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UNDERSTANDING TEACHERS' ADOPTION OF AI: INSIGHTS FROM INNOVATION DIFFUSION AND SOCIAL COGNITIVE THEORIES

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ABSTRACT

Aim/Purpose	This study investigates the personal and contextual factors that influence teachers' behavioral adoption of artificial intelligence (AI) in educational settings by integrating innovation diffusion theory (IDT) and social cognitive theory (SCT). Specifically, the study investigates how teachers' perceptions of AI (relative advantage, compatibility, trialability/observability), cognitive beliefs, and environmental support shape their intention and behavior toward adopting AI tools. The study also explores the moderating role of environmental support and the mediating role of cognitive beliefs within this adoption process.
Background	AI technologies offer significant potential to transform education, but their successful adoption in education depends on teachers' intention and willingness to utilize them. This study provides an understanding of teachers' AI adoption behaviors in the UAE, a country that aims for AI-driven educational transformation.
Methodology	Using a quantitative cross-sectional design, data were collected from 249 teachers across multiple educational levels. A validated survey was used, and data analysis involved hierarchical multiple regression, structural equation modeling (SEM), and moderation and mediation analyses using SPSS and SmartPLS.

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Contribution	Unlike prior studies, this research uniquely integrates IDT and SCT in the context of K–12 education in the UAE. These results highlight the need for multidimensional strategies that combine institutional support, experiential learning opportunities, and cognitive engagement to promote effective AI integration in education. The study contributes to theory by demonstrating the value of an integrated IDT-SCT framework and offers actionable insights for educational leaders, policymakers, and professional development designers.
Findings	The findings indicate that relative advantage and trialability/observability are the strongest predictors of behavioral adoption, while cognitive beliefs and environmental support also play significant and complementary roles. Furthermore, environmental support moderates the influence of compatibility and trialability/observability on adoption, and cognitive beliefs mediate the effects of relative advantage and compatibility.
Recommendations for Practitioners	Educational leaders should provide strong institutional support, hands-on opportunities to trial AI tools, and training that fosters positive cognitive beliefs to facilitate effective AI adoption.
Recommendations for Researchers	Future studies should explore longitudinal studies, contextual influences such as institutional culture, and cross-cultural differences to deepen understanding of AI integration in education.
Impact on Society	This study fills a critical gap by integrating IDT and SCT to explain teachers' adoption of AI in K–12 education in the UAE, a context that has received limited prior attention. The findings inform efforts to promote equitable and effective integration of AI in education, aligned with sustainable development goals and national innovation strategies. This contributes to the development of future-ready education systems that prepare students for the demands of a digital and AI-driven world.
Future Research	Future research should investigate how teachers' adoption of AI changes longitudinally and across different educational levels and contexts. Studies could explore the impact of AI literacy initiatives, leadership styles, and institutional culture on adoption behaviors.

Keywords	artificial intelligence adoption, innovation diffusion theory, social cognitive theory, teacher professional development, educational technology integration

INTRODUCTION

Artificial intelligence (AI) in education is transforming the way teaching and learning occur, offering innovative ways to address challenges across various levels, from K-12 to higher education (Akgun & Greenhow, 2021; Chatwal et al., 2023). AI applications in education have the potential to enhance student engagement, improve learning outcomes, and increase efficiency in educational processes. For instance, AI-driven adaptive learning systems or personalized learning platforms can tailor instruction to individual students' needs, abilities, and learning styles, potentially addressing issues of academic inequality (Ansor et al., 2023; Katiyar et al., 2024). Additionally, it supports educators in various areas, including automated assessment systems, virtual tutoring, and administrative tasks (Akgun & Greenhow, 2021; Chatwal et al., 2023). However, the rapid advancement of AI in education also raises important ethical considerations and challenges. Issues such as data privacy, algorithmic bias, and the potential for over-reliance on technology need to be carefully addressed (Akgun &

Greenhow, 2021; Dimeli & Kostas, 2025; Zhou et al., 2024). Furthermore, there is a need for educators and institutions to develop technological leadership and prepare for the increasing presence of AI in educational settings (Pham & Sampson, 2022).

It became increasingly important for teachers to understand the adoption of AI technologies in education. For instance, open educational resources offer teachers free access to high-quality materials; however, adopting these materials remains a challenge due to the difficulty in finding relevant, up-to-date, and high-quality resources, as well as time constraints and issues with institutional support (Admiraal, 2021). Other important factors, such as teachers' well-being and professional commitment, affect the way they adopt technology, while self-development and pedagogical competence play indirect roles (Juliana et al., 2024). This highlights the need for comprehensive support systems and ongoing professional development to facilitate the effective integration of technology. For example, the adoption of educational computer games faces resistance in K-12 education despite their potential for engaging learning. Factors such as compatibility, relative advantage, complexity, and trialability play crucial roles in the adoption of games (Kebritchi, 2010). This suggests that addressing these factors could improve the integration of educational games in classrooms, allowing teachers to utilize technology for enhanced teaching and learning experiences (Admiraal, 2021; Juliana et al., 2024; Kebritchi, 2010).

It is important to consider the adoption of AI in education through the lenses of innovation diffusion theory (IDT) and social cognitive theory (SCT). Although existing research has explored AI adoption in various contexts, notable gaps remain in understanding teachers' specific adoption patterns and the challenges they face. IDT emphasizes the importance of relative advantage, compatibility, complexity, observability, and social influence in the adoption of technology (Min et al., 2018; Raman et al., 2024; Straub, 2017). These studies focus on technology acceptance, benefits, and usage, but the teachers' adoption of AI tools remains unexplored (Min et al., 2018; Raman et al., 2024). A previous study by Russo (2024) offers insights into AI adoption in software engineering, but its applicability to educational settings remains unexplored.

Even for technology acceptance theories, some studies have found contradictions, where results showed that compatibility with existing workflows is more influential than perceived usefulness or social factors in AI adoption (Russo, 2024; Xu et al., 2023). This finding underscores the need for context-specific research in educational settings, particularly in addressing teachers' adoption of AI, as noted by Kofahi and Husain (2025). Future studies should investigate how factors such as compatibility with existing teaching practices, perceived threats to job security (Xu et al., 2023), and the unique challenges of the educational environment impact AI adoption among teachers. Additionally, investigating the role of adaptive resilience in the context of educational AI adoption could provide valuable insights for developing effective implementation strategies in schools (Saleem et al., 2023). Unlike prior studies, this research uniquely integrates IDT and SCT to examine teachers' adoption of AI in K-12 educational settings within the UAE. This integration highlights the perceived characteristics of innovations and also emphasizes the role of cognitive beliefs and contextual support, offering a more comprehensive framework than previous research.

