



# Would you rather work with ChatGPT or a human coworker? Exploring the impact of generative AI on job satisfaction

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## Abstract

Organizations are increasingly integrating generative artificial intelligence (AI) tools like ChatGPT for task-support purposes into the workplace. While such tools have been shown to boost productivity, it is critical to understand their psychological impact on employees' job satisfaction if they are to be implemented effectively. Based on social response theory and the work design model, this study examines how the organizational integration of ChatGPT influences job satisfaction among employees, mediated by perceived organizational support, opportunity to perform, and job insecurity. Using a pre- and post-measurement design, we conducted a 2 × 2 between-subjects vignette experiment with a sample of 202 participants, manipulating the type of task support (i.e., ChatGPT vs. human coworker) (T1) and the nature of supervisor feedback (i.e., positive vs. negative) (T2) in the context of a corporate communication task (i.e., writing an article for the organization's website about a strategic shift). Our results indicate that ChatGPT task support, compared to task support by a human coworker, leads to lower perceptions of both organizational support and opportunity to perform and higher perceptions of job insecurity, ultimately hindering job satisfaction. The findings suggest that, although generative AI can serve as a form of task support, its use can negatively impact employees' perceptions. Accordingly, task support provided by human coworkers appears to still be important for maintaining job satisfaction among employees, underscoring the need for the thoughtful integration of generative AI into the workplace.

**Keywords** ChatGPT · Generative artificial intelligence · Job satisfaction · Perceived organizational support · Opportunity to perform · Job insecurity

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## 1 Introduction

Generative artificial intelligence (AI) tools, such as ChatGPT, increasingly serve as virtual assistants that support employees in their daily tasks, particularly in the areas of information seeking and writing (Noy and Zhang 2023; Yin et al. 2024; Chatterji et al. 2025). Generative AI is an umbrella term for any technology based on machine learning models that is designed to simulate human cognitive abilities in the generation of novel content (Dwivedi et al. 2023; Feuerriegel et al. 2024). As part of the ongoing digital transformation, generative AI task support exemplifies the broader shift toward increased technology use in the workplace, with 71% of organizations already employing such tools to some degree (Maslej et al. 2025). This development is transforming traditional ways of working and may impact how employees perform their work tasks (Jia et al. 2024; Ooi et al. 2025) as well as how they perceive them, thereby influencing their job attitudes.

Despite extensive research having already demonstrated the productivity and performance benefits of generative AI—varying by specific task and industry (Dell’Acqua et al. 2023; Brynjolfsson et al. 2025)—there remains a critical gap in the literature with regard to the psychological impact of generative AI task support on employees’ perceptions and attitudes, such as job satisfaction (Liu 2024; Choudhary et al. 2025; Ooi et al. 2025; Hermann et al. 2025). As organizations increasingly integrate generative AI for the purposes of task support, it is essential to understand whether these tools enhance or diminish job satisfaction among employees. Since job satisfaction functions as a predictor of both job performance and turnover intention (Tett and Meyer 1993; Judge et al. 2001), examining the psychological consequences of generative AI task support is crucial.

Therefore, this study examines the psychological impact of generative AI task support, comparing it to task support provided by a human coworker. We focus on ChatGPT (OpenAI 2022) given its status as the most prominent generative AI tool (Dwivedi et al. 2023). Our study builds upon two theoretical perspectives that complement each other in explaining *why* and *how* the type of task support (i.e., ChatGPT vs. human coworker) impacts employees’ perceptions and attitudes. Social response theory (Nass and Moon 2000) posits that employees perceive technology (e.g., generative AI tools) as social actors with social cues distinct from those of humans. Social cues encompass non-verbal elements, such as facial expressions and eye contact, as well as verbal elements, such as tone and word choice (Leathers 1976; Feine et al. 2019). We expect that the different social cues provided by ChatGPT and by human coworkers (Siemon et al. 2025) are critical in explaining *why* the type of task support can impact employees’ perceptions and job satisfaction (Ossadnik et al. 2023).

To investigate the “*how*”—the mechanisms by which the type of task support (i.e., ChatGPT vs. human coworker) influences job satisfaction—we complement social response theory with the work design model from Humphrey et al. (2007), which emphasizes that changes in the work environment (in our case, the introduction of generative AI task support) affect job satisfaction among employees through social,

motivational, and work context characteristics (Humphrey et al. 2007). This model guides our choice of mediating constructs, focusing on three employee perceptions—organizational support, opportunity to perform, and job insecurity—with job satisfaction as the outcome variable. These perceptions are essential for understanding the mechanisms by which generative AI task support influences employees' job satisfaction. Therefore, we formulate the following research questions (RQ):

*RQ1: What impact does the type of task support (ChatGPT vs. human coworker) have on employees' job satisfaction?*

*RQ2: How do employees' perceptions of organizational support, opportunity to perform, and job insecurity explain the relationship between the type of task support and job satisfaction?*

To address these research questions, we employ a  $2 \times 2$  between-subjects vignette experiment with a pre- and post-measurement design and a sample of 202 participants. The study is contextually situated within a corporate communication task—more precisely, the task of writing an article for the organization's website about a strategic change under time pressure—which represents a strategic and cognitively demanding task that requires employees to frame and tailor messages to an external audience (Christensen and Cornelissen 2011). Completing such a task typically requires support, with employees needing to integrate factual information while carefully managing tone, framing, and audience orientation (Christensen and Cornelissen 2011). Therefore, this context offers a suitable setting in which to assess how different types of task support (i.e., ChatGPT vs. a human coworker) affect employees' psychological reactions.

In the first phase of our vignette experiment, we manipulate the type of task support (i.e., ChatGPT vs. human coworker) during the aforementioned corporate communication task, after which we measure employees' perceptions of organizational support, opportunity to perform, and job insecurity. In the second phase, participants receive either positive or negative feedback from their (fictitious) supervisor, enabling us to statistically control for the effects of supervisor feedback on employee perceptions and job satisfaction, which are often outcome-dependent (Fischhoff 1975; Bankins et al. 2022). Finally, we measure the outcome variable: employees' job satisfaction.

This research makes the following contributions to the literature. First, it advances the general understanding of generative AI's psychological impact by explaining why and how task support provided by ChatGPT influences employees' job satisfaction. We integrate social response theory (Nass and Moon 2000) with the work design model (Humphrey et al. 2007) to explain why different perceptions emerge due to differences in social cues and how these perceptions translate into job satisfaction. More precisely, we demonstrate that—in line with social response theory (Nass and Moon 2000)—generative AI task support is associated with overall lower job satisfaction within the considered corporate communication context, compared to task support provided by a human coworker. This relationship is fully mediated by employees' perceptions of organizational support, opportunity to perform, and job insecurity, which function as social, motivational, and work context pathways (Humphrey et al.

2007) influencing job satisfaction. Through this process, we integrate both theoretical perspectives, extending social response theory to generative AI task support and broadening the work design model to capture how social, motivational, and work context characteristics influence employees' job satisfaction.

Second, this research contributes to the growing debate on the organizational integration of generative AI and its implications for job satisfaction, which is a key outcome for organizations (Ossadnik et al. 2023) given its impact on employees' well-being and, in turn, organizational performance (Judge et al. 2001). Despite job satisfaction's importance, empirical evidence on how it is affected by generative AI remains mixed, varying by context (Braganza et al. 2022; Chiong and Xie 2024; Chuang et al. 2025; Bosek-Rak and Kaszyński 2026). Our study clarifies this relationship within the context of a specific corporate communication task by adopting a comparative perspective, demonstrating that ChatGPT task support incurs lower job satisfaction than task support provided by a human coworker. This finding offers empirical evidence of the adverse implications of generative AI task support, highlighting that the specific type of task support is central to evaluations of the psychological impact of workplace AI integration.

