# A Three-Stage Dynamic Model of AI Adoption in Generative Environments

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## Abstract

As generative AI becomes deeply integrated into work settings, the abundance of AI-related cues in the environment is reshaping the psychological foundation of technology adoption. This paper reviews existing theories and, from a cue-processing perspective, develops a three-stage dynamic model comprising alertness triggering, cue processing, and outcome feedback. The model conceptualizes the adoption process as a continuous cognitive processing of cues, systematically revealing the formation mechanisms of differentiated adoption patterns and providing an integrative explanatory framework for understanding human-AI collaboration. Future research may examine the moderating roles of individual and contextual factors, develop multimodal measurement paradigms, and translate theory into actionable design and training interventions to optimize the effectiveness of human–machine collaboration.

## Full Text

## Preamble

### A Three-Stage Dynamic Model for Predicting AI Adoption in a Generative Environment

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## Abstract

AI technology is rapidly permeating the workplace and becoming a critical information and communication technology that profoundly reshapes work contexts. The abundant and ubiquitous AI cues in work environments (e.g., AI logos, generative content, voice assistance) significantly influence patterns and outcomes of AI adoption. However, in the context where generative AI cues are highly ubiquitous, existing models have not yet fully revealed how these cues trigger differentiated perceptions and how they develop into stable adoption patterns through continuous human-AI interaction. Therefore, drawing on the media cue processing perspective, this paper proposes a theoretical framework to explain the cue-processing mechanisms underlying AI adoption.

To construct a theoretical model of AI adoption, we first reviewed three major theoretical perspectives in the existing literature on technology adoption mechanisms: (1) the technology acceptance and use perspective, which focuses on the predictors and moderators of technology adoption; (2) the media cue-processing perspective, which emphasizes the multi-stage cue-processing during the adoption process; (3) the human-AI collaboration perspective, which highlights the bidirectional and mutual influence between humans and AI. Building on these three perspectives, we propose a three-stage dynamic model of AI adoption. Starting from the characteristics of ubiquitous AI cues (i.e., fragmentation, repetition, and accessibility), the model systematically explores the cue-processing mechanism underlying AI adoption across the initiation, processing, and feedback stages.

First, the initiation stage. At this stage, ubiquitous AI cues induce users' vigilance toward AI. Users will present two spontaneous reactions in response to AI cues: spontaneous affective preference and spontaneous approaching behaviors. A higher spontaneous reaction indicates higher vigilance toward environmental AI cues, which will predict a greater tendency and initiation of AI adoption. Second, the processing stage. At this stage, the spontaneously triggered reactions further activate the categorization of AI cues. When cues display salient social-relational attributes (e.g., anthropomorphic representations and emotional expressions), they activate the social interaction evaluation system, leading to an anthropomorphic adoption mode. When cues display functional and utilitarian attributes (e.g., task compatibility and performance expectancy), they trigger a technology acceptance evaluation system, leading to a function-oriented instrumental adoption mode. Third, the feedback stage. At this stage, users adjust their adoption behaviors based on affective and cognitive evaluations of their adoption experiences. Users with better adoption experiences are more likely to develop spontaneous responses to environmental AI cues and to form stable, enduring adoption patterns across different cue categories. In contrast, the links between AI cues and spontaneous reactions will be disrupted, making users discontinue future AI adoption and less likely to form consistent adoption patterns.

Theoretically, the proposed three-stage dynamic model provides a theoretical framework for examining AI adoption in generative environments. From a practical perspective, the model provides novel insights for organizational strategies aimed at enhancing productivity through the integration of AI technologies. Future studies could deepen understanding of this model from three directions: (1) Further examine the boundary conditions and contextual contingencies of the model. For instance, future research could explore different types of AI cues and their effects. (2) Employ more sophisticated and precise measurement approaches (e.g., neuroscience measures), as well as more ecologically valid research designs (e.g., experience sampling methods), to provide stronger empirical evidence for the cue-processing mechanism underlying AI adoption. (3) Test and refine the theoretical model in real workplace settings. Scholars are encouraged to identify and leverage positive instances demonstrating the performance and adaptability of generative AI technologies, thereby optimizing AI system design and practical applications.