The purpose of this study is to examine the factors influencing teachers' behavioral adoption of AI in educational settings by integrating the IDT and SCT. Specifically, the study examines how teachers' perceptions of AI (relative advantage, compatibility, and trialability/observability), their cognitive beliefs, and the environmental support they receive influence their intention and behavior toward adopting AI tools in teaching and learning. The study also explores whether environmental support moderates the relationships between these perceptions and behavioral adoption, and whether cognitive beliefs mediate this relationship. Despite growing interest in AI in education, limited research explains how teachers in K–12 contexts adopt AI by integrating both innovation perceptions and psychological/contextual factors. This lack of integration creates a gap in understanding the mechanisms through which perceptions, beliefs, and environmental conditions shape adoption behavior. Addressing this gap, the present study applies an integrated IDT–SCT framework to investigate teachers'

adoption of AI in the UAE. By providing a comprehensive understanding of the personal and contextual factors driving AI adoption, the study aims to inform strategies for facilitating effective AI integration in education. Accordingly, the following questions were developed to guide this study:

1. How do teachers' perceptions of AI (relative advantage, compatibility, and trialability/observability) influence their behavioral adoption of AI in education?
2. How do teachers' cognitive beliefs about AI and environmental support influence their behavioral adoption of AI?
3. Does environmental support moderate the relationships between teachers' perceptions of AI (relative advantage, compatibility, trialability/observability, and cognitive beliefs) and their behavioral adoption of AI?
4. Do cognitive beliefs about AI mediate the relationship between teachers' perceptions of AI (relative advantage, compatibility, and trialability/observability) and their behavioral adoption of AI?

The following hypotheses were developed:

H1: Teachers' perceptions of AI, specifically relative advantage, compatibility, and trialability/observability, positively influence their behavioral adoption of AI in education.

H2: Teachers' cognitive beliefs about AI and the environmental support they receive both positively influence their behavioral adoption of AI.

H3: Environmental support moderates the relationship between teachers' perceptions of AI and their behavioral adoption of AI, strengthening the effect of compatibility and altering the influence of trialability/observability.

H4: Teachers' cognitive beliefs mediate the relationship between their perceptions of AI (relative advantage and compatibility) and their behavioral adoption of AI.

FRAMEWORK OF THE STUDY

TEACHERS' PERCEPTIONS (RELATIVE ADVANTAGE, COMPATIBILITY, AND TRIALABILITY/OBSERVABILITY

Innovation diffusion theory, proposed by Rogers (2003), offers an understanding of the processes by which individuals and organizations adopt innovations. Rogers identified several important factors to the adoption of innovations, including relative advantage, compatibility, and trialability/observability. In the context of educational technology, specifically artificial intelligence, these factors become important in examining how and why teachers adopt such innovations.

Relative advantage refers to the degree to which an innovation is perceived as an improvement over existing methods and how people benefit from it (Rogers, 2003). In educational contexts, teachers are more likely to adopt technology when they perceive clear benefits, such as improved teaching efficiency, reduced workload, enhanced learning outcomes, and improved assessment practices (Raman et al., 2024; Xu et al., 2023). Also, students who perceive the benefits of AI chatbots show a strong intention to use them for academic purposes (Ayanwale & Molefi, 2024). Similarly, in the adoption of eBook readers, relative advantage significantly influenced user intentions (Waheed et al., 2015). Additionally, the adoption of ChatGPT in higher education is perceived by students as an innovative resource that offers benefits to their education (Raman et al., 2024). Thus, relative advantage was selected for this study to assess how teachers perceive AI's benefits in enhancing teaching and learning processes.

Compatibility refers to the extent to which an innovation aligns with the existing values, past experiences, and needs of potential adopters (Rogers, 2003). Previously, it was stated that the perception of compatibility between users and AI has a positive influence on adoption intention (Ayanwale &

Molefi, 2024; Kumar et al., 2024). However, teachers' adoption of AI depends significantly on whether they perceive the technology as compatible with their teaching philosophy, curriculum demands, and instructional practices (Chai et al., 2016). For learners, the compatibility of ChatGPT was found to be a significant factor in students' intention to adopt it (Raman et al., 2024). Therefore, compatibility was chosen to understand how teachers' existing practices and values influence their adoption of AI.

Trialability and observability refer to the degree to which an innovation can be experimented with or observed before adoption (Rogers, 2003). Innovations that allow potential users to experiment or see positive results are more likely to be adopted as they reduce perceived risks and uncertainties (Straub, 2017). Educators prefer observable demonstrations or pilot projects before fully integrating AI into their teaching practices. Although some studies have found these factors to be significant (Ayanwale & Molefi, 2024; Menzli et al., 2022; Waheed et al., 2015), others have reported no significant relationship between ease of use, trialability, and attitudes toward AI adoption (Xu et al., 2023). However, in the context of ChatGPT adoption, trialability/observability were found to be significant factors influencing students' intentions to use the technology (Raman et al., 2024).

These findings highlight the need for targeted strategies to promote AI adoption in education, focusing on demonstrating the benefits and compatibility of AI with existing teaching practices, while also providing opportunities for educators to try and observe AI in action (Raman et al., 2024; Woodruff et al., 2023). Although IDT in AI adoption research reveals that relative advantage, compatibility, and to some extent, trialability and observability, play crucial roles in shaping user attitudes and adoption intentions, SCT shapes their cognitive beliefs and environmental support.

The Influence of Teachers' Cognitive Beliefs and Environmental Support

Social cognitive theory, developed by Albert Bandura (1986), emphasizes the triadic reciprocal interaction among personal (cognitive), environmental, and behavioral factors in shaping human actions. *Cognitive beliefs* encompass teachers' knowledge, awareness, attitudes, and ethical considerations related to AI. These beliefs influence an individual's perception of their ability to use new technologies effectively, which in turn affects their adoption behavior (Bandura, 2001), as proven in a previous study by Aldulaijan and Almalky (2025). Teachers' cognitive beliefs about the usage, ethical implications, and relevance of technology to students' future skills critically influence their adoption intentions (Ateş & Gündüzalp, 2025; Suseno et al., 2021). Hence, cognitive beliefs were selected to assess teachers' psychological readiness and perceptions toward AI in educational contexts. Cognitive beliefs, including perceived usefulness and ease of use, play a crucial role in shaping teachers' behavioral intention to use AI technologies (Ma & Lei, 2024). A study confirmed that attitudes toward AI integration in life sciences education encompass themes such as pedagogical benefits, practical limitations, and philosophical concerns (Mnguni, 2025). Teachers who recognize the tangible benefits and superiority of AI in teaching are more likely to adopt it in digitalized instruction.

Environmental support encompasses institutional support, infrastructure, technical resources, and professional development opportunities, which significantly influence individuals' confidence and behavioral intentions regarding the adoption of new technologies (Bandura, 1986; ElSayary, 2024; Mnguni, 2025). In educational settings, schools that provide strong leadership support, adequate infrastructure, training, and peer collaboration foster greater adoption of technology by teachers (Hew & Brush, 2007; Inan & Lowther, 2010). Environmental support, including social norms and supplier commitment, also contributes to technology adoption processes (Au & Enderwick, 2000; Lin, 2010). High-performance work systems can reduce the negative effect of AI anxiety on change readiness for AI adoption (Suseno et al., 2021). Furthermore, facilitating conditions, such as access to technology and training, are significant predictors of intention to use AI-powered tools (Ateş & Gündüzalp, 2025). However, it's interesting to note that individual external environmental forces may not significantly influence the formation of behavioral intention to adopt in some cases (Au & Enderwick,

2000; Teo et al., 2017). This contradiction highlights the complex nature of technology adoption and the need for further research on the impact of external environments on innovation diffusion. Thus, ENV was included to capture the institutional and social dimensions of AI adoption.

