar, L. A., Lachgar, M., Ouhayou, O., Laanaoui, M. D., Refki, E., Makaoui, R., & Saoud, A. (2024). SmartBlendEd: Enhancing blended learning through AI-optimized scheduling and user-centric design. *SoftwareX*, *27*. https://doi.org/10.1016/j.softx.2024.101891

Paliszkiewicz, J., & Gołuchowski, J. (Eds.). (2024). *Trust and artificial intelligence: Development and application of AI technology*. Routledge. https://doi.org/10.4324/9781032627236

Pan, X. (2020). Technology acceptance, technological self-efficacy, and attitude toward technology-based self-directed learning: Learning motivation as a mediator. *Frontiers in Psychology*, *11*, Article 564294. https://doi.org/10.3389/FPSYG.2020.564294

Park, Y. (2024). Role of AI in blended learning: A systematic literature review. *The International Review of Research in Open and Distributed Learning*, *25*(1), 164–196. https://doi.org/10.19173/irrodl.v25i1.7566

Peres, R. S., Jia, X., Lee, J., Sun, K., Colombo, A. W., & Barata, J. (2020). Industrial artificial intelligence in industry 4.0 - Systematic review, challenges and outlook. *IEEE Access*, *8*, 220121–220139. https://doi.org/10.1109/ACCESS.2020.3042874

Qin, F., Li, K., & Yan, J. (2020). Understanding user trust in artificial intelligence-based educational systems: Evidence from China. *British Journal of Educational Technology*, *51*(5), 1693–1710. https://doi.org/10.1111/BJET.12994

Queiroz, M. M., & Fosso Wamba, S. (2019). Blockchain adoption challenges in supply chain: An empirical investigation of the main drivers in India and the USA. *International Journal of Information Management*, *46*, 70–82. https://doi.org/10.1016/J.IJINFOMGT.2018.11.021

Rafique, H., Almagrabi, A. O., Shamim, A., Anwar, F., & Bashir, A. K. (2020). Investigating the acceptance of mobile library applications with an Extended Technology Acceptance Model (TAM). *Computers & Education*, *145*, Article 103732. https://doi.org/10.1016/J.COMPEDU.2019.103732

Rayyan, M., Abusalim, N., Alshanmy, S., Awwad, F. M. A., & Alghazo, S. (2024). Enhancing academic performance through blended learning: A study on the relationship between self-efficacy and student success. *International Journal of Interactive Mobile Technologies*, *18*(19), 52–67. https://doi.org/10.3991/ijim.v18i19.49835

Rehman, N., Huang, X., Sarwar, U., Fatima, H., & Maqbool, S. (2024). Exploring the impact of family, school and society on the perception and reputation of vocational training in Pakistan: A statistical analysis. *Education and Training*. Advance online publication. https://doi.org/10.1108/ET-09-2023-0375

Riva, P., Aureli, N., & Silvestrini, F. (2022). Social influences in the digital era: When do people conform more to a human being or an artificial intelligence? *Acta Psychologica*, *229*, Article 103681. https://doi.org/10.1016/J.ACTPSY.2022.103681

Roshanaei, M. (2023). Harnessing AI to foster equity in education: Opportunities, challenges, and emerging strategies. *Journal of Intelligent Learning Systems and Applications*, *15*(4), 123–143. https://doi.org/10.4236/jilsa.2023.154009

Rubiyanti, N., Abu Sujak, A. F., Madiawati, P. N., Nurutami, F., & Bt Raja Razali, R. R. (2023). Perceived usefulness: A bibliometric visualization. *2023 International Conference on Digital Business and Technology Management (ICONDBTM),* 1-6. https://doi.org/10.1109/ICONDBTM59210.2023.10327098

Sabetzadeh, F., & Chen, Y. (2023). An investigation of the impact of interpersonal and institutional trust on knowledge sharing in companies: Invisible hands for knowledge sharing. *VINE Journal of Information and Knowledge Management Systems, 55*(2), 327-350. https://doi.org/10.1108/VJIKMS-06-2022-0206

Salhab, R. (2024). AI literacy across curriculum design: Investigating college instructor's perspectives. *Online Learning*, *28*(2), 22–47. https://doi.org/10.24059/OLJ.V28I2.4426

Salim, M., Alfansi, L., Anggarawati, S., Saputra, F. E., & Afandy, C. (2021). The role of perceived usefulness in moderating the relationship between the Delone and Mclean model and user satisfaction. *Uncertain Supply Chain Management*, *9*(3), 755–766. https://doi.org/10.5267/j.uscm.2021.4.002

Samala, A. D., Zhai, X., Aoki, K., Bojic, L., & Zikic, S. (2024). An in-depth review of ChatGPT's pros and cons for learning and teaching in education. *International Journal of Interactive Mobile Technologies*, *18*(2), 96–117. https://doi.org/10.3991/IJIM.V18I02.46509