Finally, this research emphasizes that it is imperative for organizations to thoughtfully consider the negative psychological impact of generative AI on employees, especially when it comes to job satisfaction. Therefore, we provide practical guidance for organizations by offering concrete strategies with which to address social, motivational, and work context pathways when integrating generative AI into the workplace, all of which serve as critical predictors of job satisfaction among employees (Humphrey et al. 2007).

## 2 Theoretical background and hypothesis development

Our theoretical framework integrates social response theory (Nass and Moon 2000) and the work design model (Humphrey et al. 2007) to explain why and how generative AI task support impacts employees' perceptions and job satisfaction. Originally proposed by Reeves and Nass (1996) and further developed by Nass and Moon (2000), social response theory provides a useful lens for analyzing interactions between humans and computers (and other technological devices) as social actors. This theory is rooted in the observation that humans often apply social rules and human-like qualities to computers, especially when a technology features human-like characteristics (i.e., social cues) (Reeves and Nass 1996). While the theory was initially developed for analyzing human–computer interactions, recent studies have expanded its applicability to other forms of human–technology interactions, such as engagement with voice assistants (Ossadnik et al. 2023), AI tools (Dutta et al. 2023), and chatbots (Huang and Lee 2022). This study compares ChatGPT task support to task support provided by a human coworker—the focus being on their respective social cues—to explore differences in subsequent employee perceptions and, in turn, their job satisfaction. Social cues can be defined as any features that provide information and trigger a social reaction (Nass and Moon 2000). These cues may be categorized as verbal cues, such as word choice, praise, small talk, and apologies,

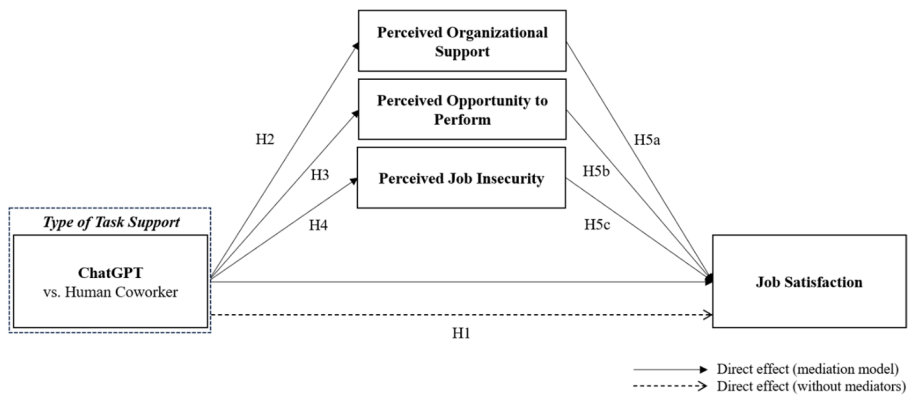
or non-verbal cues, including facial expression, eye contact, gesture, tone, and other non-linguistic signals (Leathers 1976; Feine et al. 2019).

ChatGPT is designed to produce text in a way that mimics typical human interactions (Siemon et al. 2025; Dell’Acqua et al. 2025) and can therefore be interpreted as a social actor (Huang and Lee 2022). However, prior research has shown that generative AI tools like ChatGPT offer social cues distinct from those of human coworkers, as these tools lack non-verbal cues entirely (Caldarini et al. 2022; Liu 2024). This distinction is crucial, as it may impact the degree to which employees form positive perceptions of their interaction with the type of task support (i.e., ChatGPT vs. human coworker)—and, consequently, their job satisfaction. More precisely, employees may perceive ChatGPT task support as less personable and sociable in comparison to task support provided by a human coworker (Siemon et al. 2025), which is expected to result in lower job satisfaction. Therefore, we propose the following hypothesis:

**Hypothesis 1** *ChatGPT task support negatively influences job satisfaction compared to task support provided by a human coworker.*

While Hypothesis 1 captures the overall relationship between the type of task support (i.e., ChatGPT vs. human coworker) and job satisfaction, our study also seeks to explain the mechanisms underlying the effect. Whereas social response theory explains why employees’ perceptions vary based on the type of task support (i.e., ChatGPT vs. human coworker) and the associated social cues, the work design model (Humphrey et al. 2007) complements this perspective by specifying how these perceptions translate into job satisfaction. Specifically, the work design model (Humphrey et al. 2007) conceptualizes job satisfaction as the outcome of social, motivational, and work context characteristics, which themselves are shaped by the social cues provided by the type of task support (i.e., ChatGPT vs. human coworker). In our framework, perceived organizational support represents the social characteristic, perceived opportunity to perform represents the motivational characteristic, and perceived job insecurity represents the work context characteristic. Our study focuses on the mediating impact of these three factors on job satisfaction, which is depicted in our research model in Fig. 1.

Perceived organizational support, as a social characteristic, reflects employees’ perceptions of the degree to which their organization values their contributions and cares about their well-being (Eisenberger et al. 1986). The findings of a meta-analysis by Humphrey et al. (2007) highlight that perceived social support, as a core component of perceived organizational support, is a strong predictor of job satisfaction (Rhoades and Eisenberger 2002; Ossadnik et al. 2023). According to organizational support theory (Eisenberger et al. 1986), employees develop a belief that their organization holds either a favorable or unfavorable orientation toward them (Maan et al. 2020) and that this belief is shaped by the organization’s provision of support, among other factors. This support can range from the provision of resources and technology (Na-nan et al. 2017), such as ChatGPT, to the provision of human resources, such as human coworkers (Rhoades and Eisenberger 2002). Task support provided by human coworkers is typically accompanied by a degree of emotional support in the form of



**Fig. 1** Conceptual research model

empathy, care, and reassurance, playing a crucial role in making employees feel valued by their organization (Eisenberger et al. 1986; Rhoades and Eisenberger 2002).

According to social response theory, individuals respond most positively to social actors with human-like characteristics, as rich social cues, including eye contact, conversational responsiveness, and empathetic language (Reeves and Nass 1996; Chattaraman et al. 2014), are critical to fostering emotional connections. While ChatGPT exhibits some human-like qualities through verbal cues (e.g., conversational language, contextually appropriate responses), it lacks the depth of emotional and non-verbal cues (e.g., tone, interpersonal warmth) that are typically associated with task support provided by a human coworker (Liu 2024; Siemon et al. 2025). Consequently, while ChatGPT—given the current state of AI technology—may perform task support in a manner that is functionally similar to that of a human coworker, employees may perceive ChatGPT task support on corporate communication tasks as more transactional and impersonal due to the lack of emotional and non-verbal cues (Liu 2024; Siemon et al. 2025). As perceived organizational support is highly contingent on these emotional and non-verbal cues (Ossadnik et al. 2023), we propose the following hypothesis:

**Hypothesis 2** *ChatGPT task support negatively influences perceived organizational support compared to task support provided by a human coworker.*

Opportunity to perform, originally conceptualized by Thibaut and Walker (1975), refers to employees' opportunity to satisfactorily demonstrate their knowledge, skills, and abilities (Schleicher et al. 2006). It encompasses various motivational aspects, including the ability to demonstrate one's own competencies and problem-solving skills, and it is directly tied to internal performance drivers among employees. Therefore, opportunity to perform serves as an important motivational characteristic (Humphrey et al. 2007).

