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When and how generative AI support promotes job crafting: Mediation of GenAI self-efficacy and moderation of GenAI usage

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Abstract

Research background: The rapid diffusion of generative artificial intelligence (GenAI) is transforming how employees perform and redesign their work. However, limited research has examined the psychological and contextual mechanisms through which perceived technological support translates into proactive job adaptation. This study draws on the conservation of

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resources (COR) theory, and social cognitive theory (SCT), to investigate how perceived GenAI support fosters job crafting. It focuses on self-efficacy toward GenAI as a mediating psychological resource and GenAI usage as a boundary condition that shapes this process.

Purpose of the article: This study examines the mediating role of self-efficacy toward GenAI in the relationship between perceived GenAI support and job crafting, as well as the moderating effect of GenAI usage on this relationship.

Methods: A two-wave, time-lagged survey was conducted with South Korean employees who had experience using GenAI at work. Path modeling with bootstrapping was used to test the mediation, moderation, and moderated mediation effects while controlling for demographic variables, industry, and affectivity.

Findings & value added: Perceived GenAI support was positively associated with job crafting through self-efficacy toward GenAI. Furthermore, GenAI usage strengthened the effect of perceived GenAI support on self-efficacy and the indirect effect of perceived support on job crafting through self-efficacy. This study advances the literature by clarifying how external technological support is internalized into psychological resources and activated through usage to promote proactive work redesign. The findings provide a refined theoretical explanation for adaptive employee behavior in AI-enabled workplaces by extending COR theory and SCT to human–AI collaboration contexts and highlighting the central role of domain-specific self-efficacy.

Introduction

The rapid diffusion of generative artificial intelligence (GenAI) is fundamentally transforming job structures and the execution of knowledge work in contemporary organizations (Cramarencu *et al.*, 2023; Dabija & Vătămănescu, 2023; Lazaroiu & Rogalska, 2023). Unlike earlier technologies that automated tasks based on predefined rules, GenAI—powered by large language models and generative algorithms—supports higher-order cognitive activities, including problem framing, alternative generation, and complex information integration. Consequently, GenAI is increasingly conceptualized as a collaborative partner that augments human cognitive capacity, not as a substitute for human labor (Oschinsky & Nguyen, 2025; Sigala *et al.*, 2024; Zhao *et al.*, 2026). In organizational contexts, this represents more than efficiency gains, constituting a qualitative transformation in how work is performed. By delegating repetitive and cognitively demanding tasks to GenAI, employees can conserve cognitive resources and redirect their efforts toward complex, value-adding activities (Przegalska *et al.*, 2025; Yuan, 2025). Consistent with this view, recent studies show that GenAI adoption contributes to productivity improvements and work redesign (Mayer *et al.*, 2025; Parvez *et al.*, 2025).

Despite these potential benefits, GenAI does not uniformly enhance job performance or employee well-being. Employees may experience GenAI either as a job resource that alleviates workload or as a job demand that generates technostress and a perceived loss of control, depending on individual perceptions and usage patterns (Chuang *et al.*, 2025; Cui *et al.*, 2026; Duong *et al.*, 2025; Yang *et al.*, 2026). Although GenAI facilitates rapid information processing, it can also introduce new cognitive and psychological costs, including prompt ambiguity, output unreliability, and ongoing learning demands (Oschinsky & Nguyen, 2025; Yang *et al.*, 2026). This duality suggests that GenAI's effectiveness hinges less on technical sophistication than on how employees interpret, internalize, and deploy the technology in their work. Accordingly, GenAI is best understood as a context-dependent technology whose functional value is socially and cognitively constructed through experience (Amrollahi *et al.*, 2026). Building on this perspective, we focus on perceived GenAI—employees' perception of GenAI as providing meaningful task-related assistance—as a central predictor of behavioral and performance outcomes (Brynjolfsson *et al.*, 2025).

Organizational investments in GenAI are unlikely to generate sustained benefits if employees fail to internalize the technology as a personal capability or translate it into meaningful work redesign. This limitation highlights the need for a theoretical framework to explain proactive adaptation in response to GenAI (Nobels, 2024). This study addresses this gap by examining the role of perceived GenAI support in promoting job crafting—defined as proactive behaviors through which employees modify task boundaries, social interactions, and cognitive interpretations of their work to better align with their strengths and motivations (Holúbek *et al.*, 2025). An increasing body of research has examined factors affecting job crafting in the context of GenAI, documenting that opportunity or challenge perceptions of AI promote job crafting, whereas threat perceptions of AI interfere with job crafting (Cheng *et al.*, 2023; Li *et al.*, 2024; Tan *et al.*, 2025; Xu *et al.*, 2026; Zhao *et al.*, 2025). This stream of research has mainly focused on the double-edged effect of AI; thus, little attention has been paid to when and how GenAI support fosters job crafting. To bridge this gap, our study explores the mediators and moderators that intervene in the relationship between perceived GenAI support and job crafting.

We draw on the conservation of resources (COR) theory (Hobfoll, 1989) to theorize the relationship between perceived GenAI support and job crafting. COR theory proposes that individuals seek to preserve their cur-

rent resources and allocate them toward acquiring further resources when their resource reservoirs are adequate. From this perspective, GenAI support functions as a job resource that provides employees with job-related assistance (Chuang *et al.*, 2025; Yuan, 2025). COR theory further postulates that external resources (e.g., GenAI support) influence outcomes only when they are internalized as psychological resources (e.g., self-efficacy; Siddiqi *et al.*, 2025). Similarly, social cognitive theory (SCT) assumes that individuals' behaviors are shaped through the interaction of individual characteristics (e.g., cognitive beliefs), environmental or situational factors, and behavioral factors (Bandura, 1986). In this framework, perceived environmental support (e.g., perceived GenAI support) influences individuals' beliefs about their capabilities (e.g., self-efficacy toward GenAI), guiding their job crafting. Building on these theories, we propose self-efficacy toward GenAI as a key mediating resource linking perceived GenAI support and job crafting. This construct reflects employees' confidence in their ability to collaborate effectively with GenAI and maintain control over AI-enabled work processes (Wang & Chuang, 2024). Thus, this study primarily examines the mediating role of self-efficacy toward GenAI in the relationship between perceived GenAI support and job crafting.

We further propose that this resource conversion process is contingent on GenAI usage. COR theory emphasizes that resources exert their effects only when actively mobilized in daily behaviors (Zhu *et al.*, 2025). Furthermore, drawing on the SCT proposition that individuals' beliefs in their capabilities are jointly influenced by situational and behavioral factors (Han *et al.*, 2025), we argue that self-efficacy toward GenAI is shaped by the interaction between perceived GenAI support and GenAI usage. Employees who engage frequently with GenAI are more likely to develop mastery, familiarity, and confidence, which strengthens the translation of perceived support into self-efficacy (Yang *et al.*, 2026). Accordingly, GenAI usage is conceptualized as a boundary condition that moderates the relationship between perceived GenAI support and self-efficacy toward GenAI and the indirect effect of perceived support on job crafting. This study tests this moderating effect.

The study advances the literature on GenAI and job crafting in several meaningful ways. First, it redirects scholarly attention from traditional productivity outcomes to proactive behavioral adaptation by conceptualizing job crafting as a key mechanism through which employees actively reshape their work in AI-enabled environments. Thus, it portrays employ-

ees not merely as passive users of technology but as active agents who leverage GenAI to redesign their tasks and work processes. Second, it extends the literature on job crafting by offering a more nuanced explanation of how GenAI support stimulates job crafting through mediating and moderating mechanisms. It observes that the influence of perceived GenAI support operates primarily through the development of domain-specific self-efficacy. It also concludes that the psychological internalization of technological resources, rather than their mere availability, is central to promoting job crafting. Third, the study identifies GenAI usage as a critical boundary condition that enables the translation of external technological support into psychological and behavioral outcomes. This study explores the role of GenAI usage in boosting the positive effects of GenAI support. It offers novel insights into the interplay between environmental and behavioral factors in predicting self-efficacy toward GenAI and job crafting. These insights integrate COR theory and SCT into the emerging context of human–AI collaboration and offer a more precise theoretical framework to understand how technological resources can catalyze adaptive and proactive employee behavior.

The subsequent sections of this paper include a literature review and hypotheses, methods, results, and discussion. The literature review develops a research model proposing that perceived GenAI support enhances job crafting via self-efficacy toward GenAI and that this indirect effect is amplified under conditions of high GenAI usage. The methods section details a two-wave, time-lagged survey of South Korean employees who use GenAI at work, including validated measures and path modeling with bootstrapping to test mediation, moderation, and moderated mediation while controlling for demographics, industry, and affectivity. The results section presents the findings, and the discussion interprets these findings in light of their theoretical and practical implications.

Literature review and hypotheses

Perceived GenAI support and job crafting

Prior research has generally shown a positive effect of GenAI on job crafting. Li *et al.* (2024) noted a trickle-down effect, wherein leader job crafting affects employee engagement with AI through employee job crafting.

Vuong (2026) demonstrated that GenAI usage enhances job performance through job crafting and work engagement. However, there are boundary conditions affecting the link between AI and job crafting. Yan *et al.* (2025) identified harmonious passion as a mediator and perceived corporate social responsibility as a moderator linking GenAI awareness to job crafting. Wang *et al.* (2025) showed that although employees' opportunity perceptions of AI are positively related to job crafting, this relationship is weakened by threat perceptions of AI. Cheng *et al.* (2023) found that organizational AI adoption positively affects promotion-focused job crafting among employees with an internal locus of control by creating challenge appraisal. They also found that organizational AI adoption leads to prevention-focused job crafting among employees with an external locus of control by eliciting hindrance appraisal. Zhao *et al.* (2025) indicated that employees who perceive dependence on GenAI as a positive stimulus are more likely to engage in approach-oriented job crafting, whereas those who perceive such dependence as a negative stimulus tend to engage in avoidance-oriented job crafting. Similarly, Xu *et al.* (2026) reported that challenge appraisal toward AI indirectly promotes promotion-focused job crafting through creative process engagement, whereas hindrance appraisal toward AI indirectly promotes prevention-focused job crafting through job insecurity. These findings generally suggest that employees who perceive AI a positive stimulus engage in the approach form of job crafting, whereas employees who consider AI a negative stimulus prefer the avoidance form of job crafting. As prior work mainly focused on opportunity/challenge versus threat/hindrance perceptions of AI, knowledge of the mediating and moderating processes underlying the relationship between perceived GenAI support and job crafting remains incomplete. To fill this gap, this study models self-efficacy toward GenAI as a mediator and GenAI usage as a moderator.