Sarstedt, M., Ringle, C. M., Smith, D., Reams, R., & Hair, J. F. (2014). Partial least squares structural equation modeling (PLS-SEM): A useful tool for family business researchers. *Journal of Family Business Strategy*, *5*(1), 105–115. https://doi.org/10.1016/J.JFBS.2014.01.002

Sriwindono, H., & Yahya, S. (2012). The effects of cultural dimension on MIS acceptance. *IEEE 6th International Conference on Management of Innovation and Technology (ICMIT)*, 424–429. https://doi.org/10.1109/ICMIT.2012.6225843

Stewart, B. J., Park, S., & Ju, B. (2024). Social influence, trust and future usage: A study of BIPOC Users of ChatGPT and other AI chatbots. *Proceedings of the Association for Information Science and Technology*, *61*(1), 1083–1085. https://doi.org/10.1002/PRA2.1192

Straub, E. T. (2009). Understanding technology adoption: Theory and future directions for informal learning. *Review of Educational Research*, *79*(2), 625–649. https://doi.org/10.3102/0034654308325896

Šumak, B., Heričko, M., & Pušnik, M. (2011). A meta-analysis of e-learning technology acceptance: The role of user types and e-learning technology types. *Computers in Human Behavior*, *27*(6), 2067–2077. https://doi.org/10.1016/J.CHB.2011.08.005

Surdjono, H. D., Fadli, R., Sari, R. C., Eliza, F., Yassin, A., Kulanthaivel, G., Ramadhan, M. A., Mukhaiyar, R., Hamid, M. A., Ridwan, M. R., Purnomo, S., & Asnimawati. (2025). Effectiveness of cybersecurity awareness program based on mobile learning to improve cyber hygiene. *International Journal of Information and Education Technology*, *15*(2), 220–229. https://doi.org/10.18178/IJIET.2025.15.2.2235

Swindell, A. (2024). Against artificial education: Towards an ethical framework for generative Artificial Intelligence (AI) use in education. *Online Learning*, *28*(2). https://doi.org/10.24059/olj.v28i2.4438

Taherdoost, H. (2018). Development of an adoption model to assess user acceptance of e-service technology: E-Service Technology Acceptance Model. *Behaviour & Information Technology*, *37*(2), 173–197. https://doi.org/10.1080/0144929X.2018.1427793

Tang, K. Y., Chang, C. Y., & Hwang, G. J. (2021). Trends in artificial intelligence-supported e-learning: A systematic review and co-citation network analysis (1998–2019). *Interactive Learning Environments, 31*(4), 2134–2152. https://doi.org/10.1080/10494820.2021.1875001

Tlili, A., Shehata, B., Adarkwah, M. A., Bozkurt, A., Hickey, D. T., Huang, R., & Agyemang, B. (2023). What if the devil is my guardian angel: ChatGPT as a case study of using chatbots in education. *Smart Learning Environments*, *10,* Article 15. https://doi.org/10.1186/s40561-023-00237-x

Tondeur, J., van Braak, J., Ertmer, P. A., & Ottenbreit-Leftwich, A. (2017). Understanding the relationship between teachers' pedagogical beliefs and technology use in education: A systematic review of qualitative evidence. *Educational Technology Research and Development*, *65*(3), 555–575. https://doi.org/10.1007/S11423-016-9481-2

Tucci, V., Saary, J., & Doyle, T. E. (2022). Factors influencing trust in medical artificial intelligence for healthcare professionals: A narrative review. *Journal of Medical Artificial Intelligence*, *5*, Article 4. https://doi.org/10.21037/JMAI-21-25

Velezmoro-Abanto, L., Cuba-Lagos, R., Taico-Valverde, B., Iparraguirre-Villanueva, O., & Cabanillas-Carbonell, M. (2024). Lean construction strategies supported by artificial intelligence techniques for construction project management—A review. *International Journal of Online and Biomedical Engineering*, *20*(3), 99–114. https://doi.org/10.3991/IJOE.V20I03.46769

Velli, K., & Zafiropoulos, K. (2024). Factors that affect the acceptance of educational AI tools by Greek Teachers—A structural equation modelling study. *European Journal of Investigation in Health, Psychology and Education*, *14*(9), 2560–2579. https://doi.org/10.3390/EJIHPE14090169

Verganti, R., Vendraminelli, L., & Iansiti, M. (2020). Innovation and design in the age of artificial intelligence. *Journal of Product Innovation Management*, *37*(3), 212–227. https://doi.org/10.1111/JPIM.12523

Wang, Q., & Rao, Y. (2024). Research on the enhancement of digital capabilities in AI-based blended teaching processes. *ICCMT '24: Proceedings of the 2024 International Conference on Computer and Multimedia Technology,* 330–336. https://doi.org/10.1145/3675249.3675308

