Offloading to Digital Minds: How Generative AI Can Help to Craft Jobs

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Abstract. In the era of ChatGPT and other generative AI tools, white-collar workers are given tremendous potential to simplify everyday tasks. Within vocational psychology, this phenomenon is known as job crafting. We conduct an electroencephalography-based mixed-factorial experiment to explore the underlying mechanisms of how and why the use of generative AI tools can lead to job crafting. Relying on cognitive load theory and resource demand theory, we measure the effects of ChatGPT use and prompt engineering guidance in strategic thinking tasks. We hypothesize that individuals who use ChatGPT without and with prompting examples rely on cognitive offloading to avoid cognitive effort, affecting resource demands. An initial evaluation of our experiment task design provides promising results. We plan our experiment with participants who are familiar with executive assistant tasks. Our expected results contribute to the ongoing discussion of ICT-enabled job crafting and provide empirical-driven explanations of AI-enabled job crafting mechanisms.

Keywords: Generative AI · ChatGPT · Job Crafting · Cognitive Offloading.

1 Introduction

The fast-paced acceleration of digitalization demands extensive re-& upskilling efforts, impacting a significant proportion of jobs worldwide [1]. This increases job demands for employees, including the adoption of a lifelong learning mindset. One form of this mindset manifests within the phenomenon of job crafting, referring to activities of employees who voluntarily change their work environment for self-perceived positive benefits, like increased work engagement, well-being, or job satisfaction [2]. Previous information systems (IS) research found that employees can use information and communication technology (ICT) to tackle high job demands, contribute to job crafting behavior, and elevate employees' occupational well-being [3]. Li et al.[4] argue that certain ICTs act as job crafting enablers. Moreover, a study by Perez et al. [5] found that implementing AI led to employees reframing their jobs, thereby increasing their well-being. Accordingly, our research aims to understand how employees can use generative AI (GAI) to increase their job crafting behaviors.

White-collar work is changing with the rise of GAI tools like ChatGPT. Studies propose that GAI is expected to increase the productivity and efficiency of service tasks [6] and outperform humans in creativity assessments [6]. However, evidence shows that with GAI, freelancers experience declining jobs and a devaluation of their work [7]. As a result, exploring human-AI interaction has become one of the most significant pursuits in today's society. For instance, a differentiation was shown between employees who use ChatGPT by delegating activities between each other and employees who completely incorporate their task flow with GAI [8]. Drawing on findings of the job crafting and job demands-resources model (JD-R) [9], we conduct a neurophysiological experiment to investigate the effects of GAI-enabled job crafting practices. In addition, we explore to what extent participants rely on GAI and analyze the influence of resource-seeking behavior, termed cognitive offloading [10]. We therefore pose the following research question (RQ): *What are the effects of GAI use on employees' job crafting behavior?*

Building on the job crafting model and JD-R framework, we empirically expose the influence of GAI use and the effect of prompting guidance as a means of increased job resources on job crafting behavior and productivity. We also investigate the moderating effect of cognitive offloading on this relationship by combining behavioral with neurophysiological measurements. We aim to test if the theoretical concept of ICT-enabled job crafting holds for the use of GAI and contribute an empirical-driven explanation of individual AI-enabled job crafting mechanisms.

2 Theoretical Background and Hypothesis Development

2.1 The Influence of Human-Generative AI Interaction on Job Crafting

To study the potential of employing GAI in the workforce, we draw upon the concept of job crafting from vocational psychology [11]. Job crafting is described as changes employees voluntarily make to their job demands and job resources to optimize reaching their work-related goals [12]. Recent studies have shown that ICT has the potential to influence job crafting behavior [3]. The framework delineates how employees can thrive in their work roles and attain job satisfaction by focusing on positive behaviors, attributes, structures, and processes that enhance organizational performance [13]. Job crafting positively affects individuals and organizations [14]. For individuals, job crafting is positively related to positive outcomes like well-being [15], positive affect [16], and work engagement [17]. Previous research points out that contextual factors like ICT influence employees' perceived opportunities to craft in the workplace [18, 19]. Similarly, Bakker and Demerouti [9] assume that the demands and the resources incorporated in each job and task can influence job crafting by positing the JD-R model [20]. Job demands refer to certain challenging conditions at work that lead to strain, whereas job resources are viewed as contributing to motivation in the workplace [11]. Previous studies have explored the positive effects of various resource-seeking behaviors, including feedback and support [21].

Existing research elucidated that ICT enables job crafting behavior, for instance, by offering social support and access to cognitive resources for employees [3]. However, the phenomenon of ICT-enabled job crafting remains understudied [4]. In line with the JD-R model, technologies like GAI can be classified as resources that enable individuals to change their behavior and attitudes. Several studies within the literature delve into the affirmative impact of contemporary IS and technologies on the phenomenon of employee job crafting. In that vein, Tarafdar & Saunders [3] call for research on "factors and processes that encourage ICT-enabled job crafting" (p. 730). However, GAI can be differentiated from other ICT technologies (such as IoT) due to its conversational nature and its domain-independent application, quickly becoming a widely accepted general-purpose technology [22]. To study GAI as our main ICT enabler for job crafting as our phenomenon of interest, we hypothesize the following relationship:
H1: *The use of generative AI positively influences perceived job crafting.*

2.2 The Influence of Prompt Engineering on Job Crafting

Since the rise of ChatGPT and other GAI tools, there is a discourse on communicating most efficiently through prompt engineering. These prompts are programmed instructions given to GAI to ensure high-quality generated outcomes, for instance, by compelling rules [23, 24]. Thus, we also want to delve into the effects that prompting examples as an intervention can have during ChatGPT use on job crafting behaviors. Recent research on prompt engineering has analyzed how to design prompts to improve the GAI output. Moreover, incorporating a prompt engineering overview can increase familiarity with AI and improve tool usage [8]. Dell' Aqua et al. [8] found that participants with GPT use and a prompting overview led to superior task performance. We design a prompting resource in the form of seven prompt examples based on the prompt patterns of [24] for participants and thereby increase their job resources. These examples provide a step-by-step illustration to complete a task and are the most suitable form for providing information [25]. Thus, we hypothesize:
H2: Prompting support in the use of generative AI positively influences perceived job crafting.

2.3 Human-Generative AI Interaction: The Role of Cognitive Offloading

While the use of GAI and prompting examples represent increased job resources, we aim to analyze the influence of resource-seeking behavior and explore to what extent participants rely on these job resources. This phenomenon is well-known in human-computer interaction literature and is termed cognitive offloading. Offloading describes a psychological phenomenon where individuals rely on external tools to free mental resources for extra tasks [10], thereby reducing their cognitive load [26]. Cognitive load theory [27] explains the exchange between mental load associated with work and external tools. Journals, calendars, and to-do lists are other tools that help reduce cognitive load [28]. For instance, students' use of calculators frees their minds of cognitive load for complex calculations [26]. This allows them to use the newly freed-up mental capacity to work on the underlying concepts rather than the mechanistic calculation. Cognitive offloading shows how individuals can actively manage their cognitive resources by engaging in resource-seeking behavior. Actively increasing or reducing cognitive load thereby serves as an individual resource within the workplace [29]. When used correctly, offloading can even lead to increased performance [30]. Previous work on offloading has demonstrated that the intentional use of offloading tools to avoid cognitive effort can lead to both intended benefits and unintended negative outcomes and is influenced by metacognition [31]. We propose that GAI is a tool that affords cognitive offloading with cognitively demanding tasks. Thus, we argue that employee behavior that facilitates offloading without compromising task outcomes is a form of job crafting. We combine self-reporting-based cognitive load measurement with neurophysiological measures for an increased understanding of the neural process behind the influence of offloading on our main effect. The use of electroencephalography (EEG) to measure cognitive offloading increases the study's internal validity. Based on the concept of cognitive offloading and its effect on reducing task demand, we hypothesize that the relationship between GAI use without and with prompting support on job crafting would be moderated by cognitive offloading:

H3a: The positive effect of generative AI use on job crafting is positively moderated by cognitive offloading.

H3b: The positive effect of generative AI use with prompting support on job crafting is positively moderated by cognitive offloading.

Figure 1 illustrates our research model, including all hypotheses.

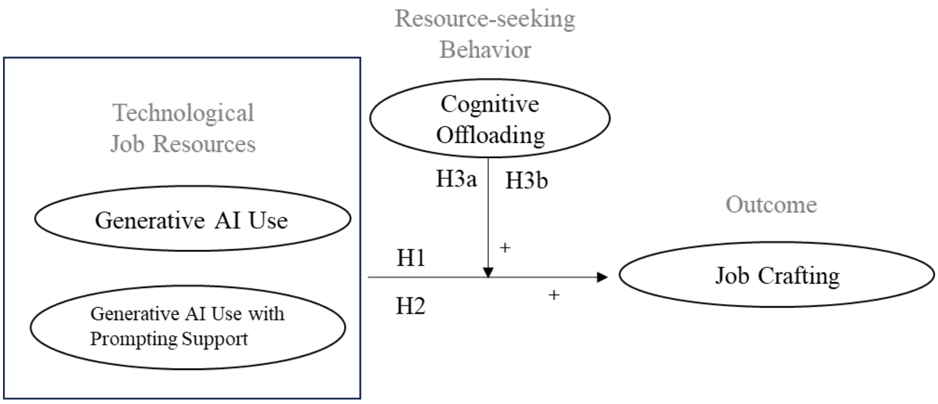

Fig. 1. Research model and hypotheses

3 Research Approach

3.1 Experimental Design

Our research model investigates the influence of GAI on job crafting, and we explore the moderating effects of cognitive offloading using EEG measurements. Due to the non-comparability of brain structures between participants [32], we opted for a mixed factorial design [33]. As we analyze cognitive offloading while using GAI, we require a brainwave comparison between the control condition (no GAI support) and the treatment conditions (GAI or GAI + prompting examples). All participants went through the control condition, receiving a strategic thinking task. GAI or GAI + prompting examples was the between-subject manipulation. Participants were randomly assigned to either one of those conditions. In the former, participants get ChatGPT support (version 4.0) integrated into the platform during task completion. In the latter, participants first get prompting examples and then ChatGPT support.

Participants first get briefed and ask questions about the EEG and risks, then consent to join. We use a 14-channel Emotiv Epoc EEG device, attach sensors, and calibrate with a 60-second impedance test. After the setup, participants answer a pre-survey covering demographic data, questions about their work situation, AI literacy level, and general attitude towards AI. Participants were then randomly assigned to the between-subject manipulation. Then, participants received both conditions (control + one of the treatment conditions) in random order to minimize order and learning effects. Post-task, they complete a survey on job crafting behavior and undergo checks for attention, suspicion, and manipulation. The EEG is removed, and a debrief follows.

3.2 Tasks

The tasks, simulating high job demand and cognitive load, are crafted to necessitate cognitive offloading and demand executive functioning skills tailored for an executive assistant role [34]. All participants conduct two tasks. Webb's [35] depth of knowledge concept aims to categorize learning tasks based on the complexity of thinking required of the participants. Both tasks were designed to foster strategic thinking. The structure and word count of the tasks were designed to avoid significant differences in complexity. Participants have a 12-minute time limit for each task. A pre-test with 14 participants assessed complexity, strategic thinking potential, and cognitive offloading. The evaluation encompassed the task domain, comprehensiveness, strategic thinking [35], and cognitive offloading potential [10]. The results of the pre-test are visualized in Table 1.

Table 1. Results of pre-test for task calibration (SD = Standard deviation).

Principle	Items	Task 1		Task 2	
		Mean	SD	Mean	SD

Domain of task	Could you imagine that this task is typical for an Executive Assistant?	3.36	1.34	3.92	1.08
Comprehensiveness	Is the task comprehensive?	3.93	0.73	4.00	1.28
Strategic thinking (Webb, 1997)	The task requires developing a plan.	4.77	0.44	4.33	0.78
	The task requires collecting evidence and data and using it as a basis.	3.92	1.25	3.42	1.31
	The task requires several solutions to be compared with each other.	3.53	1.13	3.18	1.08
	The task requires logical thinking when making decisions.	4.08	0.67	3.73	1.01
Potential for GenAI cognitive offloading (Lodge et al., 2023)	Do you see the potential for Generative AI (e.g., ChatGPT) to take over parts of this task?	4.31	0.49	4.18	0.60

The feedback led to task duration standardization, focus on concept development (no execution), and solution format specification. The tasks now involve writing a one-pager for executive assistants, one on communication strategy, and the other on organizing a C-Level executive event.

3.3 Participants

We recruit 80 participants who have been employed for at least 6 months, with a minimum employment status of part-time. Participants are required to be well-rested for high-quality EEG measurement. Given that a third of left-handers have variations in their brain structure [32], we exclude those from our experiment.

3.4 Measurements

Job crafting: A modified version of the Job Crafting Scale [12] is used to measure the extent of job crafting. To capture the ICT-related dimensions of job crafting, we assessed three dimensions: increasing structural job resources, increasing challenging job demands, and decreasing hindering job demands. Participants indicate how they engaged in each behavior after each task on a 5-point Likert scale.

Cognitive offloading: Cognitive load is the load imposed on the working memory and generally explains the level of resources used when an individual completes a task [36]. To get a deeper understanding of the resource-seeking behavior during GAI use, we combine EEG-based and behavioral measures [37]. The EEG is evaluated as a promising tool for continuous cognitive load monitoring [38] and allows for richer cognitive load assessment in different phases of the task solutions, such as during prompting, receiving answers from ChatGPT, or writing the final solution, without interfering with their working experience. In line with previous studies, we focus on alpha activities to measure cognitive load [36, 39]. We follow the measurement method based on

Klimesch [40]. Concerning the behavioral measures, we use the NASA Task Load Index to assess cognitive demand [41].

Control variables: We control for age, gender, academic degree, AI literacy skill level [42], general attitude toward AI [43], task complexity, and task difficulty.

3.5 Planned Data Analysis

For collecting the neurophysiological data, use the consumer-grade Emotiv EPOC device, as it has been previously used in leading IS journals (for instance, [32, 44]). While there has been an ongoing discussion in the NeuroIS community about the quality of consumer-grade devices, Riedl et al. [45] found that consumer-grade devices nowadays gain broader acceptance, especially for time-frequency analyses. Different analytical techniques are used for EEG data analysis. We selected event-related spectral perturbation (ERSP) because of its ability to model time and frequency changes over a specific time epoch [39]. We focus on generating ERSPs in the alpha band frequency (8-13 Hz), because it is closely related to cognitive load [39]. Thereby, decreases in log power within the time window imply increased load. The time windows we aim to investigate are after participants have read the task, such as when they prompt, when they receive advice from ChatGPT as well as during the writing of their solution. For performing the EEG analysis, we use EEGLab, an established open-source toolbox [46]. We first remove eye-movement artifacts by visual inspection and automated probability calculations. Then, we apply independent component analysis decomposition to isolate the different activations of components. Finally, we perform the ERSP to investigate changes in alpha activities.

For the behavioral data analysis, we will use a linear regression model with moderation using PROCESS [47].

4 Conclusion and Future Outlook

The experiment explores how GAI use with and without prompting examples, influences job crafting behavior. It also examines cognitive offloading's positive moderation of this effect through EEG measurements. Pre-test results confirm that the tasks encourage strategic thinking [35] and allow for cognitive offloading with GAI use. This can be used for other researchers interested in similar research. While our expected results indicate that GAI tools enable job-crafting practices, our lab experiment only simulates how GAI can lead to job-crafting within the work context. To study actual long-term effects within real-world settings, one requires a natural experiment. Upon conducting our study, we aim to enrich the research on factors behind ICT-enabled job crafting by providing an empirically driven analysis of individual AI-enabled job crafting mechanisms.

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