Article

Communication Research
2024, Vol. 51(7) 843–866

DOI: 10.1177/00936502231191832
journals.sagepub.com/home/crx
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Examining the Diffusion of Innovations from a Dynamic, Differential-Effects Perspective: A Longitudinal Study on AI Adoption Among Employees

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Abstract

This study extends the diffusion of innovations theory by considering the threat of technology and examining the adoption of artificial intelligence (AI) in the workplace over time from a dynamic, differential-effects perspective. Findings from a three-wave survey study reveal an association between the threat of AI (i.e., job security concerns) and increasingly negative attitudes toward AI adoption among employees over time. Relative advantage, compatibility, and observability correlated with more positive attitudes, whereas ease of use and trialability showed no significant association. In testing the differential effects on attitudes toward AI adoption among different groups of potential adopters, we found that trialability positively influenced attitudes only among employees who held a positive attitude previously. Observability and the threat of AI, however, were more influential among employees who held a negative attitude previously. Theoretical and practical implications were discussed.

Keywords

diffusion of innovations, innovation attributes, artificial intelligence, AI, adoption, longitudinal, dynamic, threat, employment

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Artificial Intelligence (AI) refers to the array of technologies or systems that possess the capabilities to emulate human cognitive processes (Kelly et al., 2023; Rai et al., 2019). Often termed "intelligent technologies" (Bailey & Barley, 2020), AI describes fast-paced, data-driven advancements, prompting notable changes across various business sectors (Stahl, 2021). Compared to business leaders exploring AI to reduce labor costs and increase profits, many Americans are worried about AI posing a threat to their employment. It is estimated that one-third of existing jobs today could be replaced by AI by 2025 (Thibodeau, 2014), and 81% of Americans see AI development in general as leading to work layoffs (Rainie et al., 2022). In healthcare, for example, AI's ability for swift and precise screening and detection could jeopardize the job security of medical technicians. Moreover, the proficiency of generative AI, exemplified by technologies like ChatGPT and Midjourney, in swiftly creating news stories and artwork raises potential concerns about the displacement of journalists and graphic designers, respectively. Finally, the transportation industry may also confront challenges as the emergence of self-driving vehicles could potentially render the role of truck drivers obsolete. These illustrate the far-reaching implications of AI's progression on employment across various sectors.

History seems to be repeating itself. At the dawn of the Industrial Revolution in the 1800s, workers in Britain feared job losses due to the introduction of modern machinery, and they broke into factories to destroy machines and attacked employers. Is the same resistance to innovations occurring for the adoption of AI in the workplace today? How can employers, organizations, and governments better communicate with employees regarding the adoption of AI? Such sociotechnical changes in the work environment and the concomitant concerns over the threat of AI have urged scholars to carefully theorize how AI adoption takes place in the workplace.

The diffusion of innovations theory, one of the most influential theories in communication research, has helped describe, predict, and explain the adoption process for a wide range of innovations over the past 60 years (Rogers, 1962, 1995, 2003), from agricultural products, health interventions, education programs, to emerging media technologies (Atkin et al., 2015; Dearing, 2021; Rogers, 2003). Diffusion is a process by which an innovation is adopted or rejected over time among members of a social system (Rogers, 2003). Decades of diffusion research have identified five attributes that explain most of the variance in adoption: relative advantage, complexity, compatibility, trialability, and observability (Rogers, 2003). The current study extends the theory by incorporating *the threat of technologies*, which has not been captured by the existing five attributes in the diffusion model. The threat of technologies refers to individuals' perceptions regarding their susceptibility to and the resulting severity of technologies (Carpenter et al., 2019), and it is more pronounced than ever with advancements in machine learning and artificial intelligence (Cheng et al., 2022; Sundar, 2020). In the context of AI adoption among employees, the threat of AI in the workplace is captured as the extent to which an employee views the likelihood of AI impacting their future career prospects, job security and employment opportunities.

In addition, diffusion inquiry differs from most other social science research by the fact that time is a key theoretical variable (Rogers, 1995), as diffusion is a process that occurs over time. Rogers (1995) suggested that instead of gathering recall data at the end of the diffusion period, it would be more valuable to consider longitudinal data collection and evaluation of the diffusion process while it is in the course. The current study aims to gather data at multiple time points in the early-diffusion stages of AI technologies in general. This approach overcomes the limitation of previous diffusion studies, which depend on one-time cross-sectional datasets (Meyer, 2004; Rogers, 2003). In exploring the over-time process of AI adoption, we build on the dynamic system's framework to extend the diffusion of innovations theory from a dynamic, differential-effects perspective (Wang et al., 2011, 2015). Specifically, considering innovation adoption as a dynamic process at the individual level, we propose that employees' current attitude toward AI adoption should be influenced by the accumulation of their previously held attitudes, based on the self-causing property of a dynamic system. Further, we posit that how attributes of AI technologies may determine people's attitudes cannot be fully understood by looking at the AI attributes alone. Instead, the self-causing nature of human emotion and cognition (i.e., previous attitudes), should be accounted for if we wish to understand how AI attributes are associated with current attitudes toward AI adoption.

Examining the moderation effect of previous attitudes on the relationship between innovation attributes and current attitudes can advance the theory and practice paradigms by exploring the differential effects or the boundary conditions. In essence, some attributes may carry more weight for certain groups of potential adopters. By exploring this moderating effect, this study integrates two lines of long-standing diffusion research. On one hand, a long line of research has categorized different types of potential adopters (Rogers, 2003) (e.g., the early adopter, the late majority, and the laggards), which can be predicted by potential adopters' attitude toward the innovation (Dearing, 2021). On the other hand, as elaborated above, extant diffusion research has identified key attributes of innovation in persuading potential adopters. Bridging these two lines of research provides insights into what attributes may be more influential for certain groups of potential adopters, especially the late majority and the laggards who tend to hold a more negative attitude toward adoption. Practitioners then can tailor persuasive messages, tutorials, and workshops focusing on promoting and/or addressing certain attributes to specific audiences.

The overarching goal of this study is to provide an understanding of the overall adoption of AI within the workplace context. Three waves of surveys were conducted over a period of 3 months to investigate how employees' responses to and evaluations of AI technologies in the workplace vary over time across various industries as the diffusion process unfolds. Then, formal, time-series dynamic models are used to systematically tease apart the self-causing effects of previous attitudes and the influences of AI attributes on current attitudes toward AI adoption. Further, different attributes of AI that may be more influential for certain groups of employees in their attitude formation are examined.