Wang, X., Lu, A., Lin, T., Liu, S., Song, T., Huang, X., & Jiang, L. (2022). Perceived usefulness predicts second language learners' continuance intention toward language learning applications: A serial multiple mediation model of integrative motivation and flow. *Education and Information Technologies*, *27*(4), 5033–5049. https://doi.org/10.1007/s10639-021-10822-7

Willaby, H. W., Costa, D. S. J., Burns, B. D., MacCann, C., & Roberts, R. D. (2015). Testing complex models with small sample sizes: A historical overview and empirical demonstration of what Partial Least Squares (PLS) can offer differential psychology. *Personality and Individual Differences*, *84*, 73–78. https://doi.org/10.1016/J.PAID.2014.09.008

Wilson, K., & Narayan, A. (2016). Relationships among individual task self-efficacy, self-regulated learning strategy use and academic performance in a computer-supported collaborative learning environment. *Educational Psychology*, *36*(2), 236–253. https://doi.org/10.1080/01443410.2014.926312

Wu, D., Li, C.-C., Zhou, W.-T., Tsai, C.-C., & Lu, C. (2019). Relationship between ICT supporting conditions and ICT application in Chinese urban and rural basic education. *Asia Pacific Education Review*, *20*(1), 147–157. https://doi.org/10.1007/s12564-018-9568-z

Wu, K., Zhao, Y., Zhu, Q., Tan, X., & Zheng, H. (2011). A meta-analysis of the impact of trust on technology acceptance model: Investigation of moderating influence of subject and context type. *International Journal of Information Management*, *31*(6), 572–581. https://doi.org/10.1016/J.IJINFOMGT.2011.03.004

Wu, W., Zhang, B., Li, S., & Liu, H. (2022). Exploring factors of the willingness to accept AI-assisted learning environments: An empirical investigation based on the UTAUT Model and perceived risk theory. *Frontiers in Psychology*, *13*, Article 870777. https://doi.org/10.3389/FPSYG.2022.870777

Wu, Y., Kim, K. J., & Mou, Y. (2022). Minority social influence and moral decision-making in human–AI interaction: The effects of identity and specialization cues. *New Media and Society*, *26*(10), 5619-5637. https://doi.org/10.1177/14614448221138072

Xiang, J., & Ma, C. (2023). Modeling the effectiveness of blended learning promotion with artificial intelligence adaptive learning system. *Journal of Logistics, Informatics and Service Science*, *10*(3), 88–97. https://doi.org/10.33168/JLISS.2023.0307

Xie, Z. (2019). Bridging MOOC education and information sciences: Empirical studies. *IEEE Access*, *7*, 74206–74216. https://doi.org/10.1109/ACCESS.2019.2921009

Xue, L., Rashid, A. M., & Ouyang, S. (2024). The Unified Theory of Acceptance and Use of Technology (UTAUT) in higher education: A systematic review. *SAGE Open*, *14*(1). https://doi.org/10.1177/21582440241229570

Yang, Y.-F., Tseng, C. C., & Lai, S.-C. (2024). Enhancing teachers' self-efficacy beliefs in AI-based technology integration into English speaking teaching through a professional development program. *Teaching and Teacher Education*, *144,* Article 104582. https://doi.org/10.1016/j.tate.2024.104582

Yao, S., Xie, L., Chen, Y., Zhang, Y., Chen, Y., & Gao, M. (2023). Influence of perceived safety in the technology acceptance model. *Transportation Research Part F: Traffic Psychology and Behaviour*, *99*, 36–51. https://doi.org/10.1016/J.TRF.2023.10.010

Yildiz Durak, H. (2019). Examining the acceptance and use of online social networks by preservice teachers within the context of unified theory of acceptance and use of technology model. *Journal of Computing in Higher Education*, *31*(1), 173–209. https://doi.org/10.1007/S12528-018-9200-6

Yokoyama, S. (2024). Impact of academic self-efficacy on online learning outcomes: A recent literature review. *EXCLI Journal*, *23*, 960–966. https://doi.org/10.17179/excli2024-7502

Zahidi, S. (2023). *Future of Jobs Report 2023*. World Economic Forum. https://www3.weforum.org/docs/WEF_Future_of_Jobs_2023.pdf

Zhao, X., & Yang, Y. (2021). A study on the application of blended teaching to English Reading Course under the background of artificial intelligence. *IOP Conference Series: Earth and Environmental Science*, *693*(1), Article 012019. https://doi.org/10.1088/1755-1315/693/1/012019

Zhao, Y., Wang, N., Li, Y., Zhou, R., & Li, S. (2021). Do cultural differences affect users' e-learning adoption? A meta-analysis. *British Journal of Educational Technology*, *52*(1), 20–41. https://doi.org/10.1111/BJET.13002

Zheng, G. (2020). The optimization and application of blended teaching based on artificial intelligence. *Proceedings 2020 3rd International Conference on Advanced Electronic Materials, Computers and Software Engineering (AEMCSE),* 71–74. https://doi.org/10.1109/AEMCSE50948.2020.00023