Prior research suggests that employees' perceived opportunity to perform depends on the organization's provision of adequate resources (i.e., task support from either ChatGPT or a human coworker) that enable them to apply their skills (Schleicher et

al. 2006). A central mechanism behind this dynamic lies in the social cues associated with each type of task support (i.e., ChatGPT vs. human coworker). Support from human coworkers can come alongside emotional and non-verbal cues, such as eye contact, nodding, and a supportive tone of voice (Liu 2024). Such cues shape the social presence of task support provided by human coworkers, fostering employees' psychological safety and trust in the source of support (Lechner and Mortlock 2022; Siemon et al. 2025). When employees perceive the organizational environment as trustworthy and safe, they may feel more capable of exhibiting their skills. In contrast, ChatGPT task support is reliant on a text-based medium and, therefore, cannot convey such emotional and physical cues, which may be particularly important in the context of demanding corporate communication tasks. We therefore propose the following hypothesis:

**Hypothesis 3** *ChatGPT task support negatively influences perceived opportunity to perform compared to task support provided by a human coworker.*

Perceived job insecurity, defined as concern about the continued viability or existence of one's job in the future (Hartley et al. 1990), may be categorized as a work context characteristic (Humphrey et al. 2007), as it pertains to external aspects of the work environment. It reflects a subjective experience; some employees may feel insecure without objective reasons, while others may feel secure even if their job is in fact threatened (De Witte 1999). We chose job insecurity as our third mediating factor because it has been shown by prior research to negatively impact job satisfaction (De Witte et al. 2016) and may be particularly salient in AI-enabled work settings (Presbitero and Teng-Calleja 2023; Cao and Song 2025). However, this mechanism remains largely unexplored in the context of generative AI, especially when it comes to its role in task support for employees.

The absence of social cues (Siemon et al. 2025) may prevent employees from forming emotional connections during interactions with generative AI task support, leading to a sense of uncertainty and reduced psychological safety (Hermann et al. 2025). Furthermore, generative AI tools can perform tasks autonomously and are increasingly capable of replicating complex cognitive functions traditionally performed by human employees (Dell'Acqua et al. 2025). This potential for task substitution has heightened public concerns about the potential for job loss (Polyportis and Pahos 2024; Liu 2024). Consequently, ChatGPT task support may be perceived as a direct competitor for certain employee tasks. Therefore, we propose the following hypothesis:

**Hypothesis 4** *ChatGPT task support positively influences perceived job insecurity compared to task support provided by a human coworker.*

According to the work design model from Humphrey et al. (2007), social, motivational, and work context characteristics are all key predictors of job satisfaction. Perceived organizational support, as a social characteristic, has consistently exhibited a positive relationship with employees' job attitudes, job satisfaction included (Riggle et al. 2009; Maan et al. 2020), as it fosters a sense among employees that they



are valued and cared for, strengthening their bond with their organization (Rhoades and Eisenberger 2002). Emotional support in particular, as a key aspect of perceived organizational support, has been shown in meta-analyses to positively impact job satisfaction (Mathieu et al. 2019).

Perceived opportunity to perform, as a motivational and thus intrinsic characteristic, is also likely to directly affect job outcomes, including job satisfaction (Hackman and Oldham 1976; Humphrey et al. 2007). When employees perceive themselves as capable of exhibiting their skills in the workplace, it boosts their sense of competence and achievement. This, in turn, strengthens employees' intrinsic motivation and reinforces their sense that they are contributing to their organization, both of which are key drivers of job satisfaction (Hackman and Oldham 1976).

Perceived job insecurity, an important factor in the work environment (De Witte et al. 2016)—and, therefore, a work context characteristic (Humphrey et al. 2007)—can be a significant source of stress, which can undermine employee well-being and organizational commitment (Lingmont and Alexiou 2020; Polypartis and Pahos 2024). Job insecurity fosters uncertainty about the future, giving way to greater perceptions of stress and a more challenging work environment, ultimately impacting workplace outcomes. Given that employees' well-being and organizational commitment align closely with job satisfaction (Humphrey et al. 2007), it may be inferred that perceived job insecurity leads to a decline in job satisfaction in our study context. Therefore, we propose the following hypotheses:

**Hypothesis 5a** *Perceived organizational support positively influences job satisfaction.*

**Hypothesis 5b** *Perceived opportunity to perform positively influences job satisfaction.*

**Hypothesis 5c** *Perceived job insecurity negatively influences job satisfaction.*

Since our hypotheses incorporate the effects of task support on our mediators (Hypotheses 2–4) and the effects between the three mediators and our outcome variable of job satisfaction (Hypotheses 5a–c), we additionally anticipate negative indirect effects of ChatGPT task support, compared to task support provided by a human coworker, on job satisfaction. These indirect effects are expected to operate through our mediators: perceived organizational support, opportunity to perform, and job insecurity. Thus, we propose the following hypothesis:

**Hypothesis 6** *The type of task support (i.e., ChatGPT vs. human coworker) indirectly influences job satisfaction through (a) perceived organizational support, (b) perceived opportunity to perform, and (c) perceived job insecurity.*



### 3 Method

#### 3.1 Sample

We conducted a  $2 \times 2$  between-subjects online vignette experiment (Aguinis and Bradley 2014) to systematically investigate the effect of the type of task support (i.e., ChatGPT vs. human coworker) on perceived organizational support, opportunity to perform, and job insecurity as well as overall job satisfaction with two scenarios (one with ChatGPT providing task support, the other with a human coworker providing task support; see Appendix A for details). Given the limitations of implementing randomized field experiments on AI–employee collaboration, scenario-based experiments are frequently conducted to explore the psychological impact of such interactions (Yin et al. 2024; Köchling et al. 2025).

Prior to the start of data collection, we approximated the necessary sample size using the power-analysis program G\*Power (Faul et al. 2007). The sample size was calculated a priori based on a significance level of  $\alpha=0.05$  and a power level of  $1-\beta=0.9$ . Following Cohen's (1988) recommendation, we chose a medium effect-size index of 0.25 and estimated that 171 participants would provide sufficient statistical power for this study design. To recruit our participants, we used an ISO 20252:19-certified online sample provider, aiming for a quota-based sample representative of the German working population. To ensure robustness, we slightly oversampled, resulting in a sample of 202 participants.

Table 1 provides demographic information on the participants, including their work experience, academic background, and occupational sector. Most participants had between four and ten years of work experience (49.01%) and reported either an apprenticeship (39.11%), a bachelor's degree (23.76%), or a master's degree (26.73%) as their highest level of education. In terms of industry, most participants worked in IT and communication (16.83%), public administration (14.85%), or healthcare and social services (13.86%), indicating that the sample covered a broad range of sectors. Additional descriptive statistics for each vignette are presented in Table 2, showing only minor differences across conditions.

#### 3.2 Scenarios and procedure

Initially, the participants were instructed to put themselves in the role of an employee in the communications department of Marzeo AG, a fictitious company name created for research purposes and used in prior studies (Evertz et al. 2021), ensuring that the participants would not uncover information about the company that might skew their perceptions. Participants were told that their corporate communication task was to draft a text for the company's website about a change in corporate strategy, incorporating information from a list of bullet points provided by their supervisor (see Appendix A). Corporate communication involves strategically aligning both internal and external messages with organizational objectives and maintaining favorable stakeholder relations (Christensen and Cornelissen 2011). Through this lens, our task required participants to prepare a website text for external communication, requiring both the consideration of certain pieces of information and cognitive effort in fram-

**Table 1** Demographic information on participants

Variable	Category	<i>n</i>	%
Work Experience	0–3 years	36	17.82
	4–6 years	55	27.23
	7–10 years	44	21.78
	11–15 years	17	8.42
	16–20 years	17	8.42
	>20 years	33	16.34
Highest Education Level	No diploma	0	0
	High school diploma	14	6.93
	Apprenticeship	79	39.11
	Bachelor's degree	48	23.76
	Master's degree	54	26.73
	Doctorate	5	2.48
Industry	Other	2	0.99
	Agriculture	5	2.48
	Production & manufacturing	13	6.44
	Construction	10	4.95
	Trade & service	17	8.42
	Transport & logistics	12	5.94
	IT & communication	34	16.83
	Finance & insurance	13	6.44
	Education & research	16	7.92
	Healthcare & social services	28	13.86
	Art & culture	3	1.49
	Public administration	30	14.85
	Other	21	10.40

**Table 2** Descriptive statistics of the vignettes

	Total sample	Vignette 1 (Human Coworker Task Support)	Vignette 2 (ChatGPT Task Support)
<i>n</i>	202	102	100
<i>M</i> <sub>age</sub> ( <i>SD</i> )	32.56 (8.03)	33.53 (8.63)	31.58 (7.27)
% Female	49.01%	53.92%	44.00%
Technological Affinity ( <i>SD</i> )	4.83 (1.46)	4.42 (1.56)	5.24 (1.23)

*M* and *SD* represent mean and standard deviation, respectively; technological affinity was measured along a seven-point Likert scale

ing, tone, and audience orientation. This task, which involved both mechanical and substantial cognitive work, was designed to be achievable with task support from either ChatGPT or a human coworker (Choudhary et al. 2025). Furthermore, participants were told that the deadline to submit the text to their supervisor was set for the end of the same day. Lastly, participants were told that, due to time constraints, they would be unable to complete the assignment within the allotted time, thereby emphasizing the need to interact with the provided form of task support (i.e., ChatGPT vs. human coworker) to carry out the task (Bamberger 2009; Ossadnik et al. 2023).

