Understanding Employee AI Adoption Process: The Role of Innovation Characteristics and Psychological Constraints in AI Adoption

ABSTRACT

Organizations are increasing AI investments, but employee acceptance of AI technologies is still not fully understood, which might derail these AI initiatives. This study leverages and extends the DOI theory's Innovation Characteristics framework to examine the factors that influence employees' adoption of AI technology. A sample of 263 users was used to test the model using SEM analysis. The study found that ease of use, compatibility, visibility, image, and trust are key factors affecting current use, whereas relative advantage, discomfort, and current use affect future use intentions. The study confirms that the factors required for behavioral change to drive initial adoption of AI differ from those necessary to sustain continued use. This research contributes to the growing body of knowledge by demonstrating the relevance of DOI Theory's Innovation Characteristics in explaining the AI adoption process, successfully extending the theory to include psychological constraints, offering a holistic understanding of the process, offering actionable insights for executives to drive AI initiatives in their organizations based on strong empirical evidence, and providing future research directions.

Keywords:

Artificial intelligence, technology adoption, diffusion of innovation, current use of AI, future use of AI, innovation characteristics, psychological constraints.

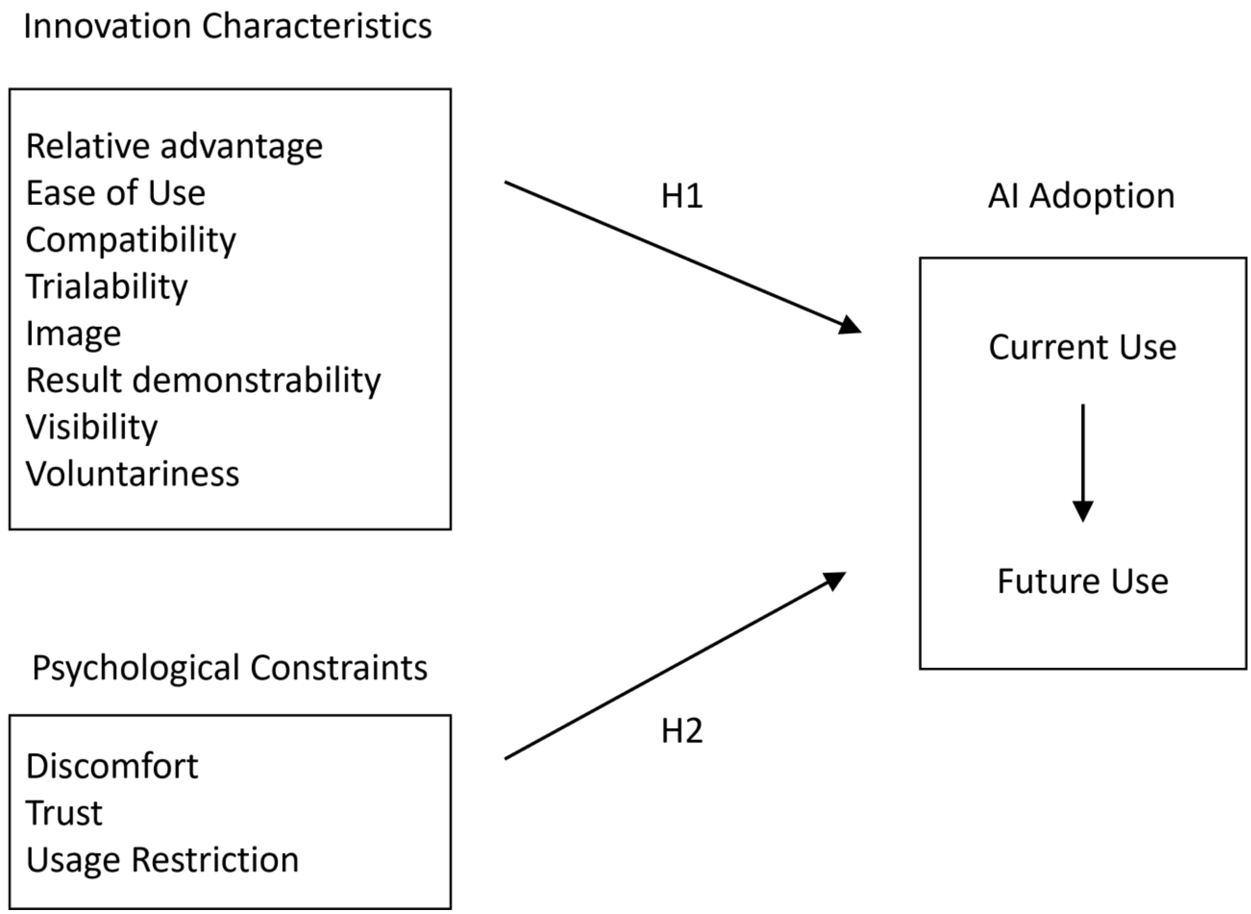
INTRODUCTION

Artificial intelligence (AI) is a revolutionary technology, and like computers and internet-based technologies, it is reshaping many aspects of our lives at a tremendous pace (Agrawal, Gans, & Goldfarb, 2022; Mikalef et al., 2023; Shao, Nah, Makady, & McNealy, 2025). AI is rapidly becoming a key tool in improving organizational performance and executive leaders are actively using AI strategies to drive growth and efficiency (Belhadi, Mani, Kamble, Khan, & Verma, 2024; Gnanamoorthy, 2024; Wimoolka, 2022). This technological shift has raised discomfort among employees regarding the rapid adoption and integration of AI in their work environment (Glikson & Woolley, 2020). There is a sense of apprehension within the workforce about AI adoption in the workplace (Tabrizi & Pahlavan, 2023; Zirar, Ali, & Islam, 2023). As companies are investing at a rapid pace in AI technologies, there is an increasing number of questions about whether this investment will yield a substantial return (Coyle & Poquiz, 2025; McElheran, Yang, Brynjolfsson, & Kroff, 2025). We saw a similar set of questions being asked for other information technologies (IT), such as computers, the WWW, and Industry 4.0, where those technologies promised organizational gains, but the predicted productivity was late to arrive (Brynjolfsson, 1993; Triplett, 1999). In all those cases, it was found that to gain a true advantage, organizations needed three things in the adoption process of information technologies (IT): availability of technologies to the users (typically employees), user acceptance of the technology, and, finally, continued/sustained usage of the technology (Moore & Benbasat, 1991).

In the last few years, there has been an explosion of research focused on user acceptance of AI technologies. There are several frameworks for examining the technology adoption process, with the three most popular being the aptly named Technology Acceptance Model (Davis, 1985), Diffusion of Innovation Theory (Rogers, 1983), and Theory of Reasoned Action (Fishbein & Ajzen, 1975). Of the three frameworks, the Diffusion of Innovation theory is the most apt one for analyzing the AI adoption process. The reason being that while both Technology Adoption Model (TAM) and Theory of Reasoned Action (TRA) have been used previously to analyze the AI adoption process for AI technologies, the biggest challenge with these two framework is that they measure only why people intent to adopt a technology (initial acceptance) while ignoring the other two facets of technology adoption, which are availability and continued/sustained usage (Agarwal & Prasad, 1997; Moore & Benbasat, 1991). Consequently, the studies using TAM or TRA may be limited in their ability to explain the full process of user adoption of AI technology. On the other hand, DOI examines the progression of technology as it moves from initial acceptance to continued/sustained usage across different user segments within the organization (Rogers, 1983). Agarwal and Prasad, in their seminal paper ‘Role of Innovation Characteristics’, extended this theory by including additional factors to examine the technology adoption process of WWW technologies (Agarwal & Prasad, 1997). The DOI framework has been successfully applied to examine the adoption process of several IT technologies, including Industry 4.0 (Hopkins, 2021), smart homes (Hubert et al., 2019), virtual reality (Sagnier, Loup-Escande, Lourdeaux, Thouvenin, & Valléry, 2020), and mobile health technologies (Nadal, Sas, & Doherty, 2020). As such, DOI remains the best framework for the analysis of the technology adoption process.

