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Prompting for Perks: Enhancing Generative AI-Enabled Job Crafting in Knowledge Work

Research-in-progress

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Abstract

The increasing use of Generative AI (GAI) has captivated industries seeking to enhance productivity, particularly among white-collar workers. Drawing upon job crafting theory from occupational psychology, prior research suggests that GAI applications can also enhance employee well-being by modifying their work environment for self-perceived benefits. However, the conditions facilitating job crafting behaviours in this context remain underexplored. This study posits that prompt engineering can promote job crafting behaviour. To explore this, we conducted a between-subjects online experiment, manipulating a prompt support intervention through worked examples. Additionally, we examined the moderating role of participants' AI literacy in influencing the effectiveness of the prompt intervention. A pre-test with 42 participants indicated that prompt support can increase GAI-enabled job crafting, but only for those with high AI literacy. The findings underscore the importance of AI literacy and prompt engineering in optimising job crafting behaviour, advocating for organisational training programs to support these skills.

Keywords Generative AI, ChatGPT, Job Crafting, Prompt Support, AI Literacy

1 Introduction

The potential of generative artificial intelligence (GAI) tools in workplace settings is rapidly spreading due to their ability to enhance productivity and creativity across several sectors (Brynjolfsson et al., 2023). Because of its ability to perform tasks that traditionally required human input, GAI tools especially augment white-collar work across various sectors (Benbya et al., 2024). Mahmud et al. (2024) argue that the collaboration between humans and AI can lead to an amalgamation of AI's capabilities with human domain knowledge to enhance performance and generate value. The rise of GAI triggers a broader debate on GAI's real influence on our lives, particularly concerning the future of employment, in an era distinguished by the rise of ChatGPT and other GAI tools.

Prior research found that information and communication technologies (ICT), such as GAI applications, can potentially improve employees' well-being, as new technologies provide a new resource for coping with existing work demands (Tarafdar & Saunders, 2022). A well-established theoretical concept for evaluating the potential impact of work characteristics (including ICT) on professionals' jobs is *job crafting (JC)* with the *job demands-resources* (JD-R) model. JC refers to the process by which employees make changes within their job boundaries to improve their work environment for self-perceived benefits (Wrzesniewski & Dutton, 2001). When professionals engage in JC with new technologies, they modify their job resources and demands, which include all aspects necessary to achieve work goals. This can either stimulate their personal development, thus further increasing their job resources, or reduce their psychological costs, thus reducing their job demands. Consequently, professionals engage in two primary JC behaviours: increasing job resources (such as personal growth, learning, and development) or decreasing job demands (including mental, cognitive, and emotional aspects) when they adopt new job resources, such as novel technologies (Bakker & Demerouti, 2007). First studies already investigated GAI's impact on employees' JC behaviour. For instance, Perez et al. (2022) found how AI technology in financial advice led to cognitive, task, and relational crafting.

However, the conditions under which employees can engage in JC behaviours remain unexplored. These conditions can be decisive concerning the use of GAI in the workplace. In that regard, user prompt engineering is an important factor, as it can help users by giving clear instructions to GAI for better results and, consequently, may reinforce job crafting (Cetindamar et al., 2024; White et al., 2023). For instance, Dell'Acqua et al. (2023) observed a positive influence of prompting engineering interventions on the familiarity of users with AI. Due to the importance of user input in GAI use, we aim to provide employees with a prompting intervention and see how it helps collaborate with the tool, leading to higher JC activities. Thus, we are analysing the effect of a prompt support intervention on JC's behaviour. As the impact of such an intervention is prone to contextual factors like employees AI literacy (Sabherwal & Grover, 2024), we additionally aim to examine the boundary conditions for such prompt support interventions by analysing the moderating role of AI literacy in this effect. This leads to the following research question (RQ): *Under what conditions does a prompt support intervention positively influence job crafting behaviour of employees?*

Drawing on the JC and JD-R findings, we conduct a between-subjects web experiment to investigate under what conditions employees can utilize the GAI tool ChatGPT for JC activities in knowledge work. We also explore the moderating effect of employees' AI literacy level on this relationship. As GAI requires high-quality user input during use in knowledge work, we aim to contribute to the literature by testing how a prompting intervention can increase GAI-enabled JC. We also emphasize the importance of AI literacy in GAI-enabled JC behaviour. In addition, our study aims to help organizations foster GAI-enabled JC and reveals the importance of comprehensive training programs to promote AI literacy and bridge potential skill gaps among employees.