**Key words:** generative environment, AI adoption, three-stage dynamic model

## 1 Introduction

Generative Artificial Intelligence—self-training conversational AI technologies based on neural networks and generative adversarial networks—is unleashing transformative potential in economic development, driving a new wave of cross-domain value co-creation and deep digital-intelligence integration across society (Holmström & Carroll, 2024). Against the backdrop of representative generative AI technologies such as Deepseek and ChatGPT being widely applied in work contexts, this technology has rapidly integrated into daily practice and exhibits two salient characteristics. First, human-AI interaction has become more profound. Compared with traditional discriminative AI embedded in production workflows, generative AI' s conversational interfaces and humanized experiences have substantially lowered the threshold for human-computer interaction (Epstein et al., 2023). Second, the weight of individual factors in AI usage outcomes has increased significantly. More humanized applications such as assistant agents and emotional companionship have amplified the role of individual feedback, making human contextual judgment and decision-making flexibility increasingly critical for integrating technology effectiveness (Qin et al., 2025). Consequently, as the ubiquity of AI technology and the diversity of human-AI collaboration continue to deepen, exploring the intrinsic mechanisms of AI adoption in generative environments from the perspective of individual mental characteristics holds important forward-looking significance.

From the digital divide perspective, the comprehensive integration of a new technology into society requires sequentially bridging three gaps: the access gap (exposure opportunities), the usage gap (application knowledge), and the effectiveness gap (actual outcomes) (Kitsara, 2022). Examining the current application landscape of generative AI, although rapid user growth has initially bridged the access gap, beneath the surface of widespread adoption, disparities in the usage and effectiveness gaps are becoming increasingly pronounced (Humlum & Vestergaard, 2025). Research indicates that even when facing identical generative AI technologies, users exhibit clear divergence in adoption paths, usage depth, and interaction patterns. Some users tend to view AI as an efficiency-enhancing tool, focusing on functional fit and task completion, while others are more inclined to establish human-like interactive relationships, attending to social cues and emotional experiences (Xia & Chen, 2025). This cognitive differentiation further shapes adoption behaviors, making adoption outcomes dependent not only on individual skill levels but also closely related to users' role understanding of and interaction expectations with AI (Sharma et al., 2023). Although existing research has explored AI adoption from perspectives such as technology acceptance, processing mechanisms, and human-AI collaboration, most have focused on a single cognitive level or interaction stage, failing to systematically connect the complete cognitive process from cue triggering to behavioral feedback. Particularly in the new context where generative AI technology cues are highly ubiquitous, existing models have not fully revealed how environmental cues trigger differentiated perceptions and subsequently solidify into relatively stable adoption patterns through continuous human-AI interaction. In light of this, this study aims to construct a three-stage dynamic model comprising triggering, processing, and feedback to address this question.

## 2 AI Adoption in Generative Environments

Previous research on technological ubiquity has primarily focused on communication studies, examining the pervasive integration of information and communication technologies such as social media at the individual level and their multidimensional impacts (Reinecke et al., 2018). The "generative environment" addressed in this paper specifically refers to a new form of technological ubiquity constituted by the deep integration of artificial intelligence technologies represented by generative AI in work contexts (Zhan & Li, 2024). With its significant efficiency gains for knowledge work, this technology is rapidly becoming another large-scale information and communication technology reshaping work scenarios, following social media. According to Microsoft' s 2024 survey, over 75% of knowledge workers worldwide have used generative AI, and this number doubled within six months (Microsoft & LinkedIn Inc., 2024). Domestic scholars have synthesized the interaction forms and patterns of generative AI across five domains—daily life, services, entertainment, technology, and commerce—highlighting its extensive penetration capabilities and scenario-based application potential (Zhan & Li, 2024). Overall, the ubiquity of generative AI technology already has a realistic foundation, and its continuous evolution is constantly broadening the conceptual connotations of generative environments and profoundly shaping related adoption patterns and application outcomes.

