GAS Journal of Economics and Business Management (GASJEBM)
Volume 3 | Issue 1, 2026 Homepage: https://gaspublishers.com/gasjebm-home/ ISSN: 3048-782X

Exploring the Adoption of AI in Leadership through the Lens of the Generative AI Era

Huynh Tai

Ho Chi Minh City University of Foreign Languages – Information Technology

Received: *25.11.2025* | ***Accepted:*** *13.12.2025* | ***Published:*** *01.01.2026*

***Corresponding Author:** Huynh Tai

DOI: *10.5281/zenodo.18113653*

Abstract **Original Research Article**

With the era of generative AI redefining how organizations make decisions, it is more essential to comprehend the process through which leaders embrace and incorporate AI technologies. This research used a quantitative method to gather data on 186 Vietnamese participants who have leadership experience and used AI-based systems or were exposed to AI-driven leadership. Through the application of PLS-SEM, the research proposes the role of technology readiness dimensions and innovation attributes on the intentions of adoption to AI. The findings indicate that AI adoption is largely motivated by technology optimism and perceived compatibility and obstructed by discomfort and insecurity. This paper explores the factors that affect AI adoption by leaders by combining the Technology Readiness Index (TRI) and Diffusion of Innovation (DOI) models which expanding its applications to leadership context to provide both theoretical and managerial insights of building AI-ready leadership attitudes in companies which adjust to the digital change.

Keywords: DOI, TRI, Cognitive Trust, Leadership, AI Leadership.

1. Introduction

The fast development of the generative Artificial Intelligence (AI) has significantly changed the managerial practice where AI is not only a means of automation but also an intellectual companion that assist in making strategic decisions (Gonesh et al., 2023; Kumar et al., 2025; Rezazadeh et al., 2025). The generative AI systems have the capacity to process an enormous amount of data, create predictive insights, and simulate strategic scenarios that can help the leader to process complicated information and predict change (Corvello, 2025; López-Solís et al., 2025; Storey et al., 2025). Because of that, Chhatre & Singh (2024) and Kassa & Worku (2025) have stated that AI-driven leadership has become a vital part of organizational change and digital competitiveness. Nevertheless, AI acceptance among leaders is not uniform and not all leaders show their willingness to use AI-assisted application to make decisions (Gerlich, 2023; Van Quaquebeke & Gerpott, 2023). This brings up the necessity to know the behavioral and psychological antecedents that determine the readiness of leaders to use AI technologies (Uren & Edwards, 2023a).

Previous research has covered the technological aspects or organizational aspects in the majority, and fewer examples have been on individual level mechanisms like cognitive trust that define AI acceptance (Eftimov & Kitanovikj, 2023; Uren & Edwards, 2023a). The first stage of influencing the adoption behavior is cognitive trust, which refers to the belief of the leader in the capabilities and predictability of the AI systems (Shi et al., 2020). In order to describe this process, this paper combines two theoretical approaches that are complementary: the Diffusion of Innovation (DOI) theory and the Technology Readiness Index (TRI). DOI focuses on the characteristics of innovation, like adaptability and compatibility that help to accept (Almaiah et al., 2022; Overbye-Thompson & Hamilton, 2025) whereas TRI concerns the psychological ones, i.e., innovativeness and discomfort, which determines readiness to new technologies (O'Hern & St. Louis, 2023; A. P. Parasuraman & Colby, 2014).

Thus, the purpose of the study includes exploring the use of adaptability, compatibility, innovativeness and discomfort using the Diffusion of Innovation (DOI) and Technology Readiness Index (TRI) models to influence leaders to have cognitive trust in the generative AI. It also focuses on the role of cognitive trust in mediating the connection between these antecedents and intention to use AI in strategic decision making among leaders. Theoretically, the present research is a combination of DOI and TRI to offer a more profound insight into the process of leadership preparedness in the age of generative AI. In practice, it provides an idea of how organizations can build trust based and ethical use of AI in the managerial practice.

2. Literature review

2.1. AI in Leadership

The integration of Artificial Intelligence in leadership has become an emerging trend within the modern realm of digital transformation (Rashid & Kausik, 2024; Sacavém et al., 2025). While transformational leadership emphasizes vision, motivation, and inspiration, the use of AI in leadership primarily supports these goals through data-driven insights and predictive analytics, ethical application of artificial intelligence, and the support of human-machine collaboration (Boudreaux, 2024; Peifer et al., 2022)

The recent empirical studies demonstrate that strong leaders who adopt AI in their strategies should also be technologically (and emotionally) competent in order to deal with emerging uncertainties and build trust toward the decisions made with the help of AI (Mariani & Dwivedi, 2024; Watson et al., 2021). Compared to that, therefore, the growing adoption of AI in leadership represents a shift toward more evidence-based and data-informed decision-making. Nevertheless, there is very little empirical literature that identifies how individual preparedness and diffusion of innovations explains this change, which serves as a strong argument in favor of considering theoretical frameworks like the Diffusion of Innovation and the Technology Readiness Index to clarify the precursors of the use of AI in leadership (Tigre et al., 2025; Uren & Edwards, 2023b).

2.2. Diffusion of Innovation (DOI)

Introduced by Rogers (1995), the Diffusion of Innovation (DOI) theory explains how new ideas and technologies spread and are adopted in a social system through time. It outlines four key factors including innovation, communication channels, time, and social system, and categorizes adopters into five groups, including innovators, early adopters, early majority, late majority, and laggards. This process of adoption follows five steps: knowledge, persuasion, decision, implementation, and confirmation, explaining why some individuals or organizations adopt technological change faster than others.

In leadership transformation, DOI is a good lens through which leaders can be described in terms of how they develop out of transformational leadership, which focuses on inspiration, vision and human connection, to AI leadership, which is a combination of intelligent systems and data driven decision making (Hossain et al., 2025; Korejan & Shahbazi, 2016). The system explains the varying rates of adoption with the key innovation attributes relative advantage, compatibility, complexity, trialability and observability (Moore & Benbasat, 1991; Tornatzky & Klein, 1982). As an example, leaders who view artificial intelligence as beneficial and consistent with their existing practices have a higher tendency to implement it, and perceptions of high complexity or low visibility can postpone diffusion (Sahin, 2006). Therefore, the transformation of leadership presupposes both the introduction of new technologies and changes in attitude, culture, and organizational values.

Despite the fact that DOI has been criticized for its linearity and lacking in addressing social resistance (Agocs, 1997; Carreno, 2024), it is a strong theoretical framework used to study how generative artificial intelligence spreads in a leadership context. Thus, DOI offers a holistic perspective to describe the patterns of diffusion of AI leadership adoption in organizational hierarchies (Phillips, 2025). Nonetheless, there is a scarcity of studies that focus on cognitive and behavioral adaptations of leaders in response to AI transformation, which is why a substantial gap in the theoretical literature exists and this research is designed to fill it.

2.3. Technology Readiness Index (TRI)

Technology Readiness Index (TRI) that was originally conceptualized by Parasuraman (2000) was aimed to measure an individual tendency to use and gain emergent technologies. Later update, such as TRI2.0, added 4 dimensions to the index including optimism, innovativeness, discomfort, and insecurity (A. P. Parasuraman & Colby, 2014). Optimism refers to the belief that technology has more to offer in terms of control, flexibility and efficiency, but innovativeness is the preference to be an innovator in the use of new tools (Walczuch et al., 2007). Discomfort reproduces the sense of lack of control and being overwhelmed by technology, and the insecurity implies distrust in technology or about its reliability as well as its security (A. P. Parasuraman & Colby, 2014).

In the field of leadership change, TRI provides a theoretical framework by which the rationale can be achieved as to why certain leaders are willing to embrace AI-based tools more effectively than others. Higher scores on optimism and innovativeness can also lead leaders to the belief that AI could facilitate the process of decision-making and communication (Stilgoe et al., 2013; Zhang et al., 2023). On the other hand, high levels of chagin or insecurity may breed adverse reactions characterized by concerns about losing control, the possibility of data bias or even some sense of moralness (A. P. Parasuraman & Colby, 2014). Empirical research proves that TRI is one of the significant predictors of adaptive performance through work engagement (Schnitzler & Bohnet-Joschko, 2025). Thus, the Technology Readiness Index (TRI) provides an integrative lens regarding leaders perceptions and adaptive reactions to technological change. However, its application to leadership situations is not well empirically studied thus, should be subject to an additional investigation.

2.4. Hypotheses and Conceptual framework

Adaptability, Compatibility and Cognitive Trust

In the Diffusion of Innovation (DOI) theory, two aspects are relevant namely, adaptability and compatibility, which determine the level of acceptance and trust that users have with regard to technology (Rogers, 1995). Adaptability can be defined as the degree at which an innovation can be altered or modified to suit the needs of the users and the operating conditions (Askar et al., 2021; Boudreaux, 2024; Collie & Martin, 2017). On the other hand, compatibility indicates the extent to which an innovation is seen to align with the values, experiences and practices of the users (Overbye-Thompson & Hamilton, 2025). Their combination defines how readily leaders can embrace AI and trust it rationally in their leadership. Previously, many research established that adaptability and compatibility play a very important role in leading to cognitive trust which is based on rational judgments on competence, reliability and predictability (Shamim et al., 2023a; Webber, 2008). Xu et al. (2014) established that technologies that are perceived as flexible and able to match the requirements of the users would increase the confidence in the performance of the systems, which would build trust. Lai & Lee (2020) and Wanner et al (2022) also elaborated that when the users believe that a system is reliable, and the technology integrates smoothly with the current workflows and can be adjusted to suit different situations, then users have an increased belief that the system is reliable. Taken together, these research results indicate that leaders are better inclined to trust AI cognitively when they feel that it is adaptable to their unique needs as well as being compatible with their leadership style and organizational values. When AI systems have the potential to conform to the current systems of leadership, as well as adapt to the evolving state of the organization, leaders gain greater trust in the system and its analytical skills. Such qualities assist to decrease the level of uncertainty, enhance predictability and rational confidence in AI assisted leadership behaviors. As a result, the following hypotheses are proposed:

H1: Adaptability have a positive effect to Cognitive Trust

H2: Compatibility have a positive effect to Cognitve Trust.