While the DOI theory’s Innovation Characteristics model is most effective at explaining the adoption of most technologies, this study recognizes that AI technology has unique characteristics. For example, there is increasing discomfort among employees regarding the adoption and integration of AI in their work environment (Glikson & Woolley, 2020). These psychological constraints should be considered when analyzing AI adoption. On the other hand, organizations are concerned about legal challenges, copyright compliance, and privacy/confidentiality issues (Grossman, 2024; Müller, 2023). To account for these differences, any study analyzing AI adoption must incorporate additional factors (psychological constraints), such as discomfort, trust, and usage restrictions, that capture the psychological aspects prominent in AI use. The purpose of this research is to leverage the DOI theory’s Innovation Characteristics model, as prescribed by Agarwal and Prasad (1997), and extend its application by including psychological constraints, to explain the AI adoption process. The research model is represented in Figure 1.

FIGURE 1: RESEARCH MODEL



By doing so, this research makes several important contributions. Firstly, it aims to demonstrate that the DOI theory's Innovation Characteristics model still remains a robust theoretical framework for understanding the technology adoption process. Secondly, it helps provide a holistic understanding of employees' adoption of AI technology. Thirdly, based on empirical research, it provides actionable insights for executives to drive AI adoption within their organizations. Finally, it provides additional suggestions for directions for further research on this topic.

THEORETICAL BACKGROUND

Innovation is defined as the implementation and sustained use of novel and useful ideas in practice, such that they create value for individuals, organizations, or systems (Shalley, Hitt, & Zhou, 2015). As such, the process of adoption of innovation across different disciplines, such as marketing (Clifford, O'Brien, & Southern, 2011), technology (Trantopoulos, von Krogh, Wallin,

& Woerter, 2017), psychology, and entrepreneurship (Shalley et al., 2015) has been analyzed in detail. In particular, the adoption of technological innovations is a key area of research (Mustonen-Ollila & Lyytinen, 2003; Trantopoulos et al., 2017).

Theoretical Frameworks Analyzing Technology Adoption Outcomes

Defining the "success" of a technological innovation is a multifaceted problem. While outcomes in technology adoption can be measured in a variety of ways (DeLone & McLean, 1992), including qualitative measures (such as perceived usefulness), attitudes towards technology (such as user satisfaction), performance-related (such as productivity gains), or behavioral (such as continued system use), the definition of success in IT implementation has been primarily behavioral such as usage or adoption (Agarwal & Prasad, 1997). This is because all other outcomes, such as satisfaction and impact, are predicated on usage.

There are three popular frameworks to analyze the technology adoption process: TAM, TRA, and DOI. The Technology Acceptance Model (TAM) was originally proposed to explain why individuals accept or reject new technologies (Davis, 1985). TAM is based on the idea that user perceptions of the target system are key to driving behavioral intent to adopt and use it. TAM has been proposed specifically for the IT domain, making it a popular choice to analyze the AI adoption of AI (Aziz, Rami, Razali, & Mahadi, 2020; Davis, 1985). The Theory of Reasoned Action (TRA) was developed to explain how an individual's attitudes and subjective perceptions impact their behavioral intentions (Fishbein & Ajzen, 1975). TRA is based on the idea that behaviors are a rational, voluntary process in which intentions (that are formed through personal perceptions and social pressures) act as the primary determinants of actions. Even though TRA was not explicitly designed for analyzing technology adoption, in recent years, there has been an explosion of studies analyzing AI adoption across various industries and sectors using these two frameworks (Ahmad Khan, Khan, & Aslam, 2024; Alka'awneh et al., 2025; Pinto et al., 2025; Saad, Ramli, M. S., & Ali, 2025; Shao et al., 2025; Zogheib & Zogheib, 2024). The primary challenge with TAM and TRA is that they account for only initial adoption and are insufficient to account for the technology's sustained long-term adoption across time and social contexts (Marikyan & Papagiannidis, 2025; Venkatesh et al., 2012). Studies (DeLone & McLean, 1992; Moore & Benbasat, 1991) have shown that both the outcomes, i.e., initial adoption and continued/sustained usage, are critical to define how successfully a technology has been integrated into an organization and that the organization can reap its benefits.

Diffusion of Innovation Theory: Technology Adoption as a Two-Stage Process

Diffusion of innovation theory explains how, why, and at what rate new ideas and technology spread through a social system (Rogers, 1983). It defines diffusion as the process by which an innovation is communicated through internal channels over time among the members of a social system. DOI explicitly distinguishes between initial adoption and continued, sustained usage and posits that different sets of factors, known as innovation characteristics, affect each outcome. The reason is that social networks, in this case organizations, operate at an equilibrium in a particular state, and have a certain amount of inertia built into the system. When a change is needed, a large force is required to displace the system from its equilibrium state into a new equilibrium state (Beer, Voelpel, Leibold, & Tekie, 2005; Okumus, 2001). Once the system is set to the new equilibrium, it may still revert to the old equilibrium; hence, a small but constant force is required to maintain it in the new equilibrium. Drawing from these change management philosophies, Rogers (1983) argued that the degree of behavioral change required to adopt a new technology initially is far greater than that is necessary to sustain the momentum. Rogers segmented users into five categories (innovators, early adopters, early majority, late majority, and laggards) to explain how the technology propagated within an organization. Innovators and early adopters enthusiastically adopt the new technology and are the primary drivers of change. As adoption becomes more visible within the social system, innovation characteristics facilitate the diffusion of the technology from early users to the early and late majority, at which point the technology becomes fully institutionalized. Laggards are the last to adopt, completing the full transformation. This diffusion process implies that technology adoption is not based on a single outcome, rather it is a process that involves different user groups with different outcomes, and each outcome is shaped by potentially different behavioral mechanisms. This makes DOI a better framework for analyzing the technology adoption process than TAM and TRA.