Technology adoption refers to the complete process through which individuals, groups, or organizations move from initial exposure to a new technology, through cognition, evaluation, and trial, to ultimately deciding to continuously use the technology to meet their needs (Venkatesh et al., 2003). This process encompasses not only the single behavior of using technology but also decision-making, behavioral transformation, and value realization. As generative AI becomes embedded in diverse work scenarios, AI cues encountered during user-AI interaction exhibit characteristics of fragmentation, high frequency, and high accessibility (Klein, 2025). Whether real-time assistance from creative tools, humanized feedback from chat interfaces, or digital cues such as AI-generated text styles, visual symbols, and interaction prompts, all shape users' cognitive habits and behavioral patterns in subtle yet continuous ways (Epstein et al., 2023). From the cue-processing perspective, AI adoption in generative environments primarily manifests as a series of psychological and behavioral evolutions where individuals begin with perceiving AI cues in the environment, undergo continuous recognition and evaluation, gradually construct AI adoption patterns, and form sustained adoption behaviors. However, to systematically construct a new model that can explain differentiated adoption patterns, we must first review and examine existing mainstream research perspectives to clarify their explanatory power and limitations. Therefore, we will sequentially analyze three AI adoption perspectives below to lay the theoretical foundation for subsequently constructing an integrated cue-processing pathway three-stage dynamic model.

## 3.1 Technology Acceptance Perspective on AI Adoption Models

From the technology acceptance theoretical perspective, technology adoption is essentially a process where a series of individual factors influence technology usage intention, which in turn affects usage behavior. Representative theories in this perspective include the Technology Acceptance Model and the Theory of Planned Behavior, which have been extensively validated in media technology adoption research (Tamilmani et al., 2021). The core assumption is that users' technology usage intention and behavior are primarily determined by two factors: perceived usefulness and perceived ease of use. Perceived usefulness refers to users' belief that using the technology can enhance their work efficiency or quality of life, while perceived ease of use refers to the degree of effort users believe is required to use the technology. When users perceive a technology (such as generative AI) as easy to operate and capable of significantly improving efficiency, they tend to accept and use it (De Freitas et al., 2023). As empirical research has progressed, this perspective has also introduced external factors (e.g., system characteristics, environmental factors) and user characteristics (e.g., attitudes, abilities) as mediating variables, further strengthening the explanatory power of the theoretical framework. For example, functional design and user technology familiarity indirectly determine technology adoption by influencing perceived usefulness and ease of use (Venkatesh et al., 2003). Therefore, this theoretical perspective holds important value for exploring individual, technological, and environmental factors influencing AI adoption.

### 3.2 Processing Perspective on AI Adoption Models

With the rise of research on digital media such as social media, scholars have begun to examine the behavioral mechanisms of technology adoption from a processing perspective. This perspective focuses on users' perception, evaluation, behavioral initiation, and maintenance processes regarding media cues, emphasizing the key moderating role of self-control, with representative theories including the Media Use Self-Control Theory and the Reflective-Impulsive Dual-System Model (Hofmann et al., 2017). This perspective views media adoption behavior as a multi-stage dynamic feedback process, focusing on the continuous processing mechanisms of media adoption during the triggering, maintenance, and feedback stages. In the triggering stage, users' automated processing of media cues based on previous usage experiences directly determines their initial preferences and triggering tendencies toward the media (Van Koningsbruggen et al., 2017). In the evaluation stage, users decide whether to continue using the media by evaluating their usage experience (e.g., degree of goal satisfaction) and invoking self-control (Reinecke & Meier, 2021). In the feedback stage, users form positive or negative behavioral feedback based on accumulated usage experience, which subsequently influences the triggering threshold and intensity of future adoption (Slater, 2007). This perspective emphasizes that the various stages of media use behavior are not simple linear progressions but involve dynamic interactions and cyclical reinforcement effects. This stage-based processing mechanism explains the continuous interaction between users and technology at the micro level, thereby helping to reveal the dynamic characteristics of AI adoption from cue triggering to behavioral feedback.