Innovativeness, Discomfort and Cognitive Trust

Innovativeness is a feature of individuals to be technology pioneers, that is, willing to explore and utilize new tools (A. Parasuraman, 2000). Conversely, discomfort is the experience of being overpowered or not being in control when utilizing technology (A. P. Parasuraman & Colby, 2014). In the case of AI assisted leadership, the innovative leaders are more willing to explore the use of generative AI to make decisions whereas those who feel uncomfortable feel that AI is complex or unreliable and this has a direct impact on their cognitive trust (McAllister, 1995; Shamim et al., 2023b).

Although the earlier research indicates that innovativeness increases rational confidence in technology through familiarity and perceived competence, the previous researchers have omitted the evaluation of the effect of innovativeness on technology rational confidence levels in the robotic industry (Jalo & Pirkkalainen, 2024; Salhieh & Al-Abdallat, 2022). Innovative users are more likely to develop stronger cognitive trust than users who are not because of their curiosity and more often they are exposed to new technologies (Erdem & Ozen, 2003). On the same note, Yuan et al. (2024) observed that such interaction minimizes doubt and strengthens the sense of trustworthiness.

On the contrary, discomfort compromises trust by making issues regarding control and precision. A. P. Parasuraman & Colby (2014) and Godoe & Johansen (2012) revealed that more uncomfortable users exhibit less perceived usefulness and trust. Highly innovativeness leaders have more chances to view AI as competent and reliable, thus developing cognitive trust. On the other hand, more uncomfortable people would not be that sure about the reliability of AI. Thus, the following hypotheses are established:

H3: Innovativeness have a positive effect to Cognitive Trust

H4: Discomfort have a positive effect to Cognitve Trust.

Cognitive Trust and Adoption to AI

Cognitive trust is defined as personal confidence in the reliability, dependability and capability of the individuals one trusts (Moorman et al., 1992). Cognitive trust is used in the context of AI adoption as a way to assess the credibility and performance of the AI-based solutions by the users (Davenport et al., 2018). In cases where people trust AI and believe it to be reliable and able to deliver correct outcomes, they tend to adopt it and incorporate it into their work (Choung et al., 2022).

Past studies always indicated that cognitive trust is a crucial factor in fueling the uptake of technology as it helps to reduce uncertainty and perceived risk (Shamim et al., 2023c). Indicatively, Daly et al. (2025) highlighted that trust is one of the antecedents of AI acceptance that promotes the perception of its functionality and reliability. That aligns with the research of Jacovi et al. (2021) who concluded that increased cognitive trust enhanced the desire of users to embrace and keep on using AI-based technologies.

According to this argument, people with a higher level of cognitive trust are more likely to use AI tools in decision-making and the execution of tasks. Thus, the hypothesis below has been suggested:

H5: Cognitive Trust have a positive effect to Adoption to AI..

Base on the above discussion, the research model will be presented by Figure 1

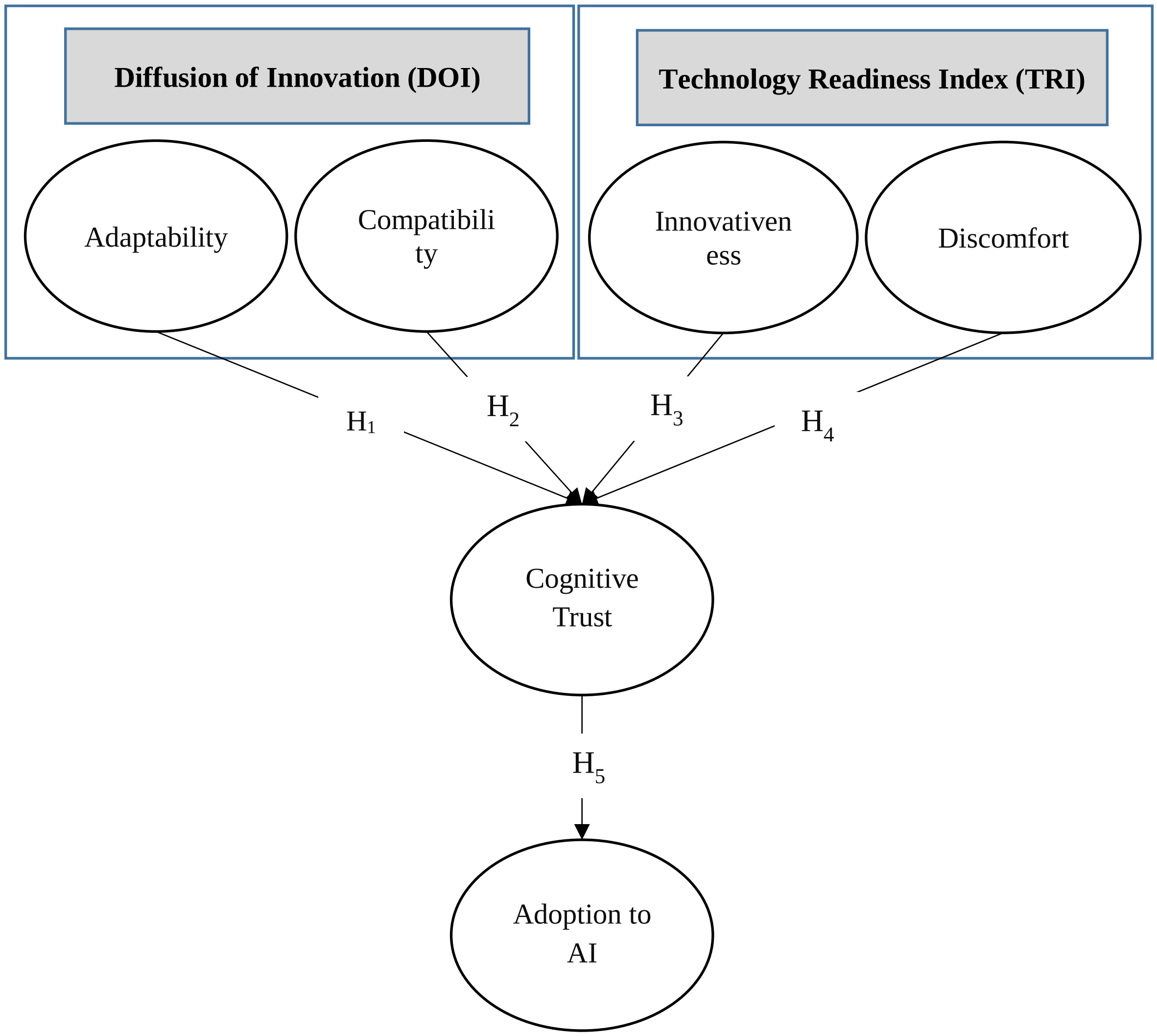


Figure 1. Research Model

3. Methodology

Target population

To assure the accuracy of the research data and to guarantee the quality, a filter question at the beginning of the questionnaire was used to gauge the aptness of the potential respondents (T.-Q. Dang, Nguyen, & Thi, 2025; Dao et al., 2023; B.-H. T. Nguyen et al., 2024; B.-T. H. Nguyen, Le, et al., 2023; L.-T. Nguyen et al., 2024) . Participation in the survey was limited to individuals who have experience working with AI-based systems or have been exposed to AI leadership practices. For this study to assess the transition from transformational leadership to AI leadership, participants' familiarity with leadership or management contexts was required. Participants were guaranteed anonymity and data use for academic research (Binh et al., 2024; T. – T. C. Phan et al., 2025; Thi Viet & Nguyen, 2025). Moreover, the participants were told that they were taking part in the research on a voluntary basis. Then, we requested possible participants to respond to questions regarding our central concepts and give personal data. The questionnaire was completed, and the respondent was instructed to distribute the link with friends and motivate them to complete the online survey.

Measure, Questionnaire Design and Data Collection

This study was conducted using Google Form, which is among the most popular professional online survey tools (Duc et al., 2025; L.-T. Nguyen, Duc, et al., 2023; L.-T. Nguyen, Nguyen, et al., 2023; L.-T. Nguyen, Phan, et al., 2025; N. T. T. Nguyen et al., 2024) . Questionnaire items were revised on the basis of a thorough literature review to achieve content validity, then its content will then be verified by a team of experts (T. Q. Dang, Nguyen, et al., 2025; Duc et al., 2024; Le, Lin, et al., 2025; L.-T. Nguyen, Tran, et al., 2025; L.-G. N. Phan et al., 2025) . The first modification of the questionnaire was on the basis of English-language research. It was translated and formed in Vietnamese, the official language and the most spoken language of the Vietnamese e-commerce users. Then it was reverted back to English to be consistent. Any literature was adapted into the study. Adaptability and Compatibility were assessed using four items for each was adapted from Rogers (1995). Also, with Innovativeness and Discomfort, four items of each construct was adapted from Parasuraman & Colby (2014). For the Cognitive Trust, it was measured by using four item from Komiak & Benbasat (2006). To capture the Adoption of AI in leadership, four measurement items were drawn from the scales of Chan & Petrikat (2022), Oliveira et al. (2016) and Venkatesh et al. (2012). To improve respondents' understanding of the measurement items, we asked them to choose their answers based on their genuine feelings while using e-commerce platform for shopping. This study used a 7-point Likert scale to increase dispersion and reduce neutral responses, allowing for more accurate quantification of statement agreement. The agreement scale ranges from (1) strongly disagree to (7) strongly agree. The study's minimum sample size was determined using G-Power software (version 3.1.9.7) (Erdfelder et al., 2009). The parameters included 0.80 power, 0.05 alpha, 0.15 effect size, and 5 predictors. The analysis showed that 118 participants were needed. In addition, using the Sloper calculation method, with an anticipated effect size of 0.15, a desired power level of 0.8, six latent variables, twenty four variables, and a probability level of 0.05, the recommended sample size is 123. After comparing and considering the results from these three approaches, the minimum sample size of 98 was selected to ensure the findings of the study are both accurate and reliable (T. Q. Dang, Duc, et al., 2025; T.-Q. Dang, Nguyen, Tran, et al., 2025; Le, Nguyen, et al., 2025; A.-H. D. Nguyen et al., 2024; L.-T. Nguyen et al., 2022). Empirical data from 186 valid responses validated the conceptual model and tested the hypotheses.