The Moderation Effect of Environmental Support

Based on the provided context, there is insufficient information to understand whether environmental support moderates the relationships between teachers' perceptions of AI and their behavioral adoption of AI. However, Sanusi et al. (2023) introduced the concept of "AI for social good" as a moderator in their research model, examining teachers' perceptions and behavioral intentions regarding the teaching of AI. Although this is not exactly environmental support, it suggests that contextual factors can play a moderating role in the relationship between perceptions and adoption intentions. In another study by Al-Abdullatif (2024), the importance of intelligent technological pedagogical content knowledge (TPACK) and perceived trust as mediators in the relationship between AI literacy and teachers' acceptance of generative AI was highlighted. This suggests that the educational environment and support structures could potentially influence the adoption process. The provided papers do not directly address environmental support as a moderator; however, they indicate that various contextual and environmental factors can influence the relationship between perceptions and the adoption of AI in educational settings. Further research specifically focusing on environmental support as a moderator would be needed to provide a definitive answer to the question.

The Mediation Role of Cognitive Beliefs

Cognitive beliefs about AI appear to play a mediating role in the relationship between teachers' perceptions of AI and their behavioral adoption of AI. However, this relationship is complex and not always direct. For instance, Xu et al. (2023) reveal that relative advantage, compatibility, and observability correlated with more positive attitudes toward AI adoption among employees over time. Similarly, Ayanwale and Molefi (2024) confirm that relative advantages, compatibility, and trialability positively influence students' intention to use AI chatbots for educational purposes; however, they did not establish direct relationships between cognitive beliefs (perceived usefulness and ease of use) and behavioral intention. This suggests that cognitive beliefs may mediate the relationship between teachers' perceptions and the adoption of behavior. Still, the process is not always straightforward, and the strength and nature of this mediation may vary.

Conceptual Framework

The Integrated IDT-SCT Model, which combines the Diffusion of Innovation Theory (IDT) and Social Cognitive Theory (SCT), provides a comprehensive framework for examining AI adoption in educational settings (Russo, 2024). IDT offers a clear lens to understand the perceived characteristics of the innovation itself (relative advantage, compatibility, trialability/observability), SCT complements this perspective by emphasizing personal cognitive beliefs and contextual environmental factors (Riley et al., 2015). Moreover, this integrated approach enables the examination of the mediating roles of cognitive beliefs and the moderating influences of environmental support, aligning with the study's aim of providing actionable insights for fostering effective AI integration in educational practices.

Prior studies have investigated AI adoption using different theoretical frameworks. For instance, the Technology Acceptance Model (TAM) has been applied to understand researchers' perceptions of Generative AI in higher education (Abdullah & Zaid, 2023; Al-Rahmi et al., 2019). The Technology-Organization-Environment (TOE) framework, combined with institutional theory and diffusion of innovation theory, has been used to study the adoption of generative AI in organizational settings (Agrawal, 2023). Additionally, the integration of big data analytics and AI adoption has been examined using the TOE model, Rogers' diffusion of innovation theory, and resource-based view theory (Chen et al., 2024). Although these studies employed different frameworks and provided valuable insights, the focus has primarily been on organizational-level adoption, with limited focus on individual-level factors in educational contexts (Kurup & Gupta, 2022; Schwaeke et al., 2024). Moreover,

the ethical and cultural aspects of AI adoption in education, particularly in diverse settings like Vietnam, have been underexplored (Nguyen, 2023). Additionally, this integrated approach enables the examination of the mediating roles of cognitive beliefs and the moderating influences of environmental support, aligning with the study's aim of providing actionable insights for fostering effective AI integration in educational practices.

Figure 1 presents the integrated conceptual framework of this study. The framework combines innovation diffusion theory (relative advantage, compatibility, and trialability/observability) with social cognitive theory (cognitive beliefs and environmental support) to explain teachers' adoption of AI. As shown, cognitive beliefs mediate the effects of relative advantage, compatibility, and trialability, while environmental support directly influences adoption and acts as a moderator of these effects.

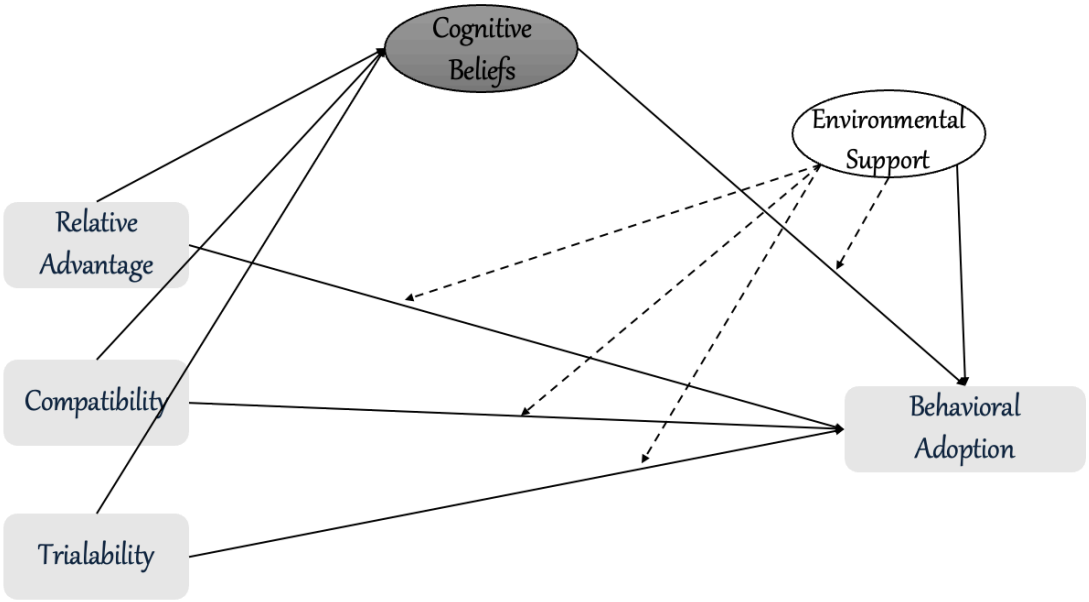

Figure 1. Integrated IDT-SCT conceptual framework

The model illustrates how teachers' perceptions of AI (relative advantage, compatibility, trialability/observability) influence behavioral adoption directly and indirectly through cognitive beliefs, with environmental support acting as both a direct predictor and a moderator.