Subsequently, participants were randomly assigned to one of two task-support scenarios. In the first scenario, they were informed that, to complete their task in time, they would receive task support from a human coworker on their team. In the second scenario, that support would come in the form of ChatGPT instead of a human coworker. Following the scenarios, participants responded to the time 1 (T1) measures, assessing their perceptions of organizational support, opportunity to perform, and job insecurity.

Afterward, participants received randomized feedback—either positive or negative—through an email from a fictitious supervisor (see Appendix B). Negative feedback indicated a failure to meet organizational quality standards, as not all relevant points from the provided list were incorporated into the drafted text. Positive feedback commended the successful incorporation of all the key points and indicated that the text could be published on the organization's website. Following this, participants rated their job satisfaction based on the provided task support and the nature of the feedback that they received as the time 2 (T2) measure. The use of two measurement points here is methodologically advantageous for testing mediation effects, as it allows for the temporal separation of mediators (T1) from the outcome variable (T2). This mitigates the risk of common method bias and strengthens the validity of causal interpretations (Podsakoff et al. 2012).

### 3.3 Pretest and quality checks

Several procedures were implemented to ensure high-quality data. Before starting the data-collection process, we obtained ethical clearance for our study design from the German Association for Experimental Economic Research and pretested the wording of our scenarios and questionnaire with a sample of 20 participants, which led to minor but necessary changes.

To participate in the experiment, respondents needed to be employed and within the 18–55 age range, as we were targeting individuals in the early to mid-stages of their careers, where job insecurity is a salient concern. The participant sample had an average age of 32.56 years ( $SD=8.03$ ), with a gender distribution of 99 female and 103 male participants. Prior experience with ChatGPT was a prerequisite to facilitate realistic engagement with the ChatGPT task support scenario (Ma and Huo 2023). We conducted t-tests to check for differences between the vignettes in terms of age, gender, technology affinity, and perception of ChatGPT. The results only indicated significant differences for technology affinity and perception of ChatGPT, which were higher in the vignette with ChatGPT task support. Consequently, these two variables were included as control variables in subsequent analyses. In addition, we included age as a control variable given its theoretical relevance to job insecurity (De Witte 1999).

Moreover, we implemented an attention check (“For this item, please select strongly agree”), as suggested by Kung et al. (2018), with incorrect responses leading to automatic exclusion from the study. Post-vignette checks were also conducted to confirm participants' awareness of the type of task support that they received, with over 90% responding correctly. However, remaining participants were retained in the sample, because placeholders were embedded in each item to remind them of

the type of task support they received. As an additional implementation check, we asked respondents to rate how realistic the scenario was to them (1=very unrealistic; 7=very realistic) and how effectively they were able to put themselves into the described situation (1=very poorly; 7=very well) (Maute and Dubés 1999). Overall, the results showed high realism across both scenarios ( $M=5.54$ ) and indicated that participants were able to effectively put themselves into the described situation ( $M=5.80$ ).

### 3.4 Measures

We employed established multi-item scales in our questionnaire to evaluate all constructs, making minor adaptations to the included items to fit our scenarios and translating all scales into German (Brislin 1970). Generally, we measured all variables on a seven-point Likert scale, with anchors ranging from 1 (*strongly disagree*) to 7 (*strongly agree*). To test our treatment, we constructed a dichotomous variable for the type of task support (i.e., ChatGPT, with task support provided by a human coworker serving as the reference group).

We measured *perceived organizational support* using the three-item short version of the perceived organizational support scale developed by Eisenberger et al. (1986), which was later translated and validated in German by Siebenaler and Fischer (2020). A sample item is “Marzeo AG really cares about my well-being.” Cronbach’s alpha was 0.89. For *perceived opportunity to perform*, we used the four-item subscale capturing opportunity to perform developed by Bauer et al. (2001). A sample item is “I could really show my skills and abilities through the support provided by ChatGPT/a coworker.” Cronbach’s alpha was 0.94. We measured *perceived job insecurity* with three items from the job insecurity scale developed by De Witte (1999), which was translated and validated by Vander Elst et al. (2014). A sample item is “I feel insecure about the future of my job at Marzeo AG.” Cronbach’s alpha was 0.94. We measured *job satisfaction* with three items from the Job Diagnostic Survey developed by Hackman and Oldham (1976). A sample item is “Generally speaking, I am very satisfied with my job at Marzeo AG.” Cronbach’s alpha was 0.88.

To enhance robustness, we included control variables for participants’ age, perception of ChatGPT, and technological affinity. Perception of ChatGPT was measured using two items, yielding an overall Cronbach’s alpha of 0.93. Technological affinity was measured using three items from a scale by Agarwal and Prasad (1998), yielding a Cronbach’s alpha of 0.87. We also controlled for supervisor feedback (i.e., negative vs. positive) and constructed a dichotomous variable for negative supervisor feedback, with positive feedback as the reference group. The variables’ means, standard deviations, and correlations are presented in Table 3.

To assess the validity criteria, we conducted a confirmatory factor analysis (CFA) for the four latent variables included in the study. The CFA exhibited good fit with the data ( $\chi^2=91.78$ ;  $df=59$ ;  $\chi^2/df=1.56$ ;  $p=0.004$ ; SRMR = 0.03; RMSEA = 0.05; CFI = 0.98) (Bollen 1989). All factor loadings are significant and above the cut-off criterion of 0.7 (Hair et al. 2019). The average variance extracted for all constructs is above the 0.5 threshold (perceived organizational support: 0.73; perceived opportunity to perform: 0.81; perceived job insecurity: 0.85; job satisfaction: 0.70), indicating con-

**Table 3** Cronbach alphas, means, standard deviations, and correlations

Variable	<i>a</i>	<i>M</i>	<i>SD</i>	1	2	3	4	5	6	7	8	9
1. ChatGPT vs. Human Coworker Task Support	~	0.50	0.50									
2. Perceived Organizational Support	0.89	4.95	1.27	-0.04								
3. Perceived Opportunity to Perform	0.94	5.06	1.46	-0.18**	0.59**							
4. Perceived Job Insecurity	0.94	3.37	1.73	0.20**	-0.24**	-0.23**						
5. Job Satisfaction	0.88	4.94	1.37	-0.05	0.48**	0.39**	-0.21**					
6. Negative Feedback	~	0.51	0.50	0.01	-0.07	0.01	-0.01	-0.42**				
7. Perception of ChatGPT	0.93	4.85	1.99	0.40**	0.17*	0.09	-0.05	0.10	-0.01			
8. Technological Affinity	0.87	4.83	1.46	0.28**	0.27**	0.22**	0.06	0.23**	-0.04	0.54**		
9. Age	~	32.56	8.03	-0.12	0.04	0.13	-0.20**	-0.05	0.05	-0.23**	-0.09	
10. Gender	~	1.51	0.50	0.10	0.03	0.02	0.15*	-0.00	0.02	0.12	0.25**	0.08

*a* represents the internal consistency reliability coefficient (Cronbach's alpha); *M* and *SD* represent mean and standard deviation, respectively; *n*=202

\**p* < 0.05

\*\**p* < 0.01

vergent validity, and composite reliabilities are above the 0.7 threshold (perceived organizational support: 0.89; perceived opportunity to perform: 0.95; perceived job insecurity: 0.94; job satisfaction: 0.88), confirming construct reliability (Fornell and Larcker 1981). Furthermore, discriminant validity is demonstrated for all constructs, as the average variance extracted exceeds its squared correlations with other constructs (Fornell and Larcker 1981).

## 4 Results

### 4.1 Main findings

For the analysis of the hypothesized research model, we employed covariance-based structural equation modeling (SEM) using the lavaan R package (Rosseel 2012). To test Hypothesis 1, we included only job satisfaction as the dependent variable in Model 1. The model, including all control variables, exhibited an excellent fit to the data ( $\chi^2 = 7.97$ ;  $df = 10$ ;  $\chi^2/df = 0.80$ ;  $p = 0.632$ ; SRMR = 0.02; RMSEA = 0.00; CFI = 1.00). Our findings, shown in Table 4, reveal that ChatGPT task support, in comparison to that provided by a human coworker, incurred lower job satisfaction at the 10% significance level ( $\beta = -0.12$ ;  $p = 0.086$ ), thus lending marginal support to Hypothesis 1.

To test Hypotheses 2–6, we estimated a full model (Model 2) that included our control variables as well as our three mediators—perceived organizational support, opportunity to perform, and job insecurity—allowing us to examine their direct and indirect effects on job satisfaction. Once again, the model exhibited a good fit to our data ( $\chi^2 = 160.15$ ;  $df = 107$ ;  $\chi^2/df = 1.50$ ;  $p = 0.001$ ; SRMR = 0.03; RMSEA = 0.05; CFI = 0.98). Table 5; Fig. 2 show the estimated SEM coefficients.

According to our findings from Model 2, ChatGPT task support, in comparison to task support provided by a human coworker, led to weaker perceptions of organizational support ( $\beta = -0.16$ ;  $p = 0.043$ ), supporting Hypothesis 2. This provides initial evidence that, in the context of a corporate communication writing task, employees feel less supported when their task support comes in the form of generative AI rather than a coworker. Hypothesis 3 and Hypothesis 4 are also fully supported by the findings, as employees who received ChatGPT task support perceived less of an opportunity to perform ( $\beta = -0.28$ ;  $p < 0.001$ ) and greater job insecurity ( $\beta = 0.26$ ;  $p = 0.001$ ) than those who received task support from a human coworker. The proposed influence of the mediators on job satisfaction was also validated; perceived organizational support ( $\beta = 0.31$ ;  $p = 0.008$ ) and perceived opportunity to perform ( $\beta = 0.20$ ;  $p = 0.043$ ) positively impacted job satisfaction, while perceived job insecurity negatively influenced job satisfaction ( $\beta = -0.14$ ;  $p = 0.030$ ), thereby supporting Hypotheses 5a, 5b, and 5c.

Moreover, we examined the mediating mechanisms between ChatGPT task support and job satisfaction through perceived organizational support, opportunity to perform, and job insecurity, which are shown in Table 6. Our results reveal negative indirect effects of ChatGPT task support on job satisfaction via perceived organizational support ( $\beta = -0.05$ ; 95% CI  $[-0.33, -0.00]$ ), perceived opportunity to perform

**Table 4** SEM results, model 1

	<i>B</i>	<i>SE</i>	$\beta$	<i>p</i> -value
<i>Direct Effects of the Treatment and Controls on Job Satisfaction (<math>R^2 = 0.27</math>)</i>				
ChatGPT Task Support <sup>a</sup> → Job Satisfaction	<b>-0.29</b>	<b>0.17</b>	<b>-0.12</b>	<b>0.086</b>
Negative Feedback <sup>b</sup> → Job Satisfaction	<b>-0.99</b>	<b>0.17</b>	<b>-0.42</b>	<b>&lt;0.001</b>
Perception of ChatGPT → Job Satisfaction	-0.00	0.06	-0.01	0.949
Technological Affinity → Job Satisfaction	<b>0.23</b>	<b>0.09</b>	<b>0.29</b>	<b>0.008</b>
Age → Job Satisfaction	0.00	0.01	0.01	0.909

<sup>a</sup>Reference category is human coworker task support; <sup>b</sup>reference category is positive feedback; number of bootstrap samples=5000; bias-corrected standard errors are given; *B*=unstandardized effect;  $\beta$ =standardized effect; *SE*=standard error; significant coefficients at  $p < 0.10$  are in boldface;  $n=202$

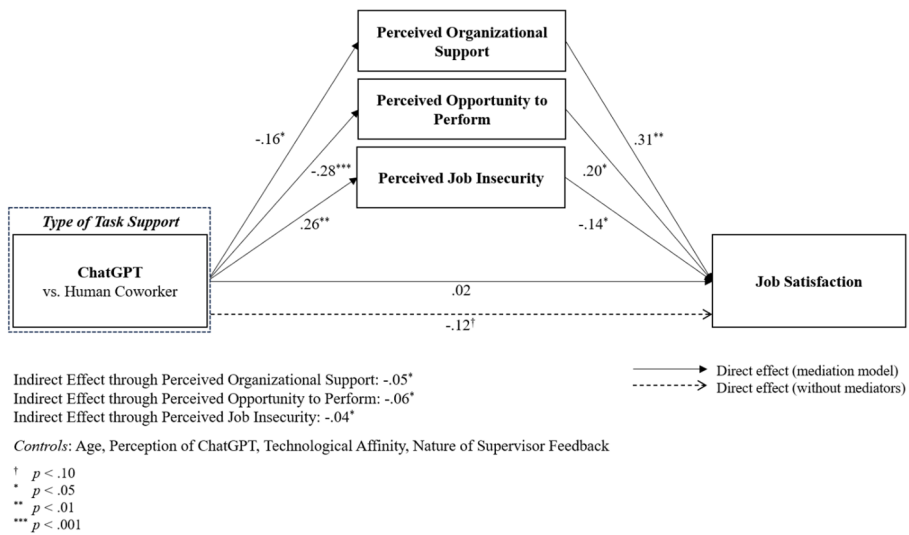
**Table 5** SEM results, model 2

	<i>B</i>	<i>SE</i>	$\beta$	<i>p</i> -value
<i>Treatment effects and control effects on mediators</i>				
ChatGPT Task Support <sup>a</sup> → Perceived Organizational Support	<b>-0.33</b>	<b>0.16</b>	<b>-0.16</b>	<b>0.043</b>
ChatGPT Task Support <sup>a</sup> → Perceived Opportunity to Perform	<b>-0.61</b>	<b>0.16</b>	<b>-0.28</b>	<b>&lt;0.001</b>
ChatGPT Task Support <sup>a</sup> → Perceived Job Insecurity	<b>0.55</b>	<b>0.16</b>	<b>0.26</b>	<b>0.001</b>
Perception of ChatGPT → Perceived Organizational Support	0.07	0.06	0.12	0.260
Technological Affinity → Perceived Organizational Support	<b>0.19</b>	<b>0.09</b>	<b>0.26</b>	<b>0.028</b>
Age → Perceived Organizational Support	0.01	0.01	0.07	0.410
Perception of ChatGPT → Perceived Opportunity to Perform	0.04	0.05	0.08	0.390
Technological Affinity → Perceived Opportunity to Perform	<b>0.20</b>	<b>0.07</b>	<b>0.27</b>	<b>0.006</b>
Age → Perceived Opportunity to Perform	<b>0.02</b>	<b>0.01</b>	<b>0.13</b>	<b>0.074</b>
Perception of ChatGPT → Perceived Job Insecurity	<b>-0.14</b>	<b>0.05</b>	<b>-0.26</b>	<b>0.006</b>
Technological Affinity → Perceived Job Insecurity	0.07	0.06	0.10	0.241
Age → Perceived Job Insecurity	<b>-0.03</b>	<b>0.01</b>	<b>-0.23</b>	<b>0.002</b>
<i>Direct Effects of the Treatment, Mediators, and Controls on Job Satisfaction (<math>R^2 = 0.50</math>)</i>				
ChatGPT Task Support <sup>a</sup> → Job Satisfaction	0.06	0.19	0.02	0.755
Perceived Organizational Support → Job Satisfaction	<b>0.42</b>	<b>0.16</b>	<b>0.31</b>	<b>0.008</b>
Perceived Opportunity to Perform → Job Satisfaction	<b>0.27</b>	<b>0.13</b>	<b>0.20</b>	<b>0.043</b>
Perceived Job Insecurity → Job Satisfaction	<b>-0.19</b>	<b>0.09</b>	<b>-0.14</b>	<b>0.030</b>
Negative Feedback <sup>b</sup> → Job Satisfaction	<b>-1.17</b>	<b>0.18</b>	<b>-0.42</b>	<b>&lt;0.001</b>
Perception of ChatGPT → Job Satisfaction	-0.07	0.06	-0.10	0.215
Technological Affinity → Job Satisfaction	<b>0.16</b>	<b>0.08</b>	<b>0.16</b>	<b>0.062</b>
Age → Job Satisfaction	-0.01	0.01	-0.07	0.269
<i>Total Effect on Job Satisfaction</i>				
ChatGPT Task Support <sup>a</sup> → Job Satisfaction	<b>-0.34</b>	<b>0.21</b>	<b>-0.12</b>	<b>0.098</b>

<sup>a</sup>Reference category is human coworker task support; <sup>b</sup>reference category is positive feedback; number of bootstrap samples=5000; bias-corrected standard errors are given; *B*=unstandardized effect;  $\beta$ =standardized effect; *SE*=standard error; significant coefficients at  $p < 0.10$  are in boldface;  $n=202$

( $\beta = -0.06$ ; 95% CI  $[-0.38, -0.02]$ ), and perceived job insecurity ( $\beta = -0.04$ ; 95% CI  $[-0.26, -0.01]$ ). As the 95% bootstrapped confidence intervals did not include zero, these indirect effects are significant, supporting Hypotheses 6a, 6b, and 6c. Notably, ChatGPT task support's direct effect on job satisfaction, when the mediators are included in the model, was not statistically significant. However, the total effect





**Fig. 2** Research model with SEM results

**Table 6** Indirect effects

	<i>B</i>	$\beta$	95% CI
ChatGPT Task Support <sup>a</sup> → Perceived Organizational Support → Job Satisfaction	<b>-0.14</b>	<b>-0.05</b>	<b>[-0.33, -0.00]</b>
ChatGPT Task Support <sup>a</sup> → Perceived Opportunity to Perform → Job Satisfaction	<b>-0.16</b>	<b>-0.06</b>	<b>[-0.38, -0.02]</b>
ChatGPT Task Support <sup>a</sup> → Perceived Job Insecurity → Job Satisfaction	<b>-0.10</b>	<b>-0.04</b>	<b>[-0.26, -0.01]</b>

<sup>a</sup>Reference category is human coworker task support; *B*=unstandardized effect;  $\beta$ =standardized effect; 95% bias-corrected confidence intervals computed with 5000 bootstrapped samples; indirect effects for which zero was not included in the 95% confidence interval are in boldface;  $n=202$

of the model, combining the direct and indirect pathways, was marginally significant ( $\beta = -0.12$ ,  $p = 0.098$ ), in line with our findings from Model 1.

Taken together, our findings indicate that ChatGPT task support's negative impact on job satisfaction operates entirely through these indirect psychological mechanisms (i.e., perceived organizational support, opportunity to perform, and job insecurity). In line with this, the inclusion of the mediators strongly increased the explained variance in job satisfaction ( $R^2 = 0.27$  vs.  $R^2 = 0.50$ ), further underscoring their central role in the relationship.

## 4.2 Robustness checks

We conducted additional analyses to assess the robustness of our findings. In addition to age, technological affinity, and perception of ChatGPT, which were retained as controls across all models, we tested whether including gender and industry as further controls would change the results. These additional controls did not alter the overall

pattern of the results; the indirect effect of ChatGPT task support on job satisfaction via perceived opportunity to perform and job insecurity remained significantly negative, while the pathway through perceived organizational support was non-significant within the 95% confidence interval but reached marginal significance within the 90% confidence interval. These results indicate that our main findings are robust against the inclusion of these additional controls. Notably, however, including gender and industry reduced overall model fit, which is why we did not retain them in the final models. To address multicollinearity, we inspected correlations among the predictors, all of which were below 0.60. In addition, we calculated VIFs for all manifest predictors, which ranged between 1.00 and 1.61, clearly below the threshold of 5, indicating no issue with multicollinearity (Hair et al. 2019). To mitigate the risk of common method bias, we randomized the item order to minimize sequential response tendencies and conducted Harman's single-factor test (Podsakoff et al. 2012). The largest factor accounted for less than 50% of the variance, indicating that common method bias is not a major concern.

## 5 Discussion

The aim of this study was to examine the impact of generative AI task support on employees' job satisfaction and to investigate the psychological mechanisms underlying this relationship. Our findings show that, in the context of corporate communication, ChatGPT task support is associated with lower job satisfaction compared to task support provided by a human coworker. Moreover, our results demonstrate that this relationship is fully mediated by three employee perceptions—organizational support, opportunity to perform, and job insecurity—underscoring their critical role in determining the impact of ChatGPT task support on employees' job satisfaction. Prior research on generative AI at work has predominantly emphasized performance-related outcomes (Dell'Acqua et al. 2023; Brynjolfsson et al. 2025), whereas evidence on employees' job satisfaction and related attitudes remains mixed and appears to be context-contingent (Chiong and Xie 2024; Chuang et al. 2025; Hermann et al. 2025; Bosek-Rak and Kaszyński 2026). In addition, prior studies often contrast generative AI use with no use, but rarely benchmark generative AI task support against task support provided by a human coworker. Against this background, our study contributes to the literature by investigating the psychological mechanisms linking generative AI task support—relative to human coworker task support—to employees' job attitudes, identifying three distinct pathways and offering insights into its association with lower job satisfaction. Taken together, these results highlight the continued relevance of human coworker task support for employees' job satisfaction, particularly in the corporate communication context. Our findings have theoretical and practical implications.

### 5.1 Theoretical implications

First, our results advance the literature's understanding of the psychological impact of generative AI tools by integrating social response theory (Reeves and Nass 1996;

Nass and Moon 2000) with the work design model (Humphrey et al. 2007) to explain *why* and *how* ChatGPT task support negatively impacts employees' perceptions and job satisfaction, compared to task support provided by a human coworker. While social response theory explains *why* perceptions differ between generative AI task support and task support provided by a human coworker, the work design model explains *how* these perceptions (i.e., social, motivational, and work context characteristics) predict job satisfaction.

In line with social response theory (Nass and Moon 2000), our findings indicate that ChatGPT task support negatively affects employees' perceptions of organizational support and opportunity to perform, while increasing perceived job insecurity, which, in turn, negatively affect their overall job satisfaction. These findings can be attributed to generative AI's lack of emotional and non-verbal cues (Liu 2024; Siemon et al. 2025). Despite their human-like conversational capabilities, generative AI tools such as ChatGPT lack the richer social cues offered by human coworkers (Caldarini et al. 2022). Therefore, our findings broaden the applicability of social response theory to the context of generative AI. The work design model, in turn, explains how employees' job satisfaction is affected by social, motivational, and work context characteristics (Humphrey et al. 2007). Our findings demonstrate that the link between ChatGPT task support and job satisfaction is fully mediated by social (i.e., perceived organizational support), motivational (i.e., perceived opportunity to perform), and work context characteristics (i.e., perceived job insecurity), showing that the type of task support (i.e., ChatGPT vs. human coworker) is not directly linked to lower job satisfaction but that this relationship is mediated through these three pathways. Therefore, our study advances the literature's understanding of job satisfaction predictors and extends the applicability of the work design model (Humphrey et al. 2007) to the context of generative AI by identifying these three distinct pathways.

With regard to the social pathway via perceived organizational support, our results indicate lower levels when employees are supported by ChatGPT compared to a human coworker. This finding aligns with social response theory and prior research indicating that employees' perceived organizational support depends strongly on the social cues embedded in task support (Eisenberger et al. 1986; Nass and Moon 2000). As ChatGPT lacks the emotional and non-verbal cues that typically characterize support provided by human coworkers, such as empathy, reassurance, and interpersonal warmth (Caldarini et al. 2022), employees may feel less valued and interpret ChatGPT task support as a sign of lower organizational care and investment. This aligns with prior research showing that extensive interaction with generative AI can reduce daily social contact and exacerbate feelings of isolation (Bankins and Formosa 2023; Hermann et al. 2025), which may also be associated with lower perceived organizational support. In line with the work design model (Humphrey et al. 2007), perceived organizational support is positively related to job satisfaction among employees. This can be explained by the notion that perceived organizational support fosters feelings of security and emotional stability, which in turn enhance employees' job satisfaction

(Humphrey et al. 2007). Accordingly, the link between ChatGPT task support and job satisfaction functions indirectly through reduced perceived organizational support, underscoring the central role of social characteristics in the integration of generative AI task support into the workplace.

With regard to the motivational pathway via perceived opportunity to perform, our results indicate that ChatGPT task support gives way to weakened perceptions of opportunity to perform compared to task support provided by a human coworker. While prior studies have highlighted generative AI as capable of enhancing *objective* performance (Dell’Acqua et al. 2023; Brynjolfsson et al. 2025), our findings point to the opposite pattern when it comes to *perceived* opportunity to perform. This finding may be understood in light of the lack of emotional and non-verbal cues that typically foster social presence and psychological safety in human interactions (Lechner and Mortlock 2022; Siemon et al. 2025). Without such cues, ChatGPT-based interactions can appear less predictable and less trustworthy, thereby reducing employees’ perceived ability to showcase their skills (Mayer et al. 2020; Jia et al. 2024; Liu 2024). Moreover, our findings resonate with prior research indicating that employees are generally less familiar with generative AI tools than they are with human collaboration (Horowitz et al. 2024); thus, the integration of such tools can disrupt established workflows and routines (Brynjolfsson et al. 2025; Hermann et al. 2025). Perceived opportunity to perform, in turn, functions as a motivational characteristic (Humphrey et al. 2007) that enhances job satisfaction by fostering competence and intrinsic motivation (Hackman and Oldham 1976; Humphrey et al. 2007). Accordingly, our results indicate that ChatGPT task support reduces job satisfaction indirectly through a reduction in employees’ perceived opportunity to perform, highlighting this motivational pathway as a key mechanism linking generative AI integration to job satisfaction among employees.

With regard to the work context pathway via perceived job insecurity, our results indicate higher insecurity among employees supported by ChatGPT than among those supported by a human coworker. This may be explained by the fact that ChatGPT lacks the interpersonal connection that helps employees feel secure and stable in their roles (Voorveld and Araujo 2020). Our findings add to the broader debate on the relationship between task support by (generative) AI tools and job insecurity, which has thus far provided inconsistent results. While some studies have uncovered no significant effect of AI tool integration on job insecurity (e.g., Brougham and Haar 2018; Nazareno and Schiff 2021; Walczok et al. 2026), others have identified a positive effect of AI tool integration on feelings of job insecurity (e.g., Presbitero and Teng-Calleja 2023) Lingmont and Alexiou 2020. Job insecurity, in turn, serves as a work context characteristic and mediator that hinders job satisfaction. Accordingly, in our specific context, employees seemingly perceive generative AI tools less as supportive resources and more as potential threats to their jobs.

Second, our findings extend the literature on generative AI and job satisfaction. Notably, prior research has offered mixed evidence of how generative AI affects

employees' job satisfaction. For example, prior studies link AI technostress to lower job satisfaction (Chuang et al. 2025; Bosek-Rak and Kaszyński 2026), particularly in roles with higher exposure to AI transformation, yet also suggest that the benefits of generative AI may depend on effective leadership and organizational support (Bosek-Rak and Kaszyński 2026). Other studies uncovered positive effects on job satisfaction in AI-enabled work (Braganza et al. 2022) and for generative AI in particular (Chiong and Xie 2024), although both studies noted that the benefits diminish when it comes to roles more susceptible to automation. Building on this prior research, our study offers a comparative perspective by directly contrasting generative AI task support with task support provided by a human coworker and demonstrating that the former is associated with lower job satisfaction. Our findings align with recent work indicating that generative AI tools like ChatGPT are often perceived as potential replacements for human roles rather than complementary resources (Polyportis and Pahos 2024; Liu 2024; Zhou et al. 2025). Notably, our results remained robust even after statistically controlling for the nature of supervisor feedback (i.e., positive vs. negative), highlighting that the observed negative effects on job satisfaction are not contingent on task outcomes (Fischhoff 1975; Banks et al. 2022) but rather primarily driven by the type of task support (i.e., ChatGPT vs. human coworker) and the underlying mediators.

## 5.2 Practical implications

The implementation of generative AI in organizational settings is rapidly gathering pace (Yin et al. 2024). In our experimental context of corporate communication, however, employees preferred traditional task support (i.e., that provided by a human coworker) over ChatGPT task support. Organizations aiming to implement generative AI tools like ChatGPT must be mindful of their potential negative impact on employees' job satisfaction, as this has direct implications for performance, retention, and overall workplace outcomes (Tett and Mayer 1993; Judge et al. 2001; Brougham and Haar 2018). In our experiment, the preference for task support provided by a human coworker was found to arise indirectly via three pathways: the social pathway (i.e., perceived organizational support), the motivational pathway (i.e., perceived opportunity to perform), and the work context pathway (i.e., perceived job insecurity). Accordingly, organizations must implement integration strategies for generative AI task support that deliberately address the three pathways.

First, as our findings show, employees perceive lower organizational support when their task support is provided in the form of ChatGPT, rather than by a human coworker. To address this social pathway, organizational leadership plays an important role in maintaining job satisfaction (Bosek-Rak and Kaszyński 2026). Specifically, leaders should communicate the advantages and boundaries of generative AI tools as means of task support (e.g., 24/7 availability, potential for writing assistance when appropriately prompted) (Dwivedi et al. 2023). By clearly understanding the

tools' potential benefits and recognizing their purpose, employees may feel more valued and supported by their organization. Another strategy is to embed regular human touchpoints into workflows in which employees frequently interact with generative AI, counteracting the negative effects of reduced human contact and mitigating feelings of social isolation (Bankins and Formosa 2023; Hermann et al. 2025).

Second, employees rated their opportunity to perform as lower when their task support was provided in the form of ChatGPT. To address this motivational pathway, employees should be trained to build confidence and competence for interacting effectively with generative AI task support (Dwivedi et al. 2023). However, training is effective only if employees are willing and able to engage in learning how to make use of the tools. This readiness may be fostered by clarifying that the final task outcome remains the employee's responsibility and empowering employees accordingly (Xu et al. 2024; Hermann et al. 2025). When employees develop more sophisticated generative AI-relevant strategies and prompting skills, the advantages of those tools can greatly increase (Dell'Acqua et al. 2025). Therefore, organizations should implement workshops to develop employees' generative AI literacy (e.g., prompt iteration, personalization of chatbots) and domain expertise so they are more capable of identifying and correcting potential hallucinations by these tools (Hermann et al. 2025).

Third, beyond the social and motivational pathways, it is particularly important that organizations address the work context pathway via perceived job insecurity, as it currently represents a major concern among employees (Boston Consulting Group et al. 2024). Employees often view generative AI tools as a threat to their roles, interpreting their use as a signal of task automation rather than task support (Liu 2024). To counter these perceptions, organizations should position and communicate generative AI as a supportive collaborative tool that complements—rather than replaces—human work (Kaplan and Haenlein 2019; Cao and Song 2025). While such communication strategies may serve to alleviate short-term concerns about job insecurity, long-term initiatives are still necessary. Managers should consistently highlight the intention behind the integration of generative AI tools and offer examples of such tools complementing human work (Kaplan and Haenlein 2019). As the introduction of generative AI can challenge employees' professional identity (e.g., by questioning the distinctiveness of their expertise), amplifying feelings of insecurity (Hermann et al. 2025), organizations should emphasize that human contributions (e.g., judgment, creativity, accountability) are essential components of work. Moreover, some groups (e.g., younger employees and employees in highly automatable roles) are more prone to insecurity (Lingmont and Alexiou 2020). Organizations should actively identify and support such employees (e.g., through surveys and communication with supervisors), as they are particularly vulnerable to perceiving generative AI as a threat to their roles. Regular interventions, such as one-on-one meetings with supervisors, can give these employees a platform to voice their concerns and strengthen psychological safety (Cao and Song 2025), thereby mitigating job insecurity.

### 5.3 Limitations and future research

Our study has the following limitations that provide avenues for future research. First, our study focused on a corporate communication writing task to assess the psychological effects of ChatGPT task support. However, research suggests that generative AI tools exhibit varying levels of efficacy and performance benefits across different types of tasks, excelling in areas like routine work, programming, and writing while struggling with tasks that require critical thinking and high levels of collaboration (Dell’Acqua et al. 2023; Eloundou et al. 2023; Brynjolfsson et al. 2025). These differences may give way to varying psychological perceptions of the technology depending on the task at hand (Hermann et al. 2025). Therefore, future research should investigate how task type moderates the psychological impact of generative AI task support, particularly as organizations are adopting such tools for an increasingly wide range of tasks. Moreover, our study design did not include a vignette in which participants had to imagine completing the task without any support. While such a scenario seemed unrealistic in this specific context (i.e., a corporate communication task under time pressure), future research could compare a no-support condition with both ChatGPT and human coworkers across different task contexts (Dell’Acqua et al. 2025).

Second, despite our efforts to craft highly realistic hypothetical scenarios, participants were not actually performing tasks with support from ChatGPT or a human coworker at their real job. While this experimental approach upholds a high degree of internal validity and is often deemed effective for exploring real-life sentiments, attitudes, behaviors, and perceptions (Maute and Dubés 1999), its external validity—and, thus, the generalizability of our findings—is limited (Aguinis and Bradley 2014). Nonetheless, in the context of AI–employee collaboration, vignette studies are frequently employed to investigate psychological impacts, as they enable researchers to simulate controlled scenarios that are difficult to standardize in real-world field studies (Yin et al. 2024). The participants in our study reported a high level of realism and immersion in the vignettes, suggesting that our experiment closely approximates real-world scenarios. Future research could extend these findings by replicating the study within real-world workplace environments.

Third, prior studies have indicated that perceptions of AI are profoundly influenced by contextual factors, such as employees’ job types, industries, and cultural backgrounds (Duan et al. 2019; Hermann et al. 2025). As our sample consisted solely of German participants, it was relatively homogeneous. Therefore, future research should examine whether cultural context influences employees’ perceptions of generative AI task support. With regard to job type and industry, we controlled for participants’ industry as a robustness check, though this did not reveal any systematic differences. However, due to the limited sample size, we were unable to conduct robust subgroup analyses. Future studies with larger and more diverse samples should



explore whether occupational roles or industry affiliations systematically moderate employees' perceptions of generative AI task support.

Fourth, our participants had no choice between ChatGPT task support and task support provided by a human coworker, as they were randomly assigned to one or the other experimental condition. Thus, the lack of agency in our design may have influenced our results. Future research could address this by conducting a choice-based experiment to explore potential differences in the psychological impact of various types of task support.

Fifth, this study relied on quantitative evidence from an experimental vignette design, allowing for causal inference but providing only limited insights into employees' individual emotions. Complementary qualitative approaches (e.g., brief post-task interviews) could provide richer insights into employees' perceptions and emotions and help identify additional factors, such as personality differences (e.g., introversion vs. extraversion) or level of trust in AI (Hernández-Tamurejo et al. 2025), that shape how employees respond to generative AI task support. Moreover, incorporating physiological measures (e.g., heart-rate variability as an indicator of stress) and behavioral measures could provide objective data to complement self-reports, thereby mitigating potential common method bias in future research (Podsakoff et al. 2012).

Sixth, our study captured the short-term psychological effects of ChatGPT task support. While this provided valuable insights into employees' immediate perceptions, it left unclear how these perceptions evolve over time. Future research could employ a longitudinal design to investigate the long-term impact of generative AI, exploring whether its psychological impact changes as employees gain more experience and literacy with such tools.

## 6 Conclusion

While generative AI tools like ChatGPT offer numerous advantages in the workplace, such as increased productivity and performance, our study highlights the need for organizations to be mindful of generative AI's potential negative psychological impact on employees' perceptions and, in turn, their job satisfaction. By combining social response theory with the work design model, we explain why and how task support provided by ChatGPT hinders job satisfaction, showing that weakened perceptions of organizational support and opportunity to perform as well as greater perceptions of job insecurity account for this effect. From both theoretical and practical perspectives, our findings underscore the enduring importance of task support provided by human coworkers when it comes to promoting positive employee perceptions and job satisfaction as well as, more broadly, the need to strengthen social, motivational, and work context characteristics to mitigate the negative effects of generative AI on job satisfaction.

## Appendix A

Situation description and vignette design (T1).

### **Situation description for every participant:** (translated from German to English)

You work in the communications department of Marzeo AG and are asked to write an article for the company website on a change in corporate strategy. Your manager sends you a list of information to be used in the article.

You are to complete the article by the end of the day and send it to your manager. You do not manage to complete the task by then due to time constraints because the task is very extensive. For relevant tasks such as these, it is common practice at Marzeo AG for you to receive support.

### **Human coworker/ChatGPT scenario**

Task support from *a member of your team/ChatGPT*.

In order to complete your contribution for the company website on time and in high quality, you can get task support from *a member of your team/ChatGPT*. *Your team member/ChatGPT* will use the list to make suggestions on how the text can be formulated. From these suggestions, you alone form the final version of the text.

Thanks to the task support, you will finish the task on time and send the final version to your manager by email.

## Appendix B

Vignette design (T2).

**E-Mail:** Positive/Negative feedback:

### Positive feedback on the text for the company website



Supervisor Marzeo AG 

Many thanks for your contribution to the company homepage.

I have checked the text you created and it can be used very well in the current form. All points on the list, which I sent to you, have been implemented.

This corresponds exactly to our established quality standards for contributions on the company homepage. The contribution does not need to be revised and will be uploaded to the company homepage.

Thank you for your good work!

Best regards,

Your Executive

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Marzeo AG Executive

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### Negative feedback on the text for the company website



Supervisor Marzeo AG 

Many thanks for your contribution to the company homepage.

I have checked the text you created and must unfortunately determine that it is not usable in its current form. Many points on the list, which I sent to you, have not been implemented. This does not meet our established quality standards for contributions on the company homepage.

I am extending your deadline by one day. Please revise the contribution and send it back to me so that it can be uploaded to the company homepage.

Best regards,

Your Executive

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Marzeo AG Executive

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**Author contributions** Dominik Zahs: Conceptualization, Data Curation, Formal analysis, Methodology, Project administration, Supervision, Visualization, Writing—original draft, Writing—review and editing. Lynn Schmodde: Conceptualization, Data Curation, Methodology, Supervision, Visualization, Writing—review and editing.

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**Data availability** The data that supports the findings of this study are available from the corresponding author upon request.

## Declarations

**Competing interests** 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.

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