Common Method Bias (CMB)

The simultaneous gathering of both independent and dependent variables raises the possibility that common method bias (CMB) could affect the study. To minimize potential bias, a dual approach is employed, combining procedural controls and statistical validation methods (Podsakoff et al., 2003). The single-factor test of Harman was applied to determine the possibility of the hazard of CMB, following Nguyen et al., (2023). The results showed that the independent component explained 40.111% of all the variation. Since the outcome was not more than 50%, the CMB problem in the dataset was unlikely.

4. Result and Discussion

4.1. Result

Demographic perspective

Table 1 shows demographic profile of the respondents. Among all the respondents, 61.4% weremale, and 38.6% were women. In terms of age, 28.3% of the respondents were aged between 18 and 22 years, 54.8% were aged between 22 and 27 years, 10.4% and 6.5% fell between 27 and 32 years of age and above respectively.

Regarding employment, 68.4 percent of the respondents were employees, 21.5 percent student, and 10.1 percent was self-employment. According to this composition, the workforce members were the majority of the participants, which makes this study insightful regarding how the latter view and adjust to AI-based leadership in the work environment.

Over 17.2% of participants earned less than 5 million VND per month, while 58.8% earned between 6 and 10 million. About 20% and 4% of participants earn 10 million to 15 million VND or more per month.

In terms of frequency of AI use, 51.7% of the people were frequent users of generative AI applications in work-related decisions, 46.5% were occasional users, and only 1.8% of the respondents were low or non-users who had little experience using such applications. The distribution shows that the majority of the participants were actively working with the generative AI technologies in their work-related tasks which guaranteed a representative level of the employee perception of AI-assisted leadership in the workplace.

Table 1. Demographic Distribution of the Participants

Demographic Characteristics		Frequency (Total: 186)	Percentage
Age	18 – 21	53	28.3
	22 – 27	102	54.8
	28 – 32	19	10.4
	Over 32	12	6.5
Gender	Male	114	61.4
	Female	72	38.6
Employment status	Student	40	21.5
	Employee	127	68.4
	Self-employment	19	10.1
Monthy income (in VND)	Below 5,000,000	32	17.2
	6,000,000 – 10,000,000	109	58.8
	10,000,000 – 15,000,000	37	20
	Over 15,000,000	7	4
Frequency of AI using	Low/Non-user	3	1.8
	Occasional user	86	46.5
	Regularly	96	51.7

Assessing the Outer Measurement Model

Before initial testing of hypotheses in the inner model (structural model), the testing of the outer model (measurement model) should be guaranteed. More specifically, this kind of assessment would include the reliability testing (Cronbachs Alpha, Composite Reliability and Dijkstra-Henselers rho) and the validity testing (Convergent and Discriminant Validities testing).

Construct Validity and Reliability

We need to evaluate the outer model first before we test the hypotheses with the help of structural model analysis, in order to check the appropriateness and reliability of the measured variables. Hair et al. (2010) stated that internal consistency reliability is tested using Cronbachs Alpha and Composite Reliability (CR) that evaluates the correlation between observed variables. The values should exceed 0.7 to depict satisfactory reliability (Hair et al., 2022). Table 2 results indicate that the values of all Cronbachs Alpha and Composite Reliability (CR) are above the cut-off point of 0.7 which proves that the constructs possess high levels of internal reliability. Meanwhile, the Average Variance Extraction (AVE) of all constructs is more than 0.5 as is the case with the AVE of COM which is 0.727, which means that that construct can explain the majority of the variance in the observed variables.

Table 2. Overview of Measurement Model Quality

Constructs	Items	Loadings (FL)	Cronbach's Alpha (CA)	Dijkstra Henseler rho_A (pA)	Composite Reliability rho_C (CR)	Average Variance Extracted (AVE)	VIF
Adaptability	ADA1	0.835	0.854	0.859	0.901	0.695	2.104
	ADA2	0.809					1.932
	ADA3	0.837					2.007
	ADA4	0.853					2.042
Compatibility	COM1	0.803	0.874	0.876	0.914	0.727	1.740
	COM2	0.860					2.201
	COM3	0.860					2.364
	COM4	0.885					2.820
Innovativeness	INN1	0.808	0.848	0.854	0.898	0.687	1.868
	INN2	0.879					2.711
	INN3	0.856					2.427
	INN4	0.768					1.664
Discomfort	DIS1	0.760	0.817	0.819	0.880	0.647	1.498
	DIS2	0.807					1.857
	DIS3	0.873					2.273
	DIS4	0.773					1.579
Cognitive Trust	COG1	0.831	0.830	0.832	0.887	0.663	2.100
	COG2	0.831					2.121
	COG3	0.779					1.729

	COG4	0.815					1.817
Adoption to AI	ADO1	0.810	0.833	0.833	0.889	0.667	1.864
	ADO2	0.842					2.136
	ADO3	0.837					2.040
	ADO4	0.776					1.647

Source: by author

As shown in Table 3, the square root of AVE for each construct is higher than the correlations between different constructs, confirming discriminant validity. For example, the square root of the AVE for COM is 0.858, which is higher than its correlations with the other constructs, providing evidence that each construct is distinct from the others.

Furthermore, from table 4 shows that all indicators have higher loadings on their respective constructs compared to other constructs, supporting discriminant validity. These results provide strong evidence of validity and reliability, allowing for the structural model evaluation to proceed.

Table 3. Fornell-Lacker's Criterion

	ADA	ADO	COG	COM	DIS	INN
ADA	0.834					
ADO	0.602	0.816				
COG	0.643	0.707	0.814			
COM	0.652	0.633	0.672	0.858		
DIS	0.588	0.741	0.747	0.605	0.804	
INN	0.715	0.634	0.779	0.733	0.709	0.829

Source: by author

Table 4. Cross-loadings

	ADA	COM	INN	DIS	COG	ADO
ADA1	**0.835**	0.738	0.549	0.455	0.5	0.459
ADA2	**0.809**	0.683	0.635	0.541	0.492	0.536
ADA3	**0.837**	0.703	0.569	0.493	0.543	0.502
ADA4	**0.853**	0.736	0.63	0.477	0.598	0.512
COM1	0.692	**0.803**	0.58	0.422	0.567	0.471
COM2	0.737	**0.86**	0.678	0.526	0.618	0.542
COM3	0.731	**0.86**	0.597	0.585	0.567	0.613
COM4	0.763	**0.885**	0.637	0.529	0.531	0.53
INN1	0.599	0.651	**0.808**	0.508	0.601	0.589
INN2	0.58	0.579	**0.879**	0.594	0.677	0.445

	ADA	COM	INN	DIS	COG	ADO
INN3	0.597	0.609	**0.856**	0.647	0.708	0.499
INN4	0.602	0.6	**0.768**	0.596	0.586	0.59
DIS1	0.473	0.469	0.591	**0.76**	0.604	0.511
DIS2	0.512	0.493	0.578	**0.807**	0.56	0.524
DIS3	0.427	0.445	0.587	**0.873**	0.639	0.627
DIS4	0.486	0.544	0.524	**0.773**	0.593	0.719
COG1	0.541	0.604	0.641	0.643	**0.831**	0.586
COG2	0.484	0.566	0.655	0.58	**0.831**	0.524
COG3	0.619	0.574	0.645	0.514	**0.779**	0.552
COG4	0.456	0.45	0.599	0.685	**0.815**	0.635
ADO1	0.472	0.503	0.559	0.634	0.574	**0.81**
ADO2	0.553	0.541	0.54	0.636	0.593	**0.842**
ADO3	0.471	0.52	0.484	0.581	0.567	**0.837**
ADO4	0.468	0.503	0.484	0.568	0.573	**0.776**

Source: by author

Inspecting The Inner Structural Model

We conducted a collinearity test to rule out the possibility of multicollinearity before testing the preliminary hypotheses proposed in this study (Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, 2017). The variance inflation factor (VIF) for all constructs was found to be below the recommended threshold of 5.0, indicating that multicollinearity is not a concern (Wei-Han Tan & Ooi, 2018).

Also, the structural model will consist of the evaluation of the determination coefficient (R2) and the direction coefficients of 5000 re-samples with the help of a bootstrapping test. The significance of a path is considered before a future analysis of the proposed hypotheses using the p-value. A p-value with a value below 0.05 is considered statistically significant. Therefore, convergent validity has been demonstrated in the research.

Table 5. Hypotheses Testing

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Decision
ADA -> COG^{NS}	-0.140	-0.112	0.138	1.014	0.311	Unsupported
COG -> ADO***	0.688	0.688	0.101	6.793	0.000	Supported
COM -> COG*	0.259	0.260	0.122	2.126	0.034	Supported
DIS -> COG***	0.427	0.413	0.109	3.917	0.000	Supported
INN -> COG***	0.354	0.344	0.092	3.870	0.000	Supported