Innovation Attributes in Existing Diffusion Literature

The diffusion of innovations theory is essentially an uncertainty reduction process in which individuals are motivated to seek information about characteristics and attributes of innovations (Rogers, 2003). Among many attributes of innovations, diffusion research has identified five attributes to explain most of the variance in adoption: relative advantage, complexity, compatibility, trialability, and observability.

Relative advantage is the degree to which an innovation is perceived as advantageous. The greater the perceived benefits of innovation in the workplace, such as improving work productivity and quality, the more likely employees will adopt it. Relative advantage was found to be one of the strongest predictors of adoption (Atkin et al., 2015; Rogers, 2003). Complexity refers to the degree to which an innovation is perceived as easy or difficult to understand and use. It is usually measured as simplicity or ease of use, the opposite of complexity (Dearing et al., 2018). New technologies that are simpler to use are adopted more rapidly than innovations that require more effort to learn (Rogers, 2003).

Compatibility is the degree to which an innovation is viewed as being consistent with current practice and the needs of potential adopters. Innovations that are considered as more compatible with an individual's current work style and fitting closely with their work situation are more likely to be adopted (Rogers, 2003). Trialability is the degree to which an innovation can be experimented with on a limited basis. Having the opportunities to try out innovations can help reduce uncertainty. Innovations that can be tried on are generally readily adopted (Rogers, 2003). Observability is the degree to which the adoption of an innovation is visible to others. The easier it is for employees to see AI's applications in the workplace, the more likely they are to adopt, because visibility stimulates social modeling and peer discussion. Research has found that innovations with relatively high observability diffuse more quickly, for example, cellphone compared to personal computer (Rogers, 2003).

Rogers (2003) further emphasized that what mattered was the subjective evaluation of an innovation, not necessarily its objective attributes. Such subjective evaluations, derived from individuals' personal experiences and perceptions, can fluctuate over time to determine one's attitude toward the innovation and subsequent adoption behaviors. In addition, the five attributes may play differential roles in determining adoption attitudes, depending on different types of innovations. For instance, relative advantage and compatibility were the most important determinants for farmers' adoption of dairy innovations, but ease of use, observability, and trialability were not (Rogers, 2003). In other cases, observability and trialability were found to be more significant antecedents of adoption than others (Gross, 1942; Rogers, 2003).

Threat of AI

Over the past decades, the five attributes of innovation outlined above have garnered considerable attention in diffusion research. However, as technologies evolved, the growing power of machines' self-learning abilities has raised concerns about the rise of machine agency and the threats of technologies and the potential threats posed by such technologies (Cheng et al., 2022; Shinn et al., 2023; Sundar, 2020). AI systems can analyze vast amounts of data from sensors, remote inputs, and various other sources in real-time or near real-time, and subsequently act on the insights derived from this analysis. Consequently, AI has been applied in many sectors. In healthcare, AI can conduct medical imaging analysis and provide diagnostic suggestions; in human resources management, AI can be embedded in the hiring screening and employee assessment processes; in banking and finance, AI can identify high-risk cases and detect fraudulent transactions. These tasks that required decision-making were dominantly conducted by human workers.

Unlike earlier technological innovations that mainly rely on human input and are limited to mechanical or predetermined responses, AI exhibits several unique characteristics. These include the ability to exercise its own agency (Sundar, 2020), engage in self-learning and self-improvement (Shinn et al., 2023), offer explanations or justifications for its answers or decisions (Angelov et al., 2021), and personalize output based on interaction history (Hermann, 2022). These unique attributes of AI may collectively contribute to a broader concept—the threat of technologies, which encompasses potential consequences for job security, human dignity, and ethical concerns (Liu, 2021), and thus may present unique barriers to adoption of AI.

The threat of technologies eliminating human jobs is more pronounced than ever in the age of AI (Mirbabaie et al., 2022), and it cannot be ignored as a determinant factor in the adoption process. Existing literature on AI has examined and explored the threat and fear of AI. For instance, large majorities of Americans (81%) worried about AI adoption in the workplace causing worker layoffs (Rainie et al., 2022). Research has also shown that when management is exploring ways to replace workers with AI, employees perceive that they are undervalued and not regarded highly by employers (Brougham & Haar, 2018). Another study also found that the fear of AI and robots was associated with the fear of becoming unemployed (Liang & Lee, 2017). In a recent systematic review, the authors suggested that AI's threat to job security represents a potentially influential yet under-explored concept in explaining technology acceptance (Kelly et al., 2023). Therefore, in the context of AI adoption in the workplace, we focus on the threat to job security, which is probably the biggest threat for employees in the workplace when considering adopting AI (Kelly et al., 2023; Rainie et al., 2022). In adding the threat of technologies into the model of innovation attributes, we follow the spirit posited by Rogers (2003), "diffusion scholars should keep an open mind toward other possible attributes that may be important in a specific situation for a particular set of individuals adopting a unique set of innovations" (p. 294).

The important role of perceived threat in the adoption process can be explained by the mechanism of negativity bias. Negativity bias refers to the principle that negative information is salient, potent and dominant in information processing and decision making (Lilienfeld & Latzman, 2014). Humans generally respond more strongly, to be more attentive, and to give more weight to unpleasant, particularly threat-related information (Cacioppo et al., 1999). This tendency has been demonstrated in a large body of research, including loss aversion (Kahneman & Tversky, 1979), quick recognition of angry versus happy faces (Hansen & Hansen, 1988), and supported by behavioral, and psychophysiological, and neuroscientific evidence (e.g., McSorley & van Reekum, 2013). The threat to job security is probably one of the most negative situations that employees are highly reactive to, and employees are less likely to endorse adopting AI in the workplace if they perceive AI as capable of replacing them at work.