GenAI alleviates cognitive load by automating repetitive and standardized tasks while supporting the integration and application of large volumes of information and complementing employees' capabilities during task execution (Cui *et al.*, 2026; Oschinsky & Nguyen, 2025; Parvez *et al.*, 2025; Sigala *et al.*, 2024). These features allow GenAI to function as a job resource that provides temporal and cognitive flexibility and enhances employees' sense of control over their work (Xu *et al.*, 2026; Yuan, 2025).

Even within identical technological environments, GenAI may be experienced either as a supportive resource or as a job demand that intensifies

psychological strain, depending on employees' perceptions and usage patterns (Chuang *et al.*, 2025; Cui *et al.*, 2026; Yang *et al.*, 2026). This finding underscores the idea that the effects of GenAI are shaped less by its functional attributes than by how employees interpret and engage with it. Accordingly, GenAI is best understood as a context-dependent technology whose functional role is constructed through subjective experience rather than as a fixed automation tool (Amrollahi *et al.*, 2026; Przegalinska *et al.*, 2025). Building on this perspective, this study conceptualizes GenAI as a job resource that alleviates temporal and cognitive burdens and provides instrumental support during demanding tasks rather than as a technology that directly replaces human labor (Chuang *et al.*, 2025; Yuan, 2025). Central to this view is perceived GenAI support, which is defined as the extent to which employees perceive GenAI as providing task-related information and assistance (Tews *et al.*, 2013). Beyond mere technological availability, perceived GenAI support constitutes a critical instrumental resource that enhances task efficiency and motivates proactive behaviors, such as job crafting (Nobels, 2024; Wang & Chuang, 2024; Xu *et al.*, 2026).

Job crafting refers to employees' efforts to actively modify the task, relational, and cognitive boundaries of their jobs to better align with their strengths, motivations, and interests (Holúbek *et al.*, 2025). As a bottom-up change process, job crafting requires additional effort and resource investment, as individuals deliberately move beyond prescribed job responsibilities (Bruning & Campion, 2018; Xu *et al.*, 2026). Consequently, perceptions of available resources become a crucial precondition for engaging in such behaviors (Lim *et al.*, 2025).

From the COR perspective, job crafting constitutes a form of resource investment behavior in which individuals deploy existing resources to acquire additional resources in the future (Lim *et al.*, 2025). Job crafting demands substantial time and cognitive effort; hence, it is more likely to occur when individuals perceive their resource reservoir as sufficient. COR theory posits that individuals strive to acquire, maintain, and protect valued resources, and that resource sufficiency enables proactive and agentic behaviors, whereas resource loss elicits strain and defensiveness (Hobfoll, 1989). Perceived GenAI support functions as a job resource that secures temporal flexibility and cognitive energy, lowering the psychological costs associated with experimenting with new work methods (Cui *et al.*, 2026; Yuan, 2025). As employees perceive GenAI as supportive, they are likely to explore more efficient, challenging, or meaningful ways of performing their

jobs rather than relying on established routines (Cui *et al.*, 2026; Xu *et al.*, 2026). The time and effort saved by delegating repetitive tasks may also enable cognitive adjustments, such as reinterpreting the meaning of work or one's contribution within the organization (Sigala *et al.*, 2024; Zhao *et al.*, 2026).

The relationship between perceived GenAI support and job crafting can also be explained by SCT, which asserts that individuals' behavior is shaped through the reciprocal interaction among environmental factors, cognitive beliefs, and behavioral factors (Han *et al.*, 2025). Environmental support influences how individuals interpret their capabilities and opportunities for action within this framework. Perceived GenAI support facilitates an environmental condition that provides employees with information assistance, idea generation, and problem-solving support during task execution. When employees perceive GenAI as a reliable and supportive tool, they are more likely to view their work environment as enabling experimentation and exploration of alternative ways to perform tasks (Marimon *et al.*, 2025). Such supportive environmental cues can encourage employees to take the initiative to adjust their work processes and explore new approaches to accomplish their tasks. Employees who perceive higher levels of GenAI support are likelier to engage in job crafting by modifying aspects of their jobs to improve effectiveness and aligning their work with their strengths and preferences. Accordingly, perceived GenAI support is expected to be positively related to job crafting. Based on this reasoning, we propose the following hypothesis:

Hypothesis 1: *Perceived GenAI support is positively related to job crafting.*

Self-efficacy toward GenAI as a mediator between GenAI support and job crafting

Self-efficacy refers to an individual's belief in his or her ability to perform specific tasks successfully and represents a core psychological resource that shapes effort, persistence, and behavioral choices under conditions of uncertainty (Bandura, 1997). By enhancing motivation and resilience, self-efficacy provides a foundation for proactive responses to environmental change. Extending this concept to AI-enabled work, we define self-efficacy toward GenAI as a domain-specific psychological resource, conceptually distinct from general self-efficacy (Wang & Chuang, 2024; Xu *et al.*, 2026). This construct reflects employees' belief that they can effective-

ly collaborate with GenAI to accomplish work tasks in a controllable and capable manner despite technological uncertainty. In this sense, self-efficacy toward GenAI embodies the belief that one can execute tasks using GenAI while maintaining control over the work process and fulfilling role expectations.

From a COR theory perspective, employees' behavior is shaped less by objective environmental conditions than by their subjective assessments of available resources and their overall resource configuration (Hobfoll, 1989). A key principle of COR theory is the resource caravan, which emphasizes that resources accumulate and function synergistically through interactions between environmental support and personal resources (Fletcher & Lysova, 2026). Accordingly, job resources facilitate proactive behavior only when internalized and transformed into personal psychological resources. Self-efficacy is critical in this process because it influences how individuals interpret and respond to change (Siddiqi *et al.*, 2025). Given COR theory's emphasis on the primacy of resource loss, employees are typically more sensitive to potential losses than to equivalent gains. Thus, self-efficacy acts as a cognitive filter through which employees determine whether GenAI represents a threat to existing resources or an opportunity for resource acquisition (Chuang *et al.*, 2025; Xu *et al.*, 2026). When employees experience GenAI as reducing workload pressure and assisting with complex problem-solving, they are more likely to construe the technological environment as supportive of resource gain rather than as a potential source of loss (Chuang *et al.*, 2025; Xu *et al.*, 2026). GenAI becomes integrated into individuals' resource caravans through repeated supportive experiences and shifts from being an external, uncontrollable technology to an accessible, reliable work resource. Once established, self-efficacy toward GenAI expands the range of feasible resource investment behaviors, particularly job crafting (Xu *et al.*, 2026).

From an SCT perspective, perceived support from GenAI can function as an important environmental factor (Han *et al.*, 2025; Hu *et al.*, 2025). When employees perceive that GenAI tools effectively assist them in generating ideas, solving problems, or completing tasks more efficiently, they are likely to develop stronger confidence in their ability to utilize these technologies in their work (Xu *et al.*, 2026). Such experiences can strengthen self-efficacy toward GenAI because employees perceive that they possess the capability to integrate GenAI into their task performance. Higher self-efficacy encourages employees to engage in job crafting behaviors that

improve their work effectiveness (Ramadhani *et al.*, 2025). Employees who believe they can effectively use GenAI are more likely to experiment with new approaches, adjust task boundaries, and proactively redesign aspects of their jobs (Xu *et al.*, 2026). Accordingly, employees with higher self-efficacy toward GenAI are more likely to leverage AI capabilities to reshape how they perform their work. Thus, based on COR theory and SCT, we propose the following mediation:

Hypothesis 2: *Self-efficacy toward GenAI mediates the positive relationship between perceived GenAI support and job crafting.*

Moderation of GenAI on the relationship between perceived Gen AI support, self-efficacy toward GenAI, and job crafting

COR theory distinguishes resource availability, the objective presence of support, from resource activation, the extent to which individuals engage with and extract value from that support (Hobfoll, 1989). Therefore, perceiving technological support is necessary but insufficient for developing personal resources. Transforming environmental support into a psychological capability relies on repeated and intentional usage experiences, which allow employees to test, refine, and appropriate the resource in practice (Wang & Chuang, 2024).

This activation process is particularly salient for emerging technologies such as GenAI, in which novelty and ambiguity heighten sensitivity to potential resource loss. COR theory emphasizes that individuals weigh prospective losses more heavily than equivalent gains, leading them to perceive the learning costs, trial-and-error processes, and time investments associated with new systems as threats to their existing resource pools (Qian *et al.*, 2025). Frequent and routine GenAI usage mitigates these concerns by promoting experiential learning and increasing the predictability of technological outputs (Oschinsky & Nguyen, 2025; Yang *et al.*, 2026). Sustained engagement enables employees to develop a more accurate understanding of GenAI's functional boundaries, reliability, and task relevance, which reduces uncertainty about the returns on their resource investments. Consequently, perceived GenAI support is more likely to be interpreted as a stable and dependable resource rather than as a provisional or ambiguous aid (Chuang *et al.*, 2025; Yang *et al.*, 2026).

The resource caravan perspective clarifies the mechanism underlying this moderating role. Resources operate in interconnected systems in which

repeated activation strengthens the linkages among environmental, cognitive, and motivational resources (Fletcher & Lysova, 2026). Employees who frequently engage with GenAI are more likely to integrate technological support into their broader resource system, allowing it to function as an extension of cognitive capacity rather than as an external aid (Cui *et al.*, 2026; Przegalinska *et al.*, 2025). The psychological association between perceived GenAI support and self-efficacy toward GenAI becomes stronger and more enduring through repeated activation cycles (Wang & Chuang, 2024). Conversely, infrequent or sporadic use leaves perceived support as a latent resource weakly connected to the individual's internal resource reservoir. Without sufficient opportunities for experiential learning and mastery, perceptions of support may remain abstract and fail to translate into the confidence needed to exercise control over AI-enabled work processes.