### 3.3 Human-AI Collaboration Perspective on AI Adoption Models

As artificial intelligence technology gradually advances toward generalization, AI adoption under the human-AI collaboration perspective places greater emphasis on the bidirectional collaborative process between humans and AI. Models in this perspective, such as human-machine labor division and digital intelligence affordance theories, break through traditional technology adoption frameworks, emphasizing that human adoption of AI is not unidirectional tool usage but a bidirectional collaborative mechanism based on complementary capabilities (Einola & Khoreva, 2023). The core viewpoint is that the degree and effectiveness of AI technology adoption depend on the dynamic adaptation between technology and human cognitive, emotional, and behavioral patterns, manifesting as a bidirectional shaping process. On one hand, humans continuously strengthen and utilize AI' s generative capabilities during adoption and task division; on the other hand, the technical affordances provided by AI can reverse broaden individuals' cognitive bandwidth, thereby influencing the depth and pattern of adoption (Zhan & Li, 2024). Human users dynamically shape AI interaction through command input, information feedback, and strategy adjustment, while AI enhances human capabilities through data analysis and pattern recognition, with the synergistic effect formed by the two directly influencing adoption outcomes. Therefore, the human-AI collaboration perspective views AI adoption as a continuous process requiring comprehensive consideration of dynamic division mechanisms, technical affordances, and bidirectional interaction effects. This perspective provides a theoretical foundation for understanding technology adoption behaviors with new characteristics such as AI technology and human-AI collaboration.

## 3.4 Comprehensive Comparison and Analysis of Previous Models

Existing technology adoption models have primarily explored three perspectives: technology acceptance, processing mechanisms, and human-AI collaboration. Each perspective has distinct focuses and theoretical limitations in theoretical construction, core elements, and application scenarios. The technology acceptance perspective centers on users' perceived usefulness and ease of use of technological systems, explaining how functional antecedents influence user adoption behavior. However, it overly focuses on the static transformation of behavioral intention into actual use, failing to adequately reveal the dynamic feedback mechanisms post-adoption. The processing perspective introduces cue-processing mechanisms, dividing technology adoption into dynamic processes of triggering, evaluation, and feedback, focusing on users' perceptual evaluation and self-regulation mechanisms regarding environmental cues. While it emphasizes the explanation of user psychological mechanisms, it struggles to explain the unique impacts of AI technology' s new characteristics on AI adoption. The human-AI collaboration perspective emphasizes functional complementarity and dynamic adaptation between humans and AI in task execution, focusing on task division optimization and digital empowerment potential during collaborative processes, but lacks theoretical attention to the reality of AI cue ubiquity in generative environments. Overall, the high ubiquity, uncertainty, and complexity of human-AI interaction of AI technology cues in generative environments make traditional single-perspective theoretical models unable to encompass the new characteristics of AI adoption.

# 4 A New Model for AI Adoption in Generative Environments

In light of these limitations, this study constructs a three-stage dynamic model comprising cue triggering, processing, and feedback from the cue-processing perspective (Figure 1 [Figure 1: see original paper]).

## 4.1 Initiation Stage: AI Cue-Induced Vigilance Mechanism

In the initiation stage of AI adoption, ubiquitous AI cues in the environment (e.g., generative content, icons, interfaces, voice assistants) first induce individuals' cue vigilance. According to cue-processing theory, vigilance refers to individuals' spontaneous detection and orientation toward repeatedly appearing and highly accessible cues in the environment (Johannes et al., 2021). The characteristics of fragmentation, high frequency, and high accessibility of AI cues in generative environments (Go & Sundar, 2019) precisely constitute an ideal environment for activating such vigilance. Research shows that even when individuals are not consciously aware of a stimulus, repeated presentation of that stimulus can alter their preferences and accessibility (Bargh et al., 2012). This automated associative activation mechanism has been thoroughly elaborated in media cue-processing theory. Specifically, when high-frequency fragmented cue stimuli accumulate to a certain degree, they automatically activate the associative network related to long-term memory, which then directly influences individuals' judgments, attitudes, and subsequent behaviors toward the cues through the emotional reactions and behavioral tendencies associated with that network (Hofmann et al., 2008). Consequently, the ubiquitous AI cues in generative environments essentially constitute a continuous, extensive cue priming environment, creating sufficient conditions for activating AI-related concepts, attitudes, and behavioral tendencies.