TABLE 1:

REVIEW OF RECENT STUDIES THAT USE INNOVATION CHARACTERISTICS TO EXAMINE AI ADOPTION

Research	Research Field	Output / Dependent Variable(s)	Current vs Future Use	Innovation Characteristics Used	Sample Size
AI adoption in higher education using DOI–TOE–TAM (Abulail et al., 2025)	Higher Education	AI adoption intention	Future Use	Relative Advantage, Ease of Use, Compatibility, Trialability	487
Responsible AI & continued IoMT use (Al-Dhaen et al., 2023)	Healthcare	Continued use intention	Future Use	Relative Advantage, Compatibility, Trust (non-DOI extension)	428
Generative AI use in teaching (Campbell & Cox, 2024)	Higher Education	Teaching adoption & pedagogical use	Current use	Relative Advantage, Compatibility, Ease of Use	42
Social status in acceptance of AI (Hong, 2022)	Individual-level/ Consumer context	AI adoption intention	Future Use	Relative Advantage (perceived), Image, Compatibility	1,050
AI pedagogy (Hsieh et al., 2025)	K-12 Education	AI integration; AI pedagogy	Current use	Relative Advantage (implicit), Compatibility, Observability; Trust tested as moderator	842
AI in social engineering attacks (Njenga & Matemane, 2025)	Information Systems	AI adoption intention	Future Use	Relative Advantage, Observability, Trialability	210
AI investments and Productivity Gains using Innovation Characteristics (Park, Kang, Yi, & Kim, 2026)	Cross-industry/ Firm-level	Firm productivity performance	-	Relative Advantage (implicit), Compatibility (industry fit)	8,125
Organizational AI adoption using DOI (Patnaik & Bakkar, 2024)	Cross-industry/ Organizational	AI adoption intention	Future Use	Relative Advantage, Compatibility, Ease of Use, Trialability, Observability	312
Generational differences in AI adoption in higher education institutions (Phillips, 2025)	Higher Education	AI Adoption stage & usage level	Both	Relative Advantage, Compatibility, Ease of Use, Image, Voluntariness	183
ChatGPT adoption by university students (Raman et al., 2024)	Higher Education	AI (ChatGPT) adoption intention	Future Use	Relative Advantage, Compatibility, Ease of Use, Trialability, Observability	503
AI adoption in libraries (Tella et al., 2025)	Education	Extent of AI adoption	Current use	Relative Advantage, Compatibility, Observability	6 libraries (qualitative)

A review of the current body of knowledge on DOI theory to explain AI adoption reveals important limitations. While these studies provide continuity with DOI theory, they underutilize its diffusion perspective. For example, many studies (Al-Dhaen, Hou, Rana, & Weerakkody, 2023; Njenga & Matemane, 2025; Patnaik & Bakkar, 2024; Tella, Dunmade, Ajani, & Abdullahi, 2025) analyze only one outcome, either initial adoption (current use) or continued, sustained usage (future use). This obscures the central point of DOI as it operates across different stages of the adoption process from initial manifestation to institutionalization. Another challenge is that many studies introduce additional factors at the expense of the innovation characteristics, thereby deviating from the core of DOI theory. Moreover, given the outsized role of AI technologies in education, especially with the use of generative AI tools such as ChatGPT, many studies on AI adoption are focused on the education sector (Abulail, Badran, Shkoukani, & Omeish, 2025; Hsieh, Bali, & Li, 2025; Phillips, 2025; Raman et al., 2024). Given that the technology adoption dynamics in a classroom environment with a student-teacher-university relationship differ from those in a workplace environment with an employee-manager-organization relationship, findings from these studies may not generalize well to organizational settings. Collectively, these literary gaps suggest a need for a more faithful theoretical application of the DOI theory with the impact of innovation Characteristics on technology adoption (as prescribed by Agarwal & Prasad (1997)) while simultaneously extending the model to include additional factors that are unique to AI technologies. This study, therefore, is needed to address the gap in understanding the full process of technology adoption. This study aims to leverage the DOI framework to address the following research question:

What factors influence the employee's current use of AI and future adoption of AI?

Role of Innovation Characteristics

While the initial DOI theory defined five factors under innovation characteristics (relative advantage, complexity, compatibility, trialability, and observability), Moore and Benbasat (1991) expanded this into seven constructs (relative advantage, ease of use, compatibility, trialability, image, visibility, result demonstrability, and voluntariness) to explain the adoption process.

Relative advantage, ease of use, compatibility, and trialability are individual characteristics as these are defined by the user's personal interaction with the innovation (Agarwal & Prasad, 1997; Moore & Benbasat, 1991). Relative advantage is the degree to which an innovation is perceived as being better than the current method or technology it replaces. Ease of use is defined as the degree to which an innovation is perceived as relatively free of effort. These two variables are the only ones defined in TAM, but DOI includes five additional ones. Compatibility is defined as the degree to which an innovation is perceived to conform to a user's personal values and past experiences. Trialability is defined as the degree to which a user perceives they have an opportunity to experiment with the innovation before fully committing to using it.

The next three variables (image, result demonstrability, and visibility) represent social characteristics because they reflect how users perceive the innovation in social contexts (Agarwal & Prasad, 1997). Image is defined as the user's perception that the innovation will contribute to improving their social status. Image construct was part of the relative advantage construct in Rogers' initial list, but Moore and Benbasat showed that it is an independent construct. Similarly, Moore and Benbasat separated observability as result demonstrability, defined as the tangibility of results, and visibility, defined as the degree to which the use and result of an innovation are observable to others.

The final construct, voluntariness, measures the degree to which the decision to adopt is non-mandated. In addition to individual and social dimensions that impact user adoption, Moore and Benbasat found that mandates from their superiors may also influence technology acceptance. While not part of the initial set of innovation characteristics, Moore and Benbasat included it in their analysis. Other technology acceptance models, such as the TRA (Fishbein & Ajzen, 1975), include voluntariness as part of the acceptance process, whereas TAM does not explicitly include it.

Agarwal and Prasad (1997) used these eight factors to analyze the technology adoption process and to determine which factors affect the initial manifestation (current use) and institutionalization (future use). Based on these constructs, the study will test the following hypothesis:

Hypothesis 1: Perceived innovation characteristics of AI will positively influence future AI adoption through the mediator of current use.

Extending the DOI Theory

While the DOI theory's innovation characteristics may explain the individual and social dimensions in the adoption process, AI is a unique technology because it has a significant psychological impact on users (Hsieh et al., 2025; Sison, Ferrero, García Ruiz, & Kim, 2023). Compared with other IT technologies that support decision-making but rely on humans as the final decision-makers, AI systems are different as they can make decisions independently without human interventions (Anagnostou et al., 2022; Felzmann, Fosch-Villaronga, Lutz, & Tamò-Larrieux, 2020; Shao et al., 2025). Because of the absence of a transparent, linear relationship between input variables and final output, decisions made by AI systems are difficult to interpret, and the entire decision-making process is shrouded in mystery (Colson, 2019; McKendrick & Thurai, 2022). This black-box decision-making has raised several ethical concerns from both employees and organizations. Employees perceive that AI lacks emotion and the personal touch of human decision-making, which can cause discomfort with AI and potentially lead to distrust of AI systems (Kim & Hinds, 2006, 2006; Yu & Li, 2022). As employees perceive AI as a job threat, this leads to distrust of workplace AI (Yu & Li, 2022; Zirar et al., 2023). Hence, any research on adoption needs to account for the discomfort and trust associated with technology, in addition to the innovation characteristics. Organizations, on the other hand, are concerned about the legal and copyright compliance, privacy/confidentiality concerns (Grossman, 2024; Müller, 2023). Hence, many organizations use access control to AI technologies as a key lever for controlling the negative impact of AI. A recent systematic literature review of 36 AI studies on factors impacting decision-making found that usage restriction, such as limits on tasks, data types, or decision authority, has a significant impact on the use and adoption of AI (Bukar, Sayeed, Fatimah Abdul Razak, Yogarayan, & Sneesl, 2024). Usage restriction differs from voluntariness in the fact that voluntariness is concerned with whether the user is mandated to use the technology, while usage restriction is concerned with the availability of the technology for use. Based on these psychological constraints, the study will test the following hypothesis:

Hypothesis 2: Employees' psychological constraints will negatively influence future AI adoption through the mediator of current use.