AI Diffusion From a Dynamic, Differential-Effects Perspective

Members in a social system do not all adopt an innovation at the same time. Rather, they adopt or reject the innovation in an over-time sequence. Time is an important dimension in understanding the diffusion process (Rogers, 2003). Previous research examines the time dimension by counting the cumulative number of adopters over time, and they found that an S-shaped curve with the percentage of adopters on the y-axis and time on the x-axis (Rogers, 2003). This method uses descriptive statistics to provide a general idea of trends of adoption over time, which is valuable. However, for diffusion of innovations as a relatively mature area of research, a more nuanced understanding of the longitudinal dynamic processes of adoption over time is essential to advance its theoretical development and practical application (Slater, 2007). Our proposed longitudinal panel study also contributes to address criticisms toward the recall problem in diffusion research. For example, the respondents tend to be asked to reflect and reconstruct their past history of adoption experiences (Rogers, 2003). The recall problem is of particular concern because, by definition, diffusion is a process that occurs over time; however, the research designs predominantly employed (e.g., cross-sectional surveys) do not provide substantial insights into the diffusion process itself. As Rogers proposed, the most logical way to overcome the recall problem is to gather data at various periods while the diffusion process is in course (Rogers, 2003).

We draw from the framework of dynamic systems (Wang et al., 2011, 2015) to provide a differential-effects, dynamic perspective for the longitudinal diffusion process. The dynamic systems approach to information processing and decision-making proposes that human cognition is dynamically caused by both its internal system and external system over time. Internal system refers to the self-causation or self-sustaining properties of human brain (Buzsàki, 2006). Simply put, one's thoughts and beliefs are determined by their previous thoughts and beliefs. Such history-dependent effect is the defining feature of a dynamic system (Wang et al., 2011). In the context of AI adoption, people's current attitudes toward AI adoption should be influenced by their previous attitudes.

In addition, the dynamic system approach also proposes the external system, including various types of external influences, can cause large, small, or null change on human cognition and emotion, depending on the internal system of human cognition and emotion (Buzsàki, 2006). For example, Wang and colleagues' studies showed that the effects of media stimuli on individuals' emotions and cognition is moderated by their previous emotional and cognitive states over time (Wang et al., 2015). Applying this principle to understand AI adoption, how attributes of AI technologies may determine people's attitudes cannot be fully understood by looking at the AI attributes alone. Instead, the self-causing nature of attitudes, that is, previous attitudes, should be accounted for if we wish to understand the effects of AI attributes on current attitudes toward AI. Specifically, for audiences who hold different pre-existing attitudes toward AI, different attributes may play differential roles in their adoption decision over time. For example, compared to employees with a positive attitude toward AI (e.g., innovators and early adopters), employees who hold a negative attitude previously (e.g., laggards and late adopters) may be more concerned about the threat of AI and that accounts for their hesitance and resentment toward AI adoption. Audience previously not supportive of AI may be likely to adopt by observing others using AI innovations or having a chance to try out the innovation, as diffusion is often driven by social modeling (Dearing et al., 2018). The important moderating role of previous attitudes has also been long recognized in the persuasion research, as prior attitude influences, and even biases, the way individuals react to and process persuasive messages (Cacioppo & Petty, 1979; Chattopadhyay & Basu, 1990). Unlike the persuasion literature which primarily tested the moderating role of previous attitude in the experimental paradigm, the dynamic perspective examines the moderation over time with longitudinal data and formal time-series analysis (e.g., Wang et al., 2015).

In fact, this moderation effect of previous attitude toward an innovation has both theoretical and practical implications. Theoretically, integrating the two lines of long-standing diffusion research, adopter categories and attributes of innovations, can provide a complete picture and a more nuanced understanding of the adoption process, regarding what attributes carry more weight for which group of potential adopters. To predict individuals' adoption attitudes, previous diffusion research has explored individual differences, including the level of education, socioeconomic status, ability to cope with uncertainty, higher aspirations and so on (Rogers, 2003). Focusing on these demographics and/or personality variables has two limitations. First, it has received criticism of individual blame bias, which refers to the tendency that holds an individual responsible for innovation adoption (Rogers, 2003). Second, individuals' demographics and personalities are relatively difficult to alter, so following this line of research there is little that researchers, designers, and organizations can do to motivate adoption. In this study, we shift the focus to consider innovation attributes and the moderating role of previous attitude. Doing so allows practitioners to design different strategies and tailor different persuasive messages to emphasize different attributes for different groups of audiences, especially those who are hesitant to adopt.

Hypotheses and Research Question

Taken together, building on existing diffusion research and the dynamic system's perspective, we test the internal self-causing effects of employee's attitudes toward AI adoption, that is, employees' current attitudes toward AI adoption should be influenced by the accumulation of their previously held attitudes (Hypothesis 1). Based on the five key attributes identified in extant diffusion research, we hypothesize that these attributes of AI (i.e., relative advantage, complexity operationalized as ease of use, compatibility, trialability, observability) should be associated with a more positive attitude toward AI in general (Hypothesis 2). Further, we add the threat of technologies into the diffusion model and hypothesize that threat of AI should be negatively associated with a favorable attitude toward AI (Hypothesis 3). Lastly, the relationships between different AI attributes and employees' attitudes should depend on their previous attitudes, as some attributes might have greater significance to those who hold a negative attitude toward AI adoption than those who do not. The question of which specific attributes are moderated by previous attitudes will be explored (Research Question), as empirical evidence is still lacking in terms of which attributes carry more weight for audiences with different attitudes toward AI adoption.

Methods

Participants

The study was approved by the University Institutional Review Board prior to the data collection, and informed consent was obtained from participants. Participants from the United States were recruited using CloudResearch, a professional survey platform designed for academic and marketing researchers. The panel members were a national sample of U.S. employees aged 18 or older. To ensure the employee status of participants, demographic filters provided by the panel company were used, along with a screening question added by the researchers to only include participants who self-reported to be regular salaried employees at the time of the study. The first wave of data collection took place in March 2022, the second in April 2022, and the third in May 2022. After participants were eliminated who did not pass the attention check, 890 participants completed the first survey, 671 completed the second survey (75% retention rate), and 553 completed the last survey (82% retention rate). Please see Table 1 for the demographics of participants in the three waves.

Measures

Relative Advantage. The relative advantage of AI in the workplace was measured by using four items adapted from the innovation adoption instrument (Moore & Benbasat, 1991): (1) "Using AI enables me to do tasks more quickly," (2) "Using AI improves the quality of work I do," (3) "Using AI makes it easier to do my job," (4) "Using AI enhances my effectiveness on the job" on a five-point scale (*1 = strongly disagree; 5 = strongly agree*). Scores were averaged to create an index (T1: M = 3.64, SD = 0.87, α = .94; T2: M = 3.66, SD = 0.87, α = .94; T3: M = 3.64, SD = 0.89, α = .95). Intraclass correlation coefficient (ICC) for this measure over three time points was .96 with 95% CI [0.95, 0.96], indicating an excellent test-retest reliability (Koo & Li, 2016).

