



# The dark side of employee-generative AI collaboration in the workplace: An investigation on work alienation and employee expediency

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## ARTICLE INFO

### Keywords:

Generative AI  
Employee-GenAI collaboration  
Work alienation  
Expediency  
Digital job demands

## ABSTRACT

Generative AI (GenAI) has emerged as a powerful tool in the modern workplace, delivering significant benefits to both employees and organizations. As its adoption gains momentum, understanding the potential risks associated with employee-GenAI collaboration becomes increasingly important. While much of the existing research emphasizes the challenges GenAI presents to employees as individuals, this study shifts the focus to explore broader organizational risks, particularly unethical workplace behaviors. Drawing on human-AI collaboration research and the job demands-resources model, we develop and empirically test a novel model to explain how and when employee-GenAI collaboration may lead to employees' unethical behavioral outcomes in daily organizational contexts. Using an experience sampling approach with longitudinal data from 229 service industry employees, encompassing 1050 matched daily observations, our findings reveal that employee-GenAI collaboration increases work alienation—a sense of disconnection from work—which, in turn, drives employee expediency that compromises work standards. Furthermore, we demonstrate that this effect is pronounced under high digital job demands. By highlighting this unintended consequence, our study contributes to theoretical advancements in understanding the darker side of employee-GenAI collaboration and provides practical insights to help organizations harness the benefits of GenAI while mitigating its potential ethical pitfalls.

## 1. Introduction

Workplace adoption of generative artificial intelligence (GenAI) is skyrocketing, surging from 22 % in 2023 to 75 % in 2024 (Feinsod et al., 2024). This rapid integration has introduced exciting, complex, and profound changes for both employees and organizations (Dwivedi et al., 2021, 2023; Kshetri et al., 2023; Sigala et al., 2024). Unsurprisingly, the report of the exciting benefits of GenAI utilization at work is growing exponentially in literature, documenting its advancement of employee creativity, productivity, and improvement of job satisfaction across various sectors (e.g., Bankins et al., 2024; Dwivedi et al., 2021; Przegalinska et al., 2025; Shao et al., 2024; Voigt & Strauss, 2024). However, the dynamics of employee-GenAI interactions (e.g., collaboration) may be more complex than the current optimistic outlook suggests (Zirar

et al., 2023).

We identify two critical gaps in both research and practice that warrant further exploration. First, while a growing body of research has begun to examine the unfavorable outcomes associated with employee-GenAI collaboration (e.g., Kato & Koizumi, 2024; Parvez et al., 2022; Wu et al., 2024; Zhao et al., 2024), much of this work positions employees as passive victims, focusing on issues like technological anxiety, compliance-related fears, and turnover intentions. Although this emerging literature accumulates valuable insights into the risks of GenAI, it largely overlooks human agency, neglecting the possibility that employees might intentionally leverage GenAI for unethical purposes, such as utilizing it to expedite work for self-serving purposes (i.e., expediency, Greenbaum et al., 2018). Such behaviors could pose significant threats to organizations (Eissa, 2020; Zhu et al., 2023). For

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instance, a marketing team might rely on auto-generated social media posts with minimal customization, bypassing original content creation and potentially compromising organizational standards.

Second, research has scarcely examined the processes and outcomes of employee-AI collaboration from an ethical perspective. Although literature highlights potential ethical pitfalls in AI adoption (Ashok et al., 2022; Stahl & Eke, 2024), there is limited inquiry into how these processes unfold and lead to unethical outcomes. Examining these mechanisms through which GenAI misuse may result in ethically flawed consequences is essential, given the profound challenges organizations may face when employees misuse GenAI (Stahl & Eke, 2024). Furthermore, despite emerging theories and evidence of the negative implications of employee-AI collaboration (e.g., Belanche et al., 2024; Zhao et al., 2024), less is known about the conditions under which such collaboration may lead to more or fewer unethical outcomes. Contextual factors, such as job demands and resources, likely shape whether employees respond ethically or unethically to their GenAI interactions (Li et al., 2024). Investigating these boundary conditions is key to developing a holistic understanding of the ethical ramifications of employee-GenAI collaboration.

To better understand the relationship between employee-GenAI collaboration and its unethical behavioral outcomes, we draw from two theoretical perspectives. The first comes from research on human-AI collaboration (Anthony et al., 2023; Raisch & Krakowski, 2021), which suggests that employees may feel less engaged in problem-solving or decision-making processes when collaborating with GenAI on tasks previously performed by humans. The second is the job demands-resources (JD-R) model (Bakker et al., 2023), which highlights how job demands deplete individuals through an impairment process while job resources support them. Both of these extenuate the agency problem. We integrate these theoretical perspectives to build and empirically test a model of employee-GenAI collaboration (see Fig. 1) that helps explain why this collaboration may foster a sense of disconnection from work (i.e., work alienation, Shantz et al., 2014)—and why increased alienation can lead to unethical expediency. We also examine how digital job demands (Scholze & Hecker, 2024) may moderate the impact of employee-GenAI collaboration on work alienation, leading to maladaptive responses.

Through this process, we make important contributions in three key domains. First, our research advances understanding of employee-GenAI collaboration by exploring its darker side, particularly how it can lead to unethical employee behaviors. We find that this collaboration fosters employee work alienation, which, in turn, prompts expedient behaviors that compromise work standards. This work shifts the focus from GenAI's benefits to its potential downsides, adding to research on GenAI's unethical consequences on employee conduct (Ashok et al., 2022; Stahl & Eke, 2024). Second, we extend research on the antecedents of expediency by revealing that work alienation from GenAI collaboration can drive employees toward self-serving behaviors. This highlights the role of digital transformation in shaping behavioral outcomes, offering new insights into how technologies changes influence ethical decision-making in the workplace (Ye & Chen, 2024). Lastly, we expand

the JD-R model (Bakker et al., 2023; Bakker & Demerouti, 2024) and the literature on employee-GenAI collaboration (e.g., Belanche et al., 2024; Voigt & Strauss, 2024; Zhao et al., 2024) by identifying digital job demands as a critical boundary condition that moderates the effects of employee-GenAI collaboration on work alienation and subsequent expedient behaviors. This integrative approach deepens our understanding of the mechanisms linking GenAI collaboration to unethical outcomes and provides actionable insights for organizations to mitigate the risks of GenAI integration.

