Journal of Management & Organization (2026), page 1 of 16
doi:10.1017/jmo.2026.10109

ANZAM
AUSTRALIAN & NEW ZEALAND ACADEMY OF MANAGEMENT

RESEARCH ARTICLE

From self-leadership to creative process engagement: Generative AI acceptance and creative self-efficacy as serial cognitive pathways

Joseph Avery[1], Christopher B. Neck[2] and Jeffery D. Houghton[1]

[1]John Chambers College of Business and Economics, West Virginia University, Morgantown, WV, USA and [2]College of Business & Technology, University of Nebraska Kearney, Kearney, NE, USA
Corresponding author: Jeffery D. Houghton; Email: jeff.houghton@mail.wvu.edu

An earlier version of this paper was presented at the 2026 Western Academy of Management Conference, Sante Fe, NM, USA. The data that support the findings of this study are available with restricted access in Zenodo: DOI: 10.5281/zenodo.17545554. Access will be granted upon any reasonable request from editors, reviewers, or other researchers wishing to validate or replicate our findings.
(Received 25 January 2026 UTC; revised 23 May 2026 UTC; accepted 23 May 2026 UTC)

Abstract
Despite growing interest in generative artificial intelligence for creative work, the mechanisms driving individuals' psychological readiness and intention to adopt these tools remain understudied. This paper examines how self-leadership – a proactive process of self-influence – enhances generative artificial intelligence acceptance, individual confidence, and creative process engagement. Using a sample of 258 full-time employees, we tested a serial mediation model linking self-leadership to creative process engagement via artificial intelligence acceptance and creative self-efficacy. The results reveal a significant positive direct relationship between self-leadership and creative process engagement, alongside a significant indirect effect through both mediators. This study contributes to the literature by uncovering the psychological mechanisms and strategies necessary to foster technological readiness and intention within creative contexts.

Keywords: self-leadership; generative AI acceptance; creative self-efficacy; creative process engagement

Introduction

There is an increasing interest in understanding the processes through which humans conceptualize and prepare for interaction with intelligent technologies (Brougham & Haar, 2018; Zanatto, Bifani & Noyes, 2024). In recent years, the rapid evolution of artificial intelligence (AI) has reshaped modern workplaces (Hossain, Fernando & Akter, 2025), particularly in areas requiring creativity and innovative problem-solving (Amankwah-Amoah, Abdalla, Mogaji, Elbanna & Dwivedi, 2024; Ayoko, 2021). A 2024 McKinsey survey indicates that 72% of organizations have adopted AI, up from approximately 50% in previous years (McKinsey & Company, 2024). In addition, research suggests that the creative sector has been particularly proactive in exploring AI technologies (Anantrasirichai & Bull, 2022; Sajjad, 2024). For instance, a study by Adobe found that 90% of creators believe AI tools can help them save time and money by relieving them of menial tasks and supporting their creative brainstorming process (Adobe, 2024). This highlights the growing role of AI in shaping expectations surrounding cognitive efficiency and innovation potential (Füller, Tekic & Hutter, 2024).

© The Author(s), 2026. Published by Cambridge University Press in association with Australian and New Zealand Academy of Management. This is an Open Access article, distributed under the terms of the Creative Commons Attribution licence (http://creativecommons.org/licenses/by/4.0), which permits unrestricted re-use, distribution and reproduction, provided the original article is properly cited.

https://doi.org/10.1017/jmo.2026.10109 Published online by Cambridge University Press

Generative AI involves using tools such as ChatGPT, Google Gemini, and Microsoft Copilot to create new content and ideas including text, images, videos, audio, and computer code in response to user prompts (Fui-hoon Nah, Zheng, Cai, Siau & Chen, 2023). It is swiftly becoming a central focal point across industries including design, advertising, and technology, offering anticipated capabilities ranging from automating routine tasks to facilitating idea generation and creative experiences (Ayoko, 2021; Gujar & Panyam, 2024).

However, despite the impressive potential of generative AI in creative domains, the mechanisms driving individuals' psychological readiness and cognitive acceptance of these tools are not well understood. In addition, concerns are emerging regarding a possible psychological overreliance on AI, which could diminish individual agency and self-regulation in the creative process (Galindo-Domínguez, Delgado, Sainz-de-la-maza & Etxabe, 2026). This points to an important gap in the current literature. To help fill this gap, the current study explores the following research question: What proactive personal self-regulatory resources might serve to enhance an individual's psychological readiness and intention to adopt generative AI within creative endeavors? *Generative AI acceptance* is defined as one's beliefs and intentions to use AI (Yilmaz, Yilmaz & Ceylan, 2023). As AI becomes increasingly prominent in ideation contexts, understanding how technological intentionality affects the dynamic between anticipated machine support and human initiative becomes critical, especially because self-regulatory behaviors remain central to maintaining personal agency in creative work (Luthans, 2011). *Self-leadership* is conceptualized as a personal self-regulatory resource with potential for enabling individuals to actively engage in the creative process (Knotts et al., 2022). Prior research suggests that self-leadership encompasses self-regulatory strategies, such as self-goal setting, self-observation, and self-reward, which collectively empower individuals to maintain motivation, demonstrate resilience, and engage deeply with creative tasks (DiLiello & Houghton, 2006; Neck & Houghton, 2006; Ghosh, 2015).

In the current study, we explore self-leadership as a possible psychological catalyst for enhancing generative AI acceptance and subsequently creative processes at work.

Specifically, we conceptualize generative AI acceptance as a proximal cognitive–intentional outcome of self-leadership and as a proactive expression of self-regulation. Traditionally, self-leadership has facilitated proactive behaviors crucial for navigating complex problem-solving and iterative idea development (Amabile, 1983; Zhang & Bartol, 2010a). Yet, the advent of generative AI tools capable of producing novel content, such as language, images, or designs, introduces new layers of complexity to this cognitive dynamic (Ratten, 2024). Traditional perspectives on AI-augmented creative contexts often stress AI's potential to relieve lower-level cognitive tasks, allowing individuals to focus on higher-order creative thinking (Amabile & Pratt, 2016; Boden, 2016). Thus, the cognitive orientation toward adopting AI could either complement or challenge traditional self-leadership strategies (Zhou, Xiang & Xie, 2025). For some, an open orientation toward AI might support self-regulation by providing real-time feedback or managing routine tasks. For others, an excessive cognitive reliance on AI could undermine active self-regulation, leading to stress, reduced personal initiative, and a more passive orientation toward creative work (Galindo-Domínguez et al., 2026).

Central to this exploration is the concept of *creative self-efficacy*, defined as an individual's belief in their ability to achieve creative outcomes (Tierney & Farmer, 2002). Creative self-efficacy is consistently recognized as a key mediating variable that explains how self-leadership translates into creative behavior (Chughtai & Khalid, 2022; Khan, Li, Chughtai, Mushtaq & Zeng, 2023). Individuals with high creative self-efficacy are more likely to engage in and persist through creative tasks, even in the face of challenges, due to the confidence necessary to navigate complex problems (Bandura, 1997; Gong, Huang & Farh, 2009). This confidence solidifies commitment to goals and the ability to execute creative strategies. However, the role of creative self-efficacy becomes more intricate when introducing technology acceptance into the causal chain. In this study, we propose that generative AI acceptance acts as a first-stage mediator, influenced by self-leadership. This intentionality toward adopting AI tools may enhance an individual's confidence in their ability to generate novel and valuable ideas (creative self-efficacy), which then increases engagement in creative tasks.

https://doi.org/10.1017/jmo.2026.10109 Published online by Cambridge University Press

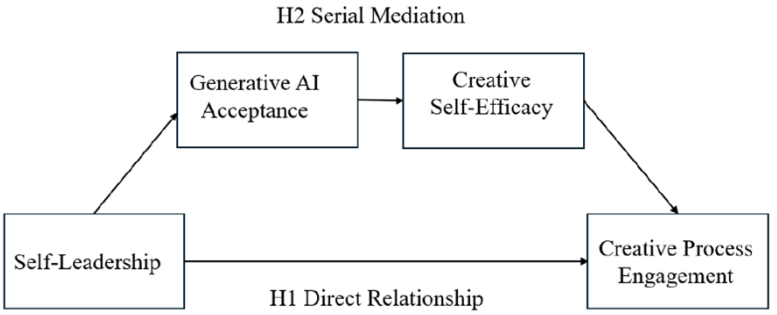


Figure 1. Hypothesized serial mediation model.