Study Context

In the context of this study, artificial intelligence (AI) refers to digital technologies that simulate human intelligence processes and are used to enhance teaching and learning in educational settings. These include tools and applications such as intelligent tutoring systems, automated assessment platforms, adaptive learning software, AI-powered chatbots (e.g., ChatGPT), and data-driven instructional tools that support decision-making and personalization of learning experiences. This research investigated the influence of teacher perceptions of AI integration on their behavioral intention within Al Ain, Abu Dhabi, UAE. The study aligns with the UAE's national innovation agenda, notably Vision 2031 and the Centennial 2071 Plan, which prioritizes the utilization of advanced technologies, such as AI, for sustainable development and a knowledge-based economy. Specifically, the UAE National AI Strategy 2031 targets sectoral transformation, including education (United Arab Emirates Government, 2023). Furthermore, the research supports Sustainable Development Goal 4 (Quality Education) by addressing the need for inclusive, equitable learning opportunities. Data collection involved 249 educators from ten national and international schools across the Emirate of Al Ain.

METHODOLOGY

This study employed a quantitative cross-sectional design to investigate how teachers' perceptions of AI (relative advantage, compatibility, and trialability/observability), along with their cognitive beliefs and the environmental support they receive, shape their intention and behavior toward adopting AI tools in teaching and learning.

PARTICIPANTS

A total of 249 teachers participated in the study, consisting mostly of females (88.4%, n = 220), with a smaller percentage of males (11.6%, n = 29). This gender imbalance may affect the generalizability of findings and is acknowledged as a limitation (see Limitations section). In terms of age, almost half of the participants (46.6%) were under 25 years old, followed by 23.7% aged 25–29, 22.1% aged 30–39, and a smaller percentage aged 40–49 (6.4%) and 50–59 (0.8%). Regarding educational qualifications, the majority of participants held a bachelor's degree (59.8%), while 29.7% had a master's degree, 7.6% had a doctoral degree, and 2.8% had completed post-doctoral studies. Participants also varied in teaching experience, where 36.1% were in their first year of teaching, 20.1% had 1–2 years of experience, 12.9% had 3–5 years, 14.1% had 6–10 years, 9.2% had 11–15 years, 5.2% had 16–20 years, and 2.4% reported having more than 20 years of teaching experience. The participants represented various teaching levels across the education system. Nearly half of the participants, 47.3% of the sample, teach in the early years, followed by teachers of Grades 1–3 (16.5%), Grades 4–6 (9.2%), Grades 7–9 (10.8%), and Grades 10–12 (16.1%).

INSTRUMENT

A survey instrument was developed based on the integrated framework that combines innovation diffusion theory (IDT) (Rogers, 2003) and social cognitive theory (SCT) (Bandura, 1986), aligning with the study's purpose. The survey items consist of two categories: IDT and SCT. In IDT, there were three sub-categories: relative advantage (4 items), compatibility (7 items), and trialability/observability (4 items). In the SCT category, three sub-categories were included: cognitive ability (6 items), environmental support (5 items), and behavioral intention (4 items). The final instrument comprised 30 items, using a 5-point Likert Scale, ranging from 1 (strongly disagree) to 5 (strongly agree) (see Table 1). The items were contextualized to align with the UAE's K–12 educational setting. For example, compatibility items emphasized alignment with curriculum goals and inclusive education priorities (e.g., supporting students with special needs, reducing dropout rates), while relative advantage items reflected teachers' workload, assessment efficiency, and student engagement. This contextualization ensures that the instrument accurately reflects the realities of UAE classrooms, allowing for replication in similar educational environments.

Table 1. Survey items were categorized based on the study constructs

Innovation diffusion theory items
A. Relative advantage
1. AI helps in the teaching process.
2. AI helps in assessment and evaluation.
3. AI improves my ability to create learning materials.
4. AI will reduce the workload in the future.
B. Compatibility
1. AI enhances personalized and adaptive learning.
2. AI helps students with special needs.
3. AI identifies student learning preferences.
4. AI helps reduce dropout rates and improve student performance.
5. AI may lead to replacing human teachers with mechanical systems (R).
6. AI helps underserved areas.

Innovation diffusion theory items
7. AI contributes to promoting educational equity.
C. Trialability/Observability
1. AI for admin tasks allows for more student interaction.
2. AI bridges gaps for underserved students.
3. AI helps classroom management.
4. AI can teach social-emotional skills.
Social cognitive theory items
A. Cognitive
1. AI provides students with real-time feedback.
2. I am aware of AI tools for education.
3. AI applicable in real life.
4. AI literacy is essential for students' future career success.
5. Concerned about the ethical implications of AI.
6. AI will change the teacher's role.
B. Environmental
1. AI saves time in lesson planning.
2. My school encourages AI use.
3. I have access to the required AI technology.
4. My colleagues are supportive of AI use.
5. AI increases the digital divide (R).
C. Behavioral
1. I am confident in using AI tools.
2. I have received adequate AI training.
3. I need more professional development for AI (R).
4. I regularly use AI tools.

For content validity, the instrument was sent to three specialists in educational technology and AI ethics, who recommended rewording three of the survey items to align them with the study's framework. For reliability purposes, a pilot test was conducted with 25 teachers to assess the clarity and relevance of the items, with minor revisions made based on the feedback. The final instrument demonstrated strong internal consistency, with Cronbach's alpha coefficients ($\alpha = .912$), exceeding the accepted thresholds across all dimensions. This ensured that the survey provided a reliable and valid measure of the personal and contextual factors shaping AI adoption.

PROCEDURE

The study obtained ethical approval from the research ethics committee at the researchers' university, ensuring compliance with ethical standards for research involving human participants. All participants received an informed consent form outlining the purpose of the study, the voluntary nature of participation, the confidentiality of responses, and their right to withdraw at any time without penalty. Consent was obtained electronically before participants proceeded to complete the survey.

The data collection was conducted online using a web survey platform. The survey was distributed via institutional email lists and professional networks, targeting teachers involved in various educational levels. Participation was voluntary and anonymous. Data were analyzed using IBM SPSS Statistics (Version 30) and SmartPLS (Version 4) to test the proposed model. Descriptive statistics were first computed to summarize participants' demographic characteristics and responses to survey items. The reliability of each scale was assessed using Cronbach's alpha. Confirmatory factor analysis (CFA) was performed to evaluate the validity of the measurement model. Hierarchical regression analysis and structural equation modeling (SEM) were then used to test the relationships between teachers'

perceptions of AI and behavioral adoption, as proposed by the integrated theoretical framework. Finally, moderation analysis was conducted to examine whether environmental support moderates the relationships between perceptions of AI (relative advantage, compatibility, trialability/observability, and cognitive beliefs) and behavioral adoption. Additionally, mediation analysis of cognitive beliefs was conducted to investigate the relationship between IDT factors and behavioral intention. Statistical significance was evaluated using standard thresholds ($p < .05$), and all model fit indices were reported to ensure the robustness of the results.