METHODS

Sample, Participants, and Procedures

A cross-sectional survey design was employed to gather empirical data from employees with current or prior experience (Creswell, 2014; Easterby-Smith, Jaspersen, Thorpe, & Valizade, 2021). The target population for this study consisted of adults aged 18 and above, residing in the United States. Eligibility was confirmed via initial survey screening questions. The study aimed to collect data from 263 employees, a sample size determined through power analysis to achieve statistical significance and generalizability as per the G*Power analysis (Kang, 2021; Kyonka, 2018). A combination of stratified sampling and convenience sampling was be used as stratified sampling ensures a proportional representation of subgroups, such as employees at different organizational levels, educational levels, and years of experience, while convenience sampling focuses on accessible participants who meet inclusion criteria through recruitment channels (Creswell & Plano Clark, 2011; Easterby-Smith et al., 2021). An effect size of 0.05 and a power of 0.95 were used to estimate the required sample size for the study. Participants were recruited through CloudResearch, an online survey platform, and compensated $2.50 for completing the survey. A total of 263 respondents completed the full survey, and all responses were included in the analysis. CloudResearch's panel-based recruitment ensured a wide demographic reach and provided access to professionals across various roles and organizational types.

This study examines the employee-level adoption of AI in a cross-industry organizational context. The study targeted working professionals from various industries. The study included various personnel (entry to mid-level professional, senior professional / manager, director / senior management, academia, and others, including self-employed) from different industries (consumer, digital and tech, education, healthcare, industrial, services, and others). The age distribution reflected a predominantly mid-career sample, with 35–44-year-olds representing the largest segment at 37%. Educational attainment was also broad, with the largest segment holding a bachelor's degree at 48%.

Measures

The survey instrument utilized established, validated scales from prior research (Agarwal & Prasad, 1997; Yu & Li, 2022). The respondents were provided with a list of statements for each variable, which were modified for analysis of AI adoption. All items were measured on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree), with an additional option of "not aware". Refer to the Appendices for details on the measures used.

Independent and Dependent Variables

The original instrument developed by Moore and Benbasat (1991) included 38 items to measure across the eight variables of innovation characteristics (relative advantage, ease of use, compatibility, trialability, visibility, result demonstrability, image, voluntary use). Agarwal and Prasad (1997) reduced it to 23 items to analyze WWW. In the current study, these 23 items were adopted for studying AI technologies. In addition, three new variables based on psychological constraints were added, namely discomfort, trust, and usage restriction. Discomfort and trust were measured using six items as defined by Yu and Li (2022), and usage restriction was measured using two items based on the study by Bukar et al (2024). The dependent variable, intention to adopt AI, was measured using two variables (current use and future use). Current use was measured using four items, and future use was measured using three items. These were developed by Davis (1993) and have since been successfully used in several studies, including Moore and Benbasat (1991) and Agarwal and Prasad (1997). Even though these studies were not longitudinal, prior research (Davis, 1989) has empirically demonstrated a link between intentions and actual usage.

For both independent and dependent variables, the respondents were provided with a Likert-type scale of 1- 5, with an additional option of “not aware”. Rather than substituting “0” or “1” for responses indicating “not aware”, they were treated as missing values, as they denote that the respondent does not have enough information to form a perception on the statement/variable provided (DeVellis & Thorpe, 2022; Hair, Black, Babin, & Anderson, 2019). This is considered the best practice as the Likert scale is designed to measure the intensity of a perception. Missing values were omitted when calculating the mean score for a variable. For some variables, such as result demonstrability, visibility, and usage restriction, reverse coding was used because the survey items were negatively worded. For the variable discomfort, although it was intended to measure a negative psychological perception, the survey items were phrased positively; therefore, the scores were not reversed.

Control Variables

Demographics (age, gender, education), job-related factors (role, industry sub-sector), and technology proficiency were included as control variables.

RESULTS

The survey results were loaded into Jamovi software for statistical analysis. The primary focus of the analysis was to examine the effects of innovation characteristics, along with discomfort, trust, and usage restriction, on the two outcome variables: current use and future use. Descriptive statistics of all the variables are noted in Table 2, including means, standard deviations, and correlations.

TABLE 2

DESCRIPTIVE STATISTICS, CORRELATIONS, AND RELIABILITIES FOR STUDY VARIABLES

Variable	Mean	SD	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.
1. Age	3.81	1.07	—														
2. Gender	1.43	0.55	-0.02	—													
3. Relative Advantage	3.98	0.79	0.02	-0.03	(0.90)												
4. Ease of Use	4.26	0.61	-0.07	-0.08	0.53***	(0.80)											
5. Compatibility	3.24	0.84	-0.05	-0.03	0.60***	0.39***	(0.71)										
6. Trialability	4.11	0.77	0.09	-0.10	0.35***	0.28***	0.26***	(0.62)									
7. Image	2.66	1.10	-0.04	-0.02	0.36***	0.13*	0.67***	0.10	(0.90)								
8. Result Demonstrability	4.03	0.57	0.06	-0.14*	0.20**	0.37***	0.10	0.22***	-0.12	(0.45)							
9. Visibility	3.27	0.98	0.07	0.06	0.30***	0.16**	0.31***	0.35***	0.09	0.17**	(0.50)						
10. Voluntariness	3.95	0.96	-0.09	0.04	-0.12*	0.01	-0.18**	-0.05	-0.09	0.09	-0.24***	(0.74)					
11. Discomfort	3.99	0.85	0.14*	-0.10	0.61***	0.46***	0.54***	0.42***	0.32***	0.20**	0.18**	-0.08	(0.89)				
12. Trust	3.30	0.97	0.01	-0.10	0.64***	0.42***	0.65***	0.30***	0.50***	0.12	0.14*	-0.10	0.65***	(0.80)			
13. Restriction	3.50	1.20	0.23***	-0.02	0.12	0.05	0.02	0.28***	-0.23***	0.27***	0.24***	-0.03	0.22***	0.02	(0.85)		
14. Current Use	3.44	1.09	-0.06	0.01	0.63***	0.41***	0.65***	0.36***	0.37***	0.08	0.46***	-0.24***	0.54***	0.58***	0.10	(0.93)	
15. Future Use	3.89	0.94	0.08	-0.06	0.69***	0.41***	0.57***	0.40***	0.33***	0.11	0.30***	-0.13*	0.67***	0.60***	0.20***	0.69***	(0.92)

n = 263. Cronbach's α reliabilities reported along the diagonal. * p<.05, ** p<.01, *** p<.001.

As some of the variables were correlated, we performed a multicollinearity analysis using variance inflation factors. The results indicated that the multicollinearity and suppression effects within various predictors were not present at levels that would indicate a bias in estimation. Hence, we proceed with regression analysis for all 11 variables without block-specific models.