Ease of Use. Participants' perceived ease of use of AI was measured by four items from the innovation adoption instrument (Moore & Benbasat, 1991): (1) "Overall, I believe that AI is easy to use," (2) "Learning to operate AI is easy for me,"

Table 1. Demographics of Participants.

Demographics	Category	*T1: N* = 890 (%)	*T2: N* = 671 (%)	*T3: N* = 553 (%)
Age	19–35	33.74	31.90	29.73
	36–46	37.33	36.35	35.86
	47–70	28.92	31.75	34.41
Gender	Male	50.28	51.78	52.25
	Female	49.72	48.22	47.75
Ethnicity (multiple selections are possible)	White, non-Hispanic or Latino	77.27	79.38	81.62
	Black or African American	11.09	9.05	6.85
	Hispanic or Latino	5.71	5.49	5.41
	Asian	9.29	9.05	8.47
	Pacific Islander	0.34	0.30	0.36
	Native American/ Alaskan	1.12	1.04	1.08
	Others	0.56	0.45	0.36
Education	High school	17.47	16.47	16.04
	Associate degree	14.78	14.84	15.50
	Bachelor's degree	43	45.85	46.31
	Master's degree	20.72	19.29	18.74
	Doctoral or equivalent	4.03	3.56	3.42
Job Level	Entry-level	30.80	29.38	26.49
	Senior level	28.67	29.23	30.45
	Supervisory level	17.81	18.10	19.46
	Managerial level	18.14	1.93	19.28
	Executive level	2.13	2.67	1.80
Organizational Size	1–4	1.34	1.48	1.44
	5–9	1.90	1.63	1.62
	10–19	6.38	6.08	5.77
	20–49	8.06	8.75	8.11
	50–99	11.87	11.57	11.35
	100–249	14.22	15.13	14.59
	250–499	10.19	9.64	9.73
	500–999	9.85	10.09	10.27
	1,000 or more	36.17	35.61	37.12
Industry	Forestry, fishing, hunting, or agriculture support	0.67	0.74	0.72
	Real estate or rental and leasing	1.90	1.04	0.90
	Mining	0	0	0

(*continued*)

Table 1. (continued)

Demographics	Category	*T1: N*=890 (%)	*T2: N*=671 (%)	*T3: N*=553 (%)
	Professional, scientific or technical services	14.56	15.13	15.14
	Utilities	1.34	1.63	1.62
	Management of companies or enterprises	1.79	1.93	1.80
	Construction	2.35	2.22	2.34
	Admin, support, waste management or remediation services	3.02	2.67	2.52
	Manufacturing	5.71	6.38	6.31
	Educational services	13.66	13.35	13.51
	Wholesale trade	0.90	0.89	0.90
	Health care or social assistance	13.10	13.20	13.87
	Retail trade	7.5	7.12	7.21
	Arts, entertainment or recreation	2.69	3.26	3.24
	Transportation or warehousing	4.26	4.30	4.68
	Accommodation or food services	3.58	4.01	4.32
	Information	5.94	5.34	5.59
	Other services (except public administration)	7.05	6.23	5.59
	Finance or insurance	8.96	9.64	9.01
	Unclassified establishments	1.01	0.89	0.72

(3) "Interaction with AI is clear and understandable," (4) "I believe that it is easy to get AI to do what I want it to do" on the same five-point scale. Answers were averaged to create an index (T1: M=3.56, SD=0.75, α=.88; T2: M=3.57, SD=0.76, α=.90; T3: M=3.57, SD=0.80, α=.91). ICC for this measure over three time points was .95 with 95% CI [0.94, 0.95].

Compatibility. Participants' perceptions of the compatibility of AI with their work was measured by three items from the innovation adoption instrument (Moore & Benbasat, 1991): (1) "Using AI is compatible with all aspects of my work," (2) "I think that using AI fits well with the way I like to work," (3) "Using AI fits into my work style" on the same five-point scale. Answers were averaged to create an index (T1: $M = 3.00$, $SD = 1.00$, $\alpha = .91$; T2: $M = 2.93$, $SD = 0.99$, $\alpha = .90$; T3: $M = 2.88$, $SD = 0.99$, $\alpha = .90$). ICC for this measure over three time points was .94 (95% CI [0.93, 0.94]).

Trialability. Participants' experiences of trying out AI at work was measured by two items from the innovation adoption instrument (Moore & Benbasat, 1991): (1) "I have opportunities to try AI for work" and (2) "I know where I can go to try out various uses of AI" on the same five-point scale. Answers were averaged to create an index (T1: $M = 2.85$, $SD = 1.11$, $\alpha = .84$; T2: $M = 2.92$, $SD = 1.13$, $\alpha = .86$; T3: $M = 2.94$, $SD = 1.16$, $\alpha = .87$). ICC for this measure over three time points was .91 (95% CI [0.91, 0.92]).

Observability. Participants' experiences of observing others using AI at work was measured by two items from the innovation adoption instrument (Moore & Benbasat, 1991): (1) "I have seen others using AI in their workplace" and (2) "AI is visible in my workplace" on the same five-point scale. Answers were averaged to create an index (T1: $M = 2.88$, $SD = 1.10$, $\alpha = .81$; T2: $M = 2.96$, $SD = 1.13$, $\alpha = .83$; T3: $M = 2.98$, $SD = 1.14$, $\alpha = .85$). ICC for this measure over three time points was .90 (95% CI [0.88, 0.91]).

Threat. Perceived threat of AI was operationalized as perceptions of jobs being replaced by AI from Brougham and Haar (2018). The three items measured by a five-point Likert scale are: (1) "I think my job could be replaced by AI," (2) "I am worried that what I do now in my job will be replaced by AI," (3) "I am worried about my future in my organization due to AI replacing employees." Answers were averaged to create an index (T1: $M = 2.19$, $SD = 1.10$, $\alpha = .92$; T2: $M = 2.13$, $SD = 1.07$, $\alpha = .93$; T3: $M = 2.03$, $SD = 1.02$, $\alpha = .93$). ICC for this measure over three time points was .96 (95% CI [0.95, 0.96]).