## 2. Theoretical development and hypotheses

### 2.1. Employee-GenAI collaboration

The remarkable advancements in AI technologies are not only redefining various aspects of organizational operations but also reshaping employees' work routines, processes, and interactions (Brown et al., 2024; Chowdhury et al., 2024). The adoption of GenAI by organizations has intensified this transformation, bringing significant economic and organizational benefits (Bankins et al., 2024; Dwivedi et al., 2021; Flavián et al., 2022; Voigt & Strauss, 2024). Research on human-AI collaboration suggests that GenAI can provide organizations with sustainable competitive advantages by boosting productivity, enhancing customer service, enabling new product creation, and reducing costs (e.g., Kemp, 2024; Raisch & Krakowski, 2021; Wang et al., 2024). This literature predominantly highlights the synergistic benefits of employee-GenAI collaboration, particularly in fostering positive outcomes of augmented collaborative intelligence (Raisch & Krakowski, 2021). For instance, GenAI-assisted employees are shown to develop more creative solutions to customer inquiries, thereby driving improvements in sales performance (Jia et al., 2024). Additionally, such collaboration has been linked to enhanced employee well-being and increased productivity, highlighting its potential to positively transform workplace dynamics (Kong et al., 2023).

Recently, emerging studies have examined the negative outcomes of organizational AI adoption, such as increased job insecurity and diminished willingness to engage with AI (e.g., Huang & Gursoy, 2024; Liang et al., 2022; Voigt & Strauss, 2024; Wu et al., 2024; Yin et al., 2024). These findings underscore the potential risks linked to GenAI adoption for both organizations and individuals, including privacy and security concerns, misuse, algorithmic bias, and the exacerbation of the digital divide (Belanche et al., 2024; Gupta & Rathore, 2024; Wirtz et al., 2023). Despite these insights, little is known about how and when employee-GenAI collaboration—the process by which employees collaborate with GenAI to facilitate daily work progress (Kong et al., 2023)—can lead to unethical work behaviors, such as employee expediency. Expediency defined as the “use of unethical practice to expedite work for self-serving purposes” (Greenbaum et al., 2018, p. 525), is a common form of unethical behavior that undermines organizational effectiveness. It is highly relevant to the AI-integrated organizational contexts (Eissa, 2020; Xu et al., 2024). Building on research in human-AI collaboration and the JD-R model, this study broadens the discussion on

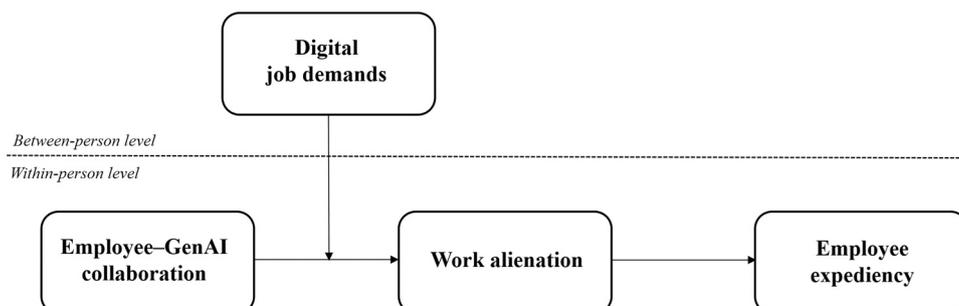


Fig. 1. The proposed research model.

the implications of human-GenAI collaboration by positing that employee-GenAI collaboration can induce work alienation, which in turn drives employees to engage in expedient behaviors, thereby allowing them to appear more productive while, in reality, withdrawing their actual effort. This nuanced understanding underscores the potential for GenAI collaboration to inadvertently generate counterproductive outcomes, offering critical insights into the complex dynamics of human-GenAI interaction in organizational settings.

Drawing on human-AI collaboration research (Anthony et al., 2023; Raisch & Krakowski, 2021; Tang et al., 2023a), we propose that GenAI systems increasingly handle daily tasks or automate previously human-performed functions, employees may feel less involved in problem-solving or decision-making, diminishing their sense of responsibility for work outcomes. This can foster a separation between the self and the work, prompting employees to reduce effort or resort to shortcuts. Human-AI collaboration also modifies traditional job characteristics, creating additional strain as employees must continuously update their machine skills and handle complex or unverified information when working with GenAI systems (Jia et al., 2024; Shao et al., 2024; Ye & Chen, 2024). These demands may heighten the disconnection from work and encourage expedient behaviors. Furthermore, the JD-R model (Bakker et al., 2023; Bakker & Demerouti, 2024) suggests that job demands (i.e., various aspects of work requirements that necessitate physical or physiological costs from employees to achieve work goals) can intensify strain, eroding employee motivation and consequently leading to negative outcomes. Extending this theory, we identify digital job demands—the demands for learning digital skills and using information and communication technologies to accomplish work tasks (Ye & Chen, 2024)—as a critical contextual factor influencing the effects of employee-GenAI collaboration.