A central premise of SCT is that individuals develop beliefs about their capabilities through interactions with environmental resources and experiences gained from performing behaviors (Han *et al.*, 2025). From this perspective, self-efficacy is shaped by mastery experiences—individuals' direct experiences of performing a behavior strengthen their confidence in their ability to perform that behavior successfully. This theory suggests that the extent to which environmental resources translate into stronger self-efficacy depends on individuals' behavioral experiences with the focal activity (Han *et al.*, 2025). Specifically, employees with higher levels of GenAI usage accumulate more direct experiences in interacting with GenAI systems. Through repeated use, employees gain opportunities to test AI-generated outputs, refine prompts, and complete tasks successfully with AI assistance. These mastery experiences reinforce employees' beliefs that they can effectively leverage GenAI in their work (Han *et al.*, 2025). Consequently, when employees frequently use GenAI, the supportive features of the technology are more salient and interpretable, allowing perceived GenAI support to enhance self-efficacy toward GenAI (Chuang *et al.*, 2025; Cui *et al.*, 2026; Xu *et al.*, 2026; Zhang *et al.*, 2026). Conversely, when GenAI usage is low, employees have limited opportunities to experience successful interactions with AI systems. Without sufficient behavioral experience, employees may find it difficult to translate perceived technological support into stronger beliefs about their capabilities. Thus, the positive relationship between perceived GenAI support and self-efficacy toward GenAI should

be weaker when GenAI usage is low. Based on this reasoning, the following hypothesis is proposed:

Hypothesis 3: GenAI usage moderates the positive relationship between perceived GenAI support and self-efficacy toward GenAI, such that this relationship is stronger when GenAI usage is high than when it is low.

As described earlier, perceived GenAI support functions as a job resource that enhances self-efficacy toward GenAI, a personal psychological resource, facilitating resource investment behaviors such as job crafting (Xu *et al.*, 2026). COR theory emphasizes that the effectiveness of these accumulation processes depends on contextual conditions that determine whether and how resources are mobilized and transformed (Fletcher & Lysova, 2026). Thus, we identify GenAI usage as a critical boundary condition that governs the strength of the resource gain spiral that links perceived support, self-efficacy, and job crafting.

According to SCT, when GenAI usage is high, employees accumulate mastery experiences by repeatedly translating organizational support into tangible task accomplishments through frequent interactions with the technology (Wang & Chuang, 2024). These repeated experiences reduce uncertainty about GenAI's reliability and effectiveness, clarifying the pathway through which perceived support is transformed into self-efficacy. Drawing on findings that self-efficacy is a key predictor of job crafting (Lin *et al.*, 2025; Oprea *et al.*, 2024; Xu *et al.*, 2026), higher self-efficacy toward GenAI fuels employees to adjust and redesign aspects of their work proactively and results in increased job crafting (Chuang *et al.*, 2025; Przegalinska *et al.*, 2025). Conversely, sporadic GenAI usage limits experiential learning and mastery experiences, which reduces the likelihood that external support is fully internalized into efficacious beliefs. This weak internalization hampers the formation of self-efficacy toward GenAI and diminishes the psychological energy required to initiate behavioral change (Qian *et al.*, 2025). Consequently, even when employees recognize the presence of GenAI support, the indirect effect of perceived support on job crafting through self-efficacy is expected to be weaker when GenAI usage is low. Based on these arguments, the following hypothesis is proposed:

Hypothesis 4: GenAI usage moderates the indirect effect of perceived GenAI support on job crafting through self-efficacy toward GenAI, such that this indirect effect is stronger when GenAI usage is high than when it is low.

This study employs a two-wave, time-lagged design to test the mediating role of self-efficacy toward GenAI, addressing empirical gaps in the literature. In the interest of methodological rigor, we performed multiple logistic regressions to rule out attrition bias and tested an alternative model to validate our structural paths. This confirmed that GenAI usage is more appropriate as a boundary condition than as a primary driver. Furthermore, this study accounts for heterogeneous characteristics across diverse industries (e.g., manufacturing, ICT, and services) and variations in GenAI tool types (free versus paid) to enhance the generalizability of our findings. This research design provides a robust empirical framework that effectively addresses the sample constraints and causal ambiguity prevalent in existing GenAI studies by demonstrating the non-significance of alternative causal relationships.

Method

Sample and procedure

We recruited full-time employees through a South Korean online panel platform. Consistent with prior research demonstrating the validity and low non-response bias of online panels (Daly & Natarajan, 2015; Miller *et al.*, 2017), this study employed a convenience sampling technique through an online platform (Lee *et al.*, 2022; Zhang & Sackett, 2023). Screening questions on employment status, job tenure, and job type identified eligible respondents, resulting in an initial sample of 302 employees who had used ChatGPT for at least three months and had held their current positions for at least one year. This approach allowed the inclusion of respondents from diverse industries, including manufacturing, trade and distribution, ICT and telecommunications, banking and finance, bio-healthcare, and services. Eligible employees received an informed consent form via email that explained the study's purpose and assured voluntary participation, anonymity, and confidentiality. A survey link was provided to those who consented.

We conducted two-wave online surveys administered three months apart to examine the time-lagged relationship between perceived GenAI support and job crafting through self-efficacy toward GenAI. Of the 399 employees who initially agreed to participate, 302 completed the Time 1 survey (November 2023), which measured perceived GenAI support, GenAI usage, self-efficacy toward GenAI, positive affectivity (PA), negative affectivity (NA), and demographic characteristics. At Time 2 (January 2024), these respondents were invited to report their job crafting. The responses were matched across waves using email addresses, yielding a final sample of 202 respondents (50.1% response rate).

Notably, 53% of the respondents were female, with a mean age of 35.42 years ($SD = 6.44$) and an average job tenure of 5.80 years ($SD = 4.70$). Respondents represented multiple industries: manufacturing (28.2%), ICT and telecommunications (27.7%), services (17.3%), trade and distribution (5.4%), banking and finance (5.5%), bio-healthcare (5.4%), and others (10.4%). Most respondents held a bachelor's degree (72.0%), followed by graduate degrees (14.9%) and high school diplomas (5.9%). Moreover, 73% of the respondents utilized the free version of GenAI, and the remainder paid for the fee-based version.

We used multiple logistic regression analyses, in accordance with previous studies, to evaluate potential attrition bias (Li *et al.*, 2022; Pek *et al.*, 2018). In this model, dropout status was the binary dependent variable, and the predictors included sex, age, GPT type, job tenure, PA, NA, perceived GenAI support, and GenAI usage. The non-significant coefficients for these predictors suggested that the missing data were random, reducing concerns that non-response bias affected the validity of the findings.

Measures

Except for GenAI usage, all measurement items were rated on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree; see Appendix). As shown in Table 1, Cronbach's alpha values for the study variables ranged from .82 to .86, exceeding the recommended reliability threshold of .70 (Nunnally, 1978).

Perceived GenAI support was assessed using six items adapted from established instrumental support scales (Settoon & Mossholder, 2002; Tews *et al.*, 2013). Self-efficacy toward GenAI was measured using the five-item scale developed by Tojib *et al.* (2022). Job crafting was measured using

Bindl *et al.*'s (2019) 12-item scale. This measure represents three distinct yet interrelated dimensions: task crafting (4 items; e.g., taking on additional tasks), relational crafting (4 items; e.g., expanding social interactions at work), and cognitive crafting (4 items; e.g., reframing the purpose of work). Scores across these three dimensions were averaged to produce a composite job crafting index ($\alpha = .82$), following established procedures (Hur & Shin, 2023; Hur *et al.*, 2024; Sekiguchi *et al.*, 2017).

GenAI usage was operationalized as the proportion of work time devoted to GenAI-related activities. Unlike Likert-scaled constructs, GenAI usage was operationalized as a ratio variable (0 to 1) to capture the intensity of GenAI integration. Respondents reported (a) the total number of hours spent using a GenAI tool (i.e., ChatGPT) for work purposes during a typical workweek and (b) their total working hours during the same period. GenAI usage was calculated as the ratio of GenAI-related hours to total working hours, standardizing usage relative to actual work engagement. This approach enables meaningful comparisons across employees with differing schedules and workloads, consistent with prior research on telework and technology use (Chin *et al.*, 2023; Golden & Eddleston, 2020; Golden & Veiga, 2005; Golden *et al.*, 2008; Hwang *et al.*, 2025), with higher values indicating greater GenAI usage.

Control variables included demographic characteristics owing to their potential associations with self-efficacy toward GenAI and job crafting (Hur *et al.*, 2022; Hwang *et al.*, 2025; Park & Hur, 2025). Age and job tenure were operationalized as continuous variables using a ratio scale. Gender (0 = female, 1 = male) and GPT type (0 = free, 1 = paid) were included as dummy variables. Additionally, six industry dummy variables were included to account for industry effects, consistent with prior studies (Hur & Shin, 2025; Hwang *et al.*, 2025). PA and NA were also controlled to mitigate common method variance, measured using six items from Watson *et al.* (1988).

Analytic strategy

The proposed mediation, moderation, and moderated mediation effects were tested using path modeling with the Mplus PROCESS macro (model numbers = 0: total effect; 1: moderation effect; 4: mediation effect; and 7: moderated mediation effect; Stride *et al.*, 2015). Continuous variables were mean-centered prior to hypothesis testing (Hayes, 2022, pp. 320–329). Gen-

der, GPT type, and industry-effect variables were used as dummy variables. Mediation and moderated mediation effects were estimated using a statistical resampling method (bootstrapping; $N = 5,000$; Hayes, 2022, pp. 99–100).

