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Automatisch generierte Beschreibung

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Master-Thesis

**Beyond Automation: Generative AI's Influence on White-Collar Job Crafting**

*Unraveling the Personality Puzzle in the Era of   
AI-Enabled Workplaces*

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**Abstract**

As the digital landscape evolves, Generative Artificial Intelligence (GenAI) is rapidly transforming workplace dynamics in white-collar professions. This research examines how GenAI influences job crafting – the proactive changes employees make to their work scope and environments to enhance job satisfaction and productivity. Existing literature primarily focuses on the automation capabilities, thereby overlooking the nuanced interplay between GenAI tools and individual personality traits in shaping job crafting behaviors. This research demonstrates that individual personality traits significantly moderate the impact of GenAI on job crafting, filling a critical gap in understanding the personalized effects of this technology at work. Utilizing a quantitative approach, white-collar professionals were surveyed to assess the job crafting dimensions of increasing structural resources and reducing hindering job demands of the Job-Demands-Resource Model, as well as levels of autonomy and competence needs of the Self-Determination Theory. The Five-Factor Model of Personality was further integrated to evaluate the dynamics between individual traits and GenAI usage. The results revealed that Openness to Experience and Agreeableness positively moderated the enhancement of structural resources through GenAI-enabled job crafting, reflecting their impact on the resource side. Conversely, Extraversion and Neuroticism positively moderated the reduction of hindering job demands, indicating their influence on the demand side. This research not only broaden the theoretical frameworks of the Job-Demand-Resources Model and Self-Determination Theory but also underscore the importance of aligning GenAI implementation strategies with employee personality profiles. The findings therefore advocate for the tailored deployment of GenAI tools, suggesting that an understanding of employee traits can significantly influence the success of technology-driven job crafting activities in modern work settings.

**Keywords:** Generative AI · ChatGPT · Job Crafting · White-Collar · Personality

Table of Contents

[List of Abbreviations IV](#_Toc166224769)

[List of Figures V](#_Toc166224770)

[List of Tables VI](#_Toc166224771)

[1 Introduction: Setting the Stage for Generative AI in the Workplace 1](#_Toc166224772)

[1.1 Stakeholder Dynamics in Navigating the Technological Impact 6](#_Toc166224773)

[1.2 Identifying the Research Gap and Question 7](#_Toc166224774)

[2 Theoretical Foundations and Hypothesis Development 9](#_Toc166224775)

[2.1 Job Crafting within the JD-R Model through a GenAI Perspective 9](#_Toc166224776)

[2.2 Exploring Self-Determination Theory in a GenAI Environment 12](#_Toc166224777)

[2.3 Personality Traits as Catalysts for GenAI-Driven Job Crafting 15](#_Toc166224778)

[2.3.1 The Five-Factor Model in GenAI Adoption 17](#_Toc166224779)

[2.3.1.1 Openness to Experience 18](#_Toc166224780)

[2.3.1.2 Agreeableness 20](#_Toc166224781)

[2.3.1.3 Conscientiousness 21](#_Toc166224782)

[2.3.1.4 Extraversion 22](#_Toc166224783)

[2.3.1.5 Neuroticism 24](#_Toc166224784)

[3 Methodology of the Research Approach 26](#_Toc166224785)

[3.1 Research Design 26](#_Toc166224786)

[3.2 Participants 28](#_Toc166224787)

[3.3 Instruments for the Data Collection 29](#_Toc166224788)

[3.3.1 Strategic Thinking Tasks 29](#_Toc166224789)

[3.3.2 Measurements 30](#_Toc166224790)

[3.4 Ethical Considerations 32](#_Toc166224791)

[3.5 Data Preparation and Descriptive Statistics 32](#_Toc166224792)

[4 Results 34](#_Toc166224793)

[4.1 Validation of Constructs 34](#_Toc166224794)

[4.2 Analysis of Hypotheses 36](#_Toc166224795)

[5 Discussion 41](#_Toc166224796)

[5.1 Theoretical Implications **Fehler! Textmarke nicht definiert.**](#_Toc166224797)

[5.2 Managerial Implications 50](#_Toc166224798)

[5.3 Limitations and Future Research 51](#_Toc166224799)

[6 Conclusion 55](#_Toc166224800)

[References 57](#_Toc166224801)

[Appendix VI](#_Toc166224802)

[Directory of Aids VIII](#_Toc166224803)

[Declaration of Authorship IX](#_Toc166224804)