Structural Equation Modeling (SEM) Results

Table 3 summarizes the results of the SEM path analysis used to examine the relationships depicted in Figure 1.

TABLE 3

STRUCTURAL EQUATION MODELLING FOR DIRECT AND INDIRECT EFFECTS ON OUTCOME VARIABLES

	Stage 1: Current Use X ⇒ M		Stage 2: Future Use M ⇒ Y		Indirect effects: X ⇒ M ⇒ Y	
	β	95% CI	β	95% CI	β	95% CI
Innovation Characteristics						
Relative Advantage	.10	[-.11, .33]	.29**	[.12, .42]	.04	[-.04, .12]
Ease of Use	.21*	[.01, .45]	.00	[-.19, .19]	.08*	[.00, .17]
Compatibility	-.15*	[-.42, -.03]	-.04	[-.23, .11]	-.06*	[-.16, -.00]
Trialability	.03	[-.17, .24]	.14+	[-.02, .29]	.01	[-.06, .09]
Image	.16*	[.02, .31]	.07	[-.01, .14]	.06*	[.00, .12]
Result Demonstrability	.40**	[.12, .64]	-.01	[-.10, .08]	.16*	[.03, .25]
Visibility	-.18+	[-.40, .01]	-.15+	[-.30, .01]	-.07+	[-.14, .00]
Voluntariness	-.07	[-.30, .09]	.05	[-.06, .19]	-.03	[-.11, .03]
Psychological Factors						
Discomfort	.10	[-.11, .31]	.27**	[.09, .44]	.04	[-.04, .11]
Trust	.38**	[.12, .85]	.02	[-.27, .32]	.15*	[.04, .31]
Restriction	-.02	[-.13, .09]	-.06	[-.15, .04]	-.01	[-.05, .03]
AI Adoption						
Current Use			.39**	[.24, .48]		

n = 263. $^{+}$p<.10, * p<.05, ** p<.01

Model Fit

Based on Hu and Bentler’s two-index presentation strategy (1999), the structural model demonstrated excellent fit to the data with a CFI score of .988 (which exceeds the recommended threshold of 0.95 and a SRMR score of .076 (which is lower than the recommended 0.threshold of 09) (Hooper, Coughlan, & Mullen, 2007). Also, the model demonstrated strong explanatory power for the key endogenous constructs with Current Use: $R^2 = .68$; and Future Use: $R^2 = .75$. These values indicate that the model explains a substantial portion of the variance in both actual AI usage and continued use intentions, with particularly strong explanatory power for future adoption intentions.

Direct Effects

We found that for current use of AI, ease of use (H1b, $p<.05$), compatibility (H1c, $p<.05$), image (H1e, $p<.05$), and result demonstrability (H1f, $p<.01$) were significant. Among the additional variables, trust (H1i, $p<0.01$) was a significant predictor of current AI use. As posited earlier, the variables for future use will differ from those for current use. We found that only relative advantage (H2a, $p<.01$) was significant among innovation characteristics. Among psychological constraints, discomfort (H2j, $p<.01$) was significant. Agarwal and Prasad did not find current use to be a significant predictor of future use in their study, whereas in our study, we found that current use was a significant predictor (H2l, $p<.01$). Also, visibility (H1g, H2g) and trialability (H2d) exhibited a partial significance ($p<.10$).

TABLE 4

HYPOTHESES RESULTS

Variables	Results
Hypothesis 1: Innovation Characteristics	
Relative Advantage	Not Supported
Ease of Use	Supported
Compatibility	Supported
Trialability	Not Supported
Image	Supported
Result Demonstrability	Supported
Visibility	Partially Supported
Voluntariness	Not Supported
Hypothesis 2: Psychological Factors	
Discomfort	Not supported
Trust	Supported
Restriction	Not supported

Indirect Effects

Analysis of indirect effects found that several innovation characteristics influenced future AI use through current use, indicating a mediated adoption process. Specifically, ease of use (H3b $p<.05$), compatibility (H3c, $p<.05$), image (H3e, $p<.05$), and result demonstrability (H3f, $p<.01$) were significant indirect effects on future use via current use. Among psychological constraints, trust (H3i, $p<0.01$) also demonstrated a significant indirect effect. Also, visibility (H3g, $p<.1$) exhibited a partial indirect significance. These findings suggest that while these factors do not directly shape future use intentions, their influence on the future use is transmitted indirectly via current use, indicating a mediated adoption process.

DISCUSSIONS

Theoretical Contributions

Juxtaposing the results of these two studies (Agarwal and Prasad (1997) and the current study), conducted across different time periods and technologies, provides many interesting insights. The results of the current study largely mirrored the results from previous studies, explaining the robustness of the model. Relative advantage, compatibility, visibility, trialability, and result demonstrability were significant in both studies. The list of innovation characteristics variables for current use and future use was different. Moreover, the number of innovation characteristics variables reduced from current use to future use in both studies. Given the close similarity between the results of the two studies, we can confidently conclude that the interaction among the innovation characteristics variables remains the same. Hence, the implications and lessons from the previous research can also be applied to this study.

On the other hand, there were some differences between the studies owing to the uniqueness of each technology. In the current study, ease of use and image replaced voluntariness and trialability in current use. Agarwal and Prasad had experienced similar slight contradictions in their effort. For example, while earlier studies had identified relative advantage as being important for current usage, Agarwal and Prasad found the contrary in their research. This was attributed to the uniqueness of the WWW technology, which elicited curiosity, thereby negating the need for usefulness for initial adoption. Also, unlike Agarwal and Prasad's study, current use was a significant predictor of future use and, in fact, the strongest predictor among all variables in this study.

These results offer a meaningful insight into how AI adoption unfolds within organizations. Unlike in the previous study, for the current use, voluntariness was not a statistically significant predictor. This suggests that initial adoption is independent of whether AI use is voluntary or organization-driven, and instead, it is shaped by employees' perceptions. Initial adoption is more likely to occur when the technology is easy to use (ease of use), fits well with their existing workflows (compatibility), and is socially visible in ways that enhance professional image (visibility and image), thereby encouraging experimentation. For future use, a different, albeit smaller, set of factors is significant. This is consistent with the assertion made by Rogers's diffusion of innovation theory. During initial adoption, the change is of large magnitude, as users must shift from the old way to the new. In contrast, during continued use, it is merely a reinforcement of existing behavior. Hence, the number of innovation characteristics factors declines. The absence of ease of use and compatibility in future use reinforces this point. Once users find the new technology easy to use and are convinced it fits their needs, resistance to change diminishes, and the new way of working can be sustained more easily.

One aspect not addressed by the framework is the role of psychological constraints. The results indicate that trust significantly affects current use, whereas discomfort significantly affects future use. This implies that continued use of the AI technologies builds trust through experiential learning, and employees may tolerate discomfort during early experimentation. However, the feeling continues to linger throughout the adoption process and shapes future use. This suggests that psychological constraints play a dominant role in shaping both the initial and continued use.