In the following sections, we review the relevant prior work on this topic and formulate the hypotheses for our experiment. Next, we describe the experimental design in detail. We then present the preliminary results from our pre-test. Finally, we discuss these initial findings, identify the limitations of our study, and outline the next steps to enhance this research project.

2 Theoretical Background and Hypotheses Development

2.1 Generative AI-Enabled Job Crafting in Knowledge Work

Contemporary GAI models are based on neural network architectures, which can be amalgamated to build large language models (LLMs) (Kushwaha & Kar, 2021). LLMs are a powerful class of technology that can learn from different data input types, such as text, image, and video, and then produce large amounts of contextual output on any given topic. The content is produced based on user inputs and instructions, termed a prompt (Knoth et al., 2024). Especially transformer-based deep learning networks have been effective in this regard. GAI's conversational nature and domain-independent application led to a rise in relevance, quickly becoming a widely accepted general-purpose technology (Banh & Strobel, 2023). Open AI's ChatGPT is one of the most prominent LLM applications (Gmyrek et al., 2023).

Benbya et al. (2024) argue that the influence of using GAI will be most significant on knowledge work. Thereby, the concept of "knowledge work" is referred to as a job that requires mental rather than physical power (Drucker, 2012) . This study focuses on problem-solving tasks, as their exploratory and knowledge-intensive nature requires a hybrid approach, forcing humans and AI to work together (Raisch & Fomina, 2024). JC can play a pivotal role in this interaction. JC is described as changes employees voluntarily make to their job demands and job resources to optimise reaching their work-related goals (Tims & Bakker, 2010). Existing research shows that ICT supports JC by providing social support and access to cognitive resources (Perez et al., 2022; Tarafdar & Saunders, 2022). It is argued that technologies like GAI are resources that can influence JC behaviour. Studies highlight the positive impact of technologies on JC, with Tarafdar & Saunders (2022) urging further research on factors influencing ICT-enabled JC. This call for action is further underlined because GAI stands out for its conversational nature and broad applicability, making it widely used for knowledge workers across almost all domains (Banh & Strobel, 2023).

2.2 The Effect of a Prompting Support Intervention on Generative AI-Enabled Job Crafting

There has been an ongoing academic discourse on using GAI tools most efficiently by engineering prompts. These prompts can be seen as user instructions given to a GAI tool to specify the quality of the generated outcome (Liu et al., 2023). In more detail, prompt engineering involves crafting, designing, and fine-tuning the user inputs to achieve specific, customised, and high-quality outputs from LLMs. It is mainly based on providing clear instructions and context to guide the model's response toward the desired outcome (Eager & Brunton, 2023).

With the rise of ChatGPT, prompt engineering has become an increasingly important skill when collaborating with LLMs (Eager & Brunton, 2023). Prompts influence and shape the LLM's generated output. For instance, defining a persona for the LLM can significantly refine its responses, making it more relevant and focused on the task. Recent studies emphasise the importance of well-structured prompts to make efficient use of the LLM's capabilities, particularly including context and information of a conversation with an LLM that is important and states the desired outcome (Gao, 2023; Liu et al., 2023; White et al., 2023). Dell'Acqua et al. (2023) found that consultants who use ChatGPT show improved quality of responses, improved users' familiarity and understanding of AI, and enhanced tool usage when getting a prompt support guideline compared to those who do not. Moreover, engineering prompts increase users' usability, familiarity, and interaction (Henrickson & Meroño-Peñuela, 2023). As such, a guideline can help interact with ChatGPT. Thus, it is expected that prompt support, when combined with GAI, will not only enhance job resources but also lead to enhanced JC behaviours. This suggests that employees can better tailor their tasks, interactions, and cognitive approaches to work, enhancing their overall job satisfaction and effectiveness. Using the prompting guideline in the form of seven prompt examples based on Tolzin et al. (2024), we state the following hypothesis:

H1) A prompt support guideline during generative AI use significantly increases perceived job crafting behaviour.