RESULTS

VALIDITY AND RELIABILITY

All constructs demonstrated acceptable levels of internal consistency. Composite reliability (CR) reflects the reliability of latent constructs in structural equation modeling. The values ranged from 0.805 to 0.884, exceeding the recommended threshold of 0.70 (Table 2). Although Cronbach's alpha (a measure of internal consistency, i.e., how closely related items are within a construct) values for compatibility ($\alpha = 0.675$) and relative advantage ($\alpha = 0.695$) were slightly below the conventional 0.70 threshold, as stated by Nunnally and Bernstein (1994), their corresponding *CR* values (0.805 and 0.816, respectively), higher than the minimum acceptable threshold of 0.70 as stated by Hair et al. (2019) and *AVE* (indicates the proportion of variance captured by the construct relative to measurement error) values (0.485 and 0.533, respectively) supported adequate construct reliability, as recommended when factor-based reliability is prioritized in SEM. All other constructs demonstrated strong Cronbach's alpha values (≥ 0.732), further supporting internal consistency. The AVE values for most constructs exceeded the recommended threshold of 0.50, as mentioned by Fornell and Larcker (1981), indicating sufficient convergent validity.

Discriminant validity was evaluated using the Heterotrait-Monotrait ratio of correlations (*HTMT*), which checks whether constructs are distinct from one another. The *HTMT* value between cognitive beliefs and behavioral intention (0.903) was high as per the cutoff value of 0.90 as mentioned by Henseler et al. (2015). However, it remains below the critical value of 1.00, indicating an acceptable relationship, given that most AVEs were above 0.50 and *CR* was strong. To mitigate potential social desirability bias, anonymity of responses was emphasized, and participation was voluntary without institutional oversight. Furthermore, statistical checks indicated no significant multicollinearity among predictors; variance inflation factor (VIF) values (which indicate how much predictors overlap with one another) were all below the commonly accepted threshold of 5.0, confirming that multicollinearity did not bias the regression estimates.

Table 2. Convergent validity using *CR*, *AVE,* and discriminant validity using HTMT

	α	CR	AVE	CO	COG	RA	TO
BEH	0.782	0.826	0.634	.851	.903	.830	.835
CO	0.675	0.805	0.485		.700	.744	.786
COG	0.840	0.884	0.559			.852	.887
RA	0.695	0.816	0.533				.898
TO	0.732	0.830	0.551				

Model fit was evaluated using SRMR (which measures the difference between observed and predicted correlations in the model), d_ULS, d_G, and NFI. The *SRMR* value of 0.095 was slightly above the conservative cutoff of 0.08 but remains within the tolerable range for PLS-SEM in complex models. The *NFI* value of 0.673 indicates an acceptable but not ideal fit, which is common in

exploratory models combining IDT and SCT constructs. Overall, the fit indices suggest that the model provides an adequate approximation of the data structure.

Hierarchical Multiple Regression

RQ1: Relative advantage, compatibility, and trialability/observability as predictors of behavioral intention

To address RQ1, regression results show that relative advantage and trialability/observability significantly predicted teachers' behavioral adoption of AI, whereas compatibility had a weaker direct effect. A hierarchical multiple regression analysis, presented in Table 3, was conducted with behavioral adoption of AI as the dependent variable, and relative advantage, compatibility, and trialability/observability as independent variables. Correlations among the study variables were all significant and positive. Behavioral adoption correlated strongly with relative advantage ($r = .642$, $p < .001$), Compatibility ($r = .540$, $p < .001$), and trialability/observability ($r = .586$, $p < .001$), indicating meaningful associations between teachers' perceptions of AI and their adoption behavior.

Table 3. Hierarchical regression analysis predicting behavioral adoption of AI

Model		β	*t*	Sig.	R^2	ΔR^2	*F*
1	RA	.642***	13.144	<.001	.412		172.76***
2	RA	.518***	7.615	<.001	.427	.015*	91.61***
	CO	.175**	2.564	.011			
3	RA	.425***	6.095	<.001	.465	.038***	70.89***
	CO	.056 (ns)	.785	.433			
	TO	.276***	4.159	<.001			

****p < .001, **p < .01, *p < .05, ns = not significant.*
RA – Relative advantage; CO – Compatability; TO – Trialability/Observatbility

In Table 2, the model of the regression analysis, which includes only Relative Advantage (Model 1), explains 41.2% of the variance in behavioral adoption ($R^2 = .412$, $p < .001$), with relative advantage being a strong and significant predictor ($\beta = .642$, $p < .001$). Adding compatibility in Model 2 significantly improved the model fit ($\Delta R^2 = .015$, $p = .011$), with both relative advantage ($\beta = .518$, $p < .001$) and compatibility ($\beta = .175$, $p = .011$) contributing significantly to behavioral adoption. In Model 3, trialability/observability was added, further improving the model fit ($\Delta R^2 = .038$, $p < .001$), with the final model explaining 46.5% of the variance in behavioral adoption ($R^2 = .465$, $p < .001$). In this final model, RA ($\beta = .425$, $p < .001$) and TOR ($\beta = .276$, $p < .001$) were significant predictors, whereas CO became non-significant ($\beta = .056$, $p = .433$). These findings suggest that teachers' perceptions of the relative advantage and trialability/observability of AI are the most salient predictors of their behavioral adoption, while compatibility plays a weaker role when all factors are considered jointly.

RQ2: Cognitive beliefs and environmental support as predictors of behavioral intention

In response to RQ2, both cognitive beliefs and environmental support emerged as significant predictors of adoption, highlighting the psychological and contextual influences alongside innovation perceptions. Correlations among cognitive beliefs, environmental support, and behavioral adoption were all significant and positive. Behavioral adoption was strongly correlated with Cognitive Beliefs ($r = .583$, $p < .001$) and Environmental Support ($r = .586$, $p < .001$). Cognitive Beliefs and Environmental Support were also strongly correlated ($r = .731$, $p < .001$), indicating substantial shared variance.

In Table 4, the model of the regression analysis, including only Cognitive Beliefs (Model 1), explained 33.9% of the variance in behavioral adoption ($R^2 = .339$, $p < .001$), with COG being a strong and sig-

nificant predictor (β = .583, $p < .001$). Adding Environmental Support in Model 2 significantly improved the model fit ($\Delta R^2 = .055$, $p < .001$), with both COG (β = .331, $p < .001$) and ENV (β = .345, $p < .001$) making significant contributions to behavioral adoption. These findings suggest that both teachers' cognitive beliefs about AI and the environmental support they receive are significant and complementary predictors of their behavioral adoption of AI. Notably, both predictors contributed almost equally in the final model, highlighting the importance of addressing both personal beliefs and contextual support in fostering AI adoption among teachers.