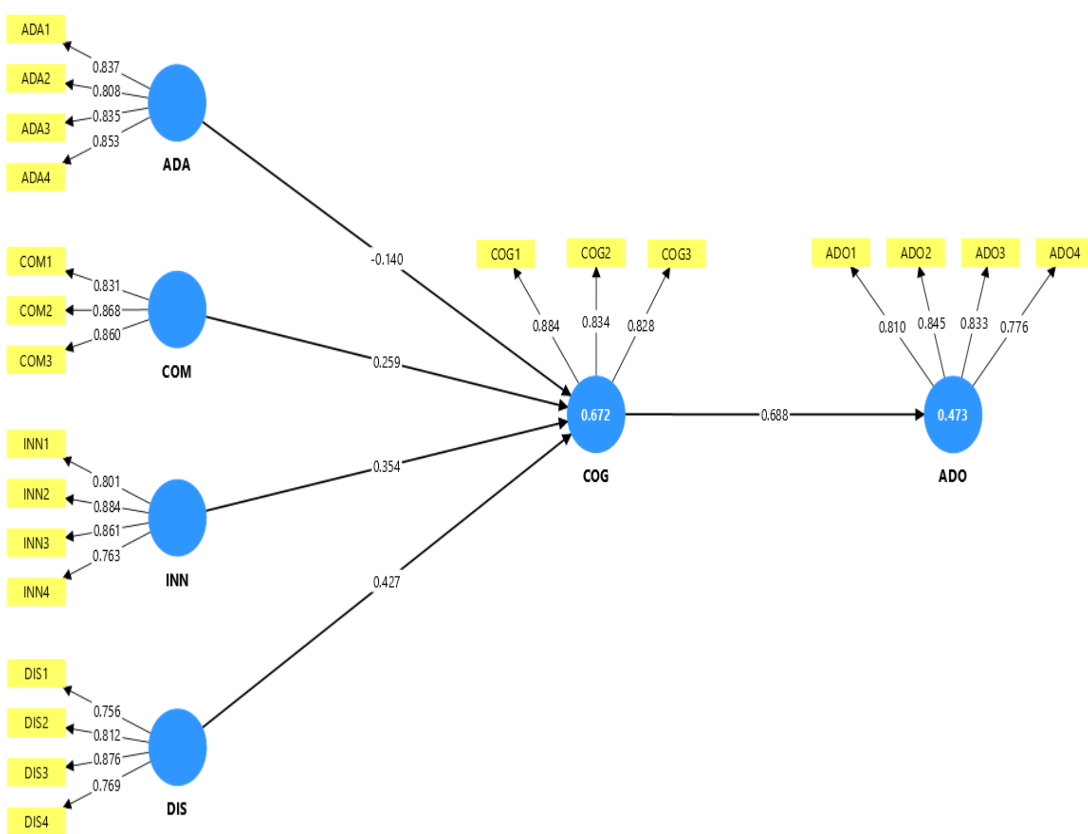
Note(s):

a. Note(s): Adaptability = ADA, Compatibility = COM, Innovativeness = INN, Discomfort = DIS, Cognitive Trust = COG, Adoption to AI = ADO.

*b. ***Significant at p < 0.001 level.*
*c. **Significant at p < 0.01 level*
*d. *Significant at p < 0.05 level*
e. [NS] Not supported at p > 0.05 level.
Source: by author

The hypothesis testing on the structural model in Table 5 shows the path coefficients, sample means, standard deviation, t-statistic and the p-value of each of the hypothesized relationships. According to the results the adaptability (ADA) to cognitive trust (COG) is negative and non-significant (β = -0.140, t = 1.014, p = 0.311), which means that adaptability does not have a significant influence on cognitive trust; therefore, the hypothesis has been rejected. Cognitive trust (COG), on the contrary, has a positive significant effect on the adoption intention (ADO) (β = 0.688, t = 6.793, p < 0.001), which proves a supported relationship. On the same note, communication (COM) has a positive relationship with cognitive trust (β = 0.259, = 2.126, = 0.034), which is not insignificant at the 0.05 level. Both disclosure (DIS) and innovativeness (INN) have positive effects on cognitive trust which are quite significant and the path coefficients are 0.427 (t = 3.917, p < 0.001) and 0.354 (t = 3.870, p < 0.001), respectively. These results indicate that although adaptability is not significant in the construction of cognitive trust, communication, disclosure and innovativeness have significant implications in strengthening cognitive trust that, in turn, has a strong influence in catalyzing adoption intention.

Figure 2: Results of the structural model



Source: by author

4.2. Discussion

Previous research have not conducted the impact of adaptability, communication, discomfort, and innovativeness on the development of cognitive trust and adoption intention in AI-based situations. In addition, only a small number of studies have concurrently examined the mentioned variables to determine the major drivers as well as the obstacles of trust-based adoption behavior. The present research helps in filling these research gaps by incorporating numerous trust-related antecedents within the framework that allows developing a more detailed picture of how users develop cognitive trust and how it is converted into adoption intention towards AI technologies.

The negative effect of Adaptability on Cognitive Trust

Past studies have tend to underline the significance of system adaptability in improving user trust in that adaptable systems can be flexible to user needs and circumstances (Hoff & Bashir, 2015; Lee & See, 2004). This study however established that the issue of adaptability (ADA) did not significantly influence cognitive trust (COG), which is contrary to current research. Such a surprising finding can be explained by the fact that users have increasingly become more demanding when it comes to personalization and flexibility in AI-driven platforms. Adaptability has turned into a default feature to many users as opposed to an indication of system competence (Kodden, 2020). In particular, overly adaptive behavior may create uncertainty and, therefore, result in the loss of rational trust especially in such environments where predictability and stability are highly valued by the users. Moreover, in the context of the fast development of AI technologies, users can assess the credibility by other less abstract signs like transparency and communication and not flexibility per se. Thus, the lack of relevance will imply that adaptability is no longer enough of a driver of trust in the age of smart automation.

The positive effect of Compatibility on Cognitive Trust

As expected based on previous studies by Lankton et al. (2015) and Verhagen et al. (2011), compatibility (COM) was found to have a significant positive effect on cognitive trust ($\beta = 0.259$, $p = 0.034$). When users find that an AI system integrates smoothly into their routines and supports their goals without requiring major behavioral adjustments, they are more likely to view it as dependable and beneficial (Chau et al., 2025). This perceived fit enhances confidence in the system's competence and reliability. Furthermore, high compatibility reduces resistance to use and increases users' sense of control, thereby reinforcing cognitive trust formation in AI-based applications.

The positive effect of Innovativeness in Cognitive Trust

However, the analysis showed that innovativeness (INN) has a significant and positive effect on cognitive trust ($\beta = 0.354$, $p < 0.001$). This observation can be compared to what Yin et al., (2025) asserted, stating that perceived technological innovativeness is an indicator of capability and reliability. As the users will think that an AI system is developed in terms of high level, efficiency, and the ability to meet the contemporary standards of technology, they will conclude that it can provide correct and effective results. Innovativeness is therefore a trust cue, which implies constant enhancement and experience (Mohammed Kamaruddeen et al., 2010; Tran & Chang, 2022). Moreover, innovation may signify competence to the users who are highly technologically familiar and they have no doubts about the performance and reliability of the system.

The positive effect of Discomfort on Cognitive Trust

The effect of discomfort (DIS) on cognitive trust was found to be positive and significant ($\beta = 0.427$, $p < 0.001$). This finding aligns with previous research suggesting that user discomfort can sometimes encourage the development of trust when it is managed effectively (Durán & Pozzi, 2025; Omrani et al., 2022). In the context of AI applications, a certain level of discomfort may motivate users to explore the system more carefully, leading them to better understand how it functions and to recognize its reliability. Users who initially feel uncomfortable but later observe that the system operates consistently and transparently are more likely to form stronger cognitive trust (Johnson & Grayson, 2005; Lewis & Marsh, 2022). Therefore, instead of serving as a barrier to adoption, discomfort that is properly addressed through ethical design and open communication can strengthen users' rational confidence in intelligent technologies.

The positive effect of Cognitive Trust on Adoption to AI

The findings justified the hypothesis that cognitive trust positively and significantly influences adoption intention ($\beta = 0.688$, $p < 0.001$). This result is in line with the earlier research (Gefen & Straub, 2004; Lankton et al., 2015b) that has insisted on the significance of trust in facilitating the readiness of users to use technology. People will be more inclined to incorporate an AI system in the decision-making process when they believe it is competent, reliable and predictable. In this relationship, trust is emphasized as a cognitive assurance process, which diminishes the perceived uncertainty and perceived risk (Handoyo, 2024; D. J. Kim et al., 2008; Sohn, 2024). The concept of cognitive trust forms the basis of technology acceptance, especially in high-involvement situations in decision making; the user holds the view that the system will deliver correct and just results.

5. Conclusion

5.1. Summary of Key Findings

Adaptability, compatibility, innovativeness, and discomfort are behavioral and psychological antecedents that shape cognitive trust and, in turn, impact the adoption of artificial intelligence (AI) in leadership situations. This study aimed to investigate how these factors shape cognitive trust. This study offered an interdisciplinary framework that links innovation traits and technology readiness with leaders trust-based acceptance behaviors in the era of generative AI by combining the Diffusion of Innovation (DOI) theory with the Technology Readiness Index (TRI).

Several significant conclusions were drawn from the empirical data. First, there was no discernible correlation between adaptability and cognitive trust, indicating that trust creation is no longer influenced by AI systems capacity to flexibly adapt to leaders demands. This result deviates from previous research that has historically considered flexibility to be a key component of perceived competence. This may be because in technologically advanced contexts, people expectations are changing and flexibility is no longer viewed as a sign of dependability but rather as a default feature. Cognitive trust depends on predictability and ambiguity, both of which can be produced by too adaptable behavior.

Second, cognitive trust was significantly positively impacted by compatibility. AI systems are generally seen as more reliable and pertinent by leaders who believe that they are consistent with their values, work procedures, and leadership philosophies. This finding supports the DOI's hypothesis that compatibility makes it easier for people to see innovation as a logical progression of current procedures. High compatibility improves user comfort, reduces cognitive burden, and raises the possibility of recurring usage. Therefore, rather than expecting leaders to drastically alter their current methods, organizational AI projects should concentrate on creating technologies that smoothly interact with management workflows.

Third, a strong predictor of cognitive trust was shown to be innovativeness. Leaders with higher levels of openness and interest about technology showed more reasonable faith in AI's potential. Being innovative pushes executives to test, study, and assess AI tools firsthand, which reduces uncertainty and builds confidence. This is consistent with the TRI dimension, which links innovativeness to being prepared and proactive in embracing new technology.

Fourth, discomfort significantly and favorably affected cognitive trust, which was in contrast to many previous notions. This unexpected discovery suggests that mild to moderate discomfort may not always be a barrier to adopting new technology, but rather may encourage more in-depth investigation, introspection, and ultimately trust provided the technology is transparent and dependable. Discomfort in leadership settings may motivate leaders to comprehend the limits and moral ramifications of AI, resulting in a more knowledgeable and long-lasting process of establishing trust.