## 2.2. Employee-GenAI collaboration, work alienation, and employee expediency

Work alienation refers to a psychological state of disconnection from work, which arises when individuals perceive psychological distance from their work environment, processes, or outputs (Shantz et al., 2014). It is considered a form of job strain that is associated with a range of negative outcomes (Chiaburu et al., 2014). Alienation research highlights that a lack of personal control over the work environment and limited meaningful interactions are primary indicators of alienation (e.g., Chiaburu et al., 2014; Nair & Vohra, 2010; Usman et al., 2020). Emerging technologies, such as GenAI, may disrupt employees' routine work and further intensify the feelings of alienation (Ye & Chen, 2024). Drawing on human-AI collaboration literature and alienation research, we argue that employee-GenAI collaboration is positively related to work alienation. On days GenAI plays a significant role in tasks and decisions previously handled by employees, individuals may feel a loss of personal control over their work and experience a devaluation of their contribution to the organization (Tang et al., 2023b). This reduced personal control and diminished sense of self-worth can foster feelings of work alienation (Chiaburu et al., 2014; Shantz et al., 2014).

Additionally, key characteristics of GenAI systems—including rapid changes, invisibility (lack of transparency in decision-making processes), and inscrutability (the complexity and opacity of AI algorithms)—can increase uncertainty and technostress for employees, influencing their perceptions of their work environment and roles (Anthony et al., 2023). Employee-GenAI collaboration thus introduces challenges for employees in processing novel, complex information (Anthony et al., 2023; Shao et al., 2024), potentially undermining employees' sense of control and increasing alienation. The automation-augmentation paradox theory (Raisch & Krakowski, 2021) suggests that GenAI adoption may lead to deskilling, complacency, and reduced responsibility among employees, as human expertise is diminished. Over time, employees may lose skills and a sense of ownership over their tasks, fostering a disconnect between themselves and their work.

Furthermore, the mechanic nature of interactions with GenAI may lead to feelings of social disconnection from colleagues (Tang et al., 2023a), with reduced meaningful social interactions further contributing to the state of work alienation (Nair & Vohra, 2010; Usman et al., 2020). Therefore, we hypothesize:

**Hypothesis 1.** Employee-GenAI collaboration is positively related to work alienation.

We further posit that work alienation associated with employee-GenAI collaboration will influence employee expediency, such as taking shortcuts or manipulating performance metrics to expedite work (Greenbaum et al., 2018; Zhu et al., 2023). Previous studies have linked work alienation to various negative work outcomes, including increased job burnout, decreased well-being, and reduced job performance and citizenship behaviors (Chiaburu et al., 2014; Shantz et al., 2014; Usman et al., 2020). As a form of strain, work alienation reflects heightened feelings of estrangement and powerlessness, which can lead employees to withdraw effort and engage in unethical behaviors (Chiaburu et al., 2014). Work alienation positively influences employee expediency because employees who feel estranged and powerless may be less inclined to fully invest in their daily tasks. Instead, they may resort to cutting corners to conserve resources or manipulating performance metrics to appear more productive (Greenbaum et al., 2018; Zhu et al., 2023). When employees feel disconnected from work processes or outcomes due to the involvement of GenAI systems, their commitment to ethical standards may wane (Eissa, 2020). To achieve rapid results and prove their value, employees experiencing work alienation are more likely to engage in expedient behaviors in their daily tasks. Taken together, we hypothesize:

**Hypothesis 2.** Employee-GenAI collaboration has an indirect impact on employee expediency via work alienation.

## 2.3. The moderating role of digital job demands

Based on the JD-R model (Bakker et al., 2023), job demands, which require physical or physiological effort from employees, can shape their strain process (e.g., alienation) and subsequently influence their behavior and performance. High job demands require sustained effort, which depletes employees' cognitive and emotional resources (Bakker & Demerouti, 2024; Liu et al., 2022), potentially leading to maladaptive responses to employee-GenAI collaboration. The transformation of modern workplaces, driven by the widespread adoption of information technology, has intensified digital job demands (Dwivedi et al., 2021). Innovations such as chatbots and service applications have revolutionized service work by automating routine processes, enabling real-time customer interactions, and providing data-driven insights to enhance decision-making (Alonso et al., 2024; Zhang et al., 2024). These technological advancements have reshaped the skills required of employees, demanding proficiency in digital tools to effectively perform tasks and deliver superior service. For example, service employees are now expected to respond to customer needs, provide up-to-date information, and resolve inquiries using advanced information and communication technologies (Zhang et al., 2024). Consequently, employees in the service industry must continuously learn and adapt to emerging digital tools to optimize service delivery, highlighting the growing need for digital literacy and technological agility. Although these demands can boost productivity and organizational performance, they often come at the cost of employee well-being, such as increased alienation and burnout (Ye & Chen, 2024). Accordingly, we argue that digital job demands serve as a contextual factor that moderates the impact of employee-GenAI collaboration on work alienation.

Digital job demands capture the job characteristic that requires employees to learn digital skills and use information and communication technologies to solve problems (Scholze & Hecker, 2024). High digital job demands bombard employees with large volumes of

information and force them to increase their work pace, creating a stressful environment with a heightened cognitive load (Scholze & Hecker, 2024; Ye & Chen, 2024). This cognitive strain can drain employees' resources, making them more prone to experiencing estrangement and powerlessness in their daily collaboration with GenAI. For instance, when employees must monitor and interpret daily AI outputs while also managing other digital tools, this can exacerbate cognitive overload, deepen the sense of disconnection from their work processes, and contribute to greater work alienation. Furthermore, high digital demands require prolonged connectivity to digital systems, which places employees in socially isolated contexts (Scholze & Hecker, 2024). For these employees, frequent daily interactions with GenAI may further erode meaningful social connections (Tang et al., 2023a) and exacerbate feelings of alienation.