The purpose of this study is to develop and test a hypothesized serial mediation model of the relationship between self-leadership, generative AI acceptance, and creative self-efficacy within creative work contexts. Specifically, we examine how generative AI acceptance – as an expression of technological readiness – serves as a vital upstream mechanism that enhances creative self-efficacy, which subsequently drives creative process engagement. This study contributes to the literature by probing the cognitive mechanisms through which individuals prepare to share creative contexts with intelligent machines. By exploring these relationships, this research challenges the oversimplified view of AI as merely a displacement tool and highlights how technological readiness and intention can serve as psychological means for augmenting human creative work processes.

Theoretical framework and model development

In the following sections, we review the existing literature while using social cognitive theory (SCT; Bandura, 1986) and the job demands–resources theory (JD-R theory; Bakker, Demerouti & Sanz-Vergel, 2014, 2023; Demerouti, Bakker, Nachreiner & Schaufeli, 2001) as our primary theoretical frames for developing and presenting a hypothesized conceptual model. This model maps the relationships between self-leadership, generative AI acceptance, creative self-efficacy, and creative process engagement within work environments defined by the availability of AI tools. Within this conceptual framework, illustrated in Fig. 1, self-leadership serves as the independent variable, facilitating effective self-regulatory practices, including self-goal setting, self-regulation, and self-monitoring, that individuals employ to sustain creativity (Knotts et al., 2022; Manz, 1986). These self-leadership strategies provide individuals with a proactive structure for approaching creative work, enhancing both their ownership and accountability over creative tasks (Houghton & Neck, 2006).

Self-leadership and creative process engagement

Self-leadership, defined as a proactive process through which individuals influence and motivate themselves to pursue personal and professional goals (Manz, 1986; Neck & Houghton, 2006), serves as an important personal resource for fostering creativity within dynamic and uncertain work environments (DiLiello & Houghton, 2006; Ghosh, 2015; Knotts et al., 2022). Traditional self-leadership strategies such as self-goal setting, self-observation, and self-reward enable individuals to structure their creative efforts, remain resilient in the face of challenges, and sustain motivation throughout creative tasks (DiLiello & Houghton, 2006). Meta-analyses have shown self-leadership to be a strong predictor of numerous individual outcomes including task performance, self-efficacy, and job attitudes such as job satisfaction and work engagement (Harari, Williams, Castro & Brant, 2021; Knotts et al., 2022). Importantly, Knotts et al. (2022) found that the effect size between self-leadership and creativity/innovation ($\rho = .49$) was substantially stronger than other outcomes including task

https://doi.org/10.1017/jmo.2026.10109 Published online by Cambridge University Press

performance ($\rho = .28$), suggesting a key role for self-leadership strategies in enhancing individual creativity. Although the term creativity can broadly be used to describe both creative processes and creative outcomes (Shalley & Zhou, 2008), creativity is more often defined as an outcome involving the production of novel and useful ideas (Hennessey & Amabile, 2010). In contrast, *creative process engagement* is defined as the cognitive process through which creativity happens (Zhang & Bartol, 2010a). Creative process engagement involves three distinct creativity-related cognitive phases: problem identification, information searching and encoding, and idea and alternative generation (Zhang & Bartol, 2010a). Empirical research suggests that creative process engagement is a primary antecedent of employee creativity (Zhang & Bartol, 2010a), with employee creative performance mediating the relationship between creative process engagement and job performance (Zhang & Bartol, 2010b). Creative process engagement has been shown to be especially important in contexts requiring innovation and proactive cognitive resources (Raihan & Uddin, 2023). For example, Cheng and Yang (2019) found that creative process engagement was related to new product development speed and new product performance in a sample of 245 companies from high-tech industries in China.

Although no studies to date have explored the relationship between self-leadership and creative process engagement, researchers have suggested that self-leadership may play a crucial role in shaping creative process engagement (Yang, Xie, Tang, Hou & Ming, 2025). This supposition is supported by both theoretical and empirical evidence. JD-R theory (Bakker et al., 2014, 2023; Demerouti et al., 2001) posits that employees are influenced by both job demands (job aspects requiring sustained emotional, physical, or cognitive effort) and job resources (job or personal factors that can help achieve work goals, reduce job demands, or enhance individual development). Importantly, JD-R theory positions work engagement as a proximal outcome of job resources that mediates their effects on distal outcomes such as job performance (Bakker et al., 2014).

Self-leadership is often conceptualized as a cognitive job resource that can facilitate important individual outcomes (Maykrantz, Langlinais, Houghton & Neck, 2021; Neck, Houghton, Sardeshmukh, Goldsby & Godwin, 2013) such as work engagement and work intensity (Bäcklander, Rosengren & Kaulio, 2021; Knotts & Houghton, 2021; van Dorssen-boog, van Vuuren, de Jong & Veld, 2021). For instance, Gomes, Curral and Caetano (2015) found that work engagement mediated the relationship between self-leadership and individual innovation. Consequently, and in harmony with JD-R theory, it seems reasonable to suggest that self-leadership will be positively related to creative process engagement, a specific type of cognitive engagement essential in creative work contexts.

Tangential empirical evidence adds weight to these theoretical arguments. For example, Henker, Sonnentag and Unger (2015) provided support for a promotion focus as an antecedent of creative process engagement. Regulatory focus theory (Higgins, 2012) contends that a promotion focus involves a motivation to attain desirable end-states, while a prevention focus entails the motivation to avoid undesirable end-states. Research findings have shown a positive relationship between promotion focus and self-leadership's behavior-focused strategies (Lin, 2017). Similarly, Mahmood, Uddin and Fan (2019) reported that intrinsic motivation, a key conceptual underpinning of self-leadership (Manz, 1986; Neck & Houghton, 2006), serves as a primary predictor of creative process engagement. Accordingly, based on these theoretical and empirical lines of reasoning, we advance:

Hypothesis 1: Self-leadership is positively related to creative process engagement.