Table 4. Hierarchical regression analysis predicting behavioral adoption of AI

Model		β	*t*	Sig.	R^2	ΔR^2	*F*
1	COG	.583***	11.265	<.001	.339		126.90***
2	COG	.331***	4.551	<.001	.395	.055*	80.25***
	ENV	.345**	4.746	<.001			

****p < .001, **p < .01, *p < .05, ns = not significant*
COG – Cognitive Beliefs; ENV – Environmental support

RQ3: Moderation of environmental support

Addressing RQ3, interaction analyses confirmed that environmental support moderated the effects of compatibility and trialability/observability on adoption, amplifying their impact when support was high. To assess the moderating effect of environmental support, a hierarchical multiple regression analysis was conducted. In Block 1, the centered main effects of relative advantage, compatibility, trialability/observability, cognitive beliefs, and environmental support were entered. In Block 2, the interaction terms between each predictor and Environmental Support were included (Table 5). The main effects model (Block 1) was significant, $F(5, 243) = 46.15$, $p < .001$, and accounted for 48.7% of the variance in behavioral adoption ($R^2 = .487$). Relative advantage (β = .326, $p < .001$), trialability/observability (β = .281, $p < .001$), and environmental support (β = .234, $p = .002$) were significant predictors of behavioral adoption. Compatibility and cognitive beliefs were non-significant when controlling for the other variables. Adding the interaction terms in Block 2 significantly improved model fit, $\Delta R^2 = .033$, $p = .003$, with the full model explaining 52.0% of the variance ($R^2 = .520$). Two significant interaction effects were found: Compatibility × Environmental Support (β = .193, $p = .015$) and Trialability/Observability × Environmental Support (β = -.229, $p = .004$). The interactions for Relative Advantage × Environmental Support (β = .056, $p = .561$) and Cognitive Beliefs × Environmental Support (β = .041, $p = .722$) were not significant.

The interaction between compatibility and environmental support indicated that compatibility had a stronger positive relationship with behavioral adoption when environmental support was high. Conversely, the interaction between trialability/observability and environmental support suggested that the positive effect of trialability/observability on behavioral adoption weakened slightly when environmental support was high. These findings highlight the role of contextual support in shaping the impact of specific AI perceptions on teachers' adoption behavior.

Table 5. Hierarchical regression analysis predicting behavioral adoption of AI

Model		β	*t*	Sig.	R^2	ΔR^2	*F*
1	RA	.326***	4.017	<.001	.487	-	46.15***
	CO	-.020 (ns)	-.253	.800			
	TOR	.281***	4.154	<.001			
	COG	-.022 (ns)	-.248	.804			
	ENV	.234***	3.185	.002			
2	RA	.355***	4.263	<.001	.520	.033*	37.71***
	CO	.071 (ns)	.851	.396			

Model		β	*t*	Sig.	R^2	ΔR^2	*F*
	TOR	.190**	2.700	.007			
	COG	-.022 (ns)	-.233	.816			
	ENV	.227**	3.084	.002			
	RA x ENV	.056 (ns)	.583	.561			
	CO x ENV	.193*	2.445	.015			
	TOR x ENV	-.229**	-2.902	.004			
	COG x ENV	.041 (ns)	.356	.722			

****p < .001, **p < .01, *p < .05, ns = not significant.*
RA – Relative advantage; CO – Compatability; TO – Trialability/Observatbility; COG – Cognitive Beliefs; ENV – Environmental support

RQ4: Mediation model (IDT → Cognitive → Behavior)

For RQ4, mediation analysis indicated that cognitive beliefs partially mediated the effects of relative advantage and compatibility on adoption, clarifying the indirect pathways through which perceptions shape behavior. To examine the mediating role of cognitive beliefs, a structural model was tested using SmartPLS. Bootstrapping with 5,000 resamples was employed to assess the significance of the indirect effects. The results indicated that cognitive beliefs significantly mediated the relationship between both relative advantage and compatibility and teachers' behavioral adoption of AI. Specifically, the indirect effect of relative advantage on behavioral adoption through cognitive beliefs was significant (β = 0.080, *p* = .011, 95% CI excludes 0), as was the indirect effect of compatibility (β = 0.091, p = .016). These results suggest **partial mediation** for relative advantage (as the direct effect remained significant; β = 0.433, *p* < .001) and **full mediation** for compatibility (as the direct effect became non-significant; β = 0.121, *p* = .275) (see Figure 1 and Table 6). In contrast, the indirect effect of trialability/observability on behavioral adoption through cognitive beliefs was not statistically significant (β = 0.020, *p* = .264), indicating no mediation in this path.

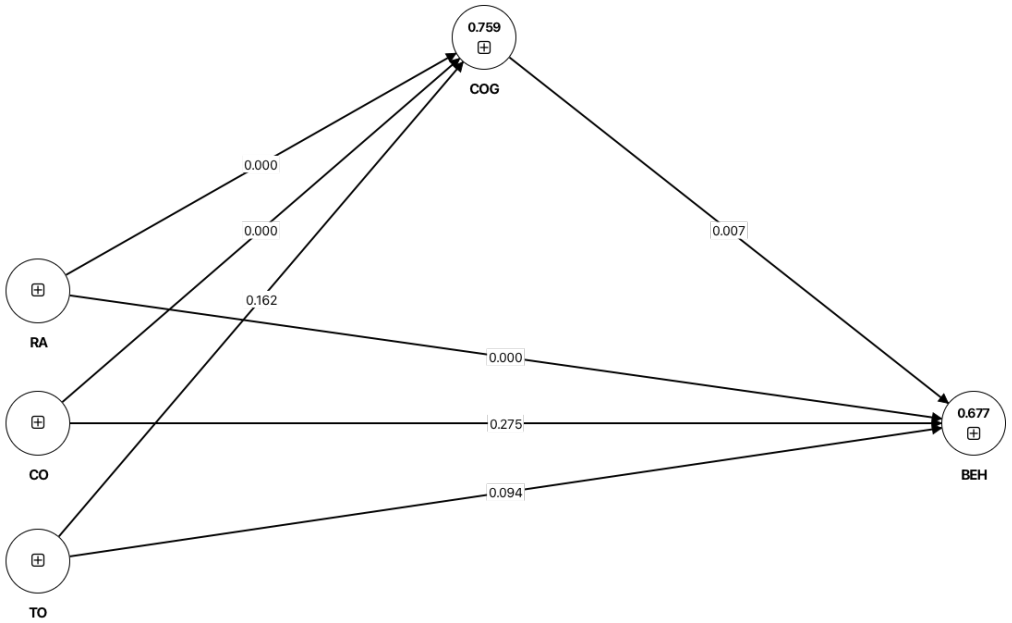

Figure 1. Mediation model of cognitive beliefs on the relationship between AI perceptions and behavioral adoption using SEM

Thus, cognitive beliefs function as a significant psychological mechanism through which perceptions of relative advantage and compatibility shape teachers' willingness to adopt AI in educational settings. However, trialability/observability appears to influence behavioral adoption more directly rather than through cognitive interpretation.