Conversely, when digital job demands are low, employees face reduced pressure to navigate technological tasks (Ye & Chen, 2024). This alleviation of strain may decrease the likelihood of experiencing estrangement and powerlessness during daily collaboration with GenAI, allowing employees to maintain a sense of connection to their work. Furthermore, lower digital job demands create greater opportunities for employees to engage in meaningful social interactions in the workplace (Scholze & Hecker, 2024), serving as a protective buffer against feelings of alienation (Tang et al., 2023a). Based on the above reasoning, we hypothesize:

**Hypothesis 3.** Digital job demands moderate the effect of employee-GenAI collaboration on work alienation. Such an effect is pronounced when employees perceive high (vs. low) digital job demands.

Integrating Hypotheses 2 and 3, we further propose that higher levels of digital job demands intensify the indirect effect of employee-GenAI collaboration on employee expediency through work alienation. That is, employees facing elevated digital job demands are more likely to experience work alienation after collaboration with GenAI, which, in turn, increases their propensity to engage in expedient behaviors at work. Conversely, employees experiencing lower digital job demands have more cognitive resources available when collaborating with GenAI systems, making them less susceptible to information overload. This reduces their likelihood of feeling alienated and, subsequently, engaging in expedient behaviors. Thus, we hypothesize:

**Hypothesis 4.** Digital job demands moderate the indirect effect of employee-GenAI collaboration on employee expediency via work alienation. Such an indirect effect is pronounced when employees perceive high (vs. low) digital job demands.

### 3. Method

#### 3.1. Data collection and sampling

To test our proposed model, we collected data from full-time employees in the service industry (i.e., hospitality and tourism) in China using the daily experience sampling method (ESM), a widely recognized method for short-term longitudinal research (Gabriel et al., 2019; Heggstad et al., 2022). Prior studies have highlighted that interactions with GenAI and their associated outcomes are dynamic (e.g., Brown et al., 2024; Shao et al., 2024; Tang et al., 2023a). As noted by Tang et al. (2023b), employees frequently experience daily fluctuations in their engagement with AI tools due to varying work demands, such as shifting task requirements and evolving customer inquiries or complaints. For instance, employees may on a given day (1) rely heavily on GenAI for tasks like generating content or processing data, (2) focus primarily on non-GenAI tasks such as interpersonal coordination, or (3) balance both. As a result, employee-GenAI interactions exhibit significant daily variability (Shao et al., 2024; Tang et al., 2023b). Given the dynamic nature of these interactions, traditional cross-sectional research designs are insufficient to capture short-term fluctuations. ESM provides a robust

method for studying dynamic phenomena in GenAI-intensive workplaces by collecting real-time, repeated data on employees' attitudes and behaviors (Beal, 2015). This approach allows us to capture employees' lived experiences through multiple measures over time, reducing memory bias inherent in single-time surveys and capturing within-person fluctuations in employee-GenAI collaboration and its outcomes (Gabriel et al., 2019; Heggstad et al., 2022).

The widespread adoption of GenAI in service organizations has significantly impacted business operations in this sector (Belk et al., 2023; Dogru et al., 2023; Mo et al., 2024; Yin et al., 2024). Service organizations frequently employ GenAI for tasks like customer service, smart marketing, and decision optimization to improve service quality, drive business innovation, and maintain competitive advantage (Kautish & Khare, 2022; Liang et al., 2022; Yin et al., 2024). For instance, over 5700 hotels operated by the China Lodging Group have implemented GenAI to offer personalized recommendations, provide clearer property descriptions, respond to customer needs, and enhance customer experiences (Liang et al., 2022). Many other service companies use GenAI to create engaging content, such as text, images, and videos, by leveraging their databases, thereby creating added value for both companies and customers (Dogru et al., 2023). This makes the service industry an ideal context for studying the implications of employee-GenAI collaboration.

We recruited 285 full-time employees from a variety of hospitality and tourism organizations in South China that actively integrated advanced technologies (e.g., GenAI) into their operations. These participants were primarily responsible for customer service and marketing tasks, engaging in activities such as managing bookings, responding to frequently asked questions, addressing customer concerns, recommending service products, and updating customer records. To perform these tasks effectively, participants required proficiency in using digital technologies and platforms for service delivery. Most of these tasks were semi-automated and involved collaboration with GenAI. For example, during routine customer interactions, employees could rely heavily on GenAI to generate standardized responses. Conversely, when handling more customized customer requests, employees worked interactively with GenAI to analyze consumer data and deliver personalized service recommendations.

We recruited participants through personal and professional networks, such as researchers, research assistants, MBA students, and colleagues. We contacted potential participants directly, explaining the study's purpose and schedule and addressing any questions regarding data collection. Participation was voluntary, with confidentiality and anonymity assured. Of the 285 employees contacted, 246 agreed to participate in our ESM study and were given identification codes. Data collection was conducted electronically using smartphone-compatible online surveys. Following best practices of ESM studies (Gabriel et al., 2019; Heggstad et al., 2022), participants were initially asked to complete the baseline survey that assessed levels of digital job demands and demographic information; one week after the baseline survey, they were instructed to respond to two surveys per day over five consecutive workdays. For the first daily survey, participants were asked to complete the measures of employee-GenAI collaboration, negative affect, and positive affect within 1 hour (i.e., 15:00–16:00) after they received the survey links. For the second daily survey, participants were required to complete the measures of work alienation and expedient behaviors within 1 hour (i.e., 17:30–18:30). We obtained 1159 observations in the first daily survey and 1116 observations in the second daily survey. Participants received approximately \$1.5 as compensation after finishing two daily surveys per day.

In line with previous ESM studies (e.g., Amarnani et al., 2022; Junker et al., 2021), data from participants who finished both daily surveys for three or more full days were retained, leading to a final sample of 229 participants at the person-level with 1050 matched observations at the within-person level. Among the final sample, 85 were male (37.1 %) and 144 were female (62.9 %), with a mean age of 32.65 years ( $SD = 8.92$ ), a mean organizational tenure of 6.36 years ( $SD = 7.13$ ). Regarding the

educational level, 16 participants completed junior high school (7.0 %), 34 had completed senior high school (14.8 %), 46 had a two-year college degree (20.1 %), 108 held an undergraduate degree (47.2 %), and 25 had a graduate degree (10.9 %).