General Discussions: Learnings for Executives and Organizations

There are several key takeaways from the research that executives and organizations can use to help ensure that their AI adoption initiatives are successful. First, unlike other technologies, mandate-driven initiatives alone are insufficient to have a meaningful influence on adoption. As voluntariness did not significantly affect current use, executives are better served by fostering an environment that encourages collaboration and experimentation to drive adoption. Second, AI initiatives need to demonstrate net value addition for employees (relative advantage) and ensure that AI is integrated into workflows (compatibility). This implies that AI initiatives should be structured with clear, role-specific business goals (such as productivity gains, quality improvement, revenue generation, or safety improvement) while still fitting into existing workflows. AI tools that are perceived as useful and additive to existing workflow will experience lower resistance and accelerate adoption (Autor, 2019). Third, experimentation is key to success. Given the fact that trialability was important, it implies that employees need safe, low-risk opportunities to experiment with AI. An AI incubation hub that helps drive pilot programs, proof of concept, and sandbox experimentation will help employees gain familiarity without risking too much resource investment (Bouquet, Wright, & Nolan, 2026; Fountaine, McCarthy, & Saleh, 2019). Fourth, scaling AI adoption requires social cues, as image and visibility are critical for initial use. Executives need to arrange town halls, workshops, lunch and learn sessions to share AI use cases, recognize AI success stories, showcase business goal attainment, and honor early adopters and influencers to drive social adoption (Cooper, 2024). Fifth, provide a framework to address psychological constraints. Trust and discomfort are critical in adoption, implying that, for successful scaling, organizations need to ease concerns about AI. There are several steps organizations can take, including providing avenues for employees to share and address their ethical concerns (such as setting up an AI governance council with key stakeholders from HR ethics and legal teams), setting clear roles and expectations, and providing ethical guidelines on AI usage (such as human-in-the-loop designs, safeguards, and transparency and explainability in AI decision-making) (Grossman, 2024; Pflanzer, Traylor, Lyons, Dubljević, & Nam, 2023; Shao et al., 2025). Executives must proactively address concerns about job displacement, ethical challenges, AI bias, and AI-led decision-making, as addressing discomfort early is critical (Bhargava, Bester, & Bolton, 2021; Erebak & Turgut, 2021; Gallup, 2023). Finally, taken all together, a successful AI adoption and scaling requires a combination of technical, innovation, social, and psychological change management as validated by the extended innovation characteristics framework in conjunction with psychological factors.

FURTHER RESEARCH

While this study significantly advances our understanding of AI adoption and continued usage by integrating innovation characteristics from the DOI framework with psychological constraints, there are several opportunities to extend this research further. A few obvious suggestions include extending into a longitudinal research design from a cross-sectional study, as this would help understand the nuances of several key variables, such as discomfort that intensifies as usage continues. The research is focused on the US, which is considered to have relaxed regulations on AI usage and implementation compared to other regions (such as the European

Union), which has stricter rules on AI implementation, and this may have an impact on psychological factors (trust and discomfort). Moreover, expanding this research globally can uncover hidden cultural norms that impact trust and discomfort. Additionally, this research can be replicated as a mixed methods study with an initial survey followed by interviews with a select group of respondents to deepen understanding of employee perceptions, especially by juxtaposing factors that impact current usage vs future usage. Another key suggestion would be to include organizational and leadership-oriented moderators. Variables such as leadership communication, AI governance structures, and company ownership (for-profit vs non-profit vs government organizations) might uncover additional factors that help drive adoption. Finally, future research can analyze outcomes beyond adoption, such as job satisfaction, employee well-being, individual and team performances, and learning outcomes.

REFERENCES

Abulail, R. N., Badran, O. N., Shkoukani, M. A., & Omeish, F. 2025. Exploring the factors influencing AI adoption intentions in higher education: An integrated model of DOI, TOE, and TAM. ***Computers***, 14(6): 230.

Agarwal, R., & Prasad, J. 1997. The role of innovation characteristics and perceived voluntariness in the acceptance of information technologies. ***Decision Sciences***, 28(3): 557–582.

Agrawal, A., Gans, J., & Goldfarb, A. 2022. From prediction to transformation. ***Harvard Business Review***, 100(6): 100–109.

Ahmad Khan, F., Khan, N., & Aslam, D. 2024. ***Adoption of artificial intelligence in human resource management: An application of TOE-TAM model***, 22–36.

Al-Dhaen, F., Hou, J., Rana, N. P., & Weerakkody, V. 2023. Advancing the understanding of the role of responsible AI in the continued use of IoMT in healthcare. ***Information Systems Frontiers***, 25: 2159–2178.

Alka'awneh, S. M. N., Halim, H. A., Wahed, M. K. Y. A., Alqaraleh, M. K. S., Alzboon, M. S., et al. 2025. Perceived security and privacy in artificial intelligence adoption: Extending TAM in the context of jordanian SMEs. In A. Hannoon & A. Mahmood (Eds.), ***Intelligence-Driven Circular Economy: Regeneration Towards Sustainability and Social Responsibility–Volume 1***: 415–430. Cham: Springer Nature Switzerland.

Anagnostou, M., Karvounidou, O., Katritzidaki, C., Kechagia, C., Melidou, K., et al. 2022. Characteristics and challenges in the industries towards responsible AI: A systematic literature review. ***Ethics and Information Technology***, 24(3). https://doi.org/10.1007/s10676-022-09634-1.

Autor, D. H. 2019. Work of the past, work of the future. ***American Economic Association Papers and Proceedings***, 109: 1–32.

Aziz, F., Rami, A. M., Razali, F., & Mahadi, N. 2020. The influence of leadership style towards technology acceptance in organization. ***International Journal of Advanced Science and Technology***, 29(7s): 218–225.

Beer, M., Voelpel, S. C., Leibold, M., & Tekie, E. B. 2005. Strategic management as organizational learning. ***Long Range Planning***, 38(5): 445–465.

Belhadi, A., Mani, V., Kamble, S. S., Khan, S. A. R., & Verma, S. 2024. Artificial intelligence-driven innovation for enhancing supply chain resilience and performance under the effect of supply chain dynamism: An empirical investigation. ***Annals of Operations Research***, 333(2–3): 627–652.

Bhargava, A., Bester, M., & Bolton, L. 2021. Employees' perceptions of the implementation of robotics, artificial intelligence, and automation (RAIA) on job satisfaction, job security, and employability. ***Journal of Technology in Behavioral Science***, 6(1): 106–113.

Bouquet, C., Wright, C. J., & Nolan, J. 2026, January 1. Match your AI strategy to your organization's reality. ***Harvard Business Review***. https://hbr.org/2026/01/match-your-ai-strategy-to-your-organizations-reality.

Brynjolfsson, E. 1993. The productivity paradox of information technology. ***Commun. ACM***, 36(12): 66–77.

Bukar, U. A., Sayeed, Md. S., Fatimah Abdul Razak, S., Yogarayan, S., & Sneesl, R. 2024. Decision-making framework for the utilization of generative artificial intelligence in education: A case study of ChatGPT. ***IEEE Access***, 12: 95368–95389.

Campbell, L. O., & Cox, T. D. 2024. Utilizing generative AI in higher education teaching and learning. ***Journal of the Scholarship of Teaching and Learning***, 24(4): 162–173.

Clifford, S., O'Brien, E., & Southern, M. 2011. ***Knowledge management for process, organizational and marketing innovation: Tools and methods***. Hershey, PA: Information Science Reference.

Colson, E. 2019, July 8. What AI-driven decision making looks like. ***Harvard Business Review***. https://hbr.org/2019/07/what-ai-driven-decision-making-looks-like.