Mediating mechanisms: generative AI acceptance and creative self-efficacy

A mediating mechanism refers to a generative underlying process, explanatory variable, or pathway through which an independent variable (X) exerts its influence on a dependent variable (Y) (Baron & Kenny, 1986). Whereas a main effect explores whether two variables are related, a mediating mechanism explains how and why that relationship occurs by capturing the causal transmission between them (Hayes, 2022). In the current study, we conceptualize generative AI acceptance and

https://doi.org/10.1017/jmo.2026.10109 Published online by Cambridge University Press

creative self-efficacy as vital mediating mechanisms that represent the generative process through which individual self-leadership transmits its effect to creative process engagement. We define generative AI acceptance as beliefs and intentions to use AI, rooted in perceptions of usefulness and ease of use (Yilmaz et al., 2023). Acceptance reflects perceptions of usefulness and effort expectancy that motivate individuals' intentions to incorporate AI into their creative processes (Venkatesh, Morris, Davis & Davis, 2003; Venkatesh, Thong & Xu, 2012). Kim, Kim, Kim and Lee (2025) showed that perceived ease of use and perceived usefulness are positively related to generative AI usage intentions, while Huy, Nguyen, Vo-thanh, Thinh and Thi Thu Dung (2024) found that performance expectancies (perceived usefulness) and effort expectancies (perceived ease of use) resulted in greater actual use of ChatGPT. In our hypothesized model, we conceptualize AI acceptance as a self-leadership-driven cognitive–intentional state that initiates the efficacy–engagement pathway. Founded on SCT's emphasis on self-efficacy and self-regulation, we view AI acceptance as a proximal adoption orientation (beliefs/intentions) stemming from self-leadership. Consequently, generative AI acceptance is not treated as a boundary condition that moderates whether self-leadership translates into creative engagement; rather, we position AI acceptance as a direct and immediate cognitive–intentional outcome of self-leadership.

Creative self-efficacy refers to a person's belief in their ability to produce creative outcomes (Tierney & Farmer, 2002). As a central component of SCT, self-efficacy influences motivation and persistence in creative tasks (Bandura, 1997). High creative self-efficacy enables individuals to engage deeply in creative tasks and remain resilient through iterative problem-solving (Tierney & Farmer, 2002). This confidence facilitates self-leadership's influence on creativity by reinforcing individuals' belief in their ability to overcome obstacles and produce novel solutions (Gong et al., 2009). In work environments characterized by the availability of generative AI, creative self-efficacy influences how individuals orient themselves toward AI tools. Those with high creative self-efficacy are more likely to view AI as a complementary asset rather than a replacement for their creative abilities (Dwivedi et al., 2021; Gong et al., 2009). This confidence allows individuals to maintain a mindset of autonomy and focus on higher-order cognitive tasks, even with anticipated AI-generated suggestions available. Conversely, those with lower self-efficacy may anticipate a psychological dependency on AI, reducing active cognitive engagement and limiting the effectiveness of self-leadership strategies (Glikson & Woolley, 2020). Recent findings highlight the importance of fostering creative self-efficacy in contexts where AI tools are prominent. In highly automated environments, self-efficacy enables individuals to balance the prospective leverage of AI support with the preservation of personal agency to achieve creative outcomes (Dwivedi et al., 2021). Brynjolfsson and McAfee (2014) argue that teams with high collective self-efficacy can conceptualize AI's cognitive support more effectively, viewing it as a tool to enhance – not substitute – creative capabilities.

Self-leadership strategies help individuals maintain cognitive control over their work, ensuring that personal initiative remains central to creative processes. Neck and Houghton (2006) characterize self-leadership as an individual competency, one that empowers individuals to remain self-motivated and resilient. Because generative AI tools provide real-time feedback, automate task management, and enhance cognitive capabilities, they may increasingly become an important contextual factor in how self-leadership is enacted in practice. An open orientation toward AI may complement self-leadership by mapping out a path to relieve individuals of repetitive cognitive demands, allowing them to focus on higher-level creative activities. However, as Stewart et al. (2019) caution, such tools must be approached in ways that preserve autonomy and personal agency. The challenge lies in ensuring that self-leadership retains its effectiveness as AI takes a more prominent role in the cognitive landscape of creative workflows.

Originally, self-leadership was conceptualized as a set of individual competencies to help people regulate their behavior and mindset to optimize performance (Manz, 1986). Over time, it expanded to include cognitive strategies, such as constructive thought pattern management, which enable individuals to remain solution-focused and actively engaged (Manz & Sims, 2001). Self-leadership aligns closely with SCT's emphasis on environmental supports in self-regulated behavior (Bandura, 1986).

https://doi.org/10.1017/jmo.2026.10109 Published online by Cambridge University Press

Within this theoretical context, AI acceptance can be seen as a cognitive–intentional outcome shaped by self-leadership and, in turn, as an internal contextual support that fosters efficacy beliefs and enhances creative persistence.

Generative AI acceptance within creative work may thus serve as a cognitive–intentional extension of self-leadership, best understood as an intermediate mechanism through which proactive individuals enhance their perceived capacity for creativity. Intentionally accepting and intending to use AI can be seen as an expression of self-leadership – translating strategic self-regulation into a clear adoption orientation. This intentional acceptance of AI may, in turn, strengthen individuals' belief in their creative capacity by establishing anticipated gains in productivity, ideation quality, or task mastery. Therefore, generative AI acceptance can be conceptualized as a mediating bridge that links self-leadership to enhanced creative self-efficacy.

Moreover, generative AI provides a perceived source of cognitive and behavioral support that individuals can strategically plan to integrate into their creative endeavors. When intentionally adopted as a cognitive orientation, it allows self-leaders to plan the reallocation of mental effort from repetitive tasks to higher-order ideation and problem-solving. This deliberate cognitive alignment with AI strengthens the benefits of self-leadership by amplifying creative focus and reducing task-related friction. However, if individuals intend to rely too heavily on AI without exercising self-regulation, it may diminish personal agency and reduce the depth of creative engagement. Thus, the effectiveness of an individual's orientation toward AI is closely tied to how they frame its use within broader self-leadership strategies that sustain autonomy and active involvement. While AI tools have the potential to streamline cognitive processes, such as providing feedback, automating routine tasks, and supporting ideation, their impact on creativity largely depends on how much cognitive effort and control individuals intend to maintain. When approached strategically, an open orientation toward AI tools can complement self-leadership practices by offering anticipated cognitive support, enabling individuals to focus their attention on more complex, creative tasks. In such cases, AI is conceptualized as an extension of the cognitive capabilities of individuals, allowing them to stay engaged in the creative process while preserving their autonomy and motivation (Boden, 2016; Brynjolfsson & McAfee, 2014).

Theoretical support is available to bolster these logical arguments. SCT (Bandura, 1986) provides a comprehensive theoretical framework for understanding the mediating role of generative AI acceptance and creative self-efficacy in the relationship between self-leadership and creative process engagement. SCT posits that self-efficacy significantly affects individuals' motivation, resilience, and persistence in tackling challenging tasks (Bandura, 1997). SCT emphasizes that behavior is a function of both internal beliefs, such as self-efficacy, and external environmental factors, such as AI tools, which work together dynamically to shape creative engagement. In creative contexts defined by the presence of AI, SCT suggests that individuals with high self-efficacy are more likely to view AI as a supportive resource rather than a replacement for their agency. This aligns with the interaction between self-efficacy and environmental factors, where individuals actively plan to leverage AI outputs instead of relying passively on them (Oldham & Cummings, 1996). This perspective allows them to strategically position AI to extend their cognitive capacity without undermining their control or ownership over creative outputs (Dwivedi et al., 2021; Gong et al., 2009).

Furthermore, individuals rely on both automatic, heuristic-based thinking and deliberate, systematic thinking when solving complex problems (Evans & Stanovich, 2013). In generative AI-supported tasks, individuals with strong self-leadership may adopt systematic approaches that involve critically evaluating and strategically planning to iterate AI-generated content. Those with lower levels of self-leadership may fall into more heuristic patterns, intending to rely uncritically on AI output. This divergence underscores the importance of cognitive flexibility when forming an orientation toward AI – those who thoughtfully and proactively plan to engage with AI can transform it into a tool that reinforces creative self-efficacy rather than replacing personal judgment. These cognitive processes are central to understanding the functional role of generative AI acceptance as a mediator. When an open orientation toward AI supports deeper engagement by scaffolding deliberative thinking,

https://doi.org/10.1017/jmo.2026.10109 Published online by Cambridge University Press

it fosters the development of confidence and creative persistence. Conversely, when an orientation toward AI enables shortcut thinking without reflection, it may undermine creative self-efficacy by displacing agency. This suggests that AI tools are not neutral in the creative process – their anticipated effect depends on the user's regulatory approach.