### 3.2. Measures

All constructs were assessed by using well-established and validated scales.<sup>2</sup> Without further explanation, all measures were assessed on a seven-point Likert scale, ranging from 1 (*never*) to 7 (*all the time*).

#### 3.2.1. Between-person level measure

**Digital job demands.** We measured digital job demands using four items from [Ye and Chen \(2024\)](#). Participants were instructed to respond on a seven-point Likert scale ranging from 1 (*strongly disagree*) to 7 (*strongly agree*). Example items are “My job requires me to have the ability to use information and communication technology hardware or manage information systems to resolve customer problems” and “My job requires me to establish contact with internal and external personnel of the company through digital networks.” These items capture the operational demands of using digital tools and reflect the necessity for employees to continuously enhance their digital skills and adapt to new technologies as part of their work responsibilities ([Scholze & Hecker, 2024](#); [Ye & Chen, 2024](#)). The Cronbach’s alpha for the scale was .92.

#### 3.2.2. Within-person level measures

**Employee-GenAI collaboration.** We assessed employee-GenAI collaboration using five items adapted from [Kong et al. \(2023\)](#). Sample items are “Today at work, GenAI participated in my problem-solving process” and “Today at work, GenAI participated in my problems, opportunities, or risk recognition process.” Cronbach’s alpha across observations for the scale was .96.

**Work alienation.** We measured work alienation using three items from [Shantz et al. \(2014\)](#). Example items are “Today, I did not feel connected to the events in my workplace” and “Today, while I was at work, I wished I was doing something else.” Cronbach’s alpha across observations for the scale was .94.

**Employee expediency.** We assessed employee expediency with four items from [Greenbaum et al. \(2018\)](#). Sample items are “Today, I cut corners to complete work assignments more quickly” and “Today, I altered performance numbers to appear more successful.” Cronbach’s alpha across observations for the scale was .93.

#### 3.2.3. Control variables

To decrease the likelihood that demographic variables would confound the proposed relationships ([Bernerth & Aguinis, 2016](#); [Koopman et al., 2021](#)), four important demographic variables were controlled for: age, sex, education, and organizational tenure. Moreover, we considered knowledge of AI as a confounding variable because employees with a good knowledge of AI technologies may develop positive attitudes toward AI technologies and can better utilize AI technologies to improve their work ([Chiu et al., 2021](#); [He et al., 2023](#)). We used five items developed by [Chiu et al. \(2021\)](#) to assess knowledge of AI. An example item is “I know pretty much about AI.” Cronbach’s alpha was .88.

According to ESM research (e.g., [Gabriel et al., 2019](#); [Song et al., 2024](#)), we controlled for the weekday of study (i.e., the day of study takes values from 1 to 5, corresponding to Monday through Friday) to account for potential linear trends in participants’ daily states. Additionally, we controlled for negative affect and positive affect at the within-person level to reduce concerns about common method bias (CMB; [Gabriel et al., 2019](#)). Daily affective states have also been linked to employees’ daily behaviors such as task proficiency and retaliatory

behavior (e.g., [Koopman et al., 2021](#); [Lennard et al., 2022](#)). We used eight items from [To et al. \(2012\)](#) to assess negative affect (i.e., anxious, angry, ashamed, and upset) and positive affect (i.e., excited, inspired, enthusiastic, and interested). Cronbach’s alpha across observations for negative affect and positive affect were .90 and .83, respectively. We conducted a robustness check to rerun our analyses without these control variables and found no differences in the significance or patterns of our findings.<sup>3</sup>

### 3.3. Analytic strategy

We conducted multilevel path analysis with the robust maximum likelihood estimator in Mplus 7.4 ([Muthén & Muthén, 2012](#)) to account for the nested nature of our data (i.e., daily observations nested within individuals). The within-person variables (e.g., employee-GenAI collaboration, work alienation, and employee expediency) were modeled as Level 1 variables and between-person variables (e.g., digital job demands) were modeled as Level 2 variables. Based on best practices in ESM research (e.g., [Gabriel et al., 2019](#)), we group-mean-centered our Level 1 predictor and control variables to eliminate between-person confounds, enabling a more robust examination of within-person relationships. According to [Gabriel et al. \(2019\)](#), group-mean centering has significant implications for addressing “the influence of between-person characteristics that are often identified as potential sources of CMB” (p. 17). We grand-mean-centered our moderator at Level 2 to reduce concerns of multicollinearity and enhance the interpretation of the cross-level moderation effect<sup>4</sup> ([Hofmann et al., 2000](#); [Yu et al., 2013](#)). Grand-mean centering is effective in reducing collinearity when testing cross-level mediation ([Ohly et al., 2010](#)). Our choice of centering approach aligns with widely established practices in multi-level modeling studies (e.g., [Huai et al., 2024](#); [Lee et al., 2024](#); [Yu et al., 2013](#)). Further, random slopes were estimated for the effects of employee-GenAI collaboration on work alienation, and fixed slopes were estimated for other within-person relationships and control variables ([Beal, 2015](#); [Zhu et al., 2024](#)). The cross-level moderation effect was examined by modeling digital job demands as the predictor of the random slope of the relationship between employee-GenAI collaboration and work alienation. We tested the significance of mediation and moderated mediation effects by applying the Monte Carlo method with 10,000 iterations for computing their confidence intervals ([Preacher et al., 2010](#)).