List of Abbreviations

AI - Artificial Intelligence

FFM - Five-Factor Model

GenAI - Generative Artificial Intelligence

ICT - Information and Communications Technology

IS - Information Systems

JD-R - Job-Demand-Resources

LLMs - Large Language Models

SDT - Self-Determination Theory

List of Figures

List of Tables

# Introduction: Setting the Stage for Generative AI in the Workplace

Imagine a workplace where the boundaries of creativity and efficiency are constantly redefined, and the fusion of human imagination and Artificial Intelligence (AI) could create a symphony of productivity and innovation. This may sound like a scene from a science fiction movie. However, it is actually becoming a reality in today's white-collar professions (Gmyrek et al., 2023), where the next digital revolution is being initiated and has already started creating an era of change, or as often stated, the Fourth Industrial Revolution (He et al., 2023; Rutherford & Frangi, 2021). At the heart of this transformation lies the revolutionary technology of Generative AI, or GenAI for short (Gmyrek et al., 2023). Lim et al. (2023, p. 2) propose the following definition: *“Generative AI can be defined as a technology that (i) leverages deep learning models to (ii) generate human-like content (e.g., images, words) in response to (iii) complex and varied prompts (e.g., languages, instructions, questions).”* What distinguishes this surge in technology as a revolution, rather than mere progression, is the magnitude of impact as well as level of speed at which it has been and is reshaping professional landscapes (Frey & Osborne, 2023, p. 8). This marks a major departure from traditional automated systems and introduces a dynamic where the focus lies not only on the execution of tasks, but also on the mimicking human cognitive functions. In essence, GenAI is marking a shift from just the automation of routine tasks to the creation of new ways to perform work, thereby enabling humans to achieve unprecedented levels of efficiency and creativity in decision-making processes, data analysis, as well as innovative problem-solving (Chui et al., 2023, p. 40). With every disruptive shifts witnessed during previous industrial revolutions, it will alter the economic and social fabric (Bessen, 2018, p. 293). This will in turn challenge and redefine existing norms, expectations, requirements, and structures within today’s industries and workplace dynamics.

Although not a recent invention, GenAI has been recognized for its potential to transform and disrupt various industries and reshape how we live and work by taking over work initially done by humans (Felten et al., 2023). Its influence on job roles in the context of performance and work engagement has been a point of interest for many researchers and the general public in the last few months, especially concerning Generative Pre-Trained Transformers (GPTs) like OpenAI’s multimodal ChatGPT large language models (LLMs), which exposed the society in a much deeper way to such AI tools (Gmyrek et al., 2023, p. 7). The investigations of Eloundou et al. (2023, p. 11) estimated that at least 10% of work assignments performed by 80% of the U.S. workforce could be subject to change or substitution regarding the introduction of GenAI tools and further that approximately 19% of workers may experience a minimum of 50% of their work tasks affected. To illustrate this, we can look at the financial industry, where GenAI has been notably transformative according to (Kalia, 2023, p. 44). For instance, are GenAI implementations being employed to real-time decision-making processes in data analysis, trading strategies, and risk assessment, areas that traditionally required extensive human intervention. On a global spectrum, Berg et al. (2023, pp. 23–24) identified that the effect of AI ranges from 5.5% in terms of automation to 13.4% in terms of augmentation, specifically in high-income countries. The advancements in this regard significantly impact white-collar professions. With 8.6% of the global workforce falling into this category, 24% of clerical tasks are considered to have a high exposure and an additional 58% a medium exposure (Gmyrek et al., 2023, p. 23). In this context, Goldfarb et al. (2020, p. 401) additionally identified that industries such as information technology, finance, and insurance are mostly going to be affected by the adoption of AI. Felten et al. (2023, p. 7) added to these discoveries with industries such as legal services and securities, investments, and commodities. While these numbers refer to AI, which encompasses a broader spectrum of applications, and GenAI being a subset of it, with distinct capabilities focused on the generation of human-like content (Kaplan & Haenlein, 2019, p. 18), it remains still crucial to examine those metrics. The reason is that, firstly, many foundational technologies and algorithmic principles overlap, and secondly, even though the long-term implications diverge, the initial impacts on employment and task structure tend to be similar (Brynjolfsson et al., 2023, p. 7; Woodruff et al., 2024, p. 3). Even though not all assumptions are directly transferable from AI to GenAI, looking at those metrics can offer a valuable baseline for understanding the potential scope of automation and augmentation of AI-induced changes. Thus, the integration of GenAI in white-collar work environments marks a transformative shift, distinctively impacting the nature of professional, managerial, and administrative tasks. The impact of this is particularly noteworthy in white-collar industries, where cognitive tasks that include decision-making, problem-solving, and communication are prevalent (Gmyrek et al., 2023, p. 23; Goldfarb et al., 2020, p. 401) – all areas where GenAI technologies thrive and are well-suited to support the workers in their various work-fields. Unlike Industry 4.0's primal focus on the automation of manual, blue-collar work through robotics and Internet of Things (IoT), GenAI introduces a novel approach to assist with intellectual tasks (Javaid et al., 2022, p. 83). This includes analyzing vast datasets, generating insightful reports, and even drafting emails or creating content (Oztemel & Gursev, 2020, p. 165), thereby boosting productivity in the white-collar realm (e.g., Brynjolfsson et al., 2023, p. 27; Noy & Zhang, 2023, pp. 11–12). Today’s rapidly evolving and dynamic business environment demands continuous learning and adaptation from white-collar workers (OECD, 2018, p. 5). As such, the advanced capabilities of GenAI in personalized knowledge acquisition and information processing provide a significant edge (Brynjolfsson et al., 2023, p. 18). Additionally, the ability of companies to effectively incorporate and utilize new external knowledge is becoming increasingly important in maintaining a strategic agility (Kale et al., 2019, p. 281). This capability could be significantly impacted by the use of GenAI tools by white-collar employees, as they facilitate the rapid integration of innovative practices and knowledge throughout the organization (Bilgram & Laarmann, 2023, p. 24). The specific influence of GenAI on white-collar work hence arises from the technology's ability to cater to the cognitive, communicative, and innovative demands of such roles. This sets a distinct path from the technological advancements that are typically associated with blue-collar tasks. Therefore, the integration of GenAI in white-collar work environments is a significant and growing phenomenon. These findings underline the importance of preparing for and managing the current and potential future changes in the workplace introduced by GenAI. Scholars increasingly see this technology as a source of competitive advantage on a company level (Krakowski et al., 2023, pp. 1443–1446). Hence, the focus for individuals should be on adequately adapting to and using it.