In addition, JD-R theory (Demerouti et al., 2001) posits that job resources like generative AI can enhance motivation when positioned to offset high job demands, such as cognitive complexity or time constraints. For individuals high in the personal cognitive resource of self-leadership, the availability of AI serves as another potential resource that they may proactively choose to adopt to amplify their performance. As a result, the acceptance of AI becomes not just an intention to use a tool, but a cognitive–intentional manifestation of self-leadership itself – one that builds the confidence necessary for sustained creative engagement. In this framing, generative AI functions as an anticipated resource embedded in the motivational pathway from self-regulation to self-efficacy to engagement. Taken together, these theoretical frameworks support a sequential logic: individuals high in self-leadership are more likely to strategically develop an orientation to integrate AI (as both a resource and thinking aid), which then enhances their creative self-efficacy and ultimately leads to deeper creative process engagement. Hence, based on these logic- and theory-based assertions, we hypothesize:

Hypothesis 2: Generative AI acceptance and creative self-efficacy serially mediate the positive relationship between self-leadership and creative process engagement.

Method

Sample and procedures

Participants were recruited via Prolific, an online platform recognized for providing access to a diverse and high-quality sample of professionals across different creative industries such as marketing, design, and technology. This broad sampling method allows the study to reflect a range of contexts in which generative AI tools, such as ChatGPT and Google Gemini, are utilized. Prolific was chosen not only for its diversity but also for its rigorous data quality controls (Douglas, Ewell & Brauer, 2023). The platform employs mechanisms to ensure valid responses, such as attention checks, demographic verification, and prescreening for participant experience. Prolific also offers transparency in its recruitment process, allowing for the targeting of specific participant profiles. In the current study, we screened for participants using the question 'How often a week do you use AI or tools that use AI as part of your work?' to ensure that all participants were regular users of AI in their work.

The final sample consisted of 258 full-time employees. A total of 386 respondents initiated the survey, with 114 responses being removed from the final dataset for failing to complete the survey in its entirety (either voluntary returned through Prolific or removed in data cleaning). Subsequently, another 14 responses were removed for failing attention checks. Participants self-identified as female ($n = 130$, 50.4%), male ($n = 125$, 48.4%), and 'other/prefer not to answer' ($n = 3$, 1.2%). The participants were primarily Caucasian/White ($n = 171$, 66.3%), African American/Black ($n = 54$, 20.9%), Hispanic ($n = 17$, 6.6%), Asian ($n = 9$, 3.5%), Native American/American Indian ($n = 3$, 1.2%), and 'other/prefer not answer' ($n = 4$, 1.6%), with an average age of 39.66 years. A diverse range of industries was represented in the sample, with participants reporting working across 16 different trades. In these roles, participants reported utilizing AI in their work once a week ($n = 40$, 15.5%), 2–6 times per week ($n = 99$, 38.4%), every day ($n = 60$, 23.3%), and multiple times per day ($n = 59$, 22.9%).

Power analysis

As noted above, a total of 258 participants were included in the study. A statistical power analysis was conducted to determine the minimum required sample size for detecting indirect effects in the proposed serial mediation model. The analysis assumed a small-to-medium effect size ($f^2 = 0.10$), a significance level (α) of 0.05, and statistical power ($1 - \beta$) of 0.80, which aligns with standards in

https://doi.org/10.1017/jmo.2026.10109 Published online by Cambridge University Press

organizational behavior research (Cohen, 1988). Based on these parameters and using G*Power 3.1 (Faul, Erdfelder, Buchner & Lang, 2009) for an ordinary least squares regression with three predictors, a sample size of approximately 220 was required to account for potential data loss and ensure the robustness of bootstrapping procedures. Consequently, our sample size of 258 provides adequate power for detecting both direct and indirect effects in the mediation model tested (Fritz & MacKinnon, 2007).

Measures

Self-leadership

Self-leadership was assessed using 25 items from the Revised Self-Leadership Questionnaire developed by Houghton and Neck (2002). Sample items include statements like 'I use my imagination to picture myself performing well on important tasks' and 'I establish specific goals for my own performance' and were rated on a 5-point Likert scale from 'not at all accurate' to 'completely accurate'. The alpha reliability estimate for the current study was .930.

Generative AI acceptance

Generative AI acceptance was measured with 12 items from the Generative Artificial Intelligence Acceptance scale by Yilmaz et al. (2023), which was developed based on the unified theory of acceptance and use of technology (Venkatesh et al., 2003, 2012). Specifically, 7 items assess participants' performance expectancy (perceptions of usefulness) and 5 items assess participants' effort expectancy (perceptions of ease of use), which taken together indicate the participants' intention to use AI in their work (Yilmaz et al., 2023). Sample items include 'I find generative AI applications useful in my daily life' and 'The use of generative AI applications increases my chances of achieving the things that are important to me' and were rated on a 5-point Likert scale from 'strongly disagree' to 'strongly agree'. The alpha reliability coefficient for the current data set was .941.

Creative self-efficacy

Creative self-efficacy was assessed using the 3-item Creative Self-Efficacy Scale by Tierney (1997) and Tierney and Farmer (2002). This scale was based on Spreitzer's (1995) self-efficacy framework as well as the work of Bandura (1977, 1986) and reflects the efficacy perceptions for being creative workwise and includes items that gauge participants' confidence in their ability to produce creative outcomes. Participants responded on a 7-point Likert scale to statements such as 'I feel that I am good at generating novel ideas' and 'I have confidence in my ability to solve problems creatively' from 'very strongly disagree' to 'very strongly agree'. The alpha reliability for this scale was .803 for the current study.

Creative process engagement

Creative process engagement was assessed using Zhang and Bartol's (2010a) 12-item Creative Process Engagement Scale, which draws on foundational work by Amabile (1983) and Reiter-Palmon and Illies (2004). This measure evaluates participants' involvement in various creative stages, including problem identification, information searching and encoding, and idea generation. Statements like 'I spend considerable time trying to understand the nature of the problem' and 'I think about the problem from multiple perspectives' were rated on a 5-point Likert scale from 'never' to 'very frequently'. Alpha reliability for this scale was .891.

Ethical approval and informed consent

Before launching this research project, we were granted ethical approval from the Institutional Review Board of our affiliated university. Prior to the data collection, we secured the participants' informed consent, assured them that their responses would be anonymous and used in the aggregate only for research purposes, and notified them that they would be free to withdraw consent and exit the study at any time.

https://doi.org/10.1017/jmo.2026.10109 Published online by Cambridge University Press

Table 1. Correlation matrix, with alpha reliability, means, and standard deviations

Variable		*Alpha*	*M*	SD	1.	2.	3.
1.	Self-leadership	.930	3.89	0.62	–		
2.	Creative self-efficacy	.803	5.42	1.00	.502**	–	
3.	AI acceptance	.941	4.13	0.62	.442**	.475**	–
4.	Creative process engagement	.891	3.99	0.54	.617**	.644**	.449**

**$p < .001$.

Results

Means, standard deviations, alpha reliabilities, and correlations for the variables are presented in Table 1. To test our hypotheses, we examined a serial multiple mediator model with self-leadership indirectly and positively predicting creative process engagement through AI acceptance and, subsequently, creative self-efficacy. Direct and indirect effects were estimated using PROCESS 4.2 (Hayes, 2022) using 10,000 percentile bootstrap samples with 95% confidence intervals (CIs). The significance of effects was determined by whether the bootstrapped 95% CIs excluded zero. When the confidence interval does not contain zero, the effect is statistically significant, and one can confidently conclude that the relationship or indirect path is real and did not occur by chance. In contrast, if the confidence interval contains zero then the effect is not statistically significant. Because zero is a plausible value, one cannot rule out the possibility that the true effect size is zero.