Results

Reliability and validity

Table 1 presents the descriptive statistics and correlations among the study variables. To evaluate the psychometric properties of the measurement model, we conducted a confirmatory factor analysis using Mplus 8.10 (Muthén & Muthén, 2017). The results indicated that the proposed five-factor model—comprising PA, NA, perceived GenAI support, self-efficacy toward GenAI, and job crafting—provided an acceptable fit to the data ($\chi^2(364) = 682.29$, $p < .05$; comparative fit index [CFI] = .90; Tucker–Lewis index [TLI] = .90; root mean square error of approximation [RMSEA] = .07; standardized root mean square residual [SRMR] = .06). These findings support the adequacy of the measurement structure. As shown in Table 1, all constructs demonstrated satisfactory composite reliability values ranging from .84 to .87, exceeding the recommended threshold of .70 (Nunnally, 1978). Moreover, the average variance extracted for each construct surpassed the squared correlations between that construct and the others, satisfying the Fornell–Larcker criterion for discriminant validity (Fornell & Larcker, 1981). These results indicate that the measures exhibit adequate reliability, convergent validity, and discriminant validity.

As all variables were reported by the same respondents, common method variance could potentially bias the observed relationships (Podsakoff *et al.*, 2012). We conducted Harman’s single-factor test to assess this possibility. The results showed that the proposed measurement model provided a substantially better fit to the data than the single-factor model in which all items loaded onto one latent factor ($\chi^2(377) = 2154.30$, $p < .05$; CFI = .46; TLI = .41; RMSEA = .15; SRMR = .15; $\Delta\chi^2(13) = 1536.73$, $p < .01$). Furthermore, we estimated a latent common method factor (LCMF) by allowing all measurement items in the baseline model to load simultaneously onto their theoretical constructs and a common latent factor. The LCMF explained less than 6.1% of the total variance, well below the 25% median method

variance typically reported in studies relying on self-reported data (Williams *et al.*, 1989). Collectively, these findings indicate that common method variance is unlikely to pose a serious threat to the validity of the study's results.

Hypothesis testing

Hypothesis 1 suggested that perceived GenAI support is positively related to job crafting. Controlling for gender, age, job tenure, ChatGPT type, six industry dummies, PA, and NA, the total effect of perceived GenAI support on job crafting was significant ($b = .15$, $p < .05$; see Table 2), supporting Hypothesis 1.

Hypothesis 2 stated that the positive association between perceived GenAI support and job crafting is mediated by self-efficacy toward GenAI. Mediation analysis indicated that self-efficacy toward GenAI significantly mediated the association between perceived GenAI support and job crafting ($b = .105$, 95% CI [.017, .205]; see Table 2), supporting Hypothesis 2. Notably, the direct effect was non-significant ($b = .047$, $p > .05$), indicating a full mediation process. To evaluate the practical significance, we calculated the ratio of mediation (i.e., indirect effect/total effect) and found that 69.1% of the effect of GenAI support on job crafting was channeled through self-efficacy toward GenAI, confirming the substantial role of the mediator in our theoretical framework.

Hypothesis 3 postulated that GenAI usage moderates the positive effect of perceived GenAI support on self-efficacy toward GenAI. Supporting Hypothesis 3, GenAI usage significantly strengthened the positive association between perceived GenAI support and self-efficacy toward GenAI ($b = .60$, $p < .05$; see Table 3). This interaction was plotted at high and low levels of the moderator (± 1 SD; Aiken & West, 1991). As illustrated in Figure 1, the positive relationship between perceived GenAI support and self-efficacy toward GenAI was significant for employees with high GenAI usage ($b = .64$, $p < .01$) and those with low GenAI usage ($b = .41$, $p < .01$). The slope for the high-usage group was significantly steeper than that for the low-usage group.

Hypothesis 4 proposed that the indirect effect of perceived GenAI support on job crafting through self-efficacy toward GenAI varies depending on the level of GenAI usage. As depicted in Table 3, the moderated mediation effect of GenAI usage was significant ($b = .116$, 95% CI [.015, .296]).

This finding indicates that the positive indirect effect of perceived GenAI support on job crafting through self-efficacy toward GenAI is more pronounced under high GenAI usage compared with low GenAI usage. The results of the hypothesis testing are summarized in Figure 2.

Tests of alternative models

To assess the robustness of the hypothesized model, we tested two alternative models, particularly because all variables, except for job crafting (Time 2), were measured at Time 1. First, an alternative mediation path (self-efficacy toward GenAI → perceived GenAI support → job crafting) was analyzed, but the results showed no significant mediation effect ($b = .025$, 95% CI $[-.065, .118]$), supporting our original assumption that organizational support precedes psychological resources. Second, when GenAI usage was included as an additional independent variable, the original path from perceived GenAI support to job crafting through self-efficacy toward GenAI remained significant ($b = .095$, 95% CI $[.012, .191]$). However, the path from GenAI usage to job crafting through self-efficacy toward GenAI was not significant ($b = .028$, 95% CI $[-.005, .208]$). These findings confirm that GenAI usage is more appropriate as a boundary condition than a primary driver, reinforcing the structural validity and empirical superiority of the proposed model.

Discussion

This study examined the mediating role of self-efficacy in the relationship between perceived GenAI support and job crafting, as well as the moderating effect of GenAI usage on this relationship. Hypothesis testing supported all the proposed relationships. Perceived GenAI support was positively associated with job crafting measured three months later, and this relationship was mediated by self-efficacy toward GenAI. Moreover, GenAI usage strengthened the positive effect of perceived GenAI support on self-efficacy and the indirect effect of perceived support on job crafting through self-efficacy. These findings have important theoretical and practical implications for future research.

Theoretical implications

This study makes several theoretical contributions to the literature on GenAI and job crafting by clarifying the psychological and contextual conditions under which GenAI fosters proactive job redesign. Although research on GenAI has rapidly expanded, prior work has primarily focused on productivity and performance outcomes, with limited attention paid to job crafting as a key adaptive behavior in AI-enabled work contexts. Research on AI and job crafting has largely focused on examining the effects of opportunities or challenges versus threats or hindrance perceptions of GenAI on job crafting (Cheng *et al.*, 2023; Wang *et al.*, 2025; Xu *et al.*, 2026; Zhao *et al.*, 2025), leaving the underlying mechanisms of this relationship insufficiently explained. This study addresses this gap by identifying self-efficacy toward GenAI as a central mediating mechanism and GenAI usage as a key boundary condition in the GenAI–job crafting relationship. These findings offer initial empirical evidence of the mediating role of GenAI self-efficacy and the moderating role of GenAI usage in shaping job crafting in AI-enabled work contexts.

Our findings indicated full mediation wherein the relationship between perceived GenAI support and job crafting became non-significant when GenAI self-efficacy was included in the model. This mediation effect was further validated through tests of alternative models, which showed that the proposed mediation model was more viable than the alternative causal models. Although perceived GenAI support is associated with job crafting at the bivariate level, its effect operates through employees' confidence in their ability to collaborate effectively with GenAI. This finding highlights the pivotal role of domain-specific self-efficacy in job crafting. By fostering a belief in performability and control over AI-assisted work processes, self-efficacy toward GenAI empowers employees to modify task scope, content, methods, and scheduling proactively. Thus, this study enriches job crafting theory by identifying a technology-specific psychological mechanism through which external support is translated into proactive work redesign.

This study helps reconcile the mixed findings in the literature on GenAI and work outcomes. Some studies portray GenAI as a source of efficiency and work redesign, whereas others emphasize its negative consequences, including technostress and reduced perceived control (Chuang *et al.*, 2025; Cui *et al.*, 2026; Duong *et al.*, 2025; Yang *et al.*, 2026). By conceptualizing perceived GenAI support as a focal antecedent, this study shifts the theo-

retical emphasis from the technological properties of GenAI to employees' subjective interpretations and experiences. The present findings suggest that GenAI positively affects proactive behavior when perceived as genuinely supportive of task execution. This perspective explains why GenAI may function as a resource in some contexts but as a demand in others, helping to reconcile previously inconsistent findings.

This study offers a detailed understanding of the role of GenAI support by highlighting the interactive roles of GenAI support and usage. The results show that the positive effect of perceived GenAI support on self-efficacy and its positive effect on job crafting through self-efficacy are stronger when employees frequently use GenAI. This suggests that perceived support alone is insufficient to stimulate proactive behavior unless it is activated through repeated use. This underscores the theory that GenAI usage is a critical condition that enables perceived support to be internalized as a psychological resource. Without sustained engagement, GenAI support remains weakly connected to employees' resource systems, limiting its behavioral consequences. The findings provide empirical support for COR theory's resource caravan principle by showing how technological resources are converted into psychological resources that motivate resource investment behaviors such as job crafting. Additionally, this study is one of the first attempts to apply SCT to an AI-powered work environment by proposing perceived GenAI support as an environmental factor, GenAI usage as a behavioral response, and GenAI self-efficacy as an efficacy belief. By demonstrating that self-efficacy is shaped by the interplay between perceived GenAI support and GenAI usage, this study confirms the relevance of SCT in understanding adaptation to AI-augmented work environments.

This study contributes to the broader literature on self-efficacy by emphasizing the importance of domain-specific self-efficacy in technology-rich contexts. Prior job crafting research has primarily relied on generalized self-efficacy (Miraglia *et al.*, 2027; van den Heuvel *et al.*, 2015), whereas the present findings show that self-efficacy toward GenAI plays a distinct and consequential role in shaping proactive behavior. This suggests that research on AI-enabled work should move beyond generalized confidence beliefs and incorporate task- and technology-specific self-efficacy constructs. By identifying self-efficacy toward GenAI as a key psychological mechanism, this study deepens the theoretical understanding of how em-

employees adapt to AI integration and provides a more precise framework for examining proactive behavior in human–AI collaboration.

Another important consideration relates to the contextual conditions to which our findings may apply. As the data were collected from employees in South Korea, a country with a relatively advanced digital infrastructure and rapid adoption of GenAI (Jeong, 2025), the observed relationships may differ in contexts in which technological development and AI usage are less widespread. In countries where AI adoption is emerging, employees may have fewer opportunities to interact with GenAI in their daily work, limiting the development of GenAI self-efficacy through mastery experience. Consequently, perceived GenAI support may translate less strongly into job crafting. Furthermore, the meaning of self-efficacy and job crafting may differ between individualistic and collectivistic cultures. Employees in collectivist cultures (e.g., South Korea), in which group harmony and conformity are emphasized, may approach AI use in ways that align with group expectations and collaborative practices (Naiseh *et al.*, 2025). Such orientations may influence how self-efficacy toward AI develops into job crafting, potentially differing from patterns observed in more individualistic cultures that emphasize personal autonomy and independent initiative (Chi *et al.*, 2023).