Finally, it was discovered that adoption of AI was directly and substantially predicted by cognitive trust. This demonstrates that the primary method by which executives determine whether to include AI into decision-making processes is their logical assessment of the technology's dependability, proficiency, and predictability. Acceptance of technology is facilitated by cognitive trust, which lowers perceived dangers and uncertainty. The study essentially confirms that trust, particularly cognitive trust, acts as a link between true adoption behavior in AI leadership and psychological preparedness.

5.2. Theoretical Contributions

The current research contributes to the existing body of literature on leadership and technology adoption in generative AI in a number of theoretical ways. First, it combines the Diffusion of Innovation (DOI) (Almaiah et al., 2022; Overbye-Thompson & Hamilton, 2025) and the Technology Readiness Index (TRI) models (O'Hern & St. Louis, 2023; A. P. Parasuraman & Colby, 2014) to design an extended model of the role and mechanisms of cognitive trust on leaders accepting AI technologies. Other researchers have mostly focused on investigating either the psychological (Eftimov & Kitanovikj, 2023; Uren & Edwards, 2023a) or the technological aspect (Corvello, 2025; López-Solís et al., 2025; Storey et al., 2025) of AI adoption separately. This research is able to fill that gap by synthesizing the two viewpoints and make a more comprehensive picture of the relationship between technological characteristics (adaptability and compatibility) and individual psychological orientations (innovativeness and discomfort).

Second, the study also makes a contribution to theory by positioning cognitive trust (Shi et al., 2020; Uren & Edwards, 2023a) as a major mediating process which can be used to explain how these antecedents translate into leaders intention to use AI in strategic decision-making. The conceptualization builds upon current models of technology acceptance as it focuses on the cognitive process by which leaders weigh the reliability and predictability of AI systems (Gerlich, 2023; Van Quaquebeke & Gerpott, 2023) and then implement them in their managerial practice.

Lastly, placing the DOI-TRI integration into the context of AI-driven leadership Chhatre & Singh (2024) and Kassa & Worku (2025), the study becomes the extension of both of the frameworks to a new and timely environment - the environment of generative AI (Gonesh et al., 2023; Kumar et al., 2025; Rezazadeh et al., 2025) - in which technology can be not the means of automation but a partner in the sphere of decision-making. This theoretical expansion would enhance the knowledge of the preparedness of leadership and the establishment of cognitive trust during the period of the digital transformation era (Corvello, 2025; López-Solís et al., 2025; Storey et al., 2025).

5.3. Practical Implications

From a managerial perspective, this study provides a number of practical insights for companies looking to incorporate AI into strategic decision-making and leadership.

First, the cornerstone of AI adoption methods should be the development of cognitive trust. Transparency, interpretability, and ethical clarity in AI systems must be given top priority by organizations. Leaders need to know what data AI utilizes, how biases are reduced, and how it makes its decisions. Explainable AI models and transparent algorithmic design may greatly increase leaders reasonable confidence.

Second, businesses have to concentrate on improving how well AI products integrate with current managerial processes. Instead than taking the role of human intuition, AI systems ought to be developed to assist in decision-making. For instance, including AI dashboards into well-known communication platforms or corporate systems might reduce resistance and promote acceptance. AI recommendations that are in line with leadership concepts and established corporate values guarantee that technology enhances rather than replaces current procedures.

Third, companies should encourage leaders to be creative by fostering ongoing experimentation and learning. Digital literacy and AI literacy courses that promote the use of generative AI tools must be incorporated into leadership development programs. Cross-departmental AI partnerships and pilot projects may all foster interest and lessen failure-related anxiety. Organizations may turn innovation into a trust-building, sustainable competency by establishing safe spaces for testing.

Fourth, the discomfort findings highlight the significance of psychological safety and ethical communication. Organizations should use discomfort as a sign of critical reflection rather than as a barrier. Initial discomfort may be transformed into more participation and understanding by offering open routes for feedback, honest error reporting and lively discussion about ethical issues. It will be easier to transform uneasiness into informed trust if leaders are trained to handle uncertainty and critically evaluate AI's recommendations.

Fifth, as technology advances, leadership culture must change as well. A balanced perspective of AI as a cooperative collaborator rather than a replacement should be promoted by top executives and HR departments. Building a culture of augmented intelligence where accountability and trust coexist is facilitated by promoting participatory decision-making that incorporates both human judgment and AI-driven data.

Finally, by creating curriculum and policies that prioritize reliable AI ecosystems, governments and educational institutions may take use of these findings. To train upcoming managers for AI-augmented settings, leadership programs should incorporate ethics, data governance, and cognitive psychology.

5.4. Limitations and Future Research Directions

This study contains a number of limitations that provide opportunities for further investigation despite its contributions.

First, a cross-sectional design was used in the study to record impressions at a certain moment in time. To see how cognitive trust changes as leaders become more accustomed to AI systems and as technology advances, longitudinal research might be beneficial. Time-series or experimental methods may be used in future studies to document dynamic shifts in adoption and trust behavior.

Second, despite the study's emphasis on Vietnamese participants, organizational and cultural circumstances may have varying effects on the development of trust and adoption in other geographical areas. To determine whether the links found in this study are still valid in Western or international firms, future research should compare cultures. Global businesses may be able to better customize their AI leadership strategies by having a better understanding of cultural moderators.

Third, a more thorough qualitative investigation of the concepts of discomfort and adaptation is necessary. Interviews or case studies may uncover underlying cognitive mechanisms that explain why leaders interpret flexibility and discomfort in such distinctive ways, even while the quantitative data indicate limited or unanticipated impacts. Qualitative research, for instance, might reveal whether automation fatigue or excessive exposure to flexible technologies cause flexibility to lose its appeal.

Fourth, the mediating mechanism in our study was just cognitive trust. To provide a more thorough paradigm, future research may incorporate affective trust, institutional trust, or trust in data governance. Adoption of AI is not just a logical process; institutional credibility and emotional confidence may also have an impact.

Fifth, the study's sample may not accurately reflect the opinions of top executives or decision-makers in big businesses because it is mostly made up of employees and young professionals. To find hierarchical disparities in the establishment of AI trust, future study might use multi-level samples that distinguish between frontline managers, middle managers, and top leadership.

Finally, by adding perceived algorithmic fairness or ethical AI governance as further factors, future studies might expand the model. Fairness and ethical transparency may be crucial preconditions for acceptance and trust as businesses use AI more and more for strategic decision-making. Both theoretical depth and practical relevance would be improved by incorporating these elements.

5.5. Final Remarks

In conclusion, our study confirms that the transition from transformational leadership to AI leadership involves a significant cognitive and psychological evolution rather than just a technology change. Leaders' ability to embrace and trust AI is more reliant on how well human values, technology compatibility, and perceived dependability align than it is on how complex algorithms are.

This study offers an integrated model that explains how leaders develop logical confidence in AI systems and convert that confidence into adoption by combining the viewpoints of the Diffusion of Innovation and the Technology Readiness Index. The results show that while flexibility may no longer be a key factor in building trust, compatibility, innovativeness, and even discomfort-when handled ethically-are strong factors that influence cognitive trust.

In the end, developing reliable human-AI cooperation is the key to effective AI leadership. In addition to increasing adoption, companies that make investments in ethical governance, transparent design, and ongoing learning will also rethink what it means to be a leader in the age of intelligent technology. Future leaders must learn to trust AI critically, responsibly, and prudently as generative AI continues to transform strategic foresight and decision-making.

References

Agocs, C. (1997). Institutionalized Resistance to Organizational Change: Denial, Inaction and Repression. *Journal of Business Ethics*, *16*, 917–931. https://doi.org/10.1023/A:1017939404578

Almaiah, M. A., Alfaisal, R., Salloum, S. A., Hajjej, F., Shishakly, R., Lutfi, A., Alrawad, M., Al Mulhem, A., Alkhdour, T., & Al-Maroof, R. S. (2022). Measuring Institutions' Adoption of Artificial Intelligence Applications in Online Learning Environments: Integrating the Innovation Diffusion Theory with Technology Adoption Rate. *Electronics (Switzerland)*, *11*(20). https://doi.org/10.3390/electronics11203291

Askar, R., Bragança, L., & Gervásio, H. (2021). Adaptability of buildings: A critical review on the concept evolution. In *Applied Sciences (Switzerland)* (Vol. 11, Issue 10). MDPI AG. https://doi.org/10.3390/app11104483

Boudreaux, M. (2024). *Transformational Leadership in AI-Driven Industry 4.0: Cultivating Adaptive, Ethical, and Resilient Leaders*. https://doi.org/10.5281/zenodo.14847751

Binh, N. T. H., Tri-Quan, D., & and Nguyen, L.-T. (2024). Metaverse: The Future for Immersive Logistics and International Business Education. Journal of Teaching in International Business, 35(3–4), 75–107. https://doi.org/10.1080/08975930.2024.2445861

Carreno, A. (2024). *An Analytical Review of John Kotter's Change Leadership Framework: A Modern Approach to Sustainable Organizational Transformation*. https://doi.org/10.2139/ssrn.5044428

Chan, C., & Petrikat, D. (2022). Impact of Artificial Intelligence on Business and Society. *Journal of Business and Management Studies*, *4*, 1–6. https://doi.org/10.32996/jbms.2022.4.4.1

Chau, H. K. L., Ngo, T. T. A., Bui, C. T., & Tran, N. P. N. (2025). Human-AI interaction in E-Commerce: The impact of AI-powered customer service on user experience and decision-making. *Computers in Human Behavior Reports*, *19*, 100725. https://doi.org/10.1016/J.CHBR.2025.100725

Chhatre, R., & Singh, S. (2024). *AI And Organizational Change: Dynamics And Management Strategies*. https://doi.org/10.13140/RG.2.2.16082.98246

Choung, H., David, P., & Ross, A. (2022). Trust in AI and Its Role in the Acceptance of AI Technologies. In *International Journal of*

Human-Computer Interaction (Vol. 39). https://doi.org/10.1080/10447318.2022.2050543

Collie, R. J., & Martin, A. J. (2017). Teachers' sense of adaptability: Examining links with perceived autonomy support, teachers' psychological functioning, and students' numeracy achievement. *Learning and Individual Differences*, *55*, 29–39. https://doi.org/10.1016/J.LINDIF.2017.03.003