Based on this environment' s automated priming characteristics, cue vigilance can be clearly defined as an automated affective-behavioral synergistic processing system (Hofmann et al., 2017). When AI cues appear, this system parallelly initiates two implicit processing processes: spontaneous affective bias and spontaneous approach reactions (Van Koningsbruggen et al., 2017). Affective bias manifests as spontaneous positive evaluation of cues, with core evidence from implicit association research confirming that implicit positive attitudes toward technology cues can significantly positively predict usage intention (Kurdi et al., 2019). Approach reactions manifest as an automated behavioral readiness state, with eye-tracking research providing direct support, showing that AI cues can trigger visual approach behaviors, such as faster fixation localization and longer fixation duration on anthropomorphic interfaces (Chen et al., 2024). These two automated processes operate synergistically, forming an efficient pathway from cue perception to behavioral transformation, enabling spontaneous affective bias to rapidly promote adoption intention and its subsequent direct transformation into actual usage behavior through approach reactions (Reinecke et al., 2018). This pathway has been corroborated in broader media cue-processing literature. For example, beyond social media (Du et al., 2020), research also shows that similar automated processing mechanisms can predict users' usage behaviors toward other digital technologies (Araujo, 2018). This further confirms the cross-media robustness of cue-processing theory. Therefore, this study applies it to explain the specific and ubiquitous new context of generative AI, revealing cue vigilance as the cognitive foundation for behavior triggering and guidance in human-AI collaboration.

## 4.2 Processing Stage: AI Cue Categorization Mechanism

The processing stage follows the cue activation in the triggering stage and represents the phase where individuals conduct refined cognitive evaluation of AI cues already in a state of vigilance. According to cue-processing theory, the core cognitive operation in this refined evaluation is the categorization processing of AI cues. Cue categorization refers to the process by which individuals identify, classify, and provide feedback on AI based on its design characteristics and central attributes (Klein, 2025). Compared with cue categorization of information technologies such as social media, AI cue categorization involves two distinct pathways: anthropomorphization and instrumentalization (Dang et al., 2025). These two pathways are triggered by different cue attributes and correspond to different evaluation systems and empirical evidence. When AI cues display salient social-relational attributes (e.g., anthropomorphic images, emotional expressions), they activate social interaction script schemas, guiding individuals to evaluate AI' s role identity as a social actor (Gambino et al., 2020). Chatbot research provides support for this, showing that anthropomorphic cues can significantly enhance users' social presence, intimacy, and trust (Araujo, 2018). When cues display salient functional-utilitarian attributes (e.g., task compatibility, performance expectancy), they trigger a technology acceptance evaluation system, prompting individuals to evaluate the degree of match between AI' s functional attributes and target performance (Xia & Chen, 2025). Classic technology adoption research confirms that evaluation of functional usefulness and ease of use is key to predicting adoption intention (Venkatesh et al., 2003).

Based on these correspondences, existing human-AI interaction literature can be summarized into two AI adoption modes. The first is the anthropomorphic adoption mode: when social-relational cue attributes dominate human-AI interaction, individuals' social interaction evaluation pathway is activated, forming a relationship-oriented anthropomorphic adoption mode. This mode shapes a psychological and behavioral paradigm characterized by parasocial interaction, manifesting cognitively as identity acceptance or rejection of AI (Zhang & Patrick Rau, 2023), attitudinally as trust or ambivalence (Qi et al., 2024), and emotionally potentially developing into dependence or aversion tendencies (Qin et al., 2025). These dimensions collectively reveal the internal logic behind users viewing AI as an interaction target. The second is the instrumental adoption mode: when functional-utilitarian cue attributes dominate human-AI interaction, users' technology acceptance evaluation pathway is activated, forming a function-oriented instrumental adoption mode. This mode focuses on evaluating AI' s functional utility and instrumental application, specifically manifested as using AI for skill assistance to enhance individual capabilities (Kanarik et al., 2023), conducting task innovation to optimize workflow (Jia et al., 2024), and utilizing it for decision optimization to improve result quality (Krakowski et al., 2025). These behaviors collectively point toward instrumental logic aimed at performance enhancement. In summary, this study posits that different AI adoption modes formed based on cue categorization mechanisms constitute the micro-level foundation for differential adoption outcomes in generative environments.