Table 6. Mediation analysis: Indirect effects of AI perceptions on behavioral adoption via cognitive beliefs

Path	*β*	*t*	*p*	Mediation
Direct Effect				
RA → BEH	0.433	5.598	0.000	Supported
CO → BEH	0.121	1.092	0.275	Not Supported
TO → BEH	0.156	1.676	0.094	Not Supported
COG → BEH	0.200	2.680	0.007	Supported
RA → COG	0.399	7.154	0.000	Supported
CO → COG	0.454	5.607	0.000	Supported
TO → COG	0.101	1.399	0.162	Not Supported
Indirect Effect				
RA → COG → BEH	0.080	2.531	0.011	Supported
TO → COG →BEH	0.020	1.118	0.264	Not Supported
CO → COG → BEH	0.091	2.413	0.016	Supported
Total Effect				
RA → BEH	0.512	7.451	0.000	Supported
CO → BEH	0.212	2.050	0.040	Supported
TO → BEH	0.176	1.898	0.058	Partially Supported

RA – Relative advantage; CO – Compatability; TO – Trialability/Observatbility; COG – Cognitive beliefs; ENV – Environmental support

DISCUSSION

THE INFLUENCE OF TEACHERS' PERCEPTIONS OF AI (RELATIVE ADVANTAGE, COMPATIBILITY, AND TRIALABILITY/OBSERVABILITY) ON THEIR BEHAVIORAL ADOPTION OF AI

In line with RQ1, relative advantage and trialability/observability emerged as central predictors of adoption, reinforcing IDT's relevance in explaining AI uptake in schools. Building on the IDT perspective illustrated in Figure 1, the findings of this study confirm the importance of perceived value in shaping teachers' behavioral adoption of AI. Relative advantage (RA) is considered to be the most predictive of adoption behavior across all models, maintaining significance even when other factors were controlled. This emphasizes that teachers are motivated by their perception of AI's ability to deliver tangible improvements in teaching efficiency, student engagement, and learning outcomes. This result is strongly aligned with prior research, which consistently states that RA is a significant factor influencing both student and instructor intentions to engage with AI tools (Al-Rahmi et al., 2019; Ayanwale & Molefi, 2024; Breiki et al., 2022; Liu et al., 2019; Raman et al., 2024; Waheed et al., 2015). The finding suggests that teachers' perceptions are valuable in adopting AI technology. This is because the adoption of AI provides teachers with beneficial innovations that reduce the high workload and limited time in their professional environment, as stated by Rogers' (2003) theory of innovation diffusion, where RA is theorized to have the most direct impact on adoption decisions.

Trialability/observability (TO) also proved to be a significant predictor of behavioral adoption, where teachers value opportunities to experiment with AI tools and observe demonstrable outcomes before fully integrating them into their teaching practices. This result aligns with previous research

that emphasizes the importance of reducing uncertainty and perceived risk when introducing complex innovations, such as AI (Ayanwale & Molefi, 2024; Raman et al., 2024). It is also proof that teachers are aware of the ethical and pedagogical risks of untested technologies (Akgun & Greenhow, 2021), which confirms that the ability to observe peer success stories or participate in pilot implementations strongly influences adoption attitudes (Woodruff et al., 2023). This finding aligns well with IDT's assertion that TO is an important factor in adoption decisions for innovations in complex educational settings.

The most interesting finding was the unexpected role of *compatibility* in predicting teachers' behavioral intention. Although compatibility was shown to be a significant predictor of behavioral adoption, its effect became non-significant when RA and TO were introduced into the model. This contrasts with previous research in both educational and organizational contexts, where compatibility has often been shown to be a key driver of technology adoption (Ayanwale & Molefi, 2024; Kumar et al., 2024). However, the current result aligns with recent studies, such as Xu et al. (2023), which reported that compatibility was less influential than relative advantage or trialability in AI adoption (Xu et al., 2023).

The Influence of Teachers' Cognitive Beliefs and Environmental Support on Their Behavioral Adoption of AI

Addressing RQ2, the findings highlight how cognitive beliefs and environmental support complement innovation perceptions, underscoring SCT's explanatory power. As the framework suggests, the findings of this study further emphasize the crucial role of teachers' *cognitive beliefs* and *environmental support* as significant predictors of their behavioral adoption of AI. This highlights that fostering both individual psychological readiness and a supportive institutional environment is essential for promoting AI integration in education. For c*ognitive beliefs,* the finding is aligned with prior research demonstrating that teachers' knowledge, awareness, and attitudes toward AI significantly shape their willingness to utilize these technologies in their teaching (Ateş & Gündüzalp, 2025; Ma & Lei, 2024; Mnguni, 2025). The result also confirms Bandura's (1986) Social Cognitive Theory, which emphasizes that personal cognitive factors directly influence human behavior in the adoption of innovations. The result also suggests that teachers' perceptions of AI's usefulness, ethical implications, and relevance to student learning are important drivers of adoption, as highlighted by Mnguni (2025).

The significant influence of *environmental support* aligns with previous studies showing that institutional support, infrastructure, access to resources, and professional development opportunities play an important role in facilitating technology adoption among teachers (Bandura, 1986; Hew & Brush, 2007; Inan & Lowther, 2010), and foster greater acceptance of AI-powered tools (Ateş & Gündüzalp, 2025; Suseno et al., 2021). This result suggests that even when teachers hold positive cognitive beliefs about AI, adoption is unlikely to occur unless schools provide the necessary environmental support to enable effective use, as stated in previous studies (Au & Enderwick, 2000; Lin, 2010).

The Moderating Role of Environmental Support

For RQ3, environmental support was shown to moderate the influence of compatibility and trialability/observability, consistent with the framework in Figure 1. Environmental support has a significant role in moderating the relationship between teachers' perceptions of AI and their behavioral adoption. The results demonstrate that environmental support moderates the effects of compatibility (CO) and trialability/observability on behavioral adoption, while it does not significantly moderate the effects of relative advantage (RA) or cognitive beliefs (COG).

The moderation effect observed between compatibility and environmental support indicates that high environmental support leads to a positive relationship between compatibility and behavioral adoption. This finding aligns with previous research suggesting that institutional support of using compatible technology can positively influence the adoption outcomes (Au & Enderwick, 2000; Lin,

2010). It also suggests that in environments where schools provide sufficient infrastructure, leadership, and professional development for using efficient technology tools, teachers are more likely to value and utilize these tools in their teaching practices. This result aligns with Sanusi et al. (2023), who emphasized the importance of compatibility and contextual factors in shaping the adoption of AI.

In contrast, the moderation effect between trialability/observability and environmental support revealed an interesting result, where the positive effect of trialability/observability on behavioral adoption slightly weakened when environmental support was high. One possible explanation is that in resource-rich environments, teachers may rely more on institutional validation and structured implementation processes, reducing their reliance on personal experimentation or informal observation. Conversely, in resource-constrained contexts, teachers may depend more heavily on their own opportunities to trial and observe AI tools, making trialability and observability stronger drivers of adoption.

Additionally, there were no moderation effects for relative advantage and cognitive beliefs, suggesting that these factors have a direct influence on behavioral adoption, regardless of changes in environmental support. This finding aligns with the results of previous studies (Bandura, 1986; Rogers, 2003; Xu et al., 2023). In other words, when teachers perceive clear advantages or hold strong, positive beliefs about AI, they are more likely to adopt these tools, even in the absence of optimal institutional support.

The Mediation Role of Cognitive Beliefs

Finally, with respect to RQ4, cognitive beliefs mediated the relationship between relative advantage, compatibility, and adoption, confirming the indirect pathways hypothesized. Cognitive beliefs partially mediated the relationship between relative advantage and behavioral adoption, fully mediated the relationship between CO and behavioral adoption, but did not mediate the relationship between trialability/observability and behavioral adoption. The partial mediation between relative advantage and behavioral adoption suggests that while the perceived benefit of AI directly motivates adoption, it also operates indirectly by strengthening teachers' cognitive beliefs. This is theoretically consistent with Social Cognitive Theory, where personal cognition serves as a means for the influence of perceptions on behavior (Bandura, 1986). Teachers who believe that AI offers a relative advantage are more likely to adopt it and develop stronger beliefs in their ability to use it meaningfully, thus reinforcing their behavioral intention, aligning with the finding of Xu et al. (2023).