Attitudes Toward AI Adoption. Four items from Myers and Goodwin (2011) were adopted to measure attitudes toward AI in the workplace. On a 5-point semantic differential scale, participants were asked to indicate "AI in the workplace is. . ." (1) *Bad—Good*, (2) *Unfavorable—Favorable*, (3) *Unnecessary—Necessary*, (4) *Negative—Positive*. The four items were averaged (T1: $M = 3.49$, $SD = 0.88$, $\alpha = .91$; T2: $M = 3.44$, $SD = 0.86$, $\alpha = .91$; T3: $M = 3.44$, $SD = 0.87$ $\alpha = .91$). ICC for this measure over three time points was .94 (95% CI [0.94, 0.95]).

Time. Time refers to the wave of the study when the data were collected, where 1 = first wave, 2 = second wave, and 3 = third wave. Time serves as a control variable in longitudinal models (Xu & Wang, 2022). Within and between variations of each variable are in Table 2.

Analytic Approach

The fixed effects panel model was used to analyze repeated observations over time. This approach takes into account time-invariant individual heterogeneity in longitudinal

Table 2. Within and Between Variations of Key Variables.

Variables	Mean	Overall *SD*	Between *SD*	Within *SD*
Attitude toward AI adoption	3.46	0.87	0.80	0.36
Relative advantage	3.65	0.87	0.80	0.37
Ease of use	3.57	0.76	0.70	0.31
Compatibility	2.95	0.99	0.92	0.41
Trialability	2.90	1.13	1.04	0.48
Observability	2.93	1.12	1.03	0.49
Threat	2.13	1.07	1.02	0.41

data (Allison, 2009; Antonakis et al., 2010). Specifically, fixed effects models consider a myriad of observed or unobserved variables, for example, demographics, personality, organizational characteristics, by expressing variables as deviations from individual-specific means (Allison, 2009). This approach controls for all between-subject variation and leave only the within variation (Allison et al., 2017). This unobserved individual heterogeneity is presented by α_{i} in the equation below. In addition, the inclusion of the lagged dependent variable (Y_{t-1}) allows us to make more accurate estimates of the relationship between AI attributes (X_{it}) and attitudes toward AI adoption (Y_{it}) by taking account for the effects of the previous attitudes (Y_{t-1}) (Xu et al., 2023). The inclusion of the lagged dependent variable (Y_{t-1}) also has theoretical importance. First, including the lagged dependent variables in the models indicates a history-dependent effect—an essential feature of dynamic processes—because a dynamic system assumes a variable's current state is contingent on and entangled with its past state (Granger, 1980; Wang et al., 2015). Second, in the context of AI diffusion in the workplace, employees' attitudes toward AI may have an inherent persistence over time.

The below equation represents the fixed effects models in this article. For $i = 1, \ldots N$ (number of individual), and $t = 1, \ldots T$ (number of time points), $Y_{i,t-1}$ is the dependent variable at the previous time point. $X_{i,t}$ is a vector of predictors that change over time. α_i represents all differences between individuals that are stable over time, which is sometimes described as "unobserved heterogeneity." $\varepsilon_{i,t}$ is the random disturbance term not predicted by the model for individual i at time point t. Models were implemented by the *plm* command of PLM package in R (Croissant & Millo, 2008). The fixed effects models are tested again the random effects models, respectively. Based on results of the Hausman test, the fixed effects models were preferred over the random effects models (Wooldridge, 2010).

$$Y_{i,t} = \alpha_i + Y_{i,t-1} + \beta X_{i,t} + \varepsilon_{i,t}$$

H1, H2, and H3 were tested using a fixed effect model (model 1). RQ was tested using a fixed effect model with interactions between AI attributes and prior attitudes (model 2).

Table 3. Model Coefficients Predicting Attitudes Toward AI Adoption.

	Model 1		Model 2	
	Attitudes toward AI adoption $(AAA)_{i,t}$		Attitudes toward AI adoption $(AAA)_{i,t}$	
	Coef.	*SE*	Coef.	*SE*
$AAA_{i,t-1}$	−0.35***	0.04	−0.66***	0.15
$RA_{i,t}$	0.13***	0.04	0.27*	0.13
Ease of $use_{i,t}$	0.08	0.04	−0.07	0.13
$Compatibility_{i,t}$	0.18***	0.04	0.08	0.12
$Trialability_{i,t}$	0.02	0.03	−0.40***	0.12
$Observability_{i,t}$	0.07*	0.03	0.49***	0.12
$Threat_{i,t}$	−0.10**	0.03	−0.35***	0.09
$Time_{i,t}$	−0.02	0.03	−0.03	0.09
$AAA_{i,t-1} \times RA_{i,t}$			0.05	0.04
$AAA_{i,t-1} \times$ Ease of $use_{i,t}$			0.04	0.03
$AAA_{i,t-1} \times Compatibility_{i,t}$			0.03	0.04
$AAA_{i,t-1} \times Trialability_{i,t}$			0.12***	0.03
$AAA_{i,t-1} \times Observability_{i,t}$			−0.12***	0.03
$AAA_{i,t-1} \times Threat_{i,t}$			0.07**	0.02
R^2	0.26		0.30	

Note. i,t = for individual i at time point t; AAA = attitudes toward AI adoption; RA = relative advantage.
***$p < .001$. **$p < .01$. *$p < .05$.

Results

H1 predicted that employees' current attitudes toward AI adoption would be influenced by their previously held attitudes. The results of model 1 (Table 3) show that previous attitudes negatively predicted subsequent attitudes toward AI adoption ($\beta = -.35$, $SE = 0.04$, $p < .001$), indicating a downward reducing pattern. H2 stated that specific attributes of AI (i.e., relative advantage, ease of use, compatibility, trialability, observability) would be associated with employees' more positive attitudes toward AI. The results from model 1 showed that relative advantage of AI ($\beta = .13$, $SE = 0.04$, $p < .001$), compatibility ($\beta = .18$, $SE = 0.04$, $p < .001$), and observability ($\beta = .07$, $SE = 0.03$, $p = .03$) were positively associated with attitudes toward AI adoption. However, the effects of ease of use and trialability were not significant. Thus, H2 was partially supported.

H3 posited that threat of AI should be negatively associated with a favorable attitude toward AI. In support of H3, results from model 1 showed that the threat of AI was negatively associated with attitudes toward AI adoption ($\beta = -.10$, $SE = 0.03$, $p = .003$).