The results of our serial mediation analysis are summarized in Table 2. Results indicate that the direct effect of self-leadership on creative process engagement was significant ($c' = .319$, $SE = .045$, $p < .001$). Consequently, Hypothesis 1 predicting self-leadership to enhance creative process engagement was supported. Additionally, results revealed evidence for a serial indirect effect of self-leadership on creative process engagement through AI acceptance and, in turn, creative self-efficacy with an unstandardized serial indirect effect of .047 ($SE = .018$, 95% CI [.019, .089]) and completely standardized indirect effect of .054 ($SE = .019$, 95% CI [.022, .098]). The simple indirect effect of self-leadership on creative process engagement through AI acceptance included zero in the confidence interval indicating that there was no evidence of mediation through this pathway ($a_1b_1 = .037$, $SE = .023$, 95% CI [−.006, .085]; $a_1b_{1cs} = .043$, $SE = .026$, 95% CI [−.007, .097]). However, results revealed evidence for the simple indirect effect of self-leadership on creative process engagement through creative self-efficacy ($a_2b_2 = .135$, $SE = .031$, 95% CI [.078, .200]; $a_2b_2 = .155$, $SE = .035$, 95% CI [.089, .228]). In sum, these results lend support to Hypothesis 2, which predicted that generative AI acceptance and creative self-efficacy would serially mediate the relationship between self-leadership and creative process engagement. Standardized path coefficients for our serial mediation model are shown in Fig. 2.

Discussion

This study, grounded in SCT and JD-R theory, demonstrates that as generative AI transforms creative workflows, self-leadership remains a critical antecedent of creative process engagement. Findings validate a serial mediation model linking self-leadership to engagement via AI acceptance and creative self-efficacy, while also establishing that self-influence relates to engagement independently of technology. The results highlight a necessary balance where AI complements, rather than supplants, human agency, emphasizing that effective AI integration hinges on its interaction with self-regulatory processes.

The explanatory boundaries of generative AI acceptance

Our empirical findings offer a critical nuance to the burgeoning literature on AI in creative workflows. While we positioned generative AI acceptance as a central mediating mechanism linking

https://doi.org/10.1017/jmo.2026.10109 Published online by Cambridge University Press

Table 2. OLS path coefficients: serial mediation

Antecedent	Consequent								
	AI acceptance (M_1)			Creative self-efficacy (M_2)			Creative process engagement (Y)		
	B	SE	*p*	*B*	SE	*p*	*B*	SE	*p*
Self-leadership (X)	.448	.057	<.001	.606	.094	<.001	.319	.045	<.001
AI acceptance (M_1)	—	—	—	.470	.092	<.001	.083	.043	.054
Creative self-efficacy (M_2)	—	—	—	—	—	—	.223	.028	<.001
Constant	2.389	.224	<.001	1.119	.398	.005	1.194	.179	<.001
	$R^2 = .195$			$R^2 = .320$			$R^2 = .537$		
	$F(1, 256) = 62.087, p < .001$			$F(2, 255) = 60.132, p < .001$			$F(3, 254) = 98.204, p < .001$		

Note. B = unstandardized coefficient. See Fig. 2 for standardized coefficients.
Summary of indirect effects.
Indirect effect 1: Self-leadership → AI acceptance → Creative process engagement.
Not supported, $a_1b_1 = .037$, 95% CI [−.006, .085]; $a_1b_{1cs} = .043$, 95% CI [−.007, .097].
Indirect effect 2: Self-leadership → Creative self-efficacy → Creative process engagement.
Supported, $a_2b_2 = .135$, 95% CI [.078, .200]; $a_2b_2 = .155$, 95% CI [.089, .228].
Indirect effect 3 (serial mediation): Self-leadership → AI acceptance → Creative self-efficacy → Creative process engagement.
Supported, $a_2d_{21}b_2 = .047$, 95% CI [.019, .089]; $a_2d_{21}b_{2cs} = .054$, 95% CI [.022, .098].

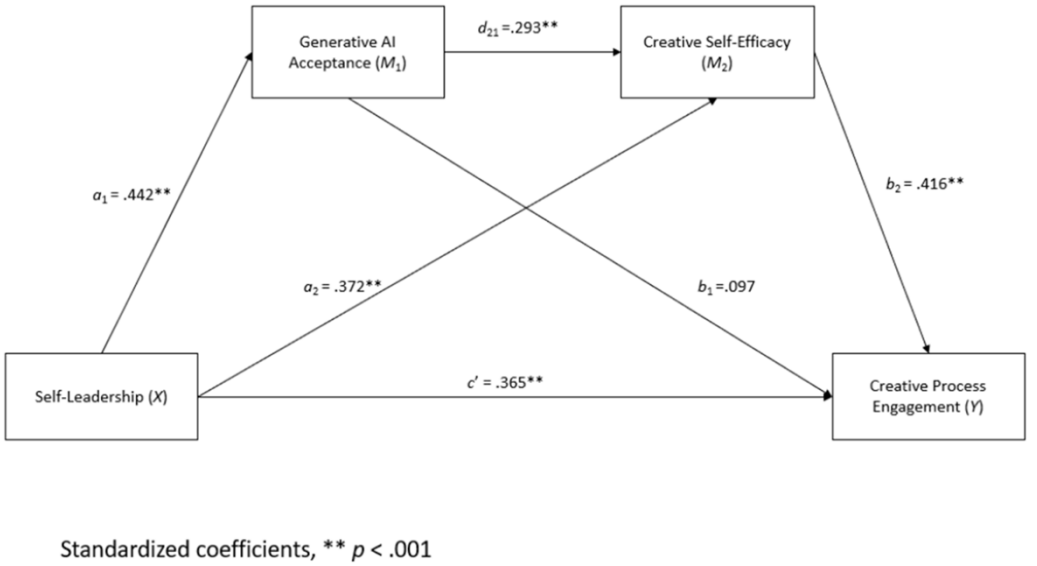


Figure 2. Serial mediation model with standardized path coefficients.

self-leadership to creative process engagement, our results reveal that its standalone indirect effect is non-significant. Instead, creative self-efficacy emerged as the dominant mediator driving behavioral engagement. This suggests that technology acceptance, on its own, represents a necessary but insufficient condition for creative action. Merely accepting or being open to utilizing generative AI does not automatically translate into deep engagement with complex creative processes. Rather, traditional self-regulatory mechanisms – specifically, an individual's belief in their own creative capabilities – remain the primary psychological engine of creative work.

https://doi.org/10.1017/jmo.2026.10109 Published online by Cambridge University Press

The incremental value of generative AI acceptance is therefore uniquely structural, operating as an upstream psychological gateway within a serial chain. Self-leadership empowers employees to accept and embrace these novel technologies. However, this technological openness must first be converted into heightened creative self-efficacy before behavioral engagement can occur. In an AI-augmented workplace, AI acceptance serves as the baseline prerequisite that allows employees to confidently leverage digital tools, which subsequently builds the domain-specific self-efficacy required to execute creative tasks. By demonstrating that AI acceptance routes through creative self-efficacy, this study tempers overly optimistic views of technology adoption by underscoring that new tools cannot bypass foundational human psychological processes.