Practical implications

The findings offer several practical implications for organizations aiming to leverage GenAI as a sustainable driver of employee effectiveness and proactive work behavior. First, organizations should shift their focus from mere GenAI adoption to the cultivation of perceived GenAI support. The importance of perceived GenAI support highlights that investment in GenAI infrastructure alone might not be sufficient. Managers should emphasize use cases in which GenAI demonstrably reduces cognitive burden, accelerates problem solving, or supports complex decision making. Clear communication on GenAI's ability to assist employees in their specific roles can strengthen their perceptions of support and reduce ambiguity regarding its value. Framing GenAI as a work companion that enhances employees' control over task execution may help them interpret the technology as a resource rather than as an additional demand.

Second, our mediation analysis highlights the central role of employees' psychological readiness in realizing the benefits of GenAI in the workplace.

The mediation ratio indicates that a substantial proportion of the influence of perceived GenAI support on job crafting operates through employees' self-efficacy toward GenAI—organizations cannot rely solely on providing access to AI technologies to stimulate proactive work redesign. Instead, the effectiveness of GenAI largely depends on whether employees develop confidence in their ability to use these tools effectively. Accordingly, managers should focus on implementing GenAI systems and strengthening employees' self-efficacy toward GenAI through training, guided experimentation, and opportunities for successful AI-assisted task completion. Programs that allow employees to gain mastery experiences with GenAI (e.g., hands-on workshops, peer learning, and sharing of effective use cases) may help employees internalize AI as a personal capability.

Third, the moderating role of GenAI usage suggests that organizations should actively encourage frequent and routine engagement with GenAI in their daily work processes. The findings indicate that GenAI support translates more effectively into self-efficacy and job crafting when employees use the technology consistently. Managers can facilitate this by embedding GenAI into standard workflows rather than positioning it as an optional or peripheral tool. For example, integrating GenAI into document preparation, data analysis, or problem-solving routines can normalize its use and increase the predictability of its output. This routinization reduces uncertainty and learning-related stress, which are key barriers to proactive behavior in technology-rich environments.

Finally, from a broader organizational perspective, GenAI implementation strategies should be aligned with job design and employee development initiatives. Job crafting has emerged as a key behavioral outcome through which GenAI contributes to adaptive work redesign. Organizations that allow flexibility in task execution, encourage autonomy, and reward proactive improvement efforts are more likely to realize the benefits of GenAI-enabled work. Viewing GenAI as part of an integrated resource system rather than as a standalone technology can foster continuous learning, resilience, and innovation in AI-augmented work environments. Managers should recognize and legitimize employees' efforts to experiment with GenAI, even when such experimentation involves initial inefficiencies or trial and error. By signaling tolerance for learning costs and encouraging reflection on how GenAI can improve work processes, managers can help employees reinterpret experimentation as a worthwhile investment rather than a risky diversion. Such a supportive climate ampli-

fies the motivational impact of self-efficacy and promotes job-crafting behaviors that enhance long-term adaptability.

Limitations and directions for future research

Despite its theoretical and practical contributions, this study has several limitations that suggest directions for future research. First, although a two-wave research design was employed, perceived GenAI support, GenAI usage, and self-efficacy toward GenAI were concurrently measured. This design constraint limits the ability to draw strong causal conclusions regarding the relationships among these variables. It is plausible that employees with higher self-efficacy toward GenAI are more likely to perceive GenAI as supportive, or that frequent GenAI use itself shapes perceptions of support. Although our test of alternative models showed that the proposed causal model is more viable than the others, the directionality of our model should be interpreted with caution. Future research could address this limitation by adopting three-wave longitudinal panel designs that temporally separate perceptions, psychological resources, and behavioral outcomes. Experimental or policy-capturing approaches that manipulate exposure to GenAI support or usage conditions can provide strong causal evidence.

Second, this study operationalized GenAI usage primarily through usage intensity, measured as the proportion of work time dedicated to AI tools. Although this approach provides a robust behavioral indicator of the extent of AI integration and helps mitigate common method variance by utilizing a ratio-scale format, it may not fully capture the qualitative nuances of engagement. Gao *et al.* (2026) conceptualized AI usage as a multi-dimensional construct comprising two distinct dimensions: usage intensity (i.e., the frequency and duration of use) and usage diversity (i.e., the range of different AI tools and functions employed). Although our study focused on the intensity dimension to establish a clear behavioral anchor for resource investment, it did not account for the diversity of tools. Future research should incorporate both dimensions, as proposed by Gao *et al.* (2026), to investigate how the sophistication and variety of AI interaction—beyond mere time investment—differentially influence employee outcomes.

Third, this study focused on the instrumental support provided by GenAI, such as task assistance and information processing, and excluded

potential emotional support functions. GenAI can also provide emotional reassurance through counseling-like interactions and help alleviate stress (Pani *et al.*, 2024; Volpato *et al.*, 2025). Investigating whether and how emotional support from GenAI influences different forms of job crafting, particularly relational and cognitive crafting, is a promising avenue for future research. Comparative analyses of instrumental versus emotional GenAI support may further clarify their distinct and interactive effects.

Fourth, although this study focused on ChatGPT owing to its widespread recognition and adoption, the diversity of the GenAI ecosystem suggests that reliance on a single tool may have influenced the participants' perceptions. We recommend that future research examine a broader range of GenAI platforms (e.g., Claude, Gemini, Perplexity, and Llama) to assess the generalizability of our findings across diverse GenAI contexts.

Finally, this study relied on a convenience sample, which may constrain the generalizability of the findings beyond the specific context in which the data were collected. Because convenience sampling does not ensure that participants are representative of the broader population, the observed relationships may not fully capture how employees in different cultural, institutional, or organizational settings respond to AI and GenAI usage. In particular, employees' perceptions, attitudes, and behavioral responses to AI may vary systematically across countries due to differences in cultural values, technological infrastructure, and regulatory environments. Likewise, variation across industries and job positions—such as differences in task complexity, autonomy, and exposure to AI technologies—may shape how employees experience and utilize GenAI in their work. To address this issue, we encourage future researchers to collect data across diverse countries, industries, and occupational groups.

Conclusions

This study demonstrates that the effectiveness of GenAI in shaping employee behavior depends not only on technological availability but also on how such support is psychologically internalized and behaviorally activated. Specifically, perceived GenAI support promotes proactive job crafting, primarily through the development of self-efficacy toward GenAI, and this resource conversion process is strengthened when employees engage in frequent GenAI usage. By integrating mediation and moderated mediation

within a COR framework, the findings illuminate how external technological resources are transformed into personal psychological capabilities that drive adaptive work redesign in human–AI collaboration contexts. Overall, this study advances the theoretical understanding of employee adaptation in AI-enabled workplaces and highlights the importance of cultivating perceived support, domain-specific self-efficacy, and sustained usage to realize the transformative potential of GenAI in organizations.

References

- Aiken, L. S., & West, S. G. (1991). *Multiple regression: Testing and interpreting interactions*. Sage.
- Amrollahi, A., Yang, J., Fazal-e-Hasan, S. M., & Badreddine, B. (2026). Knowledge workers' trust and reception of generative AI's advice in complex tasks. *International Journal of Information Management*, 88, 103031. <https://doi.org/10.1016/j.ijinfomgt.2026.103031>.
- Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Prentice-Hall.
- Bandura, A. (1997). *Self-efficacy: The exercise of control*. W. H. Freeman.
- Bindl, U. K., Unsworth, K. L., Gibson, C. B., & Stride, C. B. (2019). Job crafting revisited: Implications of an extended framework for active changes at work. *Journal of Applied Psychology*, 104(5), 605–628. <https://doi.org/10.1037/apl0000362>.
- Bruning, P. F., & Campion, M. A. (2018). A role-resource approach-avoidance model of job crafting: A multimethod integration and extension of job crafting theory. *Academy of Management Journal*, 61(2), 499–522. <https://doi.org/10.5465/amj.2015.0604>.
- Brynjolfsson, E., Li, D., & Raymond, L. R. (2025). Generative AI at Work. *Quarterly Journal of Economics*, 140(2), 889–942. <https://doi.org/10.1093/qje/qjae044>.
- Cheng, B., Lin, H., & Kong, Y. (2023). Challenge or hindrance? How and when organizational artificial intelligence adoption influences employee job crafting. *Journal of Business Research*, 164, 113987. <https://doi.org/10.1016/j.jbusres.2023.113987>.
- Chi, O. H., Chi, C. G., Gursoy, D., & Nunkoo, R. (2023). Customers' acceptance of artificially intelligent service robots: The influence of trust and culture. *International Journal of Information Management*, 70, 102623. <https://doi.org/10.1016/j.ijinfomgt.2023.102623>.
- Chin, T., Shi, Y., Del Giudice, M., Meng, J., & Xing, Z. (2023). Working from anywhere: Yin-yang cognition paradoxes of knowledge sharing and hiding for developing careers in China. *Humanities and Social Sciences Communications*, 10(1), 1–10. <https://doi.org/10.1057/s41599-023-01744-5>.