### 4.3 Feedback Stage: Dynamic Reinforcement Mechanism of AI Cues

The feedback stage is the phase where dynamic regulation occurs in the AI adoption process. At this stage, individuals adjust their adoption behaviors based on evaluations of adoption effectiveness by actively monitoring the match between actual utility and expected goals to maintain dynamic alignment between adoption behaviors and personal objectives (Reinecke & Meier, 2021). From the cue-processing perspective, whether individuals continue adopting a technology or tend toward a specific adoption mode primarily depends on evaluation results of adoption outcomes and the resulting cue feedback reinforcement mechanism (Slater, 2007). Affective evaluation represents the emotional readiness of environmental stimulus cues to guide goal-directed behavior (Scherer & Moors, 2019), while cognitive evaluation represents the deviation judgment between adoption outcomes and goal expectations (Hofmann et al., 2017). When adoption outcomes meet or exceed expectations, they consolidate the currently active cue-processing pathway, forming positive cue feedback reinforcement. This feedback not only directly strengthens the association between AI cues and positive adoption outcomes, providing endogenous motivation for continuous AI adoption, but also means that in subsequent interactions, relevant technology cues will more easily trigger vigilance and consolidate specific categorization processing pathways, thereby stabilizing existing adoption modes (anthropomorphic or instrumental) (Pelau et al., 2021).

Conversely, when adoption outcomes fail to meet expectations, signaling a conflict between adoption results and expected goals, negative cue feedback reinforcement is formed (Slater, 2007). Individuals may reduce vigilance toward relevant cues, manifested as weakened usage intention and decreased behavior initiation frequency (Van Koningsbruggen et al., 2017). If negative feedback continues to intensify, it may drive deeper cognitive re-evaluation and behavioral or strategic adjustments, prompting individuals to attempt re-categorization of AI cues or even switch to adversarial adoption modes (e.g., algorithm aversion, Singh et al., 2025) in subsequent processing. Therefore, the core of the feedback stage lies in dynamically regulating the vigilance intensity in the triggering stage and the categorization pathway in the processing stage through cue feedback (positive or negative) generated by effectiveness evaluation. Together with the previous two stages, this forms a complete cue-processing closed loop: ubiquitous AI cues trigger implicit vigilance, vigilance directs differential cue categorization and adoption modes, while cue feedback from adoption outcomes continuously shapes vigilance sensitivity and categorization stability. This demonstrates that AI adoption patterns in generative environments are not static initial preferences but dynamic processes continuously shaped through sustained cue monitoring and connection strength adjustment as human-AI interaction experience accumulates. This process not only helps explain AI adoption continuation or termination but also reveals the internal motivations for adoption modes to consolidate, adjust, or transform across different tasks and contexts, thereby providing an integrated theoretical framework for understanding the complexity and adaptability of individual behavior in human-AI collaboration.

## 4.4 Value of the New Model

This paper proposes a dynamic model of AI adoption in generative environments from the cue-processing perspective. The model focuses on three stages—environmental cue activation, categorization, and dynamic feedback regulation—to systematically explain the micro-level formation mechanisms of differentiated AI adoption patterns in work scenarios. The theoretical contributions of this study are mainly manifested in three aspects. First, it constructs an integrated theoretical framework from cue activation to behavioral feedback regulation. Unlike traditional models focusing on static cognitive evaluation, this framework views AI adoption as a continuous cue-processing process, extending the mechanism of AI adoption forward to cue-induced spontaneous reactions and running through categorization processing and cue reinforcement based on adoption outcomes, thereby comprehensively describing the multi-stage dynamic process from environmental cue perception to behavior shaping. Second, it reveals the formation mechanisms of differentiated AI adoption patterns. Through anthropomorphic and instrumental evaluations of environmental AI cues, individuals can form relatively stable adoption patterns (anthropomorphic or instrumental) under the regulation of the feedback stage. This provides a theoretical foundation for explaining and predicting behavioral diversity in human-AI collaboration and revealing the mechanisms through which individuals and AI continuously shape each other. Third, it proposes empirically testable research approaches. The processing stages defined in the model (e.g., cue vigilance, categorization) are highly compatible with cognitive neuroscience and behavioral measurement methods (e.g., EEG, eye-tracking, implicit association tests), and some mechanisms have been preliminarily validated in chatbot research (Chen et al., 2024). This lays the foundation for future fine-grained examination of cognitive and neural mechanisms in each stage using multiple methods.