Next, a test of moderation effects of previous attitudes on the relationship between AI attributes and current attitudes was conducted to answer the research question

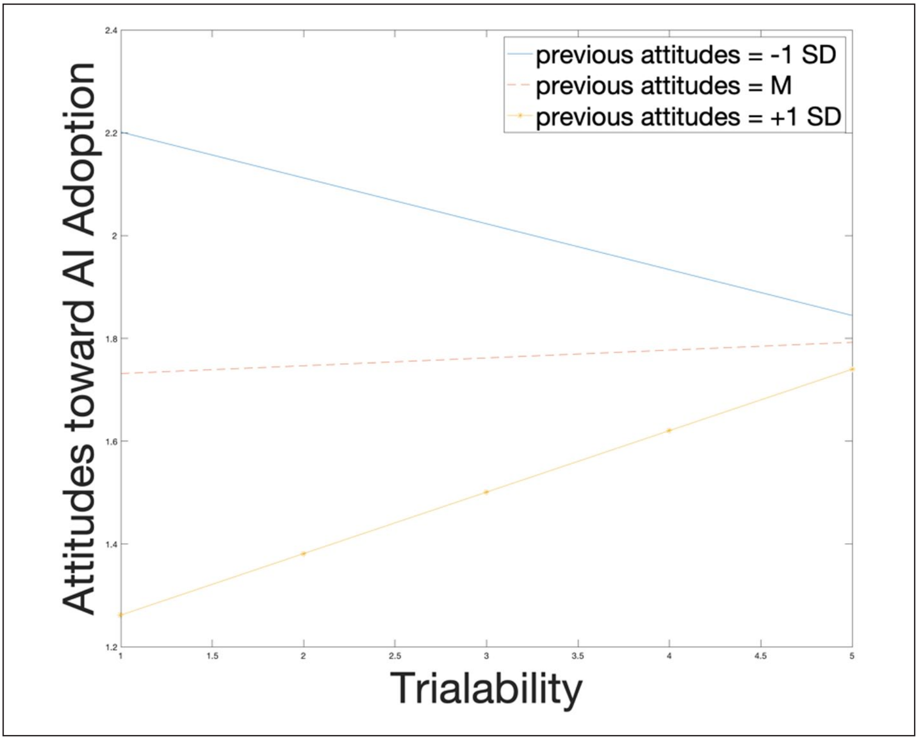

Figure 1. Relationship between trialability and current attitudes depending on previous attitudes.
Note. Interaction figures are created in MATLAB with the information provided in R.

(Model 2). Results from model 2 (Table 3) showed that trialability's influences on current attitudes depended on one's previous attitudes ($\beta = .12$, $SE = 0.03$, $p < .001$). Specifically, trialability had stronger positive relationship with attitudes among employees who held a more positive attitude toward AI adoption previously (+1 *SD*), whereas trialability had a negative relationship with attitudes among employees with a more negative attitude (−1 *SD*) (Figure 1).

Results from model 2 showed that the contingent moderation effect of previous attitudes on the relationship between observability and current attitudes was significant ($\beta = -.12$, $SE = 0.03$, $p < .001$). Observability had a positive effect on attitudes for employees who held a more negative attitude toward AI adoption (−1 *SD*), but not for employees who held a more positive attitude (+1 *SD*) (Figure 2).

Results from model 2 indicated that the contingent moderation effect of previous attitude was significant on the relationship between the threat of AI and attitudes toward AI adoption ($\beta = .07$, $SE = 0.02$, $p = .001$), meaning the threat of AI had a stronger negative effect (a steeper slope) on attitudes for employees who held a more

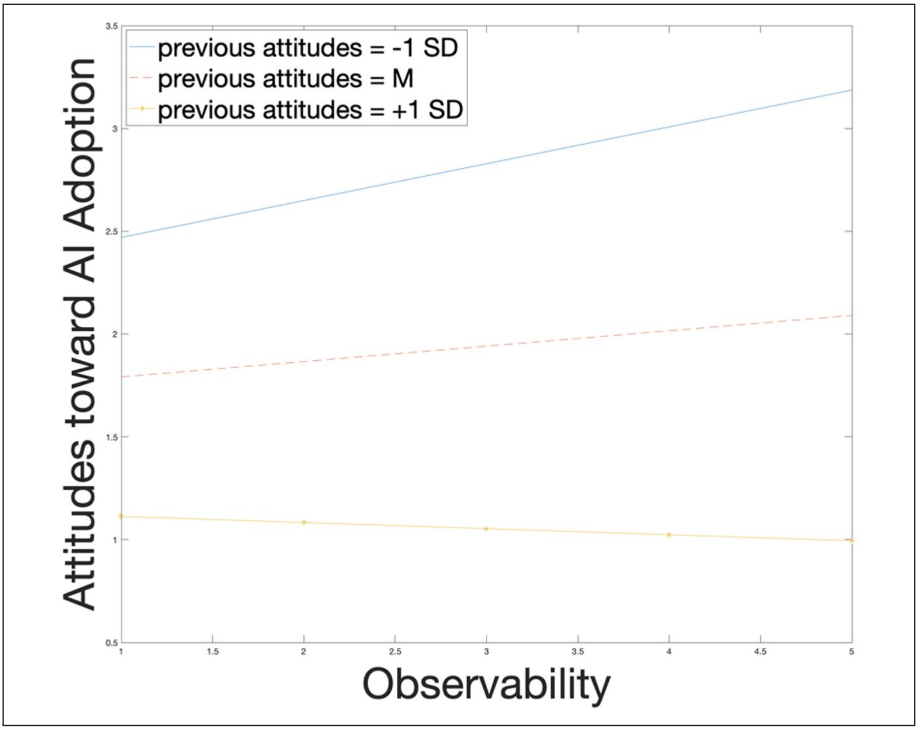

Figure 2. Relationship between observability and current attitudes depending on previous attitudes.

negative attitude toward AI (-1 *SD*), than for employees who held a more positive attitude toward AI ($+1$ *SD*) (Figure 3).