Implications for research and practice

This study offers theoretical and practical insights for organizations aiming to maintain a balance between human agency and prospective technological adoption. Theoretically, this research advances the conceptualization of generative AI acceptance as an upstream cognitive mediator in the relationship between self-leadership and creative process engagement, adding nuance to existing frameworks of human–AI interaction orientations (Xu & Wang, 2021). More specifically, our findings extend SCT by suggesting that self-leadership not only influences internal psychological states such as creative self-efficacy but also shapes proximal adoption orientations – namely, generative AI acceptance. In turn, this intentional adoption orientation strengthens creative self-efficacy, thereby broadening SCT's account of how efficacy beliefs develop in environments characterized by prominent digital tools. Thus, this study highlights critical potential roles for self-efficacy and self-regulation in determining how individuals strategically frame the utility of AI for creative tasks. This perspective underscores that a cognitive orientation toward AI is not unidimensional; instead, it can psychologically empower or potentially stifle human agency depending on the user's regulatory approach. This nuanced understanding of AI's dual role as a prospective enabler or disruptor of creative cognition underscores the importance of self-leadership as a proactive tool for allowing AI to complement, rather than psychologically displace, human creativity. Likewise, our study enriches JD-R theory by positioning self-leadership as a personal resource that frames technology adoption as an additional, accessible job resource, which subsequently fuels cognitive engagement in the creative process. Together, these insights highlight an expanded resource-based pathway – personal resources initiating a positive technological readiness orientation that builds further psychological resources.

From a practical standpoint, this research provides actionable insights for organizations seeking to manage expectations surrounding AI within creative contexts while prioritizing and maintaining human agency. By focusing on self-leadership enhancement and bolstering creative self-efficacy through targeted training and development programs, the findings suggest that organizations can cultivate an environment where the introduction of AI complements rather than overrides self-leadership practices. For instance, structured training that emphasizes self-goal setting and strategic intentionality toward AI can support employees in effectively framing AI as an assistive resource, enhancing their creative capabilities rather than diminishing their autonomy. This approach is particularly important in knowledge-intensive industries – such as marketing, design, and technology – where innovation is a critical driver of competitive advantage. For example, in a design agency setting, pairing self-leadership workshops with a structured introduction to AI tools can help foster an environment where employees view AI as a supportive cognitive asset. Training employees to leverage AI to conceptually generate initial ideas or visualize design elements, while maintaining complete psychological autonomy to adapt and personalize these outputs, can improve both anticipated productivity and the overall orientation toward creative work. This dual approach encourages ownership and enhances employees' capacity to manage their cognitive creative processes proactively.

Organizations are encouraged to prioritize the development of self-leadership skills alongside AI onboarding programs that underscore strategic, intentional orientations toward digital tools. This approach fosters environments where employees feel empowered to view AI as a supportive resource,

https://doi.org/10.1017/jmo.2026.10109 Published online by Cambridge University Press

rather than as a substitute for their own creativity. Implementing policies and training that emphasize strategic AI readiness can help employees maintain an active cognitive role in creative processes, thereby preserving the intrinsic motivation, ownership, and agency critical for innovative outcomes.

Additionally, this study provides practical recommendations for HR professionals, training specialists, and organizational leaders on balancing technological automation with human-centered creative engagement. A key recommendation is to develop policies that encourage an orientation toward AI as an assistive tool that amplifies human ingenuity, rather than one that fully automates the creative domain. These policies can support employees' intrinsic motivation and ownership of their work, promoting a dynamic where AI serves to enhance personal agency within creative processes. In practice, organizations could establish guidelines for AI adoption that emphasize the need for critical assessment and cognitive discretion, ensuring that AI outputs are framed strictly as conceptual starting points rather than definitive solutions. This approach is essential in fields where maintaining cognitive control over the creative process is key to fostering sustainable innovation and adaptive problem-solving.

Furthermore, this study sets the stage for future research on technological readiness and human agency by encouraging exploration of how different organizational structures, cultures, and industry-specific factors influence the formation of AI acceptance in creative tasks. As organizational dynamics and technological capabilities vary widely across sectors, understanding how self-leadership and creative self-efficacy interact with an orientation toward AI tools in diverse settings will be critical for identifying the specific conditions that enable AI to maximize its potential for fostering creativity and innovation. For example, future studies could examine whether flat organizational structures, which encourage autonomy, are more conducive to psychological AI readiness compared to hierarchical structures that may limit personal agency.

In sum, this study contributes both theoretically and practically by providing a comprehensive framework that addresses the strategic, intentional acceptance of AI in creativity-driven environments. This research highlights the importance of fostering self-leadership and creative self-efficacy, enabling organizations to design prospective workflows that support sustainable, human-centered innovation. Through these insights, the study offers a roadmap for organizations aiming to maintain a balanced psychological approach in an increasingly automated landscape, ensuring that AI acceptance reinforces rather than diminishes human creativity and strategic thinking. This study ultimately advances the understanding of human-technology interaction by positioning generative AI acceptance not merely as a passive stance, but as a vital cognitive mediator that activates belief-driven engagement in creative work.

Limitations and future research opportunities

Despite its theoretical and practical insights, our study is subject to several boundary conditions that present fruitful avenues for future inquiry. First, while Prolific provides access to a diverse, multi-industry cohort of working professionals, our sample remains subject to self-selection bias due to its voluntary nature. This digital sample may not perfectly reflect populations in less technologically integrated or niche sectors, potentially constraining the broader generalizability of our findings. Future research should replicate this framework utilizing targeted corporate samples or industry-specific registries to ensure generalizability across different operational contexts.

Second, our reliance on cross-sectional, self-reported data limit our ability to make definitive causal inferences and leaves the data susceptible to common method variance. Although we took proactive procedural steps to minimize common method variance by introducing varied scale metrics and anchors, the structural relationships must still be interpreted with care. Future inquiries should leverage time-lagged or multi-source data collection designs (e.g., pairing supervisor ratings of creative engagement with employee self-assessments) to establish stronger causal patterns.

Third, our study is bounded by its reliance on perceptual and intentional metrics of technology acceptance – specifically perceived usefulness and intention to use. While intention is a powerful,

https://doi.org/10.1017/jmo.2026.10109 Published online by Cambridge University Press

validated predictor of technology adoption, our data does not capture objective behavioral usage metrics such as active platform logs, prompt engineering hours, or external expert ratings of creative performance. This distinction may be particularly important in AI contexts, where favorable attitudes and intentions toward emerging technologies may not necessarily translate into sustained or strategic behavioral use. Future research should distinguish between psychological readiness for AI adoption and actual patterns of AI utilization to better understand how these constructs independently shape creative outcomes.

Finally, future research should investigate how changing macro-level variables and evolving technologies impact these psychological dynamics. Longitudinal studies tracking employees over extended periods (e.g., 6 months to a year) would reveal whether sustained exposure to AI tools continuously reinforces creative self-efficacy or whether overreliance eventually erodes intrinsic motivation and personal autonomy. Furthermore, cross-industry comparisons could uncover how varying levels of creative freedom and compliance requirements – such as comparing highly regulated healthcare fields with less restricted marketing sectors – moderate the psychological pathways between self-leadership, technology acceptance, and creative engagement.