- Chuang, Y. T., Chiang, H. L., & Lin, A. P. (2025). Insights from the job demands-resources model: AI's dual impact on employees' work and life well-being. *International Journal of Information Management*, 83, 102887. <https://doi.org/10.1016/j.ijinfomgt.2025.102887>.
- Cui, S., Wang, L., Cao, W., & Zhu, T. (2026). Gain or loss? The dual effects of dependence on AI on employees' creativity. *International Journal of Information Management*, 87, 103001. <https://doi.org/10.1016/j.ijinfomgt.2025.103001>.
- Cramarencu, R. E., Burcă-Voicu, M. I., & Dabija, D. C. (2023). The impact of artificial intelligence (AI) on employees' skills and well-being in global labor markets: A systematic review. *Oeconomia Copernicana*, 14(3), 731–767. <https://doi.org/10.24136/oc.2023.022>.
- Dabija, D. C., & Vătămănescu, E.-M. (2023). Artificial intelligence: The future is already here. *Oeconomia Copernicana*, 14(4), 1053–1056. <https://doi.org/10.24136/oc.2023.031>.
- Daly, T. M., & Nataraajan, R. (2015). Swapping bricks for clicks: Crowdsourcing longitudinal data on Amazon Turk. *Journal of Business Research*, 68(12), 2603–2609. <https://doi.org/10.1016/j.jbusres.2015.05.001>.
- Duong, C. D., Ngo, T. V. N., Khuc, T. A., Tran, N. M., & Nguyen, T. P. T. (2025). Unraveling the dark side of Chat GPT: A moderated mediation model of technology anxiety and technostress. *Information Technology & People*, 38(4), 2015–2040. <https://doi.org/10.1108/ITP-11-2023-1151>.
- Fletcher, L., & Lysova, E. I. (2026). Addressing gender in authenticity and inclusion at work: Nuancing conservation of resources theory with social role theory. *Human Resource Management*, 65(1), 219–234. <https://doi.org/10.1002/hrm.70024>.
- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39–50. <https://doi.org/10.1177/002224378101800104>.
- Gao, X., Ding, Y., Zhang, H., Liang, W., & Zuo, R. (2026). The impact of AI usage, literacy and proactive innovation behavior on scholars' mental health. *Industrial Management & Data Systems*. <https://doi.org/10.1108/IMDS-05-2025-0593>.
- Golden, T. D., & Eddleston, K. A. (2020). Is there a price telecommuters pay? Examining the relationship between telecommuting and objective career success. *Journal of Vocational Behavior*, 116, 103348. <https://doi.org/10.1016/j.jvb.2019.103348>.
- Golden, T. D., & Veiga, J. F. (2005). The impact of extent of telecommuting on job satisfaction: Resolving inconsistent findings. *Journal of Management*, 31(2), 301–318. <https://doi.org/10.1177/0149206304271768>.
- Golden, T. D., Veiga, J. F., & Dino, R. N. (2008). The impact of professional isolation on teleworker job performance and turnover intentions. *Journal of Applied Psychology*, 93(6), 1412–1421. <https://doi.org/10.1037/a0012722>.
- Han, Z., Song, G., Zhang, Y., & Li, B. (2025). Trust the machine or trust yourself: How AI usage reshapes employee self-efficacy and willingness to take risks. *Behavioral Sciences*, 15(8), 1046. <https://doi.org/10.3390/bs15081046>.

- Hayes, A. F. (2022). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach* (3rd ed.). Guilford Press.
- Hobfoll, S. E. (1989). Conservation of resources: A new attempt at conceptualizing stress. *American Psychologist*, 44(3), 513–524. <https://doi.org/10.1037/0003-066X.44.3.513>.
- Holúbek, J., Durda, L., Maňák, R., & Rózsa, Z. (2025). Job crafting as a tool to support employee work assignment in the tourism sector: A systematic literature review. *Equilibrium. Quarterly Journal of Economics and Economic Policy*, 20(2), 549–582. <https://doi.org/10.24136/eq.3771>.
- Hu, X., Gao, H., Agafari, T., Zhang, M. Q., & Cong, R. (2025). How and when artificial intelligence adoption promotes employee knowledge sharing? The role of paradoxical leadership and technophilia. *Frontiers in Psychology*, 16, 1573587. <https://doi.org/10.3389/fpsyg.2025.1573587>.
- Hur, W. M., & Shin, Y. (2023). Is resting and sleeping well helpful to job crafting? *Applied Psychology*, 72(4), 1608–1623. <https://doi.org/10.1111/apps.12454>.
- Hur, W. M., & Shin, Y. (2025). Service robot risk awareness and customer-directed helping. *Journal of Retailing and Consumer Services*, 87, 104451. <https://doi.org/10.1016/j.jretconser.2025.104451>.
- Hur, W. M., Shin, Y., & Kim, J. Y. (2024). Service employees' mindfulness and job crafting amid COVID-19. *Current Psychology*, 43(18), 16979–16991. <https://doi.org/10.1007/s12144-023-04714-x>.
- Hur, W. M., Shin, Y., & Shin, G. (2022). Daily relationships between customer incivility, organizational control, self-efficacy, and service performance. *Journal of Retailing and Consumer Services*, 69, 103092. <https://doi.org/10.1016/j.jretconser.2022.103092>.
- Hwang, H., Hur, W. M., Shin, Y., & Paik, M. S. (2025). Work-from-home satisfaction and task crafting in South Korea. *Asia Pacific Business Review*, 31(1), 157–179. <https://doi.org/10.1080/13602381.2024.2363933>.
- Jeong, J. (2025). The innovative side of AI adoption in South Korea: How job crafting and technology self-efficacy influence employee innovative work behaviour. *Asia Pacific Business Review*. <https://doi.org/10.1080/13602381.2025.2562901>.
- Lazaroiu, G., & Rogalska, E. (2023). How generative artificial intelligence technologies shape partial job displacement and labor productivity growth. *Oeconomia Copernicana*, 14(3), 703–706. <https://doi.org/10.24136/oc.2023.020>.
- Lee, J., Oh, S. H., & Park, S. (2022). Effects of organizational embeddedness on unethical pro-organizational behavior: Roles of perceived status and ethical leadership. *Journal of Business Ethics*, 176, 111–125. <https://doi.org/10.1007/s10551-020-04661-8>.
- Li, Q., She, Z., & Gu, J. (2022). Managerial coaching and employee knowledge sharing: A daily diary study. *Journal of Occupational and Organizational Psychology*, 95(4), 821–845. <https://doi.org/10.1111/joop.12402>.

- Li, W., Qin, X., Yam, K. C., Deng, H., Chen, C., Dong, X., Jiang, L., & Tang, W. (2024). Embracing artificial intelligence (AI) with job crafting: Exploring trickle-down effect and employees' outcomes. *Tourism Management*, 104, 104935. <https://doi.org/10.1016/j.tourman.2024.104935>.
- Lim, V. K. G., Ng, J. X., & Teo, T. S. H. (2025). Psychological safety, job crafting, and future work self: The moderating effect of techno-stressors. *Information & Management*, 62(5), 104143. <https://doi.org/10.1016/j.im.2025.104143>.
- Lin, X., Jiao, R., Lu, D., et al. (2025). Coworker support and kindergarten teachers' job crafting: The chain mediating role of self-efficacy and work engagement. *Current Psychology*, 44, 3299–3312. <https://doi.org/10.1007/s12144-025-07379-w>.
- Marimon, F., Mas-Machuca, M., & Akhmedova, A. (2025). Trusting in generative AI: Catalyst for employee performance and engagement in the workplace. *International Journal of Human–Computer Interaction*, 41(11), 7076–7091. <https://doi.org/10.1080/10447318.2024.2388482>.
- Mayer, A. S., Baygi, R. M., & Buwalda, R. (2025). Generation AI: Job crafting by entry-level professionals. *Business and Information Systems Engineering*, 67(5), 595–613. <https://doi.org/10.1007/s12599-025-00959-x>.
- Miller, J. D., Crowe, M., Weiss, B., Maples-Keller, J. L., & Lynam, D. R. (2017). Using online, crowdsourcing platforms for data collection in personality disorder research: The example of Amazon's Mechanical Turk. *Personality Disorders: Theory, Research, and Treatment*, 8(1), 26–34. <https://doi.org/10.1037/per0000191>.
- Miraglia, M., Cenciotti, R., Alessandri, G., & Borgogni, L. (2017). Translating self-efficacy in job performance over time. *Human Performance*, 30(5), 254–271. <https://doi.org/10.1080/08959285.2017.1373115>.
- Muthén, L. K., & Muthén, B. O. (2017). *Mplus user's guide* (8th ed.). Muthén & Muthén.
- Naiseh, M., Babiker, A., Al-Shakhsi, S., Cemiloglu, D., Al-Thani, D., Montag, C., & Ali, R. (2025). Attitudes towards AI: The interplay of self-efficacy, well-being, and competency. *Journal of Technology in Behavioral Science*, 10, 705–718. <https://doi.org/10.1007/s41347-025-00486-2>.
- Nobels, J. (2024). *The impact of employee usage of generative AI on innovative work behavior* (Master's thesis). Tilburg University.
- Nunnally, J. C. (1978). *Psychometric theory* (2nd ed.). McGraw-Hill.
- Oprea, B., Oancea, D., & Avram, E. (2024). Ethical leadership and followers' job crafting: The mediating role of followers' role-breadth self-efficacy and work engagement. *Journal of Organizational Effectiveness: People and Performance*, 12(4), 908–920. <https://doi.org/10.1108/JOEPP-02-2024-0085>.
- Oschinsky, F. M., & Nguyen, T. P. T. (2025). Cognitive processes while using artificial intelligence at work: A research agenda on challenges and opportunities. *Form@re – Open Journal per la Formazione in Rete*, 25(1), 203–222. <https://doi.org/10.36253/form-17122>.