Corvello, V. (2025). Generative AI and the future of innovation management: A human centered perspective and an agenda for future research. *Journal of Open Innovation: Technology, Market, and Complexity*, *11*(1), 100456. https://doi.org/10.1016/J.JOITMC.2024.100456

Daly, S. J., Wiewiora, A., & Hearn, G. (2025). Shifting attitudes and trust in AI: Influences on organizational AI adoption. *Technological Forecasting and Social Change*, *215*, 124108. https://doi.org/10.1016/J.TECHFORE.2025.124108

Dang, T. Q., Duc, D. T. V., Tran, L. H. P., & Nguyen, L. T. (2025). EXAMINING THE IMPACT OF TRUST ON CUSTOMER INTENTION TO USE METAVERSE PAYMENTS: A NEXT-GEN TRANSACTIONS STRATEGIC OUTLOOK. *Corporate and Business Strategy Review*, *6*(1), 166–177. https://doi.org/10.22495/cbsrv6i1art16

Dang, T. Q., Nguyen, L. T., & Duc, D. T. V. (2025). Impulsive Buying and Compulsive Buying in Social Commerce: An Integrated Analysis using the Cognitive-Affective-Behavior Model and Theory of Consumption Values with PLS-SEM. *SAGE Open*, *15*(2). https://doi.org/10.1177/21582440251334215

Dang, T.-Q., Nguyen, L.-T., & Thi, D. D. V. (2025). Comprehensive Analysis of Mobile Payment's Customer Loyalty: The SEM-ANN Approach. *Quality-Access to Success*, *26*(208). https://doi.org/10.47750/QAS/26.208.20

Dang, T.-Q., Nguyen, T.-M., Tran, P.-T., Phan, T.-T. C., Huynh, T.-B., & Nguyen, L.-T. (2025). From reality to virtuality: Unveiling Gen Z's purchasing behavior through virtual influencers in the metaverse. *Digital Business*, *5*(2), 100141. https://doi.org/10.1016/j.digbus.2025.100141

Dao, N.-Y., Nguyen, L.-T., & Dinh, V.-H. (2023). Factors Driving Vietnamese University Students' Adoption in a Smart Learning Environment: The Application of Self-determination Theory and Technology Acceptance Model. In *Lecture Notes in Educational Technology* (pp. 185–190). Springer Nature Singapore. https://doi.org/https://doi.org/10.1007/978-981-99-5961-7_22

Duc, D. T. V., Mai, L. T. V., Dang, T.-Q., Le, T.-T., & Nguyen, L.-T. (2024). Unlocking impulsive buying behavior in the metaverse commerce: a combined analysis using PLS-SEM and ANN. *Global Knowledge, Memory and Communication*. https://doi.org/10.1108/GKMC-05-2024-0266

Duc, D. T. V., Phuong, N. M., Nguyen, L.-T., & Dang, T.-Q. (2025). Open government data in Vietnam: The integrated toe and trust theory model. *International Journal of Innovative Research and Scientific Studies*, *8*(6), 2064–2082. https://doi.org/10.53894/ijirss.v8i6.10079

Dang Quan, T., Wei-Han Tan, G., Aw, E. C.-X., Cham, T.-H., Basu, S., & Ooi, K.-B. (2024). Can you resist the virtual temptations? Unveiling impulsive buying in metaverse retail. *Asia Pacific Journal of Marketing and Logistics*, *36*(10), 2259–2280. https://doi.org/10.1108/APJML-09-2023-0911

Davenport, T. H., Ronanki, R., Wheaton, J., & Nguyen, A. (2018). *FEATURE ARTIFICIAL INTELLIGENCE FOR THE REAL WORLD 108 HARVARD BUSINESS REVIEW*.

Durán, J., & Pozzi, G. (2025). Trust and Trustworthiness in AI. *Philosophy & Technology*, *38*. https://doi.org/10.1007/s13347-025-00843-2

Eftimov, L., & Kitanovikj, B. (2023). Unlocking the Path to AI Adoption: Antecedents to Behavioral Intentions in Utilizing AI for Effective Job (Re)Design. *Journal of Human Resource Management – HR Advances and Developments*, *26*, 123–134. https://doi.org/10.46287/OTTP6295

Erdem, F., & Ozen, J. (2003). Cognitive and affective dimensions of trust in developing team performance. *Team Performance Management: An International Journal*, *9*, 131–135. https://doi.org/10.1108/13527590310493846

Erdfelder, E., FAul, F., Buchner, A., & Lang, A. G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods*, *41*(4), 1149–1160. https://doi.org/10.3758/BRM.41.4.1149

Gefen, D., & Straub, D. W. (2004). Consumer trust in B2C e-Commerce and the importance of social presence: Experiments in e-Products and e-Services. *Omega*, *32*(6), 407–424. https://doi.org/10.1016/j.omega.2004.01.006

Gerlich, M. (2023). Perceptions and Acceptance of Artificial Intelligence: A Multi-Dimensional Study. *Social Sciences*, *12*(9). https://doi.org/10.3390/socsci12090502

Godoe, P., & Johansen, T. (2012). Understanding Adoption of New Technologies: Technology Readiness and Technology Acceptance as an Integrated Concept. *Journal of European Psychology Students*, *3*, 38. https://doi.org/10.5334/jeps.aq

Gonesh, C., Saha, G., Menon, R., Paulin, S., Yerasuri, S. S., Saha, H., Dongol, P., & Lalit, S. (2023). *The Impact of Artificial Intelligence on Business Strategy and Decision-Making Processes*. https://doi.org/10.52783/eel.v13i3.386

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM). Thousand Oaks. *Sage*, 165. https://www.researchgate.net/publication/303522804_A_Primer_on_Partial_Least_Squares_Structural_Equation_Modeling_PLS-SEM_2nd_edition

Hair, J., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2022). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*.

Handoyo, S. (2024). Purchasing in the digital age: A meta-analytical perspective on trust, risk, security, and e-WOM in e-commerce. *Heliyon*, *10*(8), e29714. https://doi.org/10.1016/J.HELIYON.2024.E29714

Heyder, T., Passlack, N., & Posegga, O. (2023). Ethical management of human-AI interaction: Theory development review. *The Journal of Strategic Information Systems*, *32*(3), 101772. https://doi.org/10.1016/J.JSIS.2023.101772

Hoff, K., & Bashir, M. (2015). Trust in Automation: Integrating Empirical Evidence on Factors That Influence Trust. *Human Factors The Journal of the Human Factors and Ergonomics Society*, *57*, 407–434. https://doi.org/10.1177/0018720814547570

Hossain, S., Fernando, M., & Akter, S. (2025). Digital Leadership: Towards a Dynamic Managerial Capability Perspective of Artificial Intelligence-Driven Leader Capabilities. *Journal of Leadership and Organizational Studies*, *32*(2), 189–208. https://doi.org/10.1177/15480518251319624

Jacovi, A., Marasović, A., Miller, T., & Goldberg, Y. (2021). *Formalizing Trust in Artificial Intelligence: Prerequisites, Causes and Goals of Human Trust in AI*. https://doi.org/10.1145/3442188.3445923

Jalo, H., & Pirkkalainen, H. (2024). Effect of user resistance on the organizational adoption of extended reality technologies: A mixed methods study. *International Journal of Information Management*, *75*, 102731. https://doi.org/10.1016/J.IJINFOMGT.2023.102731

Johnson, D., & Grayson, K. (2005). Cognitive and affective trust in service relationships. *Journal of Business Research*, *58*(4), 500–507. https://doi.org/10.1016/S0148-2963(03)00140-1

Kassa, B. Y., & Worku, E. K. (2025). The impact of artificial intelligence on organizational performance: The mediating role of employee productivity. *Journal of Open Innovation: Technology, Market, and Complexity*, *11*(1), 100474. https://doi.org/10.1016/J.JOITMC.2025.100474

Kim, B. J., & Kim, M. J. (2024). How artificial intelligence-induced job insecurity shapes knowledge dynamics: the mitigating role of artificial intelligence self-efficacy. *Journal of Innovation & Knowledge*, *9*(4), 100590. https://doi.org/10.1016/J.JIK.2024.100590

Kim, D. J., Ferrin, D. L., & Rao, H. R. (2008). A trust-based consumer decision-making model in electronic commerce: The role of trust, perceived risk, and their antecedents. *Decision Support Systems*, *44*(2), 544–564. https://doi.org/10.1016/J.DSS.2007.07.001

Kodden, B. (2020). *The Ability to Adapt* (pp. 25–30). https://doi.org/10.1007/978-3-030-46463-9_4

Komiak, S., & Benbasat, I. (2006). The Effects of Personalization and Familiarity on Trust and Adoption of Recommendation Agents. *MIS Quarterly*, *30*, 941–960. https://doi.org/10.2307/25148760

Korejan, M., & Shahbazi, H. (2016). An analysis of the transformational leadership theory. *Journal of Fundamental and Applied Sciences*, *8*, 452. https://doi.org/10.4314/jfas.v8i3s.192

Kumar, A., Shankar, A., Hollebeek, L. D., Behl, A., & Lim, W. M. (2025). Generative artificial intelligence (GenAI) revolution: A deep dive into GenAI adoption. *Journal of Business Research*, *189*, 115160. https://doi.org/10.1016/J.JBUSRES.2024.115160

Lai, Y., & Lee, J. (2020). Integration of Technology Readiness Index (TRI) Into the Technology Acceptance Model (TAM) for Explaining Behavior in Adoption of BIM. *Asian Education Studies*, *5*, 10. https://doi.org/10.20849/aes.v5i2.816

Lankton, N., McKnight, D., & Tripp, J. (2015b). Technology, Humanness, and Trust: Rethinking Trust in Technology. *Journal of the Association for Information Systems*, *16*, 880–918. https://doi.org/10.17705/1jais.00411

Le, T.-T., Lin, P.-T., Duc, D. T. V., Dang, T.-Q., & Nguyen, L.-T. (2025). Optimizing and restructuring resources for sustainable firm performance in the AI era: the role of dynamic capabilities and circular manufacturing. *Sustainable Futures*, *10*, 101441. https://doi.org/https://doi.org/10.1016/j.sftr.2025.101441