The mediation effect of cognitive beliefs on compatibility was significant, suggesting that compatibility alone is insufficient to influence behavioral change. It must first shape how teachers think and feel about AI. This finding aligns with studies that highlight the critical role of attitudes and self-efficacy in turning positive perceptions into behavioral outcomes (Ma & Lei, 2024; Mnguni, 2025).

The lack of a mediating effect for trialability/observability indicates that this factor influences behavioral adoption directly rather than through cognitive interpretation. In other words, when teachers are given opportunities to trial AI tools or observe them in action, they are more likely to adopt them without necessarily undergoing a deeper shift in their cognitive beliefs. This finding aligns with the study by Ayanwale and Molefi (2024), who noted that trialability/observability influenced student intentions even in the absence of strong beliefs or prior knowledge.

Taken together, the findings show that teachers adopt AI when they perceive clear benefits (relative advantage) and can observe or trial the technology directly. Their adoption is further shaped by their beliefs about AI's usefulness and by the level of institutional support available. Importantly, environmental support strengthens the effect of compatibility and alters the effect of trialability/observability, while cognitive beliefs transform perceptions of relative advantage and compatibility into actual adoption behavior. This integrated picture demonstrates that both innovation perceptions and sociocognitive factors must be addressed simultaneously to promote sustainable AI adoption in education.

IMPLICATIONS

This study employed an integrated model of Innovation Diffusion Theory (Rogers, 2003) and Social Cognitive Theory (Bandura, 1986), which provided a more comprehensive understanding of how personal perceptions, cognitive beliefs, and environmental factors jointly influence teachers' behavioral adoption of AI.

First, the strong influence of relative advantage and trialability/observability highlights the importance of institutional strategies that clearly communicate the practical value of AI tools and provide teachers with structured opportunities to trial them. Educational leaders should prioritize initiatives that demonstrate AI's value through developing pilot programs, demonstration classrooms, and peer learning networks, where teachers can observe successful AI integration and experiment with tools in low-risk environments. This is particularly critical for fostering trust in AI technologies and reducing adoption barriers rooted in uncertainty.

Second, the significant role of environmental support, as a direct predictor and as a moderator, suggests that policymakers must invest in technology infrastructure and comprehensive support ecosystems. These should include professional development, leadership engagement, and peer collaboration opportunities to ensure that teachers are fully equipped to integrate AI effectively. Importantly, schools in resource-rich contexts should recognize that while institutional support facilitates adoption, it may also reduce teachers' intrinsic motivation to trial new tools. Thus, a balanced approach that combines formal support with opportunities for exploration is recommended.

Third, the findings emphasize the importance of cognitive beliefs as both a direct influence and a mediator of AI adoption. Therefore, professional development programs should go beyond technical training to address teachers' attitudes, ethical concerns, and self-efficacy regarding AI initiatives, using approaches that foster critical reflection on AI's pedagogical implications. This means integrating reflective practice, case-based discussions, and scenario-based ethics training into training programs to deepen teachers' understanding and confidence. This implies that teachers' psychological readiness is just as critical as technical competence for successful AI adoption.

Fourth, compatibility alone does not directly predict behavioral adoption unless it influences cognitive beliefs. Accordingly, training should also focus on skills-based and values-based, promoting adaptive mindsets that align AI use with diverse teaching strategies. This highlights the need for values-based and context-responsive training designs that resonate with teachers' professional identities.

Fifth, the finding that Trialability/Observability works best through direct experience (rather than through beliefs) highlights the importance of hands-on experimentation in adoption strategies. Schools should design flexible experimentation spaces, or "sandbox environments," where teachers can test AI tools without high stakes, thereby increasing comfort and reducing perceived risk.

This study suggests that successful AI adoption in education requires integrating perceived innovation value, personal cognitive orientation, and environmental scaffolding. The theoretical contribution lies in confirming the complementary roles of IDT and SCT. In contrast, the practical contribution provides a roadmap for designing targeted, evidence-based interventions for policymakers and school leaders.

LIMITATIONS AND RECOMMENDATIONS

This study has several limitations that must be acknowledged. First, the sample was drawn from a specific educational context with a high percentage of early-career and female teachers, which may limit the generalizability of findings to more experienced teachers or more gender-balanced populations. Future studies should aim to include more diverse samples across educational levels, regions, and demographic groups to validate and extend these results.

Second, the study employed a cross-sectional design, which captures perceptions and behaviors at a single point in time and cannot fully understand how teachers' perceptions, beliefs, and behaviors toward AI may change as they gain more experience with the technology. Longitudinal research would be valuable for exploring these changes over time.

Third, the study focused on a limited set of factors drawn from IDT and SCT, which were comprehensive but did not cover the full range of influences on AI adoption. Other factors, such as institutional culture, policy mandates, perceived risks, and ethical concerns, need further exploration.

Finally, the research relied on self-reported measures, which may be subject to social desirability or self-perception biases. Future studies could include qualitative interviews or classroom observations to gain deeper insights into actual adoption behaviors.

CONCLUSION

This study advances the understanding of teachers' adoption of AI by integrating Innovation Diffusion Theory and Social Cognitive Theory into a unified framework. The findings highlight that teachers' perceptions of relative advantage and trialability/observability, along with their cognitive beliefs and environmental support, are critical drivers of adoption behavior. Furthermore, the study reveals that environmental support moderates specific perception-behavior relationships and that cognitive beliefs serve as an important mediating factor in the adoption of certain behaviors. These findings highlight that fostering effective AI integration in education requires a multidimensional strategy, one that promotes the perceived value of AI, provides opportunities for hands-on engagement, promotes positive cognitive orientations, and ensures robust institutional support. As AI technologies continue to develop, it is important that educational systems adopt evidence-informed approaches to support teachers in navigating this transformation. This study fills a critical gap in the literature by integrating Innovation Diffusion Theory (IDT) and Social Cognitive Theory (SCT) to explain teachers' adoption of AI in K–12 education in the UAE, a context that has been largely underexplored in prior research. Theoretically, it demonstrates how perceptions of innovation interact with cognitive and contextual factors, extending IDT and SCT in combination. Practically, it highlights how policymakers and school leaders can design strategies that balance institutional support with opportunities for experimentation, thereby fostering sustainable integration of AI. By addressing both personal beliefs and environmental conditions, this study offers a comprehensive framework that can guide future research and practice in the adoption of AI in education.

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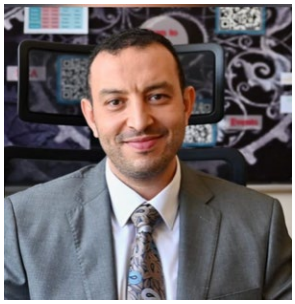

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