## 4. Results

### 4.1. Preliminary analysis

Descriptive statistics and correlations among study variables are displayed in [Table 1](#). Before hypothesis testing, we calculated the degree of within-person variations of our main variables. We found substantial proportions of within-person variance existed in employee-GenAI collaboration (29.8 %), work alienation (25.9 %), and employee expediency (35.7 %). These results indicate that employee-GenAI collaboration, work alienation, and employee expediency fluctuate meaningfully on a day-to-day basis ([Hofmann et al., 2000](#); [Liao et al., 2021](#)). Accordingly, it was appropriate for the use of multilevel analysis.

Then, multilevel confirmatory factor analyses were conducted to test the construct validity of our focal variables. We estimated a four-factor model whereby daily variables (i.e., employee-GenAI collaboration,

<sup>3</sup> The results of hypothesis tests without control variables are presented in the online [supplementary material](#).

<sup>4</sup> To confirm the robustness of our results, we conducted additional analyses by z-standardizing our predictor variables prior to hypothesis testing ([Iacobucci et al., 2016](#)). The results of these additional analyses provided further support for our hypotheses (see the online [supplementary material](#)).

<sup>2</sup> See Appendix for measurement items.



**Table 2**  
Multilevel confirmatory factor analysis results.

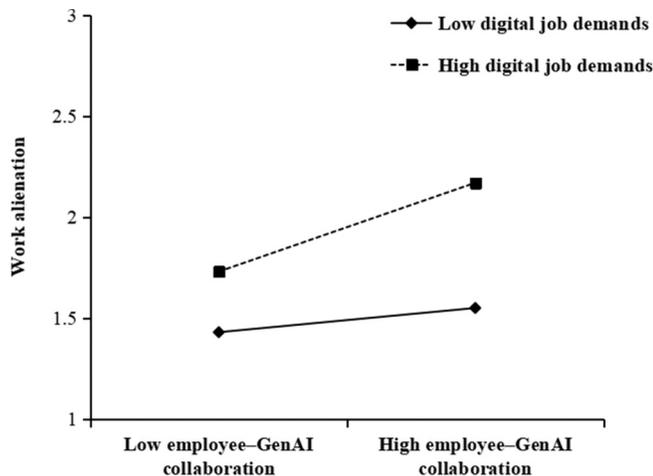
Model	$\chi^2$	df	CFI	TLI	RMSEA	SRMR <sub>within</sub>	SRMR <sub>between</sub>
The four-factor model	170.18	53	.98	.97	.04	.02	.03
Three-factor model 1: employee-GenAI collaboration and work alienation combined	1216.07	55	.78	.72	.14	.17	.02
Three-factor model 2: employee-GenAI collaboration and employee expediency combined	2027.71	55	.63	.52	.18	.24	.03
Three-factor model 3: work alienation and employee expediency combined	1163.93	55	.79	.73	.13	.16	.03

Note.  $N_{\text{between-person level}} = 229$ ;  $N_{\text{within-person level}} = 1050$ .

**Table 3**  
Multilevel path analysis results.

Variable	Work alienation $\gamma$ (SE)	Employee expediency $\gamma$ (SE)
<i>Level-1 (within-person level)</i>		
Intercept	1.72** (.60)	3.84*** (.80)
Weekday of study	-.02(.01)	.01(.02)
Negative affect	.10** (.04)	-.01(.05)
Positive affect	.03(.03)	-.10*(.05)
Employee-GenAI collaboration	.14*** (.03)	.08 <sup>†</sup> (.04)
Work alienation		.30** (.09)
<i>Level-2 (between-person level)</i>		
Age	-.01(.01)	-.01(.01)
Sex	.01(.13)	-.01(.17)
Education	-.06(.06)	.01(.10)
Organizational tenure	-.01(.01)	-.02(.01)
Knowledge of AI	-.01(.05)	-.01(.09)
Digital job demands	.23*** (.05)	.30*** (.05)
<i>Cross-level interactions</i>		
Employee-GenAI collaboration $\times$ Digital job demands	.08** (.03)	
<i>Variance components</i>		
Residual variance at Level 1	.28***	.86***
Residual variance at Level 2	.74***	1.29***

Note. <sup>†</sup> $p < .10$ ,  
\* $p < .05$ ,  
\*\* $p < .01$ ,  
\*\*\* $p < .001$ .



**Fig. 2.** The cross-level moderation effect of digital job demands.

that employee-GenAI collaboration, as a product of organizational digital transformation, is a significant driver of employee expediency. Our work is among the few studies to propose that GenAI adoption plays a pivotal role in shaping employee expediency, thereby paving the way for future research to further investigate how GenAI-driven organizational changes can inadvertently catalyze expedient behaviors among employees.

Third, our research extends the discourse on GenAI’s impact to work alienation literature, specifically addressing GenAI as a novel predictor

**Table 4**  
Conditional indirect effect of employee-GenAI collaboration on employee expediency via work alienation.

Hypothesized conditional indirect effect path	Level of digital job demands	Estimate	SE	95 % CI
Employee-GenAI collaboration $\rightarrow$ work alienation $\rightarrow$ Employee expediency	Low (-1 SD)	.02	.01	[.002,.031]
	High (+1 SD)	.06	.03	[.010,.118]
	Difference	.05	.02	[.002,.094]

Note. Moderated mediation effect is supported when the CI of the difference between two indirect effects for a given moderator does contain zero.

of alienation within employee-technology dynamics. While existing studies on work alienation have primarily focused on human-related drivers (e.g., leadership, work relationships; Nair & Vohra, 2010; Usman et al., 2020) or the nature of the job (Shantz et al., 2015), the impact of digital technology has received less attention. In response to Ye and Chen’s (2024) call to investigate underexplored determinants of work alienation, particularly in relation to technology use, we offer valuable insights into the relationship between GenAI usage and work alienation. Our findings suggest that employee collaboration with GenAI is a significant predictor of employee alienation from their jobs, underscoring the unique psychological and occupational challenges GenAI introduces. This indicates that, rather than being a neutral tool, GenAI usage in the workplace can entrap employees in a negative psychological state that is potentially detrimental to their work behaviors (Teng et al., 2024).