Conclusion

In conclusion, our study advances the literature by providing critical insights into how individual self-leadership shapes creative process engagement within work contexts defined by the prominence of generative AI. Our findings reveal that self-leadership's self-regulatory strategies actively foster creative process engagement through two distinct pathways: directly as an independent behavioral driver, and indirectly by establishing a proactive cognitive orientation toward generative AI acceptance that subsequently enhances creative self-efficacy. Ultimately, these results affirm self-leadership as a vital psychological foundation for creative work, demonstrating that technology adoption cannot bypass traditional human self-regulation; rather, technological readiness must be successfully converted into domain-specific creative confidence before deeper engagement can occur. For organizations, these findings underscore the value of pairing traditional self-leadership training with digital onboarding initiatives that emphasize the intentional, strategic framing of AI tools as assistive assets. By illuminating these serial cognitive pathways, we hope this study encourages future scholars to continue exploring the delicate balance between technological readiness, human agency, and the psychological boundaries of creativity.

Conflict(s) of Interest. The authors declare none.

References

Adobe. (2024). *Adobe's AI creative frontier study reveals creators' views, opportunities, risks of generative AI*. https://blog.adobe.com/en/publish/2024/10/08/adobes-ai-creative-frontier-study-reveals-creators-views-opportunities-risks-generative-ai

Amabile, T. M. (1983). The social psychology of creativity: A componential conceptualization. *Journal of Personality and Social Psychology*, *45*, 357–376.

Amabile, T. M., & Pratt, M. G. (2016). The dynamic componential model of creativity and innovation in organizations: Making progress, making meaning. *Research in Organizational Behavior*, *36*, 157–183.

Amankwah-Amoah, J., Abdalla, S., Mogaji, E., Elbanna, A., & Dwivedi, Y. K. (2024). The impending disruption of creative industries by generative AI: Opportunities, challenges, and research agenda. *International Journal of Information Management*, *79*, 102759.

Anantrasirichai, N., & Bull, D. (2022). Artificial intelligence in the creative industries: A review. *Artificial Intelligence Review*, *55*(1), 589–656.

Ayoko, O. B. (2021). Digital transformation, robotics, artificial intelligence, and innovation. *Journal of Management & Organization*, *27*(5), 831–835.

Bäcklander, G., Rosengren, C., & Kaulio, M. (2021). Managing intensity in knowledge work: Self-leadership practices among Danish management consultants. *Journal of Management & Organization*, *27*(2), 342–360.

Bakker, A. B., Demerouti, E., & Sanz-Vergel, A. (2023). Job demands–resources theory: Ten years later. *Annual Review of Organizational Psychology and Organizational Behavior*, *10*(1), 25–53.

https://doi.org/10.1017/jmo.2026.10109 Published online by Cambridge University Press

Bakker, A. B., Demerouti, E., & Sanz-Vergel, A. I. (2014). Burnout and work engagement: The JD–R approach. *Annual Review of Organizational Psychology and Organizational Behavior*, *1*(2014), 389–411.

Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review*, *84*(2), 191–215.

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Prentice-Hall.

Bandura, A. (1997). *Self-efficacy: The exercise of control*. Freeman.

Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*, *51*(6), 1173.

Boden, M. A. (2016). *Artificial Intelligence: A Very Short Introduction*. Oxford University Press.

Brougham, D., & Haar, J. (2018). Smart technology, artificial intelligence, robotics, and algorithms (STARA): Employees' perceptions of our future workplace. *Journal of Management & Organization*, *24*(2), 239–257.

Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. W. W. Norton & Company.

Cheng, C., & Yang, M. (2019). Creative process engagement and new product performance: The role of new product development speed and leadership encouragement of creativity. *Journal of Business Research*, *99*, 215–225.

Chughtai, M. S., & Khalid, Y. (2022). Learning organizations and innovative work behaviors: A moderated mediation model of creative self-efficacy and self-leadership from the perspective of social cognitive theory and social schema theory. *Journal of Innovative Research in Management Sciences 3*(1), 22–41.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Erlbaum.

Demerouti, E., Bakker, A. B., Nachreiner, F., & Schaufeli, W. B. (2001). The Job Demands-Resources Model of burnout. *Journal of Applied Psychology*, *86*(3), 499–512.

DiLiello, T. C., & Houghton, J. D. (2006). Maximizing organizational leadership capacity for the future: Toward a model of self-leadership, innovation, and creativity. *Journal of Managerial Psychology*, *21*(4), 319–337.

Douglas, B. D., Ewell, P. J., & Brauer, M. (2023). Data quality in online human-subjects research: Comparisons between MTurk, Prolific, CloudResearch, Qualtrics, and SONA. *Plos One*, *18*(3), e0279720.

Dwivedi, Y. K., Hughes, D. L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., & Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice, and policy. *International Journal of Information Management*, *57*, 101994.

Evans, J. S. B. T., & Stanovich, K. E. (2013). Dual-process theories of higher cognition: Advancing the debate. *Perspectives on Psychological Science*, *8*(3), 223–241.

Faul, F., Erdfelder, E., Buchner, A., & Lang, A. G. (2009). Statistical power analyses using G* Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods*, *41*(4), 1149–1160.

Fritz, M. S., & MacKinnon, D. P. (2007). Required sample size to detect the mediated effect. *Psychological Science*, *18*(3), 233–239.

Fui-hoon Nah, F., Zheng, R., Cai, J., Siau, K., & Chen, L. (2023). Generative AI and ChatGPT: Applications, challenges, and AI-human collaboration. *Journal of Information Technology Case and Application Research*, *25*(3), 277–304.

Füller, J., Tekic, Z., & Hutter, K. (2024). Rethinking innovation management—how AI is changing the way we innovate. *The Journal of Applied Behavioral Science*, *60*(4), 603–612.

Galindo-Domínguez, H., Delgado, N., Sainz-de-la-maza, M., & Etxabe, J. M. (2026). Self-regulation and overreliance on artificial intelligence: Unpacking a paradox through a mixed-methods study in higher education. *Computers in Human Behavior 181*, 108985.

Ghosh, K. (2015). Developing organizational creativity and innovation: Toward a model of self-leadership, employee creativity, creativity climate and workplace innovative orientation. *Management Research Review*, *38*(11), 1126–1148.

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

Gomes, C., Curral, L., & Caetano, A. (2015). The mediating effect of work engagement on the relationship between self-leadership and individual innovation. *International Journal of Innovation Management*, *19*(01), 1550009.

Gong, Y., Huang, J. C., & Farh, J. L. (2009). Employee learning orientation, transformational leadership, and employee creativity. *Academy of Management Journal*, *52*(4), 765–778.

Gujar, P., & Panyam, S. (2024). Generative AI in digital advertising campaigns. *International Journal of Computer Trends and Technology*, *72*(5), 51–55.

Harari, M. B., Williams, E. A., Castro, S. L., & Brant, K. K. (2021). Self-leadership: A meta-analysis of over two decades of research. *Journal of Occupational and Organizational Psychology*, *94*(4), 890–923.

Hayes, A. F. (2022). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach*. Guilford Publications.

Henker, N., Sonnentag, S., & Unger, D. (2015). Transformational leadership and employee creativity: The mediating role of promotion focus and creative process engagement. *Journal of Business and Psychology*, *30*, 235–247.

Hennessey, B. A., & Amabile, T. M. (2010). Creativity. *Annual Review of Psychology*, *61*, 569–598.

Higgins, E. T. (2012). Regulatory focus theory. *Handbook of Theories of Social Psychology*, *1*, 483–504.