- Pani, B., Crawford, J., & Allen, K. A. (2024). Can generative artificial intelligence foster belongingness, social support, and reduce loneliness? A conceptual analysis. In Lyu, Z. (Ed.). *Applications of generative AI*. Cham: Springer. https://doi.org/10.1007/978-3-031-46238-2_13.
- Park, H., & Hur, W. M. (2025). Unpacking social selling in financial services: The interplay of organizational support, social media self-efficacy, and sales technology orientation. *International Journal of Bank Marketing*, 43(9), 1990–2021. <https://doi.org/10.1108/IJBM-09-2024-0538>.
- Pek, J., Wong, O., & Wong, A. (2018). How to address non-normality: A taxonomy of approaches, reviewed, and illustrated. *Frontiers in Psychology*, 9, 398398. <https://doi.org/10.3389/fpsyg.2018.02104>.
- Parvez, M. O., Eluwole, K. K., Lasisi, T. T., & Kim, W. G. (2025). GenAI in hotel operations: Chat GPT adoption among front-office employees. *Current Issues in Tourism*. <https://doi.org/10.1080/13683500.2025.2498598>.
- Podsakoff, P. M., MacKenzie, S. B., & Podsakoff, N. P. (2012). Sources of method bias in social science research and recommendations on how to control it. *Annual Review of Psychology*, 63, 539–569. <https://doi.org/10.1146/annurev-psych-120710-100452>.
- Przegalińska, A., Triantoro, T., Kovbasiuk, A., Ciechanowski, L., Freeman, R. B., & Sowa, K. (2025). Collaborative AI in the workplace: Enhancing organizational performance through resource-based and task-technology fit perspectives. *International Journal of Information Management*, 81, 102853. <https://doi.org/10.1016/j.ijinfomgt.2024.102853>.
- Qian, J., Chen, J., & Zhao, S. (2025). Remaining vigilant while enjoying prosperity: How artificial intelligence usage impacts employees' innovative behavior and proactive skill development. *Behavioral Science*, 15(4), 465. <https://doi.org/10.3390/bs15040465>.
- Ramadhani, G. W. A., Suhariadi, F., Suyanto, B., et al. (2025). Forming innovative work behavior prospective police investigator through self-efficacy and job crafting in the post-COVID-19. *Discover Sustainability*, 6, 21. <https://doi.org/10.1007/s43621-025-00811-y>.
- Sekiguchi, T., Li, J., & Hosomi, M. (2017). Predicting job crafting from the socially embedded perspective: The interactive effect of job autonomy, social skill, and employee status. *Journal of Applied Behavioral Science*, 53(4), 470–497. <https://doi.org/10.1177/0021886317727459>.
- Settoon, R. P., & Mossholder, K. W. (2002). Relationship quality and relationship context as antecedents of person- and task-focused interpersonal citizenship behavior. *Journal of Applied Psychology*, 87(2), 255–267. <https://doi.org/10.1037/0021-9010.87.2.255>.
- Siddiqi, K. O., Rahman, M. H., Rahman, J., & Radulescu, M. (2025). Effect of perceived supervisor support, technological self-efficacy and technostress on nurses' turnover intention: A moderated mediation model. *Acta Psychologica*, 260, 105631. <https://doi.org/10.1016/j.actpsy.2025.105631>.

- Sigala, M., Ooi, K. B., Tan, G. W. H., Aw, E. C. X., Buhalis, D., Cham, T. H., & Ye, I. H. (2024). Understanding the impact of Chat GPT on tourism and hospitality: Trends, prospects and research agenda. *Journal of Hospitality and Tourism Management*, 60, 384–390. <https://doi.org/10.1016/j.jhtm.2024.08.004>.
- Stride, C. B., Gardner, S., Catley, N., & Thomas, F. (2015). Mplus code for the mediation, moderation, and moderated mediation model templates from Andrew Hayes' PROCESS analysis examples. <http://www.offbeat.group.shef.ac.uk/FIO/mplusmedmod.htm> (10.06.2025).
- Tan, K. L., Hofman, P. S., Noor, N., Tan, S. R., Hii, I. S. H., & Cham, T. H. (2025). Does artificial intelligence improve hospitality employees' individual competitive productivity? A time-lagged moderated-mediation model involving job crafting and meaningful work. *Current Issues in Tourism*, 28(20), 3284–3301. <https://doi.org/10.1080/13683500.2024.2391114>.
- Tews, M. J., Michel, J. W., & Ellingson, J. E. (2013). The impact of coworker support on employee turnover in the hospitality industry. *Group & Organization Management*, 38(5), 630–653. <https://doi.org/10.1177/1059601113503039>.
- Tojib, D., Ho, T. H., Tsarenko, Y., & Pentina, I. (2022). Service robots or human staff? The role of performance goal orientation in service robot adoption. *Computers in Human Behavior*, 134, 107339. <https://doi.org/10.1016/j.chb.2022.107339>.
- Van den Heuvel, M., Demerouti, E., & Peeters, M. C. (2015). The job crafting intervention: Effects on job resources, self-efficacy, and affective well-being. *Journal of Occupational and Organizational Psychology*, 88(3), 511–532. <https://doi.org/10.1111/joop.12128>.
- Volpato, R., DeBruine, L., & Stumpf, S. (2025). Trusting emotional support from generative artificial intelligence: A conceptual review. *Computers in Human Behavior: Artificial Humans*, 5, 100195. <https://doi.org/10.1016/j.chbah.2025.100195>.
- Vuong, B. N. (2026). The impact of generative artificial intelligence usage on job performance through job crafting and work engagement: Does digital competence matter? *Computers in Human Behavior*, 178, 108921. <https://doi.org/10.1016/j.chb.2026.108921>.
- Wang, H., Xu, G., Hu, L., & Liu, Y. (2025). Opportunity and threat: How employees' perceptions of artificial intelligence influence job crafting. *Baltic Journal of Management*, 20(4), 511–527. <https://doi.org/10.1108/BJM-09-2024-0525>.
- Wang, Y. Y., & Chuang, Y. W. (2024). Artificial intelligence self-efficacy: Scale development and validation. *Education and Information Technologies*, 29(4), 4785–4808. <https://doi.org/10.1007/s10639-023-12015-w>.
- Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: The PANAS scales. *Journal of Personality and Social Psychology*, 54(6), 1063–1070. <https://doi.org/10.1037/0022-3514.54.6.1063>.

- Williams, L. J., Cote, J. A., & Buckley, M. R. (1989). Lack of method variance in self-reported affect and perceptions at work: Reality or artifact? *Journal of Applied Psychology*, 74(3), 462–468. <https://doi.org/10.1037/0021-9010.74.3.462>.
- Xu, Y., Xie, P., Naeem, R. M., Almgren, I., Hameed, Z., & Agarwal, S. (2026). Responsible AI and employee service innovation behavior: A sequential mediation model of AI self-efficacy and AI crafting. *Technological Forecasting and Social Change*, 224, 124470. <https://doi.org/10.1016/j.techfore.2025.124470>.
- Yan, Y., Qu, X., Lei, H., & Geng, Y. (2025). Approach or avoidance: How does employees' generative AI awareness shape their job crafting behavior? A sense-making perspective. *Behavioral Sciences*, 15(6), 789. <https://doi.org/10.3390/bs15060789>.
- Yang, H., Zeng, Y., Xing, H., & Hu, P. (2026). Fatigued by uncertainties: Exploring the cognitive and emotional costs of generative AI usage. *International Journal of Information Management*, 87, 103010. <https://doi.org/10.1016/j.jinfomgt.2025.103010>.
- Yuan, J. (2025). *Generative AI transformed my work: Decoding its direct and mediated effects on work engagement among knowledge workers* (Doctoral dissertation). Hofstra University.
- Zhang, W., Chen, X., & Wei, S. (2026). How does AI knowledge empowerment influence innovative use of AI? The moderating roles of work and AI technological uncertainties. *Information Technology & People*. <https://doi.org/10.1108/ITP-09-2024-1233>.
- Zhang, C., & Sackett, P. R. (2023). Planned missingness: An underused but practical approach to reducing survey and test length. *Industrial and Organizational Psychology*, 16(1), 129–142. <https://doi.org/10.1017/iop.2022.113>.
- Zhao, H., Ma, Y., & Chen, Y. (2025). Facing or avoiding? How dependence on artificial intelligence influences hotel employees' job crafting. *International Journal of Contemporary Hospitality Management*, 37(6), 1884–1902. <https://doi.org/10.1108/IJCHM-06-2024-0939>.
- Zhao, R., Niu, L., Wang, S., & Chen, Z. (2026). Who am I with AI? Occupational identity crafting in human–AI workplaces. *International Journal of Information Management*, 86, 102990. <https://doi.org/10.1016/j.jinfomgt.2025.102990>.
- Zhu, Z., Hu, X., & Zhang, B. (2025). The role of resilience in navigating work stress and achieving daily work goals. *Journal of Organizational Behavior*, 46(8), 1107–1119. <https://doi.org/10.1002/job.2839>.

Compliance with ethical standards

This article does not contain any studies with human participants or animals performed by the authors. Extracting and inspecting publicly accessible files (scholarly sources) as evidence, before the research began no institutional ethics approval was required.

Data availability statement

All data generated or analyzed are included in the published article. The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation. The raw anonymized data can be provided by emailing the primary author.

Author contributions

All listed authors have made a substantial, direct and intellectual contribution to the work, and approved it for publication. The authors take full responsibility for the accuracy and the integrity of the source analysis.

Conflict of interest statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Annex

Table 1. Means, standard deviations, and correlations

Variables	1	2	3	4	5	6	7	8	9	10
1. Gender	–									
2. Age	.28**	–								
3. Job tenure	.19**	.57**	–							
4. Chat GPT Type	.11	–.06	.03	–						
5. Positive affectivity	.15*	.08	.09	.19**	.67					
6. Negative affectivity	–.15*	–.12	–.08	.01	–.17*	.63				
7. GenAI support	–.03	.09	.01	.11	.27**	.16*	.52			
8. GenAI usage	.07	.02	–.03	.21**	.07	.15*	.22**	–		
9. Self-efficacy toward GenAI	.07	–.05	–.01	.18**	.23**	.12	.56**	.22**	.53	
10. Job crafting	–.01	.03	.01	.13	.50**	.00	.28**	.17*	.32**	.67
Mean	.47	35.42	5.80	.27	2.90	2.71	3.46	.18	3.44	3.20
SD	.50	6.44	4.70	.44	.91	.95	.66	.18	.66	.71
α	–	–	–	–	.86	.83	.86	–	.85	.82
CR	–	–	–	–	.86	.84	.86	–	.85	.87

Note: N = 202. SD = standard deviation. α = Cronbach's alpha. CR = composite reliability. AVE = average variance extracted.

Gender: 0 = female; 1 = male. Chat Types: 0 = Chat GPT 3.5 (for free), 1 = Chat GPT 4.0 (fee-based).