Cooper, R. G. 2024. Overcoming roadblocks to AI adoption in innovation. ***Research-Technology Management***, 67(5): 23–29.

Coyle, D., & Poquiz, J. L. S. 2025. ***Making AI count: The next measurement frontier***. Working paper no. 34330, National Bureau of Economic Research, Inc. https://EconPapers.repec.org/RePEc:nbr:nberwo:34330.

Creswell, J. W. 2014. ***Research design: Qualitative, quantitative and mixed methods approaches*** (4th edition). Los Angeles, Calif.: SAGE Publications, Inc.

Creswell, J. W., & Plano Clark, V. L. 2011. ***Designing and conducting mixed methods research*** (2nd ed). Los Angeles: SAGE Publications.

Davis, F. 1985. ***A technology acceptance model for empirically testing new end-user information systems: Theory and results***. Ph. D., Massachusetts Institute of Technology, Sloan School of Management.

Davis, F. 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. ***MIS Quarterly***, 13: 319.

Davis, F. D. 1993. User acceptance of information technology: System characteristics, user perceptions and behavioral impacts. ***International Journal of Man-Machine Studies***, 38(3): 475–487.

DeLone, W. H., & McLean, E. R. 1992. Information systems success: The quest for the dependent variable. ***Information Systems Research***, 3(1): 60–95.

DeVellis, R. F., & Thorpe, C. T. 2022. ***Scale development: Theory and applications***. Los Angeles London New Delhi Singapore Washington DC Melbourne: SAGE Publications, Inc.

Easterby-Smith, M., Jaspersen, L. J., Thorpe, R., & Valizade, D. 2021. ***Management and business research*** (Seventh edition). Los Angeles London New Delhi Singapore Washington DC Melbourne: SAGE.

Erebak, S., & Turgut, T. 2021. Anxiety about the speed of technological development: Effects on job insecurity, time estimation, and automation level preference. ***The Journal of High Technology Management Research***, 32(2): 100419.

Felzmann, H., Fosch-Villaronga, E., Lutz, C., & Tamò-Larrieux, A. 2020. Towards transparency by design for artificial intelligence. ***Science and Engineering Ethics***, 26(6): 3333–3361.

Fishbein, M., & Ajzen, I. 1975. ***Belief, attitude, intention and behaviour: An introduction to theory and research***, vol. 27.

Fountaine, T., McCarthy, B., & Saleh, T. 2019, July 1. Building the AI-powered organization. ***Harvard Business Review***. https://hbr.org/2019/07/building-the-ai-powered-organization.

Gallup. 2023, September 11. More U.S. workers fear technology making their jobs obsolete. ***Gallup.com***. https://news.gallup.com/poll/510551/workers-fear-technology-making-jobs-obsolete.aspx.

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

Gnanamoorthy, A. M. 2024. Enhancing organizational performance through the AI-enhanced strategic execution framework: Literature review and future research agenda. ***International Journal of Business Information Systems Strategies***, 13(1/2/3/4). https://doi.org/10.14810/ijbiss.2024.13402.

Grossman, N. 2024, February 29. AI ethics training for employees: How to help your workforce navigate AI's ethical challenges. ***Training Industry***. https://trainingindustry.com/articles/compliance/ai-ethics-training-for-employees-how-to-help-your-workforce-navigate-ais-ethical-challenges/.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. 2019. ***Multivariate data analysis***. Cengage.

Hong, J.-W. 2022. I was born to love AI: The influence of social status on AI self-efficacy and intentions to use AI. ***International Journal of Communication***, 16: 172–191.

Hooper, D., Coughlan, J., & Mullen, M. 2007. Structural equation modeling: Guidelines for determining model fit. ***The Electronic Journal of Business Research Methods***, 6.

Hopkins, J. L. 2021. An investigation into emerging industry 4.0 technologies as drivers of supply chain innovation in Australia. ***Computers in Industry***, 125: 103323.

Hsieh, C.-C., Bali, S., & Li, H.-C. 2025. Untangling pathways from digital instructional leadership to AI pedagogy: A diffusion of innovation theory perspective. ***BMC Psychology***. https://doi.org/10.1186/s40359-025-03792-9.

Hu, L., & Bentler, P. M. 1999. Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. ***Structural Equation Modeling***, 6(1): 1–55.

Hubert, M., Blut, M., Brock, C., Zhang, R. W., Koch, V., et al. 2019. The influence of acceptance and adoption drivers on smart home usage. ***European Journal of Marketing***, 53(6): 1073–1098.

Kang, H. 2021. Sample size determination and power analysis using the G*Power software. ***Journal of Educational Evaluation for Health Professions***, 18: 17.

Kim, T., & Hinds, P. 2006. Who should I blame? Effects of autonomy and transparency on attributions in human-robot interaction. ***ROMAN 2006—The 15th IEEE International Symposium on Robot and Human Interactive Communication***, 80–85. Presented at the ROMAN 2006 - The 15th IEEE International Symposium on Robot and Human Interactive Communication, Univ. of Hertfordshire, Hatfield, UK: IEEE.

Kyonka, E. G. E. 2018. Tutorial: Small-N power analysis. ***Perspectives on Behavior Science***, 42(1): 133–152.

McElheran, K., Yang, M.-J., Brynjolfsson, E., & Kroff, Z. 2025, April 20. ***The rise of industrial AI in America: Microfoundations of the productivity J-curve(s)***. Rochester, NY: Social Science Research Network. https://doi.org/10.2139/ssrn.5036270.

McKendrick, J., & Thurai, A. 2022, September 15. AI isn't ready to make unsupervised decisions. ***Harvard Business Review***. https://hbr.org/2022/09/ai-isnt-ready-to-make-unsupervised-decisions.

Mikalef, P., Lemmer, K., Schaefer, C., Ylinen, M., Fjørtoft, S. O., et al. 2023. Examining how AI capabilities can foster organizational performance in public organizations. ***Government Information Quarterly***, 40(2): 101797.

Moore, G. C., & Benbasat, I. 1991. Development of an instrument to measure the perceptions of adopting an information technology innovation. ***Information Systems Research***, 2(3): 192–222.

Müller, V. C. 2023. Ethics of artificial intelligence and robotics. In E. N. Zalta & U. Nodelman (Eds.), ***The Stanford Encyclopedia of Philosophy***. Stanford: Metaphysics Research Lab, Stanford University. https://plato.stanford.edu/archives/fall2023/entries/ethics-ai/.

Mustonen-Ollila, E., & Lyytinen, K. 2003. Why organizations adopt information system process innovations: A longitudinal study using Diffusion of Innovation theory. ***Information Systems Journal***, 13(3): 275–297.

Nadal, C., Sas, C., & Doherty, G. 2020. Technology acceptance in mobile health: Scoping review of definitions, models, and measurement. ***Journal of Medical Internet Research***, 22(7): e17256.

Njenga, K., & Matemane, B. 2025. Augmented intelligence in social engineering attacks: A diffusion of innovation perspective. ***International Journal of Business Ecosystem & Strategy***, 7(1): 106–121.

Okumus, F. 2001. Towards a strategy implementation framework. ***International Journal of Contemporary Hospitality Management***, 13(7): 327–338.