Le, T.-T., Nguyen, L.-T., Truong Pham, N.-U., Minh Huynh, T., Thi Viet Duc, D., Chi, H., Phu, B., & Thanh District, B. (2025). *HRM strategies for sustainable performance: A focus on SDG-3 and SDG-8 in the logistics sector*. https://doi.org/10.18488/11.v14i3.4427

Lee, John D, & See, Katrina A. (2004). Trust in Automation: Designing for Appropriate Reliance. *Human Factors*, *46*(1), 50–80. https://doi.org/10.1518/hfes.46.1.50_30392

Lewis, P. R., & Marsh, S. (2022). What is it like to trust a rock? A functionalist perspective on trust and trustworthiness in artificial intelligence. *Cognitive Systems Research*, *72*, 33–49. https://doi.org/10.1016/J.COGSYS.2021.11.001

López-Solís, O., Luzuriaga-Jaramillo, A., Bedoya-Jara, M., Naranjo-Santamaría, J., Bonilla-Jurado, D., & Acosta-Vargas, P. (2025). Effect of Generative Artificial Intelligence on Strategic Decision-Making in Entrepreneurial Business Initiatives: A Systematic Literature Review. In *Administrative Sciences* (Vol. 15, Issue 2). Multidisciplinary Digital Publishing Institute (MDPI). https://doi.org/10.3390/admsci15020066

Mariani, M., & Dwivedi, Y. K. (2024). Generative artificial intelligence in innovation management: A preview of future research developments. *Journal of Business Research*, *175*, 114542. https://doi.org/10.1016/J.JBUSRES.2024.114542

McAllister, D. (1995). Affect- and Cognition-Based Trust as Foundations for Interpersonal

Cooperation in Organizations. *Academy of Management Journal*, *38*, 24–59. https://doi.org/10.5465/256727

Mohammed Kamaruddeen, A., Yusof, N., & Said, I. (2010). *Innovation and Innovativeness: Difference and Antecedent Relationship*. *2*.

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

Moorman, C., Zaltman, G., & Deshpande, R. (1992). Relationships Between Providers and Users of Market Research: The Dynamics of Trust Within and Between Organizations. *Journal of Marketing Research*, *29*, 314–328. https://doi.org/10.2307/3172742

Nguyen, A.-H. D., Pham, N.-U. T., Lin, P.-T., Dang, T.-Q., Tran, P.-T., Le, T.-T., Phan, T.-T. C., & Nguyen, L.-T. (2024). Acceptance and use of live streaming on metaverse in Vietnam: An analysis with the UTAUT2. *Journal of Infrastructure, Policy and Development*, *8*(8), 6069. https://doi.org/10.24294/jipd.v8i8.6069

Nguyen, B.-H. T., Dang, T.-Q., Nguyen, L.-T., & Tran, T.-T. T. (2024). Are we ready for education in Metaverse? PLS-SEM analysis. *Edelweiss Applied Science and Technology*, *8*(2), 73–83. https://doi.org/10.55214/25768484.v8i2.693

Nguyen, B.-T. H., Le, T. H., Dang, T. Q., & Nguyen, L.-T. (2023). What Role Does AI Chatbot Perform in the F&B Industry? Perspective from Loyalty and Value Co-Creation: Integrated PLS-SEM and ANN Techniques. *Journal of Law and Sustainable Development*, *44*(4), 1–39. https://doi.org/https://doi.org/10.55908/sdgs.v11i4.794

Nguyen, L.-T., Dang, T.-Q., & Duc, D. T. V. (2024). The Dark Sides of AI Advertising: The Integration of Cognitive Appraisal Theory and Information Quality Theory. *Social Science Computer Review*. https://doi.org/10.1177/08944393241258760

Nguyen, L.-T., Duc, D. T. V., Dang, T.-Q., & Nguyen, D. P. (2023). Metaverse Banking Service: Are We Ready to Adopt? A Deep Learning-Based Dual-Stage SEM-ANN Analysis. *Human Behavior and Emerging Technologies*, *2023*, 6617371. https://doi.org/10.1155/2023/6617371

Nguyen, L.-T., Dwivedi, Y. K., Tan, G. W. H., Aw, E. C. X., Lo, P. S., & Ooi, K. B. (2022). Unlocking Pathways to Mobile Payment Satisfaction and Commitment. *Journal of Computer Information Systems*, *00*(00), 1–18. https://doi.org/10.1080/08874417.2022.2119444

Nguyen, L.-T., Nguyen, D., Ngoc, K. N.-N., & Duc, D. T. V. (2023). Blockchain adoption in logistics companies in Ho Chi Minh City. *Cogent Business & Management*, *10*(2), 1–24. https://doi.org/10.1080/23311975.2023.2216436

Nguyen, L.-T., Phan, T.-T. C., & Dang, T.-Q. (2025). The Power of Interactive Mobile Advertising: How Self-brand Congruity Shapes Brand Engagement in Self-concept. *Journal of Creative Communications*. https://doi.org/10.1177/09732586251359718

Nguyen, L.-T., Tran, N.-T. T., Dang, T.-Q., & Duc, D. T. V. (2025). Beyond Transactions: Building Customer Loyalty and Brand Value Cocreation in Vietnamese Financial Apps. *Human Behavior and Emerging Technologies*, *2025*(1). https://doi.org/10.1155/hbe2/5599209

Nguyen, N. T. T., Tran, P. T., Dang, T. Q., & Nguyen, L. T. (2024). The future of non-contact commerce: the role of voice payments. *Journal of Financial Services Marketing*. https://doi.org/10.1057/s41264-024-00292-6

Nguyen, A.-H. D., Pham, N.-U. T., Lin, P.-T., Dang, T.-Q., Tran, P.-T., Le, T.-T., Phan, T.-T. C., & Nguyen, L.-T. (2024). Acceptance and use of live streaming on metaverse in Vietnam: An analysis with the UTAUT2. Journal of Infrastructure, Policy and Development, 8(8), 6069. https://doi.org/10.24294/jipd.v8i8.6069

Nguyen, B.-H. T., Dang, T.-Q., Nguyen, L.-T., & Tran, T.-T. T. (2024). Are we ready for education in Metaverse? PLS-SEM analysis. Edelweiss Applied Science and Technology, 8(2), 73–83. https://doi.org/10.55214/25768484.v8i2.693

Nguyen, B.-T. H., Le, T. H., Dang, T. Q., & Nguyen, L.-T. (2023). What Role Does AI Chatbot Perform in the F&B Industry? Perspective from Loyalty and Value Co-Creation: Integrated PLS-SEM and ANN Techniques. Journal of Law and Sustainable Development, 44(4), 1–39. https://doi.org/https://doi.org/10.55908/sdgs.v11i4.794

Nguyen, L.-T., Dang, T.-Q., & Duc, D. T. V. (2024). The Dark Sides of AI Advertising: The Integration of Cognitive Appraisal Theory and Information Quality Theory. Social Science Computer Review. https://doi.org/10.1177/08944393241258760

Nguyen, L.-T., Duc, D. T. V., Dang, T.-Q., & Nguyen, D. P. (2023). Metaverse Banking Service: Are We Ready to Adopt? A Deep Learning-Based Dual-Stage SEM-ANN Analysis. Human Behavior and Emerging Technologies, 2023, 6617371. https://doi.org/10.1155/2023/6617371

Nguyen, L.-T., Dwivedi, Y. K., Tan, G. W. H., Aw, E. C. X., Lo, P. S., & Ooi, K. B. (2022). Unlocking Pathways to Mobile Payment Satisfaction and Commitment. Journal of Computer Information Systems, 00(00), 1–18. https://doi.org/10.1080/08874417.2022.2119444

Nguyen, L.-T., Nguyen, D., Ngoc, K. N.-N., & Duc, D. T. V. (2023). Blockchain adoption in logistics companies in Ho Chi Minh City. Cogent Business & Management, 10(2), 1–24. https://doi.org/10.1080/23311975.2023.2216436

Nguyen, L.-T., Phan, T.-T. C., & Dang, T.-Q. (2025). The Power of Interactive Mobile Advertising: How Self-brand Congruity Shapes Brand Engagement in Self-concept. Journal of Creative Communications. https://doi.org/10.1177/09732586251359718

Nguyen, L.-T., Tran, N.-T. T., Dang, T.-Q., & Duc, D. T. V. (2025). Beyond Transactions: Building Customer Loyalty and Brand Value Cocreation in Vietnamese Financial Apps. Human Behavior and Emerging Technologies, 2025(1). https://doi.org/10.1155/hbe2/5599209

Nguyen, N. T. T., Tran, P. T., Dang, T. Q., & Nguyen, L. T. (2024). The future of non-contact commerce: the role of voice payments. Journal of Financial Services Marketing. https://doi.org/10.1057/s41264-024-00292-6

Nguyen, L.-T., Phan, T.-T. C., Dang, D.-V. T., & Tran, T.-T. T. (2023). Mobile Payment Adoption in Vietnam: A Two-Staged SEM-ANN Approach. In M. A. Al-Sharafi, M. Al-Emran, G. W.-H. Tan, & K.-B. Ooi (Eds.), *Current and Future Trends on Intelligent Technology Adoption: Volume 1* (pp. 209–228). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-48397-4_11

Nguyen, Luan-Thanh, Dang, Tri-Quan, & Duc, Dang Thi Viet. (2024). The Dark Sides of AI Advertising: The Integration of Cognitive Appraisal Theory and Information Quality Theory. *Social Science Computer Review*, *43*(2), 397–424. https://doi.org/10.1177/08944393241258760

Nguyen, N.-T., Phuc, T., Quan Dang, T., & Nguyen, L.-T. (2024). The future of non-contact commerce: the role of voice payments. *Journal of Financial Services Marketing*, *29*, 1260–1278. https://doi.org/10.1057/s41264-024-00292-6