* $p < .05$, ** $p < .01$

Table 2. Indirect effect of GenAI support on job crafting through self-efficacy toward GenAI

Path	Effect(<i>b</i>)	Significance	95%CI _{low}	95%CI _{high}
Total effect				
GenAI support → Job crafting	.15	<i>p</i> <.05	–	–
Direct effect				
GenAI support → Job crafting	.047	<i>p</i> >.05	–	–
Indirect effect				
GenAI support → Self-efficacy toward GenAI → Job crafting	.105	<i>p</i> <.05	.017	.205

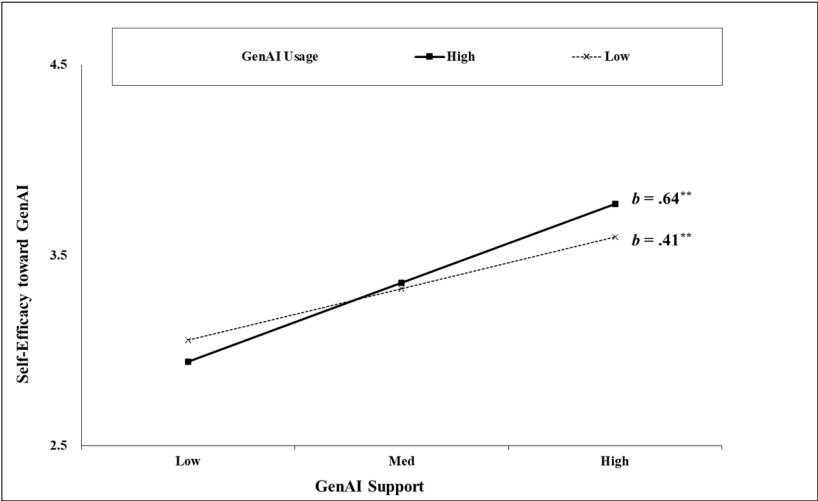
Note: N= 200, *b* = unstandardized coefficient. CI = confidence interval.

Table 3. Moderating and moderated mediation effects of GenAI usage

Variables	Self-Efficacy toward GenAI	Self-Efficacy toward GenAI	Job crafting
	<i>b</i> (SE)	<i>b</i> (SE)	<i>b</i> (SE)
Intercept	3.45(.09)**	3.45(.09)**	2.60(.29)**
Gender	.13(.08)	.10(.08)	-.10(.09)
Age	-.02(.01)*	-.02(.01)*	.01(.01)
Chat GPT type	.10(.09)	.11(.09)	.00(.10)
Job tenure	.01(.01)	.01(.01)	-.01(.01)
Positive affectivity	.05(.04)	.06(.04)	.35(.05)**
Negative affectivity	.04(.04)	.03(.04)	.04(.05)
Industry dummy1	-.22(.18)	-.22(.17)	-.02(.20)
Industry dummy2	-.10(.10)	-.13(.10)	-.00(.11)
Industry dummy3	-.21(.18)	-.22(.17)	.17(.20)
Industry dummy4	-.31(.18)	-.30(.17)*	-.11(.20)
Industry dummy5	-.15(.12)	-.16(.12)	-.18(.31)
Industry dummy6	-.03(.14)	-.03(.13)	.03(.15)
GenAI support	.54(.06)**	.52(.06)**	.05(.08)
GenAI usage		.08(.25)	
GenAI support × GenAI usage		.60(.30)*	.19(.08)*
Self-efficacy toward GenAI (T1)			32.0%
<i>R</i> ²	37.8%	39.6%	
Moderated mediation index			
GenAI support X GenAI usage → Self-Efficacy toward GenAI → Job crafting; <i>b</i> = .116, 95% CI [.015, .296]			

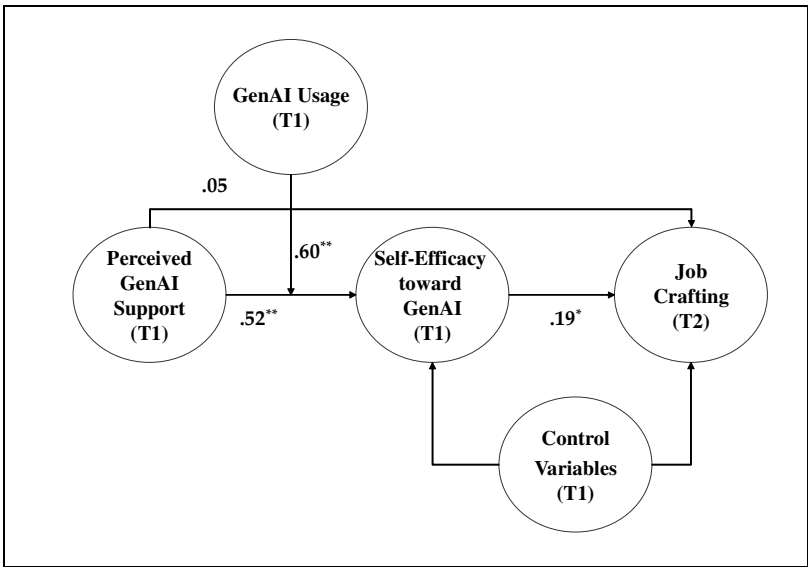
Note: N= 202, *b* = unstandardized coefficients, SE = standardized error, CI = confidence interval. **p* < .05, ***p* < .01

Figure 1. Moderating effect of GenAI usage on the relationship between GenAI support and self-efficacy



Note: $^{**}p < .01$

Figure 2. Results of proposed research model



Note: N= 202, $^*p < .05$, $^{**}p < .01$. b = unstandardized coefficients. Control variables = gender, age, job tenure, positive and negative affectivity, ChatGPT type, and industry dummies. T1 = Time 1, T2 = Time 2.

Appendix

Survey Items

1. Which of the following best describes the industry (sector) you are currently working in?

(1) Manufacturing (e.g., Automotive, Electronics, Chemicals)

(2) ICT and Telecommunications (e.g., Software, IT Services, Network)

(3) Services (e.g., Education, Hospitality, Professional Services)

(4) Trade and Distribution (e.g., Retail, Wholesale, Logistics)

(5) Banking and Finance (e.g., Insurance, Investment, FinTech)

(6) Bio-healthcare (e.g., Pharmaceuticals, Medical Devices, Healthcare Services)

(7) Other (Please specify: _____)

2. Do you currently utilize ChatGPT (a generative AI tool) for your work-related activities?

(1) Yes (2) No (→ End of survey)

3. When did you start using ChatGPT for work-related purposes?

I have been using ChatGPT for work since: [Year] / [Month].

(Note: Respondents with less than three months of usage experience were excluded from this study)

4. Which version of ChatGPT are you currently using for your work?

(1) ChatGPT-3.5 (Free version) (2) ChatGPT-4.0 (Paid/Subscription version)

5. On average, how many hours do you work per week?

On average, I work approximately [A] hours and [B] minutes per week.

6. On average, how many hours per week do you use ChatGPT for work-related purposes?

On average, I use ChatGPT for work-related tasks for approximately [C] hours and [D] minutes per week.

7. Please select your gender. (1) Male (2) Female

8. In which year were you born? [] (Please enter your 4-digit birth year, e.g., 1990)

9. How long have you been working at your current organization?

10. I have been working at my current workplace for approximately [] years and [] months.

(Note: Respondents with less than one year of tenure were excluded from this study)

Please evaluate the extent to which you have experienced the feelings or thoughts described in the following items while performing your work over the past week.

Positive and negative affectivity scale	Strongly disagree	disagree	Neutral	agree	Strongly agree
1. Enthusiastic	1	2	3	4	5
2. Active	1	2	3	4	5
3. Interested	1	2	3	4	5
4. Irritable	1	2	3	4	5
5. Upset	1	2	3	4	5
6. Distressed	1	2	3	4	5

Task crafting items	Strongly disagree	disagree	Neutral	agree	Strongly agree
1. I actively took on more tasks in my work.	1	2	3	4	5
2. I added complexity to my tasks by changing their structure or sequence.	1	2	3	4	5
3. I changed my tasks so that they were more challenging.	1	2	3	4	5
4. I increased the number of difficult decisions I made in my work.	1	2	3	4	5

Relational crafting items	Strongly disagree	disagree	Neutral	agree	Strongly agree
1. I actively sought to meet new people at work.	1	2	3	4	5
2. I made efforts to get to know other people at work better.	1	2	3	4	5
3. I sought to interact with other people at work, regardless of how well I knew them.	1	2	3	4	5
4. I tried to spend more time with numerous people at work.	1	2	3	4	5

Cognitive crafting items	Strongly disagree	disagree	Neutral	agree	Strongly agree
1. I tried to think of my job as a whole rather than as separate tasks.	1	2	3	4	5
2. I thought about how my job contributed to the organization's goals.	1	2	3	4	5
3. I thought about new ways of viewing my overall job.	1	2	3	4	5
4. I thought about ways in which my job, as a whole, contributed to society.	1	2	3	4	5

Please check the box that best represents your level of agreement or disagreement with each of the following statements

GenAI support items	Strongly disagree	disagree	Neutral	agree	Strongly agree
1. My GenAI (e.g., Chat GPT) assists me with heavy workload.	1	2	3	4	5
2. My GenAI goes out of its way to help me with work-related problems.	1	2	3	4	5
3. My GenAI helps me out when things become demanding.	1	2	3	4	5
4. My GenAI helps me when I am running behind in my work.	1	2	3	4	5
5. My GenAI helps me with difficult assignments, even when I do not directly request assistance.	1	2	3	4	5
6. My GenAI show me where things are that I need to do my job.	1	2	3	4	5

Self-efficacy toward GenAI items	Strongly disagree	disagree	Neutral	agree	Strongly agree
1. I am fully capable of using GenAI.	1	2	3	4	5
2. I am confident in my ability to use GenAI.	1	2	3	4	5
3. Using GenAI is well within the scope of my abilities.	1	2	3	4	5

4. I do not feel I am qualified for the task when using GenAI.	1	2	3	4	5
5. My past experience increases my confidence that I will be able to use GenAI successfully.	1	2	3	4	5

Item 4 = Reversed coded.