Park, G., Kang, S., Yi, S., & Kim, J. 2026. Diverse impacts of AI investments on productivity gains: Effects of industry and innovation characteristics. ***Technological Forecasting and Social Change***, 224: 124471.

Patnaik, P., & Bakkar, M. 2024. Exploring determinants influencing artificial intelligence adoption: Reference to diffusion of innovation theory. ***Technology in Society***, 79: 102750.

Pflanzer, M., Traylor, Z., Lyons, J. B., Dubljević, V., & Nam, C. S. 2023. Ethics in human–AI teaming: Principles and perspectives. ***AI and Ethics***, 3(3): 917–935.

Phillips, K. N. 2025. ***Artificial intelligence: Diffusion of innovation and generational considerations in a higher education institution***. Marymount University, Arlington, VA.

Pinto, A. S., Abreu, A., Carvalho, J. V., Carvalho, M., Martins, S., et al. 2025. The technology acceptance model (TAM): A meta-analytic structural equation modeling (MASEM) approach to explaining the adoption of GenAI tools in higher education. In J. V. Carvalho, A. Abreu, M. Silva, E. Ferreira da Costa, & J. A. F. Costa (Eds.), ***Perspectives and Trends in Education and Technology, Volume 2***, 470–480. Cham: Springer Nature Switzerland.

Raman, R., Mandal, S., Das, P., Kaur, T., Sanjanasri, J. P., et al. 2024. Exploring university students' adoption of ChatGPT using the diffusion of innovation theory and sentiment analysis with gender dimension. ***Human Behavior and Emerging Technologies***, 2024: 3085910.

Rogers, E. M. 1983. ***Diffusion of innovations*** (3rd ed). New York: Free press.

Saad, S., Ramli, Z., M. S., S., & Ali, M. N. S. 2025. Exploring the adoption of AI-driven adaptive learning in higher education: A multidimensional TAM perspective. ***International Journal of Academic Research in Business and Social Sciences***, 15(5): Pages 1011-1025.

Sagnier, C., Loup-Escande, E., Lourdeaux, D., Thouvenin, I., & Valléry, G. 2020. User acceptance of virtual reality: An extended technology acceptance model. ***International Journal of Human–Computer Interaction***, 36(11): 993–1007.

Shalley, C., Hitt, M. A., & Zhou, J. (Eds.). 2015. ***The Oxford handbook of creativity, innovation, and entrepreneurship***. Oxford University Press. https://doi.org/10.1093/oxfordhb/9780199927678.001.0001.

Shao, C., Nah, S., Makady, H., & McNealy, J. 2025. Understanding user attitudes towards AI-enabled technologies: An integrated model of self-efficacy, TAM, and AI ethics. ***International Journal of Human–Computer Interaction***, 41(5): 3053–3065.

Sison, A., Ferrero, I., García Ruiz, P., & Kim, T. W. 2023. Editorial: Artificial intelligence (AI) ethics in business. ***Frontiers in Psychology***, 14: 1258721.

Tabrizi, B., & Pahlavan, B. 2023, June 23. Companies that replace people with AI will get left behind. ***Harvard Business Review***. https://hbr.org/2023/06/companies-that-replace-people-with-ai-will-get-left-behind.

Tella, A., Dunmade, A. O., Ajani, Y. A., & Abdullahi, F. 2025. ICT application in Nigerian libraries: The need to look into the direction of 4IR technologies following the perspective of diffusion of innovation theory. ***Revista Digital de Biblioteconomia e Ciência Da Informação***, 23: e025008.

Trantopoulos, K., von Krogh, G., Wallin, M. W., & Woerter, M. 2017. External knowledge and information technology: Implications for process innovation performance. ***MIS Quarterly***, 41(1): 287–300.

Triplett, J. E. 1999. The Solow productivity paradox: What do computers do to productivity? ***The Canadian Journal of Economics / Revue Canadienne d'Economique***, 32(2): 309.

Wimoolka, S. 2022. ***The impact of artificial intelligence implementation on companies economic performance***. Doctoral dissertation, Westcliff University, United States -- California, US. ProQuest Dissertations Publishing.

Yu, L., & Li, Y. 2022. Artificial intelligence decision-making transparency and employees' trust: The parallel multiple mediating effect of effectiveness and discomfort. ***Behav. Sci.***, 12: 127.

Zirar, A., Ali, S. I., & Islam, N. 2023. Worker and workplace artificial intelligence (AI) coexistence: Emerging themes and research agenda. ***Technovation***, 124: 102747.

Zogheib, S., & Zogheib, B. 2024. Understanding university students' adoption of ChatGPT: Insights from TAM, SDT, and beyond. ***Journal of Information Technology Education: Research***, 23: 025.

APPENDIX

Survey Instrument

Items	Scale	Source
Relative Advantage	Using AI tools would make it easier to do my work.	Adapted from (Agarwal & Prasad, 1997)
	Using AI tools would help me to accomplish tasks more quickly.	
	Using AI tools would improve the quality of the work I do.	
	Using AI tools would give me greater control over my work.	
	Using AI tools would enhance my effectiveness in my academic program and/or my job.	
Ease of Use	My interaction with AI tools is clear and understandable.	
	I believe it would be easy to get AI tools to do what I want it to do.	
	Overall, I believe AI tools would be easy to use.	
	Learning to use AI tools would be easy for	
Voluntariness	Although it might be helpful, using AI tools is certainly not compulsory in my academic program and/or my workplace.	
	My supervisor/ professors do not require me to use AI tools.	
Compatibility	Using AI tools would be compatible with all aspects of my work.	
	I think that using AI tools would fit well with the way I like to work.	
Image	People who use AI tools have more prestige than those who do not.	
	People who use AI tools have a high profile.	
	Using AI tools is a status symbol.	
Result Demonstrability	I believe I could effectively communicate the results of using AI tools to others.	
	The results of using AI tools would be apparent to me.	
	I would have difficulty explaining why using AI tools may or may not be useless.*	
Visibility	In my academic program and/or my workplace one sees the use of AI tools a lot.	
	AI tools usage is not very visible in my academic program and/or my workplace.*	
Trialability	I would be permitted to use AI tools on a trial basis long enough to see what it could do.	
	Before deciding to use AI tools, I would be able to properly try it out.	
Usage Restriction	Although it might be helpful, using AI tools is certainly restricted in my college coursework and/or my workplace.	Adapted from (Bukar et al., 2024)
	My supervisor/professors have instructed me to not use AI tools.	
Discomfort	I feel comfortable with the results of AI tools.*	Adapted from (Yu & Li, 2022)
	I feel receptive to the results of AI tools.*	
	I feel at ease with the results of AI tools.*	
Trust	I would heavily rely on AI tools' feedback for decision-making processes.	
	I would trust AI tools completely in providing accurate and helpful responses.	
	I would feel comfortable relying on AI tools for assistance in my tasks.	
Current Usage	I use AI tools a lot to do my work.	Adapted from (Agarwal & Prasad, 1997)
	I use AI tools whenever possible to do my work.	
	I use AI tools frequently to do my work.	
	I use AI tools whenever appropriate to do my work.	
Future Use Intentions	I intend to increase my use of AI tools for work in the future.	
	I intend to use AI tools in the future for my work.	
	For future work I would use AI tools.	