O'Hern, S., & St. Louis, R. (2023). Technology readiness and intentions to use conditionally automated vehicles. *Transportation Research Part F: Traffic Psychology and Behaviour*, *94*, 1–8. https://doi.org/10.1016/J.TRF.2023.02.001

Oliveira, T., Thomas, M., Baptista, G., & Campos, F. (2016). Mobile payment: Understanding the determinants of customer adoption and intention to recommend the technology. *Computers in Human Behavior*, *61*, 404–414. https://doi.org/https://doi.org/10.1016/j.chb.2016.03.030

Omrani, N., Rivieccio, G., Fiore, U., Schiavone, F., & Agreda, S. G. (2022). To trust or not to trust? An assessment of trust in AI-based systems: Concerns, ethics and contexts. *Technological Forecasting and Social Change*, *181*, 121763. https://doi.org/10.1016/J.TECHFORE.2022.121763

Overbye-Thompson, H., & Hamilton, K. A. (2025). A diffusion of innovations measurement scale for reinvention, relative advantage, compatibility, complexity, trialability and observability. *PLOS ONE*, *20*(10 October). https://doi.org/10.1371/journal.pone.0334616

Parasuraman, A. (2000). Technology Readiness Index (Tri): A Multiple-Item Scale to Measure Readiness to Embrace New Technologies. *Journal of Service Research*, *2*(4), 307–320. https://doi.org/10.1177/109467050024001

Parasuraman, A. P., & Colby, C. (2014). An Updated and Streamlined Technology Readiness Index: TRI 2.0. *Journal of Service Research*, *18*, 59–74. https://doi.org/10.1177/1094670514539730

Peifer, Y., Jeske, T., & Hille, S. (2022). Artificial Intelligence and its Impact on Leaders and Leadership. *Procedia Computer Science*, *200*, 1024–1030. https://doi.org/10.1016/J.PROCS.2022.01.301

Phillips, K. (2025). *Artificial Intelligence: Diffusion of Innovation and Generational Considerations Higher Education Institutions*. https://doi.org/10.13140/RG.2.2.23573.84969

Podsakoff, P., MacKenzie, S., Lee, J.-Y., & Podsakoff, N. (2003). Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies. *The Journal of Applied Psychology*, *88*, 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Phan, L.-G. N., Tri, D. Q., Dang, S.-H., & Nguyen, L.-T. (2025). Hooked on Livestreaming: What Drives Customer Repurchase Intention in E-Commerce? *Journal of Creative Communications*. https://doi.org/10.1177/09732586241311001

Phan, T. – T. C., Nguyen, L.-T., & Dang, T.-Q. (2025). Does Impulsive Buying Lead to Compulsive Buying in Metaverse? A Dual-Stage Predictive-Analytics SEM-ANN Analysis. The Empirical Study from Vietnam. *Thailand and The World Economy*, *43*(2), 44–46. https://so05.tci-thaijo.org/index.php/TER/article/view/268273

Rashid, A. Bin, & Kausik, M. A. K. (2024). AI revolutionizing industries worldwide: A comprehensive overview of its diverse applications. *Hybrid Advances*, *7*, 100277. https://doi.org/10.1016/J.HYBADV.2024.100277

Rezazadeh, A., Kohns, M., Bohnsack, R., António, N., & Rita, P. (2025). Generative AI for growth hacking: How startups use generative AI in their growth strategies. *Journal of Business Research*, *192*, 115320. https://doi.org/10.1016/J.JBUSRES.2025.115320

Rogers, E. M. . (1995). *Diffusion of innovations*. Free Press.

Sacavém, A., de Bem Machado, A., dos Santos, J. R., Palma-Moreira, A., Belchior-Rocha, H., & Au-Yong-Oliveira, M. (2025). Leading in the Digital Age: The Role of Leadership in Organizational Digital Transformation. *Administrative Sciences*, *15*(2). https://doi.org/10.3390/admsci15020043

Sahin, I. (2006). Detailed review of Rogers' diffusion of innovations theory and educational technology-related studies based on Rogers' theory. *The Turkish Online Journal of Educational Technology*, *5*, 14–23.

Salhieh, S. M., & Al-Abdallat, Y. (2022). Technopreneurial intentions: The effect of innate innovativeness and academic self-efficacy. *Sustainability (Switzerland)*, *14*(1). https://doi.org/10.3390/su14010238

Schnitzler, C., & Bohnet-Joschko, S. (2025). Technology Readiness Drives Digital Adoption in Dentistry: Insights from a Cross-Sectional Study. *Healthcare*, *13*, 1155. https://doi.org/10.3390/healthcare13101155

Shamim, S., Yang, Y., Ul Zia, N., Khan, Z., & Shariq, S. M. (2023c). Mechanisms of cognitive trust development in artificial intelligence among front line employees: An empirical examination from a developing economy. *Journal of Business Research*, *167*, 114168. https://doi.org/10.1016/J.JBUSRES.2023.114168

Shi, S., Gong, Y., & Gursoy, D. (2020). Antecedents of Trust and Adoption Intention toward Artificially Intelligent Recommendation Systems in Travel Planning: A Heuristic–Systematic Model. *Journal of Travel Research*, *60*, 1714–1734. https://doi.org/10.1177/0047287520966395

Sohn, S. (2024). Consumer perceived risk of using autonomous retail technology. *Journal of Business Research*, *171*, 114389. https://doi.org/10.1016/J.JBUSRES.2023.114389

Stilgoe, J., Owen, R., & Macnaghten, P. (2013). Developing a framework for responsible innovation. *Research Policy*, *42*(9), 1568–1580. https://doi.org/10.1016/J.RESPOL.2013.05.008

Storey, V. C., Yue, W. T., Zhao, J. L., & Lukyanenko, R. (2025). Generative Artificial Intelligence: Evolving Technology, Growing Societal Impact, and Opportunities for Information Systems Research. *Information Systems Frontiers*. https://doi.org/10.1007/s10796-025-10581-7

Tigre, F. B., Henriques, P. L., & Curado, C. (2025). The digital leadership emerging construct: a multi-method approach. *Management Review Quarterly*, *75*(1), 789–836. https://doi.org/10.1007/s11301-023-00395-9

Tornatzky, L., & Klein, K. (1982). Innovation Characteristics and Innovation-Adoption-Implementation: A Meta-analysis of findings. *Engineering Management, IEEE Transactions On*, *EM-29*. https://doi.org/10.1109/TEM.1982.6447463

Thi Viet, D. D., & Nguyen, L.-T. (2025). Unveiling the Impact of Big Data and Predictive Analytics Adoption on Sustainable Supply Chain Management: An Employee-Centric Perspective. *SAGE Open*, *15*(3). https://doi.org/10.1177/21582440251363128

Tran, L.-A., & Chang, T.-Y. (2022). Can Brand Innovativeness Serve as a Signal to Enhance Brand Trust of Mobile Bookers? Exploring the Influence of Mobile Brand Experience. *International Journal of Hospitality & Tourism Administration*, *24*, 1–27. https://doi.org/10.1080/15256480.2022.2055695

Uren, V., & Edwards, J. S. (2023b). Technology readiness and the organizational journey towards AI adoption: An empirical study. *International Journal of Information Management*, *68*, 102588. https://doi.org/10.1016/J.IJINFOMGT.2022.102588

Van Quaquebeke, N., & Gerpott, F. (2023). The Now, New, and Next of Digital Leadership: How Artificial Intelligence (AI) Will Take Over and Change Leadership as We Know It. *Journal of Leadership & Organizational Studies*, *30*. https://doi.org/10.1177/15480518231181731

Venkatesh, V., Thong, J., & Xu, X. (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. *MIS Quarterly*, *36*, 157–178. https://doi.org/10.2307/41410412

Verhagen, T., G, N., Feldberg, F., & Dolen, W. (2011). Virtual Customer Service Agents: Using Social Presence and Personalization to Shape Online Service Encounters. *Journal of Computer-Mediated Communication*, *19*. https://doi.org/10.1111/jcc4.12066

Walczuch, R., Lemmink, J., & Streukens, S. (2007). The effect of service employees' technology readiness on technology acceptance. *Information & Management*, *44*(2), 206–215. https://doi.org/10.1016/J.IM.2006.12.005

Wanner, J., Herm, L.-V., Heinrich, K., & Janiesch, C. (2022). The effect of transparency and trust on intelligent system acceptance: Evidence from a user-based study. *Electronic Markets*, *32*. https://doi.org/10.1007/s12525-022-00593-5

Watson, G. J., Desouza, K. C., Ribiere, V. M., & Lindič, J. (2021). Will AI ever sit at the C-suite table? The future of senior leadership. *Business Horizons*, *64*(4), 465–474. https://doi.org/10.1016/J.BUSHOR.2021.02.011

Webber, S. (2008). Development of Cognitive and Affective Trust in Teams: A Longitudinal Study. *Small Group Research - SMALL GROUP RES*, *39*, 746–769. https://doi.org/10.1177/1046496408323569

Wei-Han Tan, G., & Ooi, K.-B. (2018). *Gender and age: Do they really moderate mobile tourism shopping behavior?* https://doi.org/10.1016/j.tele.2018.04.009

Xu, J., Le, K., Deitermann, A., & Montague, E. (2014). How different types of users develop trust in technology: A qualitative analysis of the antecedents of active and passive user trust in a shared technology. *Applied Ergonomics*, *45*. https://doi.org/10.1016/j.apergo.2014.04.012

Yin, J., Qiu, X., & Wang, Y. (2025). The Impact of AI-Personalized Recommendations on Clicking Intentions: Evidence from Chinese E-Commerce. *Journal of Theoretical and Applied Electronic Commerce Research* , *20*(1). https://doi.org/10.3390/jtaer20010021

Yuan, R., Chen, Y., & Mandler, T. (2024). It takes two to tango: The role of interactivity in enhancing customer engagement on sharing economy platforms. *Journal of Business Research*, *178*, 114658. https://doi.org/10.1016/J.JBUSRES.2024.114658

Zhang, S. X., Chen, J., He, L., & Choudhury, A. (2023). Responsible Innovation: The development and validation of a scale. *Technovation*, *124*, 102754. https://doi.org/10.1016/J.TECHNOVATION.2023.102754