Hossain, S., Fernando, M., & Akter, S. (2025). The influence of artificial intelligence-driven capabilities on responsible leadership: A future research agenda. *Journal of Management & Organization 31*(5), 1–25.

https://doi.org/10.1017/jmo.2026.10109 Published online by Cambridge University Press

Houghton, J. D., & Neck, C. P. (2002). The revised self-leadership questionnaire: Testing a hierarchical factor structure for self-leadership. *Journal of Managerial Psychology*, *17*(8), 672–691.
Huy, L. V., Nguyen, H. T., Vo-thanh, T., Thinh, N. H. T., & Thi Thu Dung, T. (2024). Generative AI, why, how, and outcomes: A user adoption study. *AIS Transactions on Human-Computer Interaction*, *16*(1), 1–27.
Khan, H. S., Li, P., Chughtai, M. S., Mushtaq, M. T., & Zeng, X. (2023). The role of knowledge sharing and creative self-efficacy on the self-leadership and innovative work behavior relationship. *Journal of Innovation & Knowledge*, *8*(4), 100441.
Kim, D., Kim, S., Kim, S., & Lee, B. H. (2025). Generative AI characteristics, user motivations, and usage intention. *Journal of Computer Information Systems*, 1–16. https://doi.org/10.1080/08874417.2024.2442438.
Knotts, K., Houghton, J. D., Pearce, C. L., Chen, H., Stewart, G. L., & Manz, C. C. (2022). Leading from the inside out: A meta-analysis of how, when, and why self-leadership affects individual outcomes. *European Journal of Work and Organizational Psychology*, *31*(2), 273–291.
Knotts, K. G., & Houghton, J. D. (2021). You can't make me! The role of self-leadership in enhancing organizational commitment and work engagement. *Leadership & Organization Development Journal*, *42*(5), 748–762.
Lin, C. J. (2017). A multi-level test for social regulatory focus and team member creativity: Mediating role of self-leadership strategies. *Leadership & Organization Development Journal*, *38*(8), 1057–1077.
Luthans, F. (2011). *Organizational behavior: An evidence-based approach* (12th ed.). McGraw-Hill/Irwin.
Mahmood, M., Uddin, M. A., & Fan, L. (2019). The influence of transformational leadership on employees' creative process engagement: A multi-level analysis. *Management Decision*, *57*(3), 741–764.
Manz, C. C. (1986). Self-leadership: Toward an expanded theory of self-influence processes in organizations. *Academy of Management Review*, *11*(3), 585–600.
Manz, C. C., & Sims, H. P., Jr (2001). *The new superleadership: Leading others to lead themselves*. Berrett-Koehler Publishers.
Maykrantz, S. A., Langlinais, L. A., Houghton, J. D., & Neck, C. P. (2021). Self-leadership and psychological capital as key cognitive resources for shaping health-protective behaviors during the COVID-19 pandemic. *Administrative Sciences*, *11*(2), 41.
McKinsey & Company. (2024). *The state of AI*. https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai
Neck C. P., & Houghton J. D. (2006). Two decades of self-leadership theory and research. *Journal of Managerial Psychology*, *21*(4), 270–295.
Neck, C. P., & Houghton, J. D. (2006). Two decades of self-leadership theory and research: Past developments, present trends, and future possibilities. *Journal of Managerial Psychology*, *21*(4), 270–295.
Oldham, G. R., & Cummings, A. (1996). Employee creativity: Personal and contextual factors at work. *Academy of Management Journal*, *39*(3), 607–634.
Raihan, T., & Uddin, M. A. (2023). The influence of creative self-efficacy, creative self-identity, and creative process engagement on innovative behaviour. *International Journal of Business Innovation and Research*, *30*(1), 18–35.
Ratten, V. (2024). Management trends: Artificial intelligence, Q-Day, soft skills, work patterns, diversity, and sustainability initiatives. *Journal of Management & Organization*, *30*(2), 219–222.
Reiter-Palmon, R., & Illies, J. J. (2004). Leadership and creativity: Understanding leadership from a creative problem-solving perspective. *The Leadership Quarterly*, *15*, 55–77.
Sajjad, H. (2024). Generative AI: Transforming creative industries with machine learning. *Research Corridor Journal of Engineering Science*, *1*(2), 119–134.
Shalley, C. E., & Zhou, J. (2008). Organizational creativity research: A historical overview. In J. Zhou & C. E. Shalley (Eds.), *Handbook of organizational creativity* (pp. 95–123). Taylor and Francis.
Spreitzer, G. M. (1995). Psychological empowerment in the workplace: Dimensions, measurement, and validation. *Academy of Management Journal*, *38*(5), 1442–1465.
Stewart G L, Courtright S H and Manz C C. (2019). Self-Leadership: A Paradoxical Core of Organizational Behavior. Annu. Rev. Organ. Psychol. Organ. Behav, *6*(1), 47–67. https://doi.org/10.1146/annurev-orgpsych-012218-015130
Tierney, P. (1997). The influence of cognitive climate on job satisfaction and creative efficacy. *Journal of Social Behavior and Personality*, *12*(4), 831–847.
Tierney, P., & Farmer, S. M. (2002). Creative self-efficacy: Its potential antecedents and relationship to creative performance. *Academy of Management Journal*, *45*(6), 1137–1148.
van Dorssen-boog, P., van Vuuren, T., de Jong, J. P., & Veld, M. (2021). Facilitating health care workers' self-determination: The impact of a self-leadership intervention on work engagement, health, and performance. *Journal of Occupational and Organizational Psychology*, *94*(2), 259–281.
Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425–478.
Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, *36*(1), 157–178.
Xu, N., & Wang, K. J. (2021). Adopting robot lawyer? The extending artificial intelligence robot lawyer technology acceptance model for legal industry by an exploratory study. *Journal of Management & Organization*, *27*(5), 867–885.

https://doi.org/10.1017/jmo.2026.10109 Published online by Cambridge University Press

Yang, J., Xie, P., Tang, H., Hou, Y., & Ming, X. (2025). Linking multitasking to creative process engagement through psychological detachment: Temporal leadership as a moderator. *The Journal of Creative Behavior*, *59*(2), e70015.

Yilmaz, F. G. K., Yilmaz, R., & Ceylan, M. (2023). Generative Artificial Intelligence acceptance scale: A validity and reliability study. *International Journal of Human-Computer Interaction*, *40*(24), 8703-8715.

Zanatto, D., Bifani, S., & Noyes, J. (2024). Constraining the sense of agency in human-machine interaction. *International Journal of Human–Computer Interaction*, *40*(13), 3482–3493.

Zhang, X., & Bartol, K. M. (2010a). Linking empowering leadership and employee creativity: The influence of psychological empowerment, intrinsic motivation, and creative process engagement. *Academy of Management Journal*, *53*(1), 107–128.

Zhang, X., & Bartol, K. M. (2010b). The influence of creative process engagement on employee creative performance and overall job performance: A curvilinear assessment. *Journal of Applied Psychology*, *95*(5), 862.

Zhou, Z., Xiang, S., & Xie, Q. (2025). How could fit between polychronicity and multitasking shape employees' self-leadership? The moderating role of AI-empowered task processing. *Frontiers in Artificial Intelligence*, *8*, 1451944.

Cite this article: Avery, J., Neck, C. B., & Houghton, J. D. (2026). From self-leadership to creative process engagement: Generative AI acceptance and creative self-efficacy as serial cognitive pathways. *Journal of Management & Organization*, 1–16. https://doi.org/10.1017/jmo.2026.10109

https://doi.org/10.1017/jmo.2026.10109 Published online by Cambridge University Press