Discussion

As the diffusion of a wide range of innovations continues to unfold, the current article offers an updated perspective on the diffusion of innovations theory and its application to the general adoption of AI in the workplace. Our study investigates the overall adoption of AI among employees across various industries through a dynamic, differential-effects approach, employing a three-wave longitudinal research design. Specifically, results indicated that relative advantage, compatibility, and observability were positively associated with attitudes toward AI adoption over time, but ease of use and trialability did not play a significant role. The threat of AI (i.e., concerns over job being replaced by AI) was negatively associated with attitudes over time. In testing the differential effects on AI adoption among different groups of potential adopters, trialability was found to positively impact employees with a more positive attitude toward

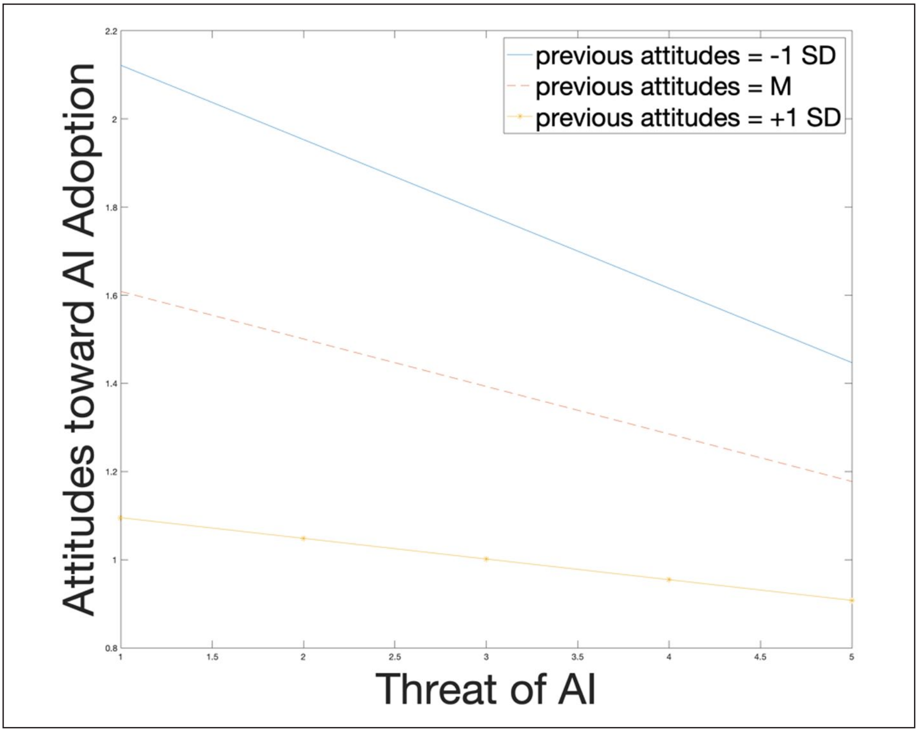

Figure 3. Relationship between threat of AI (job being replaced by AI) and current attitudes depending on previous attitudes.

AI previously, while negatively affecting those with prior negative attitudes. Observability and threat of AI, however, were more influential among employees who held a negative attitude previously. Last, results showed that attitudes toward AI adoption in the workplace had a negative, reduction effect, meaning that employees' support for AI adoption had a downward, decreasing trend over the 3 month study period. Theoretical and practical implications are discussed below.

Theoretical Contributions

Since Rogers synthesized and popularized the diffusion of innovations paradigm about 60 years ago (Rogers, 1962), scholars in a variety of academic disciplines have used, tested and contributed to the body of diffusion research (e.g., Atkin et al., 2015; Dearing et al., 2018). Building on this tradition and Rogers (2003) suggestion to develop a more nuanced understanding of the diffusion process, this study contributes to the diffusion literature by (1) proposing the threat of technology as a theoretically important innovation attribute and (2) adopting a dynamic, differential-effects perspective with a longitudinal study to examine the adoption of AI in the workplace over time. These modifications serve to update and strengthen the theory, making it more relevant and applicable to the evolving landscape of technological innovations.

Adding the threat of technologies provides new theoretical developments to better understand the complexities of social technologies. As intelligent technologies evolved, chatbots built on large language models, smart devices, recommendation algorithms, self-driven automobiles, and other AI-based innovations have raised significant concerns and heated discussions about threats of technologies (e.g., Cheng et al., 2022; Sundar, 2020), such as issues of data security, privacy, and workforce replacement. The existing innovation attributes model, however, focuses on the positive sides of innovations (e.g., relative advantage and compatibility). Although the complexity dimension touches on the limitation of innovations, such limitations can be readily addressed by training and tutorials. The threat of technologies has not been accounted for in the existing innovation attributes model but plays an increasingly important role in attitudes toward innovations (Rainie et al., 2022). Thus, adding the threat of technologies provides the missing piece of the adoption puzzle. Indeed, standardized coefficients from the models showed that threat was the third strongest attribute predictor in the main effects model (model 1) and the second strongest in the model after controlling for the interaction effects (model 2).

Our longitudinal panel study employed a dynamic, differential perspective to address criticisms toward and limitations of the existing diffusion of innovations model. First, diffusion research has been criticized for the recall problem and reconstructing adopters' past history of adoption experiences at the end of the diffusion process (Rogers, 2003). The current study monitored employees for 3 months to continuously assess their attitudes toward, and experiences with, AI adoption in the workplace. This approach offered dynamic insights rather than static snapshots, enabling the capture of the innovation's sequential diffusion throughout the social system (Rogers, 2003).

Second, this work points to fruitful directions in theorizing a more nuanced theory of innovation attributes and adoption. The diffusion processes rest on the idea that one should try to accelerate the adoption of innovations from the innovators to the laggards as quickly and precisely as possible (Atkin et al., 2015). Researchers and practitioners alike must question how to target and change late adopters or laggards' attitudes toward innovation. This approach addressed the question by investigating how different innovation attributes interacting with prior states of differential attitudes can affect current attitudes toward innovation adoption. This is an old but underdeveloped area of theoretical advancement of diffusion literature. More than half a century ago, early diffusion researchers already found that some innovation attributes were more influential for some groups of potential adopters (Ryan & Gross, 1943). Yet, this direction has received little attention in subsequent diffusion research (Rogers, 2003). The findings from the longitudinal fixed effects models confirmed that different innovation attributes influenced different groups of potential adopters' attitudes in different ways, after holding constant observed and unobserved individual differences. Therefore, instead of focusing on adopters' demographics and/or personalities that are relatively difficult to alter, researchers, designers, and organizations can change the way of designing and communicating the innovation attributes to the potential adopters.

Practical Contributions

Findings from this study provide practical implications for AI design and AI diffusion in the workplace. First, it is worth noting that attitudes toward AI adoption among employees showed a downward, reducing trend within individuals, meaning participants were increasing concerned about and holding a more negative attitude toward AI adoption over the 3 month study period. This is in stark contrast to the positive reinforcing effects of attitudes in most longitudinal studies (e.g., Wang et al., 2015; Xu et al., 2023), but in-fact resonates with the growing widespread concerns over AI adoption in all walks of life (Cheng et al., 2022). This finding poses challenges for the diffusion of AI in the workplace and highlights the importance of understanding employees' thoughts and concerns to promote AI adoption.