With employees being increasingly presented with opportunities to leverage GenAI tools within their roles, contingent upon organizational endorsement (Schepman & Rodway, 2023, p. 2724) and digitalization reshaping the global job landscape and job requirements at an unmatched pace, re- and upskilling are therefore becoming a crucial effort for a significant proportion share of jobs worldwide (OECD, 2018, p. 5). Especially the occurrence that GenAI technologies introduce completely new skills and competencies that where neither relevant in the past nor taught in the contemporary training programs and that these skills are rapidly becoming critical across various industries in the near future is a major factor (Brynjolfsson et al., 2023, p. 2). As a result, the gap between traditional educational outcomes and the demands of the modern workplace widens (Chetty, 2023, p. 3) and therefore, a crucial need arises to embrace a mindset of lifelong learning and consistently enhance one's work-related abilities. The concept of job crafting is a possible expression of this mindset. It refers to the actions of workers who willingly modify their work environments to attain self-perceived advantages such as increased work engagement, well-being, motivation, or job satisfaction (Lazazzara et al., 2020, p. 3). Research on AI's influence on job crafting has sparked much interest. Perez et al. (2022, pp. 15–16) showed that employees in the financial industries responded with job crafting to the introduction of AI in order to maintain their autonomy and positively alter the cognitive meaning of their work. Additionally, it has been observed that the resulting job crafting behavior due to the implementation of AI in the workplace has subsequently led to a boost in productivity and work engagement (Brynjolfsson et al., 2023, p. 12; He et al., 2023, pp. 11–12) as well as in well-being and job satisfaction (Cramarenco et al., 2023, pp. 740–741). The influence of job crafting is not new to technologies or specifically AI and far-reaching applications in the field of information and communication technologies (ICT) have already been found. There, scholars have been able to demonstrate that the use of ICT, for example, low-code development platforms (M. M. Li et al., 2022), can lead to job crafting and, in turn, have a positive influence on the performance (Kang et al., 2023, p. 7) and the occupational well-being (Tarafdar et al., 2022, p. 723) of employees.

While acknowledging the optimism surrounding the potential of GenAI tools in the workplace, it is also essential to direct the discussion towards how the utilization of those tools can be influenced by the attitudes of the employees’ using them. Integrating GenAI technologies presents a unique opportunity with the goal of enhancing productivity and innovation, provided there is an alignment with employee perception and acceptance (Korzynski, 2013, p. 186). Otherwise, the implementation could be accompanied by challenges and concerns, as observed by different scholars (e.g., Pachidi et al., 2021, pp. 37–38; Van Den Broek et al., 2021, p. 1574; Lebovitz et al., 2022, p. 154; C. Li et al., 2023, p. 22). One possible explanation for these mixed results surrounding the implementation of GenAI tools in the workplace could be attributed to the employees' diverse attitudes, motivational factors, and personality traits (Chiu et al., 2021, pp. 10–11). Certain employees may, for example, be more open-minded to adopting new technologies and may perceive them as beneficial and inspiring. In contrast, others may resist change and struggle to adjust to these tools. Additionally, some employees may possess a greater degree of self-motivation and initiative to learn on the job, while others may rely more on external sources of motivation. Brynjolfsson et al. (2023, pp. 20–21), for example, provide evidence that the access to GenAI tools like conversational assistants increase productivity, which is especially true among novice and low-skilled workers, by helping them sharing their tacit knowledge and assisting them in navigating their learning curve more efficiently. This suggests that the effective adoption of GenAI tools depends on the workforce's readiness to embrace these technologies, while also highlighting the importance of simultaneously fostering positive attitudes towards it in the workplace. Moreover, Bankins et al. (2024, p. 160) underscore the necessity of understanding the multilevel impact of AI on workers, including individual, group, and organizational factors that shape interactions between humans and AI-systems. Their systematic review indicates that employee attitudes towards AI, including perceptions of algorithmic capabilities and concerns about AI, play a critical role in determining the success of AI integration in organizational settings. Furthermore, Chiu et al. (2021, p. 11) emphasize the significance of pre-adoptive appraisals of AI by employees, which they state have an influence in both affective and cognitive attitudes towards AI technologies. These trigger, in turn, behavioral responses which are pivotal for the capacity of an organization to successfully leverage AI. Their findings consequently suggest the necessity to address employee attitudes regarding AI.