Lastly, our research extends the JD-R model (Bakker et al., 2023; Bakker & Demerouti, 2024) to the human-AI collaboration research by highlighting the moderating role of digital job demands in the relationship between employee-GenAI collaboration, work alienation, and employee expediency. This contributes to our understanding of how organizations can address the potential negative impacts of employee-GenAI collaboration. While GenAI collaboration can increase the likelihood of negative behaviors among employees, not all employees are equally at risk. Our research identifies digital job demands as a critical boundary condition that moderates the adverse effects of employee-GenAI collaboration. Higher digital job demands amplify the cognitive and emotional strain of employee-GenAI collaboration, making employees more likely to feel disconnected from their work and further driving them to engage in expedient behaviors. In contrast, when digital job demands are perceived to be low, employees face less pressure to manage technological tasks and have more meaningful social connections (Scholze & Hecker, 2024; Ye & Chen, 2024). Employee-GenAI collaboration in such contexts may not generate pressure or complexity to elicit work alienation, consequently mitigating the likelihood of expediency. This highlights the context-dependent nature of the impact of employee-GenAI collaboration and the importance of carefully managing digital job demands to reduce the chances of employee expediency arising from work alienation during GenAI collaboration. By elucidating when and why employees are more likely to engage in expedient practices, our study provides nuanced insights into the mechanisms and conditions that shape the ethical implications of employee-GenAI collaboration.

## 5.2. Practical implications

Our research provides valuable insights for managers, highlighting the potential adverse outcomes of GenAI adoption in management. Most notably, while GenAI becomes increasingly integrated into organizational management and can improve employee productivity and efficiency, thereby benefiting organizations, our findings emphasize the need to recognize the potential downsides of employee-GenAI collaboration, particularly regarding work alienation and its link with employee expediency. As such, when deciding to adopt GenAI, managers must adopt a balanced perspective that not only focuses on the advantages of GenAI adoption but also its potential drawbacks. Based on our findings, we offer several suggestions for mitigating the challenges of employee-GenAI collaboration. First, given that employee expediency can involve behaviors that are less aligned with moral and ethical standards (Greenbaum et al., 2018), organizations should foster a climate of integrity. This involves promoting practices consistent with ethical norms and providing guidance on ethical conduct, particularly in GenAI-related tasks. Organizations also need to implement comprehensive training programs that emphasize the importance of ethical behavior in all aspects of work, especially when interacting with AI systems.

Second, our research indicates that work alienation stemming from employee-GenAI collaboration can lead to expedient behavior. This issue arises from the inherent technological characteristics of GenAI, which limit human involvement and oversight in the work process, reducing their control over the work (Tang et al., 2023b). To address this, organizations need emphasize the importance of employee responsibility in tasks collaborated with GenAI, encouraging employees to maintain control over the work rather than deferring fully to GenAI decisions. This means that organizations should position their employees as the superordinate, rather than the subordinate within employee-GenAI teams. Moreover, organizations may also consider structuring employee-GenAI roles strategically (Guo et al., 2024). For example, delegating routine tasks to GenAI while reserving more complex, impactful tasks for employees allows them to exercise expertise and maintain control over critical work areas. Such a strategy might foster better synergy between human capabilities and artificial intelligence, maximizing the unique contributions of both GenAI and employees in team collaboration.

Third, we found that the positive effects of employee-GenAI collaboration on work alienation and employee expediency were stronger for employees with high digital job demands. This suggests that organizations should carefully consider how employees perceive the demands of their jobs at the workplace. To support effective GenAI collaboration, managers should design and set reasonable job demands. For example, creating a more flexible work environment and allowing employees greater autonomy in decision-making can enhance their sense of job control (Chen et al., 2023), especially to those who feel overwhelmed with the job. This approach ensures employees have sufficient cognitive and emotional resources, helping them feel more at ease and better able to engage meaningfully in GenAI-collaborated tasks, rather than defaulting to a passive reliance on GenAI to complete all the demanded tasks which can end up in performing expedient behaviors.

## 5.3. Limitations and directions for future studies

This study has several limitations that open avenues for future research. First, while we employed a longitudinal ESM design to capture employees' lived experiences and the dynamics of employee-GenAI interactions—thereby mitigating concerns about common method bias and enhancing ecological validity (e.g., Gabriel et al., 2019; Heggstad et al., 2022)—our survey-based approach may limit our ability to draw causal conclusions. Future research could address this by adopting experimental designs or mixed method approaches that combine both qualitative and quantitative data to replicate and extend our findings.

Such approaches could enhance internal validity by strengthening causal inferences and improve external validity by offering a robust and comprehensive test of our theory (Lee et al., 2024; Lu et al., 2024). In addition, our sample was drawn from full-time employees in China, which offers a focused context for examining the phenomena but limits the generalizability of our findings to other cultural settings. It is a fruitful direction for researchers to conduct cross-cultural studies to generalize the study findings and explore possible cultural contingencies of the functions of employee-GenAI collaboration.

Second, while we identified work alienation as a key psychological mechanism linking employee-GenAI collaboration to expedient behaviors, there are likely other mediating factors, such as affective experiences and motivational states. For instance, employee-GenAI collaboration may evoke feelings of isolation or loneliness, which can be associated with maladaptive outcomes (Tang et al., 2023a). On the other hand, it might also expose employees to new ideas, fostering creativity (Jia et al., 2024). Expanding the research scope to include multiple theoretical perspectives could provide a more nuanced understanding of the complex dynamics of employee-GenAI collaboration.