Second, the current study has identified four significant attributes that may lead to more positive attitudes toward adoption over time: relative advantage, compatibility, observability and threat. AI designs and adoption campaigns can highlight these attributes by emphasizing the benefits and upgrades AI provides to improve employees' job performance and efficiency, underlining how AI technologies can fit into employees existing work style and incorporating AI into current workstation. In terms of observability, organizations can increase visibility of AI adoption in the workplace by distributing badge stickers to those who have adopted AI, and can hold AI workshops for early adopters to share their experiences with larger audiences. These strategies can increase the visibility of AI in the workplace, and visibility stimulates peer discussion and social modeling which may ultimately contribute to diffusion (Dearing et al., 2018; Moore & Benbasat, 1991).

To address employees' concerns about AI threating job security, employers, organizations, and government could better explain to workers the consequences and implications of AI adoption. On one hand, some tasks can be substituted by AI, especially those that can pose physical dangers to human workers (e.g., exposure to high heat, chemicals, sharp objects), and tasks that are undesirable for some human workers (e.g., cleaning, repetitive/tedious work). On the other hand, AI can create many jobs as it replaces. Workers who can increase their education and training, either on the job or elsewhere, will be able to learn new skills and work with AI. For example, even while robots have replaced unskilled employees on assembly lines, they have also generated new employment opportunities for machinists, advanced welders, and other technicians who maintain the robots or use them for new duties. Additionally, government, businesses, and educational institutions could offer training on how to invest in and innovate in skills and improve job quality, including changing current labor legislation and unemployment insurance.

Lastly, results of the moderation analyses have provided insights into what attributes may be more influential for certain groups of potential adopters, especially those who held a negative attitude toward innovations and are likely to be the late majority and the laggards. Practitioners then can tailor persuasive messages focusing on promoting and/or addressing certain attributes to specific audiences. For example, observability increased positive attitudes toward AI adoption, but this effect was only significant for employees who held more negative attitudes toward AI, not for those with a more positive attitude. Similarly, threat of AI diminished positive attitudes more significantly among employees who previously were less supportive about AI adoption, as compared to those who were already enthusiastic about AI. To facilitate the adoption process, diffusion campaign messages then can be tailored to employees with unfavorable attitudes by addressing their job security concerns and by increasing the visibility of AI in the workplace. For people who were already supportive of AI adoption, results indicated that increasing trialability can further reinforce their positive attitudes. Workshops and events can be held to provide chances for enthusiasts to try out AI applications in the workplace.

Limitations and Future Directions

Several limitations of the current study should be noted. Regarding the concept of threat of technologies, we chose to focus on threats to employment in the context of AI adoption in the workplace, but the threat of technologies should be a multi-dimensional concept (Kee, 2017), and encompass different facets of threats, such as threat to privacy, equity, laws, and ethics. Future studies should develop a multi-factor scale to address this issue while balancing the parsimony and complexity of this concept. Moreover, our study tracked employees' perceptions about AI attributes and their attitudes toward AI adoption over 3 months. Yet, the AI diffusion process is likely to span over years and decades. Future research with sufficient funding should try to conduct longitudinal studies over longer periods of time to provide more data points to examine this process. Future research may benefit from integrating longitudinal self-report data with digital trace data of employees' login patterns for AI applications in the workplace, to facilitate a comprehensive analysis of the adoption process.

Due to the focus on the dynamic interplay between the innovation attributes and employees' attitudes toward AI adoption, other interesting variables in the diffusion paradigm were not analyzed. For example, communication channels through which people received information about different attributes of AI (Rice, 2017) such as interpersonal conversation, social media feeds, and news on television were not examined in this study. Diffusion networks through which AI adoption occurs, including the role of weak ties and strong ties, and concepts of change agents and opinion leaders (Atkin et al., 2015), were not included. Explorations of these variables are promising avenues for future studies to make theoretical and practical contributions to the diffusion literature and to the AI adoption. Another important topic concerns the consequences of AI adoption, specifically, but not limited to, how the adoption of AI in the workplace may raise inequality. For example, it is evident that the diffusion of innovations widens the socioeconomic gap between the higher and the lower status segments of a social system (Rice & Pearce, 2015; Rogers, 1995). Future studies should devote more attention to these topics.

Drawing on the original innovation attributes proposed by the diffusion of innovations theory, and aiming to preserve the theory's parsimony, adaptability, and generalizability, we proposed to incorporate the threat of technologies in the current study.

Indeed, the threat of AI is not the sole feature that distinguishes it from other technologies. Emerging research has identified various affordances or characteristics of AI, such as agency (Sundar, 2020), sociability (Xu & Li, 2022), explainability (Angelov et al., 2021), transparency (Liu, 2021), and personalization (Hermann, 2022), among others. This is a promising research area that warrants further investigation as AI continues to advance, particularly in light of groundbreaking developments such as ChatGPT in 2023, which occurred approximately 1 year after we collected data for this study.

It is also important to future research to examine particular AI applications by selectively recruiting employee participants from specific industries or organizations. This can be achieved by posing inquiries and questionnaires specifically tailored to unique AI implementations within their respective workplaces. We posit that both research approaches—one focused on AI in general in the current study, and the other centered on specific AI technologies—hold considerable value in advancing our comprehension of AI adoption in professional environments and daily life.

Lastly, the current study examined innovation adoption at the individual level, and longitudinal fixed effects models allow us to control for observed and unobserved individual differences including different industries and organizations they are in. Future studies, however, can examine the adoption of AI in the workplace at the organizational level. The adoption levels of AI vary across different industries and organizations (Mirbabaie et al., 2022), and it would be fruitful for future research to examine management that supports AI adoption, environments conducive to AI adoption, networks to diffuse innovations at organizational levels, and organizational policy that supports innovation diffusion.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

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Notes

1. The three-way interactions between innovation attributes, prior attitudes, and time were tested to explore if the moderation effects vary across time. The coefficient of the three-way interaction was not statistically significant.
2. Data and analysis codes of this article are available at https://osf.io/92mrf/?view_only=b75cac077f7f4baabece304e15f28f34

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