Driving Mechanisms and Impact Effects of Artificial Intelligence Feedback-Seeking Behavior

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Abstract

Facing the highly volatile, uncertain, complex, and ambiguous VUCA era, employees need to proactively seek feedback to achieve personal development and enhance workplace competitiveness. Artificial intelligence technology provides new opportunities for employees to proactively seek feedback, with Oracle's survey report indicating that over 50% of employees tend to actively seek feedback from AI. However, research on traditional feedback-seeking behavior has not incorporated AI as a target for feedback seeking, and the driving mechanisms and impact effects of employees seeking feedback from AI remain unclear. Meanwhile, research on AI feedback is just emerging and primarily treats employees as passive recipients of feedback, lacking attention to employees' proactive feedback-seeking behavior. Therefore, this paper aims to integrate research on traditional feedback-seeking behavior and emerging AI feedback, expanding the concept of feedback-seeking behavior by incorporating AI into the objects that human employees seek feedback from. Focusing on AI feedback-seeking behavior, this paper investigates the driving mechanisms of AI system's transparency and anthropomorphic characteristics on such behavior, and explores its impact on employee performance improvement. On this basis, this paper can provide research evidence for frontier directions such as "emerging technology and employee psychology and behavior," and offer implications for relevant management practices.

Full Text

Preamble

Driving Mechanisms and Impact Effects of Artificial Intelligence Feedback-Seeking Behavior: A Research Proposal

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Abstract: In today's VUCA (volatility, uncertainty, complexity, ambiguity) era, employees must proactively seek feedback to achieve personal development and enhance workplace competitiveness. Artificial intelligence technology offers new opportunities for proactive feedback-seeking, with a survey by Oracle Corporation indicating that over 50% of employees prefer actively seeking feedback from AI systems. However, traditional research on feedback-seeking behavior has not incorporated AI as a feedback source, leaving the mechanisms and consequences of employee feedback-seeking from AI largely unexplored. Moreover, emerging studies on AI feedback primarily position employees as passive recipients, paying limited attention to their proactive feedback-seeking initiatives. This research integrates traditional feedback-seeking literature with emerging AI feedback studies to expand the concept of feedback-seeking by including AI as a legitimate target. Focusing on AI feedback-seeking behavior, this study investigates how system characteristics of AI—specifically transparency and anthropomorphism—drive such behavior, and examines its impact on employee performance improvement. These contributions provide empirical evidence for frontier topics such as "emerging technologies and employee psychology and behavior," while offering practical insights for management.

Keywords: feedback-seeking from AI, transparency, anthropomorphism, performance improvement
Classification Codes: B849; C93

1. Problem Statement

The World Economic Forum's *The Future of Jobs Report 2023* predicts that due to technological adoption and shifts in human-machine labor division, 44% of core skills currently possessed by workers will require renewal within five years. Additionally, a white paper jointly released by DeDao and Renmin University's School of Labor and Human Resources indicates that over 85% of workplace professionals face career challenges, with developmental bottlenecks and competency gaps becoming core concerns. To address these challenges, employees increasingly adopt proactive feedback-seeking strategies during their tenure to clarify role expectations, enhance professional skills, and improve work performance, thereby boosting their competitiveness. This trend is particularly evident among millennials, who represent a crucial workforce segment. However, employees face significant constraints in seeking feedback, as targets remain primarily limited to direct supervisors or colleagues. Human managers may lack the expertise to provide accurate, objective feedback, and their limited time and traditional performance management philosophies often result in delayed responses.

Recent advances in artificial intelligence, particularly generative AI models, present new opportunities for proactive feedback-seeking. AI systems can efficiently process massive datasets to deliver rapid, accurate, and objective evaluations, while large language models enable high-quality conversational interactions. Pioneering companies like MetLife and Zoom have already adopted AI feedback systems in their operations. Consequently, beyond seeking feedback from human managers, will employees proactively turn to AI for feedback, and what outcomes might this produce?

According to Oracle's "AI@Work Global Study" based on a large-scale survey of 8,000 participants, over 50% of employees prefer seeking feedback from AI rather than human managers. Unfortunately, existing literature contains only limited research on how algorithmic feedback affects recipients, with most studies positioning employees as passive recipients. No theoretical or empirical work has explored the driving mechanisms and consequences of proactive AI feedback-seeking. Therefore, it is essential to incorporate AI into the spectrum of feedback sources to align with organizational realities and management needs.

Motivated by these practical challenges and research gaps, this study expands the concept of feedback-seeking behavior by incorporating AI as a target for human employees. We define *feedback-seeking from AI* as "a proactive behavior in which organizational individuals consciously seek valuable information from artificial intelligence to adapt to organizational and personal development needs." This AI includes but is not limited to robotic AI, virtual AI, and embedded AI. Building on this foundation, we examine the driving mechanisms from two perspectives: system characteristics of AI (transparency and anthropomorphism) and task characteristics (problem-solving requirements), while also investigating the impact of AI feedback-seeking on performance improvement.

2.1.1 The Connotation of Feedback-Seeking Behavior

Feedback-seeking behavior was first introduced by Ashford and Cummings (1983) as a self-regulating behavior through which individuals actively seek information to determine the correctness and adequacy of their behavior to achieve a valuable end state. Individuals employ two primary strategies: monitoring (indirectly inferring information by observing others or environmental cues) and inquiry (directly asking for information). While most research focuses on inquiry-based feedback-seeking, monitoring-based feedback-seeking has received less attention. Traditionally, feedback-seeking targets have been direct supervisors and colleagues.

2.1.2 Antecedents of Feedback-Seeking Behavior

Individual Factors

First, demographic characteristics such as age and tenure have been examined. Gupta et al. (1999) found that younger employees seek feedback more actively than older employees, and multiple studies reveal negative correlations between tenure and feedback-seeking behavior.

Second, trait dispositions including personality and goal orientation have been explored. Krasman (2010) found that extraversion positively correlates with direct and indirect inquiry-based feedback-seeking. Gong et al. (2017) demonstrated that performance goal orientation promotes self-positive and other-negative feedback-seeking, while learning goal orientation promotes self-positive, self-negative, and other-positive feedback-seeking.

Third, motivational factors such as instrumental motivation, self-protection, and impression management have been investigated. Sherf and Morrison (2020) found that perceived value of feedback-seeking positively predicts the behavior. Lin and Xu (2021) revealed that clarity of future work self positively influences feedback-seeking based on career development motivation.

Fourth, cognitive factors have been examined through frameworks like cost-value theory and social identity theory. De Stobbeleir et al. (2020) found that psychological safety promotes peer feedback-seeking. Nurmohamed and Schwingel-Sauer (2024) discovered that being aware of being an alternate choice reduces feedback-seeking by decreasing social integration.

Situational Factors

First, leadership behaviors and styles have received considerable attention. Research shows that authentic leadership, humble leadership, ethical leadership, and empowering leadership positively influence subordinates' feedback-seeking. Leader credibility, leader-member exchange, and leader humor also show positive relationships, while lack of leader rewards negatively affects feedback-seeking.

Second, work environment factors have been examined. Studies on uncertainty yield mixed results—some find positive relationships, others U-shaped or negative relationships. Whitaker and Levy (2012) found that feedback quality in the workplace influences feedback-seeking through perceived utility. Zhu et al. (2024) revealed that negative supervisor gossip can both promote and inhibit feedback-seeking through task reflection and negative emotions.

2.1.3 Consequences of Feedback-Seeking Behavior

Impact on Performance
Research on feedback-seeking and performance shows inconsistent findings. Gong et al. (2017) found that seeking self-positive feedback negatively correlates with performance, while seeking self-negative and other-positive/negative

feedback positively correlates. A meta-analysis by Zhang et al. (2020) found positive correlations, whereas Anseel et al. (2015) found only weak or non-existent relationships.

Impact on Positive Work Behaviors
Studies grounded in cost-value theory, self-determination theory, and construal level theory examine effects on managerial skills, innovation, voice, and leadership behaviors. Sherf et al. (2021) showed that manager feedback-seeking enhances justice enactment. Wang et al. (2021, 2022) found that peer feedback-seeking promotes innovation. Coutifaris and Grant (2022) revealed that leader feedback-seeking enhances team psychological safety and promotes employee voice. Jia et al. (2024) found interactive effects between employee feedback-seeking and leader attributions on developmental feedback.

Impact on Career Development and Socialization
Feedback-seeking is considered crucial for career development and socialization. Wang et al. (2018) found that apprentice feedback-seeking positively influences mentoring relationship quality. Vandenberghe et al. (2021) showed that as newcomers' feedback-seeking decreases, so does organizational commitment, increasing turnover intentions.

We have synthesized these antecedents and consequences in a summary diagram shown in Figure 1 [Figure 1: see original paper].

2.2 AI Feedback Research

With advances in deep learning and data processing capabilities, AI has entered a new stage, playing increasingly important roles in digital organizations. A new practice has emerged where AI acts as a feedback provider, tracking employee activities and using big data and machine learning to deliver timely, accurate, personalized suggestions that enhance performance. Correspondingly, scholars have begun examining AI feedback effects, though research remains nascent.

The AI Feedback Empowerment Perspective
Some research suggests that AI's advanced data analytics and learning capabilities enable comprehensive tracking of employee behaviors, accurate performance assessment, and personalized, consistent feedback. Compared to human managers, AI feedback may be more effective for performance improvement. Tong et al. (2021) and Luo et al. (2021) found AI-generated feedback more helpful than human feedback. Hall et al. (2022) found that AI feedback-rich environments positively influence sales performance and organizational commitment. Förster et al. (2025) showed that explanations accompanying AI feedback enhance perceived informativeness and learning outcomes. Pei et al. (2024) found that for face-saving concerns, AI-delivered negative feedback increases performance by enhancing learning motivation and reducing interpersonal rumination.

Negative Effects of AI Feedback
Other scholars explore detrimental effects from different perspectives. Tong

et al. (2021) found that knowing feedback came from AI reduces trust and increases job displacement concerns, hindering learning. Thuillard et al. (2022) showed that computer-delivered negative feedback is perceived as less fair than human-delivered feedback. Yam et al. (2022) revealed that anthropomorphized robot supervisors delivering negative feedback enhance perceived abusive supervision, triggering retaliatory behaviors. Feng and Zhan (2019) found that AI guidance feedback for delivery riders leads to "de-skilling" and reduced technical sophistication.

2.3 Challenges in AI Feedback-Seeking Research

Our systematic review reveals two major challenges:

First, feedback-seeking research has not kept pace with organizational AI adoption, remaining focused on supervisors and colleagues. After nearly four decades, the concept has seen limited expansion, particularly regarding feedback sources. Only a few studies have expanded beyond human sources (e.g., Krasman, 2012 incorporating documents). This limitation may reflect slower AI development historically. However, recent advances enable AI to provide timely, accurate assessments and quality conversational interfaces. Since inquiry-based feedback-seeking is the primary strategy, seeking feedback from AI may become a significant trend. Research must incorporate AI as a feedback source.

Second, AI feedback research is in its infancy and positions employees as passive recipients, neglecting human agency. Treating AI feedback merely as managerial replacement (intelligent automation) or assistance (intelligent augmentation) may trigger concerns about "panopticon" or "digital Taylorism." The discussion about human-technology priority has persisted throughout digitalization history. Overemphasizing technological agency while subordinating humans may hinder effective human-AI interaction and even provoke resistance. Scholars have called for more humanistic approaches that promote organic integration of human and artificial intelligence. Therefore, alongside research on AI feedback to humans, we must examine proactive human feedback-seeking from AI, exploring its driving mechanisms and consequences to enrich this research domain.

3.1 Research Objectives

Based on this analysis, we aim to expand feedback-seeking targets to include AI. Our specific objectives are:

1. From a human-computer interaction perspective, identify system characteristics that drive AI feedback-seeking behavior and their mechanisms. Integrating mind perception theory (Gray et al., 2007) and trust literature (McAllister, 1995), we examine how transparency and anthropomorphism influence AI feedback-seeking through chained mediation of

perceived agency, perceived experience, cognition-based trust, and affect-based trust, moderated by problem-solving requirements.

2. Focusing on core outcomes in feedback research, clarify how AI feedback-seeking influences performance improvement. Grounded in feedback process theory (Ilgen et al., 1979) and AI literature, we examine whether AI feedback-seeking enhances performance improvement through accuracy and specificity of AI feedback, moderated by objective versus subjective task characteristics.

3.2 Study 1: System Characteristics' Impact on AI Feedback-Seeking Behavior

Ashford et al. (2016) identified feedback source characteristics as key factors influencing the feedback-seeking process. We therefore examine AI system characteristics as drivers. The 2024 AI Status Report highlights that AI must address challenges like "black box decision-making mystery." Meanwhile, anthropomorphic design increasingly enhances user interaction willingness. Trust is a critical expectation in human-AI interaction—without user trust, even advanced technology may trigger algorithm aversion (Glikson & Woolley, 2020). Park et al. (2008) proposed a three-factor model of human-robot trust: internal system factors, individual characteristics, and environmental factors. Hancock et al. (2011) further divided internal factors into performance-related dimensions (transparency, failure rates, automation level) and attribute-related dimensions (anthropomorphism, personality, adaptability). Ochmann et al. (2024) note that transparency (providing algorithmic process information) and anthropomorphism (increasing familiarity with algorithmic decision-makers) are primary strategies for shaping algorithmic perceptions. Thus, transparency and anthropomorphism may influence AI feedback-seeking.

Our first research question explores whether AI system transparency and anthropomorphism affect AI feedback-seeking behavior. Integrating mind perception theory and trust literature, we propose that perceived agency, perceived experience, cognition-based trust, and affect-based trust chain-mediate these effects, with problem-solving requirements as a moderator. This yields the model shown in Figure 2 [Figure 2: see original paper].

3.2.1 Effects of AI Transparency and Anthropomorphism on AI Feedback-Seeking

AI transparency refers to the accessibility of information about AI decision processes and outcomes (Jiang et al., 2022). Transparency enhances understanding of AI decisions, overcoming "black box" obstacles, enabling effective challenge of scoring results, and mitigating negative consequences like algorithmic bias, thereby increasing perceived behavioral control and usage intention (Bauer & Gill, 2024). Research shows that chatbot transparency affects user reliance on recommendations (Wilkinson et al., 2021). We therefore propose:

Proposition 1a: AI system transparency positively influences employees' AI feedback-seeking behavior.

Humans frequently anthropomorphize non-human agents to understand complex behaviors, especially when interacting with computers, robots, and intelligent agents (Saffarizadeh et al., 2024). AI anthropomorphism refers to the degree to which AI is endowed with human characteristics like intentions, emotions, or motivations (Yam et al., 2022), representing a key factor in human-AI interaction. The media equation theory suggests that individuals treat computers as social actors rather than mere tools, applying social rules and expectations used in human interactions (Nass & Moon, 2000). When AI exhibits human-like features, people are more likely to treat it as a "real person" and engage more deeply (Epley et al., 2007). Research shows that chatbot anthropomorphism increases technology adoption intention (Sheehan et al., 2020) and purchase intention (Han, 2021). Anthropomorphism also improves perceptions of AI decision-making interactivity and interpersonal respect (Acikgoz et al., 2020). In feedback-seeking contexts, anthropomorphized AI that mimics human language, behaviors, or expressions provides more natural interaction experiences, likely making employees more receptive to AI feedback and willing to seek it proactively. We therefore propose:

Proposition 1b: AI system anthropomorphism positively influences employees' AI feedback-seeking behavior.

3.2.2 Chained Mediation of Mind Perception and Trust

Mind perception theory posits that humans form perceptions of various entities through agency and experience dimensions (Gray et al., 2007). Agency perception reflects the capacity for thinking, planning, and autonomous action, while experience perception reflects the capacity for feeling emotions, pain, and pleasure (Gray et al., 2007). Transparent AI systems that explain code module intentions help employees better understand system operations (Shin & Park, 2019). Modern AI possesses strong autonomous planning capabilities (Raisch & Krakowski, 2021), and high transparency enables employees to perceive AI's autonomy, leading to higher agency perception. We propose:

Proposition 2a: AI system transparency positively influences employees' perceived agency of AI.

In social interactions, individuals infer others' mental states to understand, predict, and establish social connections. Target characteristics influence perceivers' mind perception processes, affecting attitudes and behaviors (Waytz & Norton, 2014). Anthropomorphized AI, endowed with more human features, may be perceived as having greater autonomy, decision-making capacity, and action intention (Yam et al., 2021). Research shows anthropomorphism increases agency perception toward animals (Wegner & Gray, 2017) and robots (van der Woerdt & Haselager, 2019). Anthropomorphism also enhances perceptions of emotional capacity—when dogs are anthropomorphized, people become more sensitive to their suffering (Butterfield et al., 2012). Similarly, robots with human-like features are perceived as having emotional experiences (Gray & Wegner, 2012). Highly anthropomorphic AI designs—such as human avatars, human-like voices, or human names—lead employees to perceive AI as similar to humans, possessing motivations, intentions, and emotions (Epley et al., 2007; Yam et al., 2022). Judgments about motivation and intention enhance agency perception, while judgments about emotional capacity enhance experience perception. We propose:

Proposition 2b: AI system anthropomorphism positively influences employees' perceived agency and experience of AI.

We further propose that mind perception influences trust in AI. McAllister (1995) distinguishes cognition-based trust (assessing competence and reliability) from affect-based trust (assessing interpersonal care and emotional investment). Agency perception involves evaluations of AI's thinking, planning, and self-control capabilities (Gray et al., 2007). When employees perceive strong AI agency, they are more likely to believe AI can solve problems and adapt to environmental changes—key factors for cognition-based trust (McAllister, 1995). Experience perception reflects humanization (Heflick et al., 2011). When employees perceive strong AI experience, they view AI as a social actor capable of understanding human emotional needs and demonstrating care and empathy (Klein et al., 2002)—the foundation for affect-based trust (McAllister, 1995). We propose:

Proposition 2c: Employees' perceived agency of AI positively influences their cognition-based trust in AI.
Proposition 2d: Employees' perceived experience of AI positively influences their affect-based trust in AI.

Trust is crucial in human-AI collaboration (Wang & Yao, 2022). Trust in robots directly influences information acceptance and utilization (Glikson & Woolley, 2020). Given AI's complexity and uncertainty, trust significantly affects human-AI relationships (Glikson & Woolley, 2020). Research shows that both cognition-based and affect-based trust increase AI system usage (Seitz et al., 2022). We therefore propose:

Proposition 2e: Employees' cognition-based and affect-based trust in AI positively influence their AI feedback-seeking behavior.

Combining these propositions, we propose three chained mediation effects:

Proposition 2f: AI system transparency influences AI feedback-seeking behavior through the chained mediation of perceived agency and cognition-based trust.
Proposition 2g: AI system anthropomorphism influences AI feedback-seeking behavior through the chained mediation of perceived agency and cognition-based trust.
Proposition 2h: AI system anthropomorphism influences AI feedback-seeking

behavior through the chained mediation of perceived experience and affect-based trust.

3.2.3 Moderating Role of Problem-Solving Requirements

Task characteristics are important moderators in feedback-seeking research (Ashford et al., 2016). Modern work environments increasingly demand knowledge-related capabilities, with problem-solving requirements being a key characteristic (Gajendran et al., 2022). Problem-solving requirements reflect the degree to which work demands unique creative solutions and higher cognitive processing (Morgeson & Humphrey, 2006). High problem-solving work involves generating innovative ideas, diagnosing non-routine problems, and preventing errors (Gajendran et al., 2022).

According to conservation of resources theory, individuals seek to protect and maintain valuable resources like time, cognitive capacity, and social support (Hobfoll, 1989). High problem-solving requirements consume substantial resources and increase stress (Schmitt et al., 2012), necessitating external resource acquisition. Feedback serves as a crucial resource for performance evaluation and adjustment (Ashford & Cummings, 1983). AI systems can rapidly process vast information to provide immediate, personalized feedback, helping employees tackle complex tasks (Tong et al., 2021). When problem-solving requirements are high, employees with strong cognition-based and affect-based trust in AI are more likely to view AI as a valuable resource and seek feedback proactively. Conversely, when problem-solving requirements are low, resource depletion is minimal, reducing the likelihood of AI feedback-seeking even with high trust. We propose:

Proposition 3a: Problem-solving requirements moderate the positive relationship between trust in AI and AI feedback-seeking behavior, such that the relationship is stronger when problem-solving requirements are high.

Proposition 3b: Problem-solving requirements moderate the chained mediation effect of transparency → perceived agency → cognition-based trust → AI feedback-seeking, such that the effect is stronger when problem-solving requirements are high.

Proposition 3c: Problem-solving requirements moderate the chained mediation effect of anthropomorphism → perceived agency → cognition-based trust → AI feedback-seeking, such that the effect is stronger when problem-solving requirements are high.

Proposition 3d: Problem-solving requirements moderate the chained mediation effect of anthropomorphism → perceived experience → affect-based trust → AI feedback-seeking, such that the effect is stronger when problem-solving requirements are high.

3.3 Study 2: Impact of AI Feedback-Seeking on Performance Improvement

Building on Study 1, we examine whether proactive AI feedback-seeking yields benefits. Performance is a core outcome in feedback-seeking research, yet findings remain inconsistent (Anseel et al., 2015; Gong et al., 2017; Zhang et al., 2020). We therefore investigate how AI feedback-seeking influences performance improvement. Grounded in feedback process theory (Ilgen et al., 1979) and AI literature, we examine the mediating roles of AI feedback accuracy and specificity, and the moderating effect of objective versus subjective task characteristics. This yields the model shown in Figure 3 [Figure 3: see original paper].

3.3.1 Effect of AI Feedback-Seeking on Performance Improvement

Inconsistent findings on feedback-seeking and performance may stem from human managers' cognitive limitations and experience gaps, resulting in feedback that lacks accuracy and specificity (Ashford et al., 2016). Organizations have introduced AI into performance feedback systems to leverage its advanced analytics for more effective feedback (Luo et al., 2021; Tong et al., 2021). However, AI feedback research also shows mixed results. Tong et al. (2021) found that knowing feedback came from AI hindered learning, while Luo et al. (2021) found limited performance gains for top-performing salespeople. In these studies, employees were passive recipients prone to algorithm aversion and low trust. Our study examines proactive AI feedback-seeking, which may enable employees to fully leverage AI's advantages and enhance performance. We propose:

Proposition 4: Employees' AI feedback-seeking behavior positively influences their performance improvement.

3.3.2 Mediating Roles of AI Feedback Accuracy and Specificity

Feedback accuracy reflects correctness and objectivity (Brett & Atwater, 2001), while specificity reflects detail level (Goodman et al., 2011). Leveraging big data, IoT, deep learning, and neural networks, AI can comprehensively track and evaluate employee behaviors (Tong et al., 2021; Zhang & Zhao, 2022). AI's iterative optimization capability means more inputs generate more specific and accurate information (Raisch & Krakowski, 2021). AI feedback-seeking represents not merely "tool use" but a dynamic cognitive collaboration process (Turel, 2024). We propose that higher levels of AI feedback-seeking provide richer, more diverse data, enabling AI to deliver more accurate and specific feedback.

Higher feedback-seeking levels mean employees actively provide multidimensional organizational context data through multimodal interfaces, creating comprehensive employee "profiles" that enable more objective, accurate performance evaluation (Tong et al., 2021) and drive AI to automatically associate broader information, significantly improving cross-task feedback consistency. For example, Choi et al. (2025) analyzed 24,973 games by 1,241 professional Go players, finding that AI training increased consistency with AI-recommended moves by 30.5%. We propose:

Proposition 5a: AI feedback-seeking behavior positively influences AI feedback accuracy.
Proposition 5b: AI feedback-seeking behavior positively influences AI feedback specificity.

Based on feedback process theory, accuracy is a key factor affecting feedback acceptance and behavioral response (Ilgen et al., 1979; Steelman et al., 2004). Algorithm aversion research shows that AI systems must achieve higher decision accuracy to gain user acceptance (Mahmud et al., 2022), as inaccurate decisions erode confidence (Bogert et al., 2021; Dietvorst et al., 2015). High-accuracy AI feedback increases acceptance and behavioral response, facilitating performance improvement. Tong et al. (2021) found that employees receiving more accurate AI feedback outperformed those receiving human feedback by 12.9%. We propose:

Proposition 5c: AI feedback accuracy positively influences performance improvement.

Feedback specificity also affects acceptance and behavioral response (Ilgen et al., 1979). Specific feedback provides clear correction directions and actionable plans (Ilgen et al., 1979). Highly specific AI feedback can analyze particular employee behaviors, offering personalized and detailed improvement suggestions (Guan et al., 2024), enabling more effective action and performance improvement. We propose:

Proposition 5d: AI feedback specificity positively influences performance improvement.

Proposition 5e: AI feedback accuracy mediates the positive effect of AI feedback-seeking on performance improvement.
Proposition 5f: AI feedback specificity mediates the positive effect of AI feedback-seeking on performance improvement.

3.3.3 Moderating Role of Objective vs. Subjective Tasks

Feedback-seeking typically targets work tasks, necessitating examination of task characteristics. We investigate the moderating effect of objective versus subjective tasks, defined as quantifiable/measurable factual tasks versus open/interpretive tasks based on personal perspectives (Castelo et al., 2019). AI excels at structured, well-defined tasks where its superior data analysis and logical reasoning capabilities are most advantageous (Castelo et al., 2019; Tong et al., 2021). Since objective tasks rely on logic and rules (Inbar et al., 2010), AI can effectively process them and deliver specific, accurate results. Therefore, even with minimal AI feedback-seeking, AI output accuracy and specificity remain high for objective tasks.

Subjective tasks, which rely more on intuition and feeling, have traditionally been AI's weakness, with algorithm aversion persisting (Castelo et al., 2019). However, this represents an opportunity for AI breakthroughs. AI capabilities for subjective tasks have improved significantly through large-scale data training. Theory of Mind (ToM) abilities, previously considered uniquely human (e.g., empathy), have been demonstrated in GPT models—solving 70% of ToM tests in January 2022 and 93% in November 2022 (Kosinski, 2023). We therefore propose that for subjective tasks, frequent AI feedback-seeking provides more training data, yielding more accurate and specific feedback. Compared to objective tasks where AI feedback-seeking has limited impact on accuracy and specificity, its impact is greater for subjective tasks. We propose:

Proposition 6a: Objective versus subjective task characteristics moderate the positive relationship between AI feedback-seeking and AI information accuracy/specificity, such that the relationship is stronger for subjective tasks.

Proposition 6b: Objective versus subjective task characteristics moderate the mediated effect of AI feedback-seeking on performance improvement through feedback accuracy, such that the effect is stronger for subjective tasks.

Proposition 6c: Objective versus subjective task characteristics moderate the mediated effect of AI feedback-seeking on performance improvement through feedback specificity, such that the effect is stronger for subjective tasks.

4. Theoretical Contributions

As the core of the "Fourth Industrial Revolution," AI may profoundly transform labor structures, organizational design, and work methods. However, organizational behavior research and theory development lag behind management practice. This research expands feedback-seeking research in the AI context and enriches AI feedback research by incorporating human agency.

Theoretically, first, we innovatively incorporate AI as a feedback-seeking target, deepening feedback-seeking research in the AI era. After nearly four decades, feedback-seeking's conceptual expansion has been limited, particularly regarding sources (Ashford et al., 2016; Zhang & Yang, 2018). With rapid generative AI development, human employees increasingly seek feedback from AI at work. Yet only a few studies examine AI feedback effects (Luo et al., 2021; Thuillard et al., 2022; Tong et al., 2021; Yam et al., 2022; Feng & Zhan, 2019), neglecting proactive feedback-seeking. Incorporating AI as a feedback source establishes a foundation for understanding this phenomenon's unique antecedents and consequences.

Second, we reveal driving mechanisms of AI feedback-seeking by examining AI system characteristics. While previous research focused on leadership behaviors (e.g., authentic, humble, empowering leadership), research on AI source characteristics remains blank. We examine how transparency and anthropomorphism—key characteristics in human-AI interaction (Glikson &

Woolley, 2020; Jiang et al., 2022)—influence AI feedback-seeking. Integrating mind perception theory and trust literature, we explore chained mediation through perceived agency, perceived experience, cognition-based trust, and affect-based trust, moderated by problem-solving requirements. This deepens understanding of how system characteristics relate to AI feedback-seeking.

Third, we reveal consequences and mechanisms of AI feedback-seeking, considering human-AI interaction characteristics. Performance is the most studied outcome in feedback-seeking research (Ashford et al., 2016), yet findings remain inconsistent. AI's specific advantages—efficient big data processing and rapid, accurate, specific feedback—may clarify this relationship. Grounded in feedback process theory and AI literature, we propose that AI feedback-seeking enhances performance improvement through increased accuracy and specificity, moderated by objective/subjective task characteristics. This expands research on AI feedback-seeking consequences and clarifies its theoretical boundaries.

Practically, this research reveals factors influencing and outcomes of AI feedback-seeking, providing targeted guidance for managers to effectively encourage such behavior while leveraging benefits and mitigating risks. Specifically, by parsing how AI system characteristics influence AI feedback-seeking, we provide theoretical foundations for designing AI systems that stimulate proactive feedback-seeking. Examining how AI feedback-seeking affects performance improvement helps managers identify which tasks warrant encouraging AI feedback-seeking. Ultimately, we hope AI feedback-seeking serves as a window for understanding how emerging technologies and employees interact and co-evolve, inspiring practitioner thinking.

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Note: Figure translations are in progress. See original paper for figures.