Third, although this study controlled for the effects of demographic variables, knowledge of AI, and daily affect when testing the relationship between employee-GenAI collaboration and work alienation, factors such as intrinsic motivation and work pressure have the potential to influence employees' work alienation. For example, highly intrinsically motivated employees are more likely to invest effort and remain engaged in their work due to the enjoyment they derive from the tasks themselves (Grant, 2008). Work pressure could also be a relevant factor, as employees experiencing higher work pressure may perceive GenAI differently—either as an additional source of stress or a supportive tool—depending on the situation. To improve the robustness of our findings, future research should account for the potential effects of intrinsic motivation and work pressure on the relationship between employee-GenAI collaboration and work alienation.

Furthermore, perceptions of work alienation triggered by employee-GenAI collaboration may not only increase unethical behaviors but also result in a broader range of performance- and well-being-related outcomes including diminished intrinsic motivation for one's work. When employees feel disconnected from work processes or outcomes (e.g., service products), they may struggle to derive meaning from their work and are less likely to find enjoyment or fulfillment in their tasks (Chiaburu et al., 2014). This sense of alienation may be particularly detrimental for employees who were previously highly motivated and deeply invested in their work roles. For these employees, the integration of GenAI may fundamentally alter how they perceive the significance of their efforts. The automated nature of GenAI could overshadow their personal input, making them feel that their unique knowledge and skills are undervalued, ultimately undermining the intrinsic value they derived from their work (Tang et al., 2023b). These insights suggest potentially fruitful avenues for further research to extend the employee-GenAI collaboration and work alienation literature.

Forth, for theoretical and practical reasons, this study focused mainly on digital job demands as a contextual factor that shapes the relationship between employee-GenAI collaboration and its consequences. While this examination enhanced our understanding of when the undesirable effects of employee-GenAI collaboration are exacerbate or mitigated, other organizational contexts and individual factors may alter the effect of employee-GenAI collaboration on work alienation and subsequent expedient behaviors. For instance, for employees who work in an organization with higher levels of GenAI readiness (i.e., the organization provides sufficient financial and expert human resources, and management support for employees to implement and integrate GenAI systems into work; Yin et al., 2024), they are in a better position to leverage GenAI tools to develop new services or products and are therefore less likely to experience job strain because of digital transformation. Future research could explore more boundary conditions to offer a comprehensive understanding of the consequences of employee-GenAI

collaboration.

## 6. Conclusion

As interest in the adoption of GenAI in the workplace continues to grow among scholars and practitioners (e.g., Anthony et al., 2023; Bankins et al., 2024; Gupta & Rathore, 2024; Przegalinska et al., 2025), our study aims to illuminate the potential dark side of GenAI integration into organizational operations. Specifically, we empirically examine the potential adverse outcomes of employee-GenAI collaboration in daily organizational contexts and identifies the conditions that intensify these challenges. Our findings reveal that employee-GenAI collaboration can heighten employees' sense of work alienation, which subsequently triggers employee expediency—an unethical behavior that can undermine organizational effectiveness. Moreover, these negative outcomes are pronounced under high (vs. low) digital job demands, suggesting that certain contextual factors exacerbate the potential downsides of employee-GenAI interactions. By shedding light on these risks, our study offers valuable insights for managing employee-GenAI collaboration effectively while mitigating its hidden pitfalls. We hope this research sparks further scholarly exploration into the broader implications of GenAI adoption in modern organizational settings.

## Funding

This work was supported by the National Natural Science Foundation of China (72401078), Humanity and Social Science Youth Foundation of Ministry of Education of China (24YJC630060, 24YJC630064), Guangdong Province Nature and Basic Regional Joint Fund (2023A1515110491), and UWA Business School Research Grant.

## CRediT authorship contribution statement

**Honora Andreawan:** Writing – review & editing, Writing – original draft, Funding acquisition. **Japutra Arnold:** Writing – review & editing, Supervision. **Guo Tengfei:** Funding acquisition, Data curation. **Hai Shenyang:** Writing – original draft, Supervision, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Long Tianyi:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Funding acquisition, Conceptualization.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Appendix

### Digital job demands

1. My job requires me to have the ability to use information and communication technology hardware or manage information systems to resolve customer problems.
2. My job requires me to use appropriate digital software to communicate with others.
3. My job requires me to use information and communication technology hardware or manage information systems.
4. My job requires me to establish contact with internal and external personnel of the company through digital networks.

### Knowledge of AI

1. I know pretty much about AI.
2. Among my circle of friends, I'm one of the "experts" on AI.
3. When it comes to AI, I really don't know a lot (Reverse coded).

4. I do not feel very knowledgeable about AI (Reverse coded).
5. Compared to most other people, I know less about AI (Reverse coded).

### Employee-GenAI collaboration

1. Today at work, GenAI participated in my problem-solving process.
2. Today at work, GenAI participated in my decision-making process.
3. Today at work, GenAI participated in my problems, opportunities or risk recognition process.
4. Today at work, GenAI participated in my prediction process.
5. Today at work, GenAI participated in my information identification and evaluation process.

### Negative affect

1. Anxious
2. Angry
3. Shamed
4. Upset

### Positive affect

1. Excited
2. Inspired
3. Interested
4. Enthusiastic

### Work alienation

1. Today, I did not feel connected to the events in my workplace.
2. Today, I wished I was doing something else while I am at work.
3. Today, I had become disillusioned by my work.

### Employee expediency

1. Today, I cut corners to complete work assignments more quickly.
2. Today, I altered performance numbers to appear more successful.
3. Today, I ignored company protocols in order to get what I wanted.
4. Today, I only enforced company rules when they benefited my welfare.

## Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at [doi:10.1016/j.ijinfomgt.2025.102905](https://doi.org/10.1016/j.ijinfomgt.2025.102905).

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