2.3 Boundary Conditions: The Moderating Role of AI Literacy

With the advancement of GAI, there is a growing interest in AI literacy for employees to foster organisational AI capabilities. Without a basic understanding of AI, employees are unable to engage with this emerging technology effectively (Cetindamar et al., 2024). As one of the first studies on AI literacy, Long & Magerko (2020, p.2) define the term as "*a set of competencies that enables individuals to evaluate AI technologies critically; communicate and collaborate effectively with AI; and use AI as a tool online […] and in the workplace*". AI literacy encompasses a wide range of skills, among which four key capabilities associated with AI literacy were identified: technology-related, work-related, learning-related, and human-machine-related capabilities (Carolus et al., 2023). Within this study, we specialise in work-related capabilities, referring to the essential skills needed to operate with AI applications.

In knowledge work, AI literacy includes the capabilities and skills necessary for effective engagement with AI technologies. AI literacy reflects workers' understanding of AI technologies and how to use them best within their roles. Hence, the skill level of AI literacy influences employees' effectiveness in using

GAI as a job resource (Bakker & Demerouti, 2007). With a well-developed sense of AI's strengths and limitations, employees possessing high AI literacy are more adept at enhancing their work processes and engaging in more sophisticated JC behaviours as they are better informed about how to utilise AI technologies to their advantage (He et al., 2023). Therefore, AI literacy is expected to strengthen the influence of a prompt support intervention on JC, leading to the formulation of the following hypothesis:

H2) The positive impact of a prompt support guideline during generative AI use on job crafting is positively moderated by individuals' level of AI literacy.

3 Method

3.1 Experimental Design

To test the influence of prompt support intervention on JC and the moderating effect of AI literacy, we conducted an online between-subject pre-test via Prolific. Participants received a problem-solving task and were randomly assigned to one of two conditions. We decided on a problem-solving task as referring to the increased influence of GAI on such tasks (Benbya et al., 2024). In the first condition, participants received ChatGPT support (version 4.0). In the second condition, participants received a prompting intervention before solving the task in the form of seven prompting recommendations. These recommendations provide a step-by-step illustration, each including a description, a bad, and a good example prompt, to complete a task and are the most suitable form for providing information (Sweller, 2011). The intervention included the topics a) assigning AI a role, b) priming the AI, c) setting structural specification, d) limiting output length, e) giving precise descriptions, f) generating sequences of prompts, and g) avoiding ambiguous filler words (Tolzin et al., 2024; White et al., 2023). After reading the examples, participants received ChatGPT support to solve the task. The experimental procedure began with a briefing, data protection information, and consent forms, followed by questions on demography, AI literacy, and attitude toward AI. Participants were then assigned to manipulate between subjects. Tasks were completed on an external website integrated with ChatGPT via API. Post-task, participants completed a work behaviour questionnaire, including JC, perceived task difficulty, and productivity. They also underwent checks for attention, suspiciousness, and manipulation.

We chose problem-solving tasks to test our hypotheses because they are complex and require human-AI collaboration, unlike routine tasks that AI can easily automate (Raisch & Fomina, 2024). Moreover, Benbya et al. (2024) outline the increased influence of GAI on such tasks. These tasks simulate high work demands to assess executive-level skills relevant to an executive assistant role. Participants completed a 12-minute task, focusing on problem-solving: 1) drafting a one-week communication strategy for sustainability or 2) organising a C-level event on digital transformation. In a pretest of the task involving 14 participants (Ritz et al., 2024), we evaluated the task domain, comprehensiveness, and AI's effectiveness in these tasks.

The sample with 44 participants was recruited between March and May 2024 via the online platform Prolific. As two were excluded due to failure of attention check, the final sample consists of 42 participants. Seven participants identified as males and 35 as females, with a mean age of 30.93 years (*SD= 7.12*). Regarding educational background, most participants have completed their A-levels (11 participants, 26 %), ten have completed a bachelor's degree, and nine have completed a master's degree. Two participants have obtained a doctoral or PhD degree. In addition, eight have completed vocational training, and two have completed secondary education. For the between-subjects manipulation, participants were equally assigned to the prompt support condition (21 treatment, 50%).

3.2 Measurements

We assessed *JC* as a dependent variable using a modified version of the JC scale by Tims et al. (2012), focusing on the two most ICT-related dimensions: *increasing structural job resources* and *decreasing hindering job demands*. The behaviour was measured post-task on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). Cronbach's alpha (α) of 0.81 for increased job resources and 0.89 for decreasing hindering job demands suggests a good reliability for both constructs. We adopted the validated scale by Carolus et al. (2023) to determine AI literacy using a 5-point Likert scale. The scale involves the constructs Use & Apply AI ($\alpha = 0.90$), Know & Understand AI ($\alpha = 0.74$), Detect AI ($\alpha = 0.84$), and AI Ethics ($\alpha = 0.74$), which all show good reliability.

4 Preliminary Results

Descriptive statistics suggest that the prompting guideline during collaborative problem-solving affects the JC behaviour. On average, the value of decreasing hindering job demands is observed to be lower in the prompt guideline group (mean *(M)* = *4.09*, standard deviation *(SD)* = *0.89*) than in the control group (*M = 4.32, SD = 0.93*). The mean increasing structural job resources is incrementally higher within the prompt guidelines group (*M = 3.57, SD = 0.89*) than in the control condition (*M = 3.05, SD = 0.91*). The sample shows the highest level of AI literacy in applying AI (*M=4.02*), then understanding AI (*M= 3.95*), followed by detection of AI (*M=3.58*) and AI ethics (*M= 3.23*)

For a preliminary testing of the hypotheses with 42 participants, we conducted linear regressions with interactions. These regression models are conducted separately for each JC construct, increasing job resources (IrJR) and decreasing hindering job demands (DHrJD). The results of the regression models are presented in Tables 1 and 2 for the constructs *increasing job resources* and *decreasing hindering job demands*, respectively.

Increasing Job Resources (IrJR)				
Predictors	Estimates (B)	CI 95% LL	CI 95% UL	p-Value
Prompt Support	-0.24	-3.98	3.49	0.895
AI Literacy	0.17	-0.41	0.75	0.561
Prompt Support x AI Literacy	0.18	-0.80	1.17	0.708

***Note**: F-statistic: 1.538, p-Value= 0.220, Adjusted R^2= 0.04, B= unstandardized effect, CI= confidence interval,* $^{***}p< .001$, $^{**}p< .01$, $^{*}p< .05$.

Table 1: Regression model for increasing job resources with prompt support x AI literacy

Decreasing Hindering Job Demands (DHrJD)				
Predictors	Estimates (B)	CI 95% LL	CI 95% UL	p-Value
Prompt Support	-4.50	-8.02	-0.98	0.013*
AI Literacy	-0.24	-0.78	0.31	0.385
Prompt Support x AI Literacy	1.13	0.20	2.06	0.018*

***Note**: F-statistic*: 2.4239, *p-Value*, 0.081, Adjusted R^2= 0.09, B= unstandardised effect, CI= confidence interval, ***p< .001, **p< .01, *p< .05.

Table 2: Regression model for decreasing hindering job demands with prompt support x AI literacy

The regression models indicate a significant impact of predictors on the decrease of job demands within the context of JC (prompt guidelines: p< .05, prompt support x AI literacy: p< .05). In contrast, the effects on the increase of job resources are not statistically significant (prompt engineering: p> .05, prompt engineering x AI literacy: p> .05).

The analysis shows a significant effect of prompt engineering when using GAI on the perceived value of *decreasing hindering job demands* (*B=-4.5, p< .05*), implying that prompt engineering alone negatively affects decreasing job demands. However, this effect is positively moderated by a significant interaction between prompt engineering and AI literacy (*B= 1.13, p < .05*). Consequently, AI literacy serves as a positive moderator, providing the advantageous impact of prompt engineering on the *decrease of hindering job demands*. Notably, AI literacy alone does not directly affect *decreasing hindering job demands* (p> .05). Figure 1 illustrates the interaction effects of the two regression analyses. In the left panel, depicting the analysis on *decreasing hindering job demands*, the dark green graph shows that decreasing job demands is higher for those who use prompt engineering and possess a high level of AI literacy. Conversely, the light beige graph illustrates that the value of decreasing job demands is lower for those with low AI literacy who use prompt engineering. The right panel indicates that no significant interaction effect is observed for the construct *increasing job resources*, as previously observed.

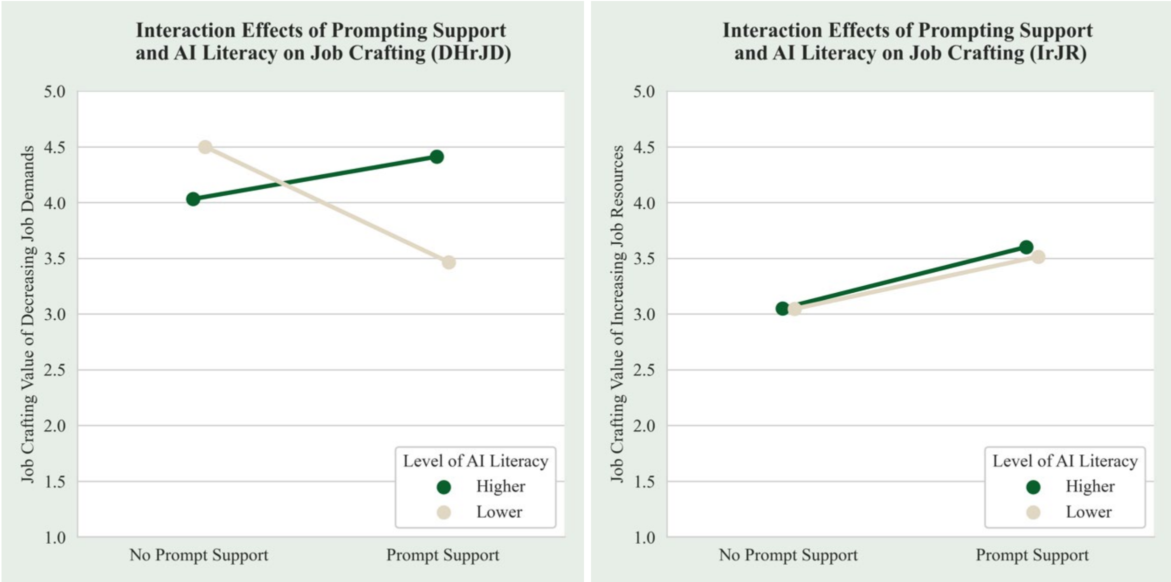

Figure 1: Interaction effects of prompt support and AI literacy on perceived JC

5 Discussion, Limitations, and Next Steps

The results further demonstrate that effective prompt engineering with GAI, particularly in environments with users with high levels of AI literacy, can significantly reduce hindering job demands. The use of a prompt support intervention, where participants underwent an intervention to learn best practice prompts for the most effective GAI usage, negatively influenced the successful reduction of job demands. The pre-test results, which showed a negative correlation of the variable, suggest that prompt engineering is perceived as an additional burden when working with GAI rather than as a means of further reducing demands. However, viewing prompting guidelines as universally unfavourable for JC behaviour would be a mistake. When deployed with a high level of AI literacy, a prompt support guideline is highly effective, leading to an additional decrease in job demands. This can be explained by the fact that professionals who lack an understanding of AI face additional challenges when given prompting support. Without a basic understanding of AI, they fail to grasp the advantages of prompt engineering, perceiving it as incomprehensible and cognitively even more demanding. Conversely, professionals who are well versed in AI, from AI usage, AI knowledge, and AI detection to ethical considerations, can make sense of prompt engineering. They can easily use it to their advantage, further promoting their JC behaviour by decreasing their job demands.

To enhance interaction with GAI, employees' AI literacy is essential when providing prompting support for effectively reducing job demands. Interestingly, the study's results indicate that professionals with low levels of AI literacy may experience negative JC consequences as they initially struggle to comprehend prompt engineering. This lack of understanding can increase their job demands rather than reduce them. Increasing AI literacy levels, encompassing AI usage, AI knowledge, AI detection, and ethical considerations, is, therefore, an essential first step to effectively using prompt engineering and GAI to decrease job demands. This insight is precious for companies adjusting their training programs to incorporate AI literacy, bridging AI skill gaps among their workforces.

This research-in-progress study has several limitations that should be acknowledged. First, the pre-test involved a relatively small sample size, which may affect the statistical significance of the analysis. Future research should be conducted with more extensive and diverse populations to validate and extend the findings. Second, participants in the GAI and prompt engineering condition were given a prompting overview with basic examples of bad and good prompts before the task. However, due to the limitations of the experiment's platform, Heroku, participants couldn't access prompt guidelines while working with GAI, which may have influenced the results. Future research should consider this limitation and explore the most effective prompt recommendations for achieving positive JC outcomes, such as using GAI to summarise information or generate specific content. However, this research is a first step to shed light on a more comprehensive understanding of under what conditions prompting guidelines can enhance job crafting behaviour. After incorporating the feedback from ACIS, we will redefine our intervention and conduct the experiment in Q1 2025.

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