# 5 Research Outlook

AI adoption from the cue-processing perspective reveals the continuous processing from environmental cues to adoption behavior, constructing a comprehensive theoretical framework for understanding differentiated patterns at the usage and effectiveness gap levels. Currently, application scenarios represented by generative AI technology are rapidly expanding, and future research can continuously test and optimize this model in three directions: theoretical deepening, methodological innovation, and practical application.

### 5.1 Theoretical Level: Deepening Mechanism Exploration and Expanding Boundary Conditions

As a theoretical construction study, this model can be validated in the following directions. First, mechanisms in each processing stage need to be deepened. For example, in the triggering stage, the effects of different categories of AI cues (e.g., visual vs. voice, active push vs. passive presentation) on vigilance induction mechanisms can be examined. In the processing stage, beyond continuously validating anthropomorphic and instrumental AI cue processing, mixed-type or other cue categorization mechanisms need to be explored in complex task scenarios, and their specific associations with final adoption behavior need to be clarified. Second, the model' s explanatory power in complex real-world scenarios needs to be expanded. Taking human-AI co-creation tasks as an example, while AI adoption enhances individual creativity, it may adversely affect collective creation quality (Doshi & Hauser, 2024). Future research needs to reveal how such complex outcomes dynamically regulate subsequent cue processing and adoption modes through feedback reinforcement mechanisms. Finally, the moderating effects of individual and contextual factors need to be examined. This model focuses on describing general paths of cue processing, while how individual differences and contextual factors systematically regulate processing mechanisms in each stage remains to be tested. For instance, in organizational contexts, innovation climate and leadership factors may also influence processing efficiency and adoption modes (Cheng et al., 2023). Investigating these moderating variables will help further clarify the boundary conditions of the model and enhance its explanatory power.

### 5.2 Methodological Level: Constructing a New Paradigm of Multimodal Measurement and Intelligence-Driven Research

To meet the precise testing needs of the model, future research must construct a methodological system integrating multimodal measurement, ecologically valid data collection, and intelligence-driven paradigms, overcoming current reliance on self-reports and single behavioral indicators to achieve fine-grained measurement of AI cue-processing processes. First, integrating cognitive neuroscience technologies and time-series analysis can provide observable neurobiological evidence for core mechanisms such as "cue vigilance"in the model. Second, research ecological validity and predictive validity need to be enhanced by employing real-context data collection methods such as combining experience sampling methods, wearable physiological devices (monitoring skin conductance, heart rate variability, etc.), and behavioral log analysis to continuously capture instantaneous adoption behaviors triggered by AI cues. Finally, AI-empowered new research paradigms should be actively explored. For example, using generative AI to construct highly controllable simulated interaction environments ( "silicon samples" ) or examining the formation process of human-AI collaboration patterns through agent-based modeling. Such intelligence-driven research paradigms can not only overcome traditional methods' limitations in variable control and cost but also are expected to open avenues for testing the model' s long-term predictive power.

## 5.3 Practical Level: Promoting Collaborative Transformation from Theory to Design, Training, and Governance

Future research should 致力于 translating the micro-level psychological mechanisms of cue processing into actionable practical solutions to optimize user experience, organizational effectiveness, and technology governance based on human-AI collaboration. At the product design level, this model can guide personalized presentation strategies for AI cues to shape differentiated adoption patterns. For example, reinforcing anthropomorphic features for relationship-oriented users to promote anthropomorphic adoption, while highlighting functional information for function-oriented users to consolidate instrumental adoption (Chen et al., 2024). At the organizational training level, structured training programs can be designed based on the model to promote employees' positive categorization processing of AI through identity guidance and functional instruction, thereby enhancing adoption effectiveness and task performance. At the technology governance level, this model provides micro-level behavioral evidence for evaluating and formulating AI usage norms. Managers can design differentiated usage guidelines, transparency standards, and human-machine responsibility frameworks based on the potential consequences of different adoption modes, thereby providing support for preventing technology risks and formulating more scientific public policies and industry standards.

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Wang Yu: Conceptualized the paper, drafted the manuscript, revised the manuscript
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*Note: Figure translations are in progress. See original paper for figures.*