These individual dissimilarities could fundamentally impact employees' interactions with newly introduced technological tools and may account for variations observed in the above-mentioned research findings. In light of the above-mentioned findings, it is crucial for organizations to not only consider the technical and operational aspects of GenAI tool integration but also to actively pay attention to individual employees using them as well as each of their unique differences. Out of the space of possible influential factors in this regard, according to Eysenck and Eysenck (1985), personality is the most relevant element for the distinction of individuals because of its enduring nature, which consistently influences the behavior and cognition of human beings in various situations. The use of personality traits to interpret the influence of adopting ICT is not a new phenomenon in information systems (IS) research but has been extensively explored for different use-cases (Agyei et al., 2020; Barnett et al., 2015; Joshi et al., 2023; Y. Kim & Jeong, 2015; M. Y.-C. Lin & Ong, 2010; Nunes et al., 2019; Tripathi et al., 2022; Xu et al., 2016), including in the research field of job crafting (Bell & Njoli, 2016; Bipp & Demerouti, 2015; Gori et al., 2021; M. Kim et al., 2019; H. Li et al., 2020; Peral & Geldenhuys, 2020; Vermooten et al., 2019; Yu et al., 2022). Building upon this extensive body of research, it becomes evident that a deeper exploration of the connection between interaction of personality traits and GenAI in the context of job crafting is both timely and essential as it presents a unique opportunity for personal and organizational development. Job crafting, as conceptualized by Wrzesniewski and Dutton (2001, p. 179), encompasses physical and cognitive changes individuals make to their work boundaries. Such modifications are inherently tied to one’s stables personality characteristics – enduring traits that catalyze differences in emotion, thought, belief, and behavior over time (Moskowitz, 1994, p. 922; Funder, 2001, p. 198) - and significant to thriving work environments (Holland, 1996, p. 397). These insights set the stage to delve into framework of the Five-Factor Model of Personalty (McCrae & Costa, 1987), also known as the Big Five, which offers a structured approach to dissect personality into five dimensions – Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism – and evaluate their influence on a more detailed level of abstraction. These foundational elements, which will be discussed in detail in the following chapters, enable exploring the unidentified effects of generative AI-assisted job crafting behaviors by observing and analyzing different personality traits of white-collar employees in the work environment.

## Stakeholder Dynamics in Navigating the Technological Impact

White-collar employees are experiencing drastic changes with the rise and implementation of generative large language models (Gmyrek et al., 2023, p. 23; Goldfarb et al., 2020, p. 401). Researchers have demonstrated that GenAI has the potential to both automate and thus eliminate jobs (Hui et al., 2023, p. 9; Yilmaz et al., 2023, pp. 19–21) but also to augment them and help white-collar workers with benefits like increased productivity and efficacy of service tasks (Dell’Acqua et al., 2023, p. 9). Ergo, it is crucial to acknowledge the capabilities and drawbacks of this technology and leverage it to enhance job satisfaction, engagement, and well-being by empowering themselves and, in return, improving efficiency and quality of work through effective use. Those re- and upskilling efforts are fundamental to adapting to this evolving work environment, even if navigating the learning curve associated with GenAI integration can look intimidating. Ignoring this rapid development could mean a lost opportunity and potentially negatively affect job security, satisfaction, well-being, and career progression in a future-oriented work environment.

The employers and management of those white-collar workers may not be affected identically but undoubtedly impacted on a similar level. As the implementation and advanced utilization of GenAI tools strengthens and is increasingly seen as a potential source of competitive advantage (Krakowski et al., 2023, pp. 1443–1446), it would be a fatal decision not to engage with it. The reason is that similar to an individual employee, the introduction and integration of GenAI could mean an improvement in productivity and efficiency as well as employee well-being and retention on a firm level. This aligns with Porter’s (1985) assumptions of leveraging technology to gain and sustain competitive advantages. Therefore, managing this transformation in work processes can and probably will become a demanding task. An essential focus is ensuring equitable access to and understanding of those tools across various employee groups and balancing technological advancement and human-centric work practices.

The integration of GenAI in the workplace also has the potential to impact society significantly. This technological advancement could be used as fuel for economic growth and innovation and hence ultimately contribute to the overall prosperity of society. Regarding the potential of the transformation of the white-collar work environment, it is difficult to estimate the direction of this impact. Nevertheless, it is inevitable that for GenAI to have the positive power in reshaping societal attitudes towards work, life, and technology and a resulting work-life revolution that benefits both individuals and society, there is an urgent need to fill the gap of uncertainty. This thesis acts as the missing puzzle piece by exploring the practical implications of implementing GenAI tools within the workplace, evaluating their efficacy, and identifying the factors contributing to their impact.

## Identifying the Research Gap and Question

In the research field of modern workplaces accompanied by the fast-paced development of ICT, a new point of interest has emerged: The integration of GenAI tools in the work environment of white-collar employees and its implications on their job-crafting behaviors. While scholars have been investigating the effect of ICT tools on job crafting, the intersection of how GenAI impacts job crafting behaviors and explicitly considering the different personality traits influencing it has remained unexplored. As scholars think that the introduction of GenAI has the potential to be the main driver of the fourth industrial revolution (He et al., 2023; Rutherford & Frangi, 2021), it could present unique challenges and opportunities. Therefore, understanding how different types of employees, characterized by their traits, are affected is crucial for a comprehensive evaluation. Addressing this gap is, consequently, essential not only to contribute to academic literature but also to have practical implications in the workplace. By shedding light on the role of personality traits in adopting GenAI and its implications on job crafting, more effective strategies for its adoption can be developed. These could maximize the benefits, such as increased efficiency and well-being, while mitigating potential risks like employee resistance or misalignments. To achieve this goal, the following research question (RQ) is pursued:

*RQ: How do specific personality traits of white-collar employees moderate the relationship between the use of GenAI tools and job crafting behavior?*

To address the research question, a comprehensive methodology is employed, grounded in both theoretical and empirical approaches. Initially, this research explores relevant theoretical frameworks, including the Job-Demands-Resources model, the Self-Determination theory, and the Five Factor model of personality, to establish a foundation for understanding the dynamic between GenAI use and job crafting behavior. Based on this foundation, hypotheses are developed to test these relationships, particularly investigating the core research question of how personality traits moderate these effects. The empirical perspective is complemented by a quantitative mixed factorial design, focusing on the within-subject component, to examine the direct effects of GenAI on job crafting as well as the potential moderation effects of personality traits. The data collected from the various questionnaires undergo statistical analysis to validate the constructs and test the hypotheses, thereby providing a fruitful groundwork for the discussion of the findings. The study’s contributions are twofold. Theoretically, it bridges a gap in existing literature by elucidating the effects of GenAI-enabled job crafting behavior and the moderating role of personality traits. Practically, it offers valuable insights for organizations aiming to integrate GenAI tools, highlighting the importance of considering employee personality traits to amplify the benefits of job crafting in enhancing job satisfaction, productivity, and innovation in white-collar work environments. Overall, this research contributes to the ongoing dialogue on the future of work in the era of GenAI-enabled workplaces.

# Theoretical Foundations and Hypothesis Development

The underlying chapter delves into the intricate interplay between GenAI and job crafting behavior with the professions of white-collar employees. Underpinned by a solid theoretical foundation the aim is to elucidate how GenAI intersects with and influences the nuances of job crafting. By integrating the Job-Demand-Resources Model and Self-Determination Theory into the context of job crafting, the foundation for exploring the dynamic processes through which white-collar employees harness GenAI to craft their jobs, i.e., redefine their work scopes, enhance their job satisfaction, and foster a conducive work environment that aligns with their intrinsic motivations and personality. The focus of this investigation is anchored in the premise that GenAI tools are not merely passive instruments, but rather can act as catalysts for transformation within the workplace. This in turns offers white-collar professionals opportunities to engage job crafting activities. This process, as inherently personalized and proactive as it is, allows the change of specific aspects within the work tasks in such a way that personal growth are accommodated and challenges are mediated. Given that the process is highly individual, it is crucial to examine how specific personality traits modulate the relationship between GenAI utilization and job crafting behaviors. This is explored through the lens of the Five-Factor Model of Personality which serves as a pivotal framework to unveil the nuanced ways in which individual differences have an influence on the effective usage of GenAI tools. Through the goal of uncovering the multifaceted effects of GenAI-assisted job crafting and by meticulously synthesizing the theoretical frameworks in combination with the five personality traits, the hypotheses for this paper are ultimately developed iteratively.

## Job Crafting within the JD-R Model through a GenAI Perspective

Job crafting, a process as dynamic as the workforce it describes, is a concept that has gained significant attention in vocational psychology (Demerouti, 2014) and forms the backbone of this thesis. Its central characteristic is that individuals voluntarily and deliberately alter their level of job resources and job demands (Demerouti, 2014, p. 237), which subsequently means a change in job task, job scope, or job characteristics (Tims et al., 2012, p. 174). Thus, it follows a self-initiated bottom-up approach (Tims et al., 2012, p. 175) to take control and enhance work-related meaning and engagement (Van Wingerden et al., 2017, p. 170). Unlike proactive work behavior, which is broader in scope (S. Parker & Collins, 2010, p. 639), Demerouti (2014, p. 238) argues that job crafters specifically aim at enhancing their work motivation and person-job fit of themselves. Based on the work of Wrzesniewski and Dutton (2001, p. 179), job crafting can be defined *“as the physical and cognitive changes individuals make in the task or relational boundaries of their work.”* This makes it more evident that it is an ongoing process to (re-)shape the work with the inherent need to make it more engaging, meaningful, and satisfying (Demerouti, 2014, p. 237) and intending to regulate needs for meaning and autonomy continuously (Perez et al., 2022, p. 5). Their definition further underscores three dimensions, encompassing task crafting – the altering of the number, scope, or form of tasks; cognitive crafting – the holistic change in perception or understanding of work; and relational crafting – the modification of the nature, extent, or quality of job-related social interactions. Parker and Ohly’s (2008, p. 253) research is in line with this definition and discovered that employees have and use the ability to exercise control by engaging in negotiations regarding different job content, choosing and prioritizing tasks, as well as assigning meaning to their work. Building upon this foundation, job crafting can be positioned in the Job-Demands-Resources (JD-R) model to provide a complementary perspective according to different scholars (Petrou et al., 2012; Tims & Bakker, 2010). The JD-R model was introduced by Bakker and Demerouti (2007) in this context and lays out job crafting as a way in which the changes by the employees are the result of balancing their job demands and job resources with their particular needs and abilities (Tims et al., 2012, p. 174). As a result of this, job demands pertain to the problematic circumstances and requirements experienced in the workplace that can cause stress and tension, while job resources are factors that contribute to employee motivation and engagement in their work (Demerouti, 2014, p. 237). Subsequently, integrating the JD-R perspective with the view of Wrzesniewski and Dutton (2001) positions job crafting beyond just task crafting. Through this point of view, according to Demerouti (2014, p. 239), task crafting involves changing job demands, and relational crafting pertains to altering job resources, while cognitive crafting, though mainly focused on internal perceptions, complements these by redefining one’s mental engagement with job tasks. In this regard, Petrou et al. (2012, pp. 1122–1123) expressly incorporate the challenges resources seeking as well as demands reducing behavioral manifestations to the concept of job crafting. As argued by the authors, the integration of these perspectives demonstrates that the significance of job crafting is evident in its positive outcomes. Research has consistently shown a variety of positive consequences, such that job crafting leads to enhanced organizational performance and work motivation (Tims et al., 2012; Lee et al., 2018), work engagement (Bakker et al., 2012; Petrou et al., 2012), job satisfaction (Lazazzara et al., 2020), meaningfulness of the job (Wrzesniewski et al., 2013), and personal well-being (Berg et al., 2010; Bruning & Campion, 2018).

Following the exploration of job crafting in the JD-R Model, it is vital to investigate the influence of information and communications technology (ICT) in this research context, leading to the emerging focus on GenAI. With its ability to autonomously generate content and solve problems (Lim et al., 2023, p. 2), GenAI tools are becoming increasingly relevant in various organizational processes, including those related to job crafting and resource optimization. Through those tools, employees are offered novel avenues to customize different work aspects by, for example, automating routine tasks, generating solutions to complex and creative problems, as well as improving the effectiveness of communication channels. In line with the JD-R Model which posits that job resources and demands are pivotal in determining work engagement (Bakker & Demerouti, 2007, p. 319), GenAI tools can be viewed as dynamic job resources that can enable employees to change their attitudes and behavior. For instance, the ability of GenAI to automate complex data analysis tasks could reduce cognitive demands on employees and in turn allowing them to focus on more strategic and engaging aspects within their roles. As such, the intersection of GenAI with job crafting activities potentially enhances the ability of employees to align their job more closely to their personal and also organizational goals. Therefore, incorporating GenAI into the JD-R framework requires a reevaluation of how job resources and demands are defined and operationalized. It can be suggested that GenAI tools do not merely function as static resources but can further actively transform the landscape of job demands and resources, while subsequently influencing the well-being and performance outcomes of employees. This dynamic interplay ultimately underscores the importance of understanding the role of GenAI in job crafting processes and its implications within the JD-R Model.

Research on IS-related job crafting has started to explore how employees proactively adopt specific information systems (IS) to alter their work processes and consequently sheds light on how employees can positively influence their work environment through independent action in IS interactions (Bruning & Campion, 2018; M. M. Li et al., 2022). These endeavors suggest that the proactive use of specific IS can help maintain high levels of work flexibility (Sturges, 2012, p. 1540) or foster innovative problem-solving approaches (Mattarelli & Tagliaventi, 2015, pp. 603–604). More specifically, recent studies also examined the potential of ICT to influence job crafting behavior significantly (Tarafdar et al., 2022, p. 729) and indicating that ICT can enable employees to thrive in their roles, enhancing their job satisfaction, as well as improve organizational performance (Mukherjee & Dhar, 2023, p. 1271). The systematic literature review conducted by M. M. Li et al. (2022, pp. 3–4) demonstrates the different findings regarding the positive effects of new IS on job crafting behavior. Contextual factors, such as ICT, were already highlighted by Wrzesniewski and Dutton (2001, p. 196) and Bakker and Demerouti (2007, p. 311) in their role of shaping job crafting opportunities within the workplace. This perspective aligns with the JD-R model (Tims & Bakker, 2010, pp. 3–4), which in turn makes it possible to consider technologies like GenAI as resources that can be utilized to facilitate changes in individuals' attitudes and behaviors. In this light, ICT, specifically GenAI, emerges as a facilitator of job crafting by providing social support and cognitive resources (Tarafdar et al., 2022, p. 727). Although it is widely accepted that ICT plays a crucial role in enabling job crafting, there is a lack of specific technology-related crafting forms in academic literature, as Lazazzara et al. (2020, p. 6) pointed out. Moreover, M. M. Li et al. (2022, pp. 3–4) highlighted that the number of publications in IS journals on this topic is limited, indicating a significant research gap, which is particularly true for the specific impact of GenAI (S. K. Parker & Grote, 2020, p. 1196). Therefore, there is an urgent need for research concentrating on the effects of such emerging technologies on the limitations and liberties within the work environment, and especially on how employees navigate and craft their jobs in response (S. K. Parker & Grote, 2020, p. 1194; Perez et al., 2022, p. 3). This gap becomes more evident when considering the rapid advancements in GenAI as well as the focus on white-collar employees rather than blue-collar workers (Tarafdar et al., 2022), which has been the primary research interest. Drawing on the theoretical context that connects the effects of job crafting, the Job-Demands-Resources Model, and the influence of ICT, particularly GenAI, on job crafting behaviors in white-collar employment, the following hypothesis can be formulated:

*H1) The integration of GenAI as a primary ICT tool to accomplish a strategic thinking task will result in increased perceived job crafting behavior among white-collar employees.*

This hypothesis aims to explore how the use of GenAI tools impacts job crafting behaviors by examining how these tools affect job demands and resources and subsequently influence white-collar employees' perception of their work and job satisfaction. The hypothesis is rooted in the understanding that GenAI, as a sophisticated form of ICT, not only changes job tasks but also alters the broader context in which these tasks are performed. As a result, GenAI plays a significant role in how white-collar employees engage in job crafting.

## Exploring Self-Determination Theory in a GenAI Environment

Self-Determination Theory is an additional pivotal framework in the context of this research project. Established by Deci and Ryan (2000), it is crucial to understand intrinsic human motivation in the workplace, particularly in the evolving context of ICT and GenAI. According to SDT, individual well-being and work motivation in the work environment depend on the satisfaction of three psychological needs: autonomy, competence, and relatedness (Deci & Ryan, 2000, p. 229). As GenAI takes center stage in the world of white-collar employment, as highlighted in Chapter 1, this theory can provide valuable insights into how employees interact with these new technological paradigms. At its core, SDT centers around the three essential needs stated above. Hereby, autonomy is the need for agency and self-direction, competence is the need to be efficient and effective in one's tasks, and lastly, relatedness refers to the need for connection and interaction with others (Deci & Ryan, 2000, p. 231). The significance of these needs can be pretty notable in the realm of job crafting, where employees can craft their jobs to align with their needs, abilities, and perspectives (H. Li et al., 2020, p. 199). In particular, the autonomy need corresponds to the desire for freedom and opportunities that employees have when crafting their job (Petrou et al., 2012, p. 1135; Slemp et al., 2015, p. 10; Sekiguchi et al., 2017, p. 474; Hyrkkänen et al., 2023, p. 878). This need allows them to take the initiative and make modifications that align with their personal and professional goals (U. Bindl & Parker, 2010, p. 28; Petrou et al., 2012, p. 1123). On the other hand, competence empowers employees to adapt to intricate and ever-changing work environments (Deci & Ryan, 2000, p. 252), as it can boost the employees' confidence and belief in their abilities and skills (Bergdahl et al., 2023, p. 3), which is especially important in the dynamic landscape shaped by GenAI. At last, regarding relatedness, positive attitudes toward environmental changes are more likely to be met when employees feel a connection and sense of belonging with colleagues who are also adapting to these changes, technologies, or, as for our case, GenAI-tools (Şahin & Şahin, 2022, p. 583; Bergdahl et al., 2023, p. 3). The primary emphasis of this research project is on the importance of autonomy and competence over relatedness. There are two reasons that support this statement. Firstly, according to the research of Deci and Ryan (2002, p. 14), relatedness needs are more distal in promoting intrinsic work motivation in comparison to autonomy and competence needs. Secondly, considering the nature of the experimental setting, it appears more plausible to believe that the use of GenAI tends to have a more apparent and direct influence on the work content and procedures rather than on the interpersonal relationships. Given that the focus is to examine the relationship between employees and their perceived job crafting behaviors in the fulfillment of strategic thinking tasks over interpersonal connections, it is more relevant to narrow it down to autonomy and competence needs. Eventually, SDT proposes that by satisfying the discussed psychological needs of employees, they are more likely to proactively make changes in their work environment, ultimately leading to improvements in their psychological well-being, performance, personal growth, and intrinsic motivation (Gagné & Deci, 2005, p. 337; Bergdahl et al., 2023, p. 3).

Recent research has underscored the pivotal significance of ICT, and by extension, GenAI, as crucial resources that facilitate job crafting (Hyrkkänen et al., 2023; Tarafdar et al., 2022). In connection to this, the JD-R model suggests that personal resources are closely tied to an individual’s ability to control and influence their environment (Hobfoll et al., 2003, p. 632). Given this, it's reasonable that GenAI can significantly impact these dynamics because, as a technological resource, GenAI can both facilitate and challenge the framework of SDT, affecting how employees satisfy their psychological needs through job crafting. Slemp and Vella-Brodrick (2014, p. 972) and Bindl et al. (2019, pp. 621–622) have thereby demonstrated and underscored the relationship between the basic psychological needs discussed in the SDT framework and job crafting. However, the specific relationship between GenAI and the satisfaction of these psychological needs remains underexplored. Although SDT has been applied to various fields, such as work-life (Van den Broeck et al., 2016), technology use (Peters et al., 2018), or education (Xia et al., 2022), according to Bergdahl et al. (2023, p. 3), the connection between GenAI and the discussed psychological needs has not been sufficiently examined. The primary research focus in the past for the area of AI was on the influence on attitudes toward the use of AI (Park & Woo, 2022; Bergdahl et al., 2023). This is a significant gap that can have a fundamental impact on how individuals adapt to and utilize these technologies through intrinsically motivated behavior (Duffy & Sedlacek, 2007, p. 591), as stated by scholars such as Cascio & Montealegre (2016, p. 356), Kaya et al. (2022, pp. 6–7) and Lu et al. (2019, pp. 155–156). Therefore, understanding how GenAI relates to the satisfaction of these psychological needs and job crafting behavior of employees is an essential area of research, especially now that the rise of GenAI has had a significant impact on individuals' autonomy (Ferrara et al., 2022, p. 9). The reason is primarily that, as suggested by SDT, environments that support these needs are more likely to promote well-being and intrinsic motivation (Deci & Ryan, 2000, p. 234). Therefore, it is crucial to determine how GenAI impacts these needs, as this will have a significant influence on job crafting behaviors. Based on the theoretical foundation provided by SDT in the context of GenAI and job crafting, the following hypotheses are proposed for this research paper:

*H2a) The integration of GenAI as a primary ICT tool to accomplish a strategic thinking task in white-collar work environments enhances the satisfaction of employees' autonomy needs.*

*H2b) The integration of GenAI as a primary ICT tool to accomplish a strategic thinking task in white-collar work environments enhances the satisfaction of employees' competence needs.*

These hypotheses aim to investigate the relationship between GenAI and the psychological needs of autonomy, competence, and relatedness as outlined in SDT, specifically focusing on how these needs influence job crafting behaviors in white-collar employees.

## Personality Traits as Catalysts for GenAI-Driven Job Crafting

In the rapidly evolving world of IS research and particularly with the upcoming interest in GenAI, it can be very interesting to understand the behavioral differences of individuals in this regard. According to Schepman and Rodway (2023, p. 2724), the analysis of personality reveals a common source of these differences in behaviors or attitudes. Exploring the composition of individual personalities may be a highly relevant approach in this context, as doing so can shed light on individuals' tendencies and perspectives, providing valuable insights into their behavior and decision-making (Lounsbury et al., 2003, p. 301). Academics such as Bettman (1979, p. 216) and Sproles and Kendall (1986, p. 268) have shown proof for this statement in research fields like consumer choice, thereby emphasizing that personality can have a profound impact on the decision-making process of an individual. This is why, subsequently, this will be explored in the context of the intricate relationship between job crafting and GenAI.

When examining personality, Elliot and Thrash (2002, pp. 804–805) stated three widely employed approaches that may be utilized to investigate its structure, which include trait adjectives, affective dispositions, and the motivational system. Hereby, personality traits are defined as stable characteristics and the driving forces in unique and individual differences in emotion, thoughts, beliefs, and finally, behaviors under different circumstances and over time (Moskowitz, 1994, p. 922; Funder, 2001, p. 198; Devaraj et al., 2008, p. 94). Park & Woo (2022, p. 69) argue that they are fundamental determinants of attitudes that reflect variations in positive or negative sensitivity towards specific stimuli and motivational expressions. As a novel stimulus that elicits functional, emotional, and social aspects (Shank et al., 2019, p. 257), AI would be an appropriate match to examine in this context. Riedl (2022, p. 2023) believes hereby that examining personality plays a crucial role in the reaction of individuals to those stimuli, mainly including interactions with AI systems. Given the complexity of human interaction with technology, it can be essential to consider these diverse dimensions when examining the introduction and usage of GenAI in the workplace and its influence on job crafting. The reason behind this is that every individual will have their own understanding and interpretation of this disruptive technology depending on their personality traits (Srivastava et al., 2015, p. 362). Expanding the scope, numerous recent studies in the context of IS have shed light on the significant impact of personality traits on the behavior of accepting and using technologies. For instance, research highlights a strong link between personality traits and the use of various technologies, such as the internet (Landers & Lounsbury, 2006; McElroy et al., 2007), collaborative technologies (Devaraj et al., 2008), hypothetical software tools (Svendsen et al., 2013), diverse mobile apps (Xu et al., 2016), or mobile Banking services (Agyei et al., 2020). These findings underscored the importance of understanding individual differences in attitudes and behaviors toward technology. This has also been the case in the realm of AI, where scholars like Matthews et al. (2021, p. 9) and Riedl (2022, p. 2022) state that personality research has gained increasing relevance. The growing interest is rooted in the realization that individual differences in personality can have profound consequences on the development (Riedl, 2022, p. 2022), design, and adoption of AI systems (Tapus et al., 2008, p. 169; Hoff & Bashir, 2015, p. 422). According to vom Brocke et al. (2020, p. 9), examining and understanding users’ different personalities is a foundational element to develop adaptive systems that aim to improve human-computer interactions, which has become a key area in IS research (Astor et al., 2013, p. 270; Demazure et al., 2021, p. 655). The incorporation of personality in the context of technology acceptance and usage is consequently not a new phenomenon and has already been addressed by various scholars in different research contexts (e.g., Davis, 1989; Venkatesh et al., 2003), under which also in the field of AI, more specifically in regards to the attitudes concerning its application (e.g., Kaya et al., 2022; Park & Woo, 2022; Riedl, 2022; Schepman & Rodway, 2023). However, regarding GenAI, the exploration of personality remains relatively unexplored, especially in the context of job crafting (Peral & Geldenhuys, 2020, p. 2). This gap emphasizes the need for further research into the influence of those traits in relation to the job crafting behavior in the workplace.

Summa summarum, understanding how different personality traits influence the adoption and utilization of GenAI-tools in the work context is crucial. The notion that employees flourish in work environments that align with their personality traits (Holland, 1996, p. 397) makes this statement particularly relevant in coherence with the fast-moving introduction of GenAI systems. The degree of this alignment can substantially impact overall job satisfaction and the inclination to engage in job crafting behaviors (Lounsbury et al., 2007, p. 176). Understanding this is, thus, not only critical to foster effective technology adoption but also to ensure that the introduction of GenAI enhances, rather than impedes, job crafting, employee satisfaction, and well-being in the workplace.

### The Five-Factor Model in GenAI Adoption

Trying to measure and understand the personality of an employee is crucial in the sphere of job crafting within white-collar employment. The Five-Factor Model (FFM) of personality (McCrae & Costa, 1987) presents a fundamental classification framework discussed in this sub-chapter. Commonly known as the Big Five (Goldberg, 1981; McCrae & Costa, 1987; Digman, 1990), it encompasses five dimensions of personality: Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism. Openness to Experience is associated with being curious, creative, imaginative, flexible, and open-minded (Costa & McCrae, 1992, pp. 244–245). Conscientiousness represents being thorough, well-organized, responsible, and planful (Costa & McCrae, 1992, p. 245). Extraversion is perceived as sociable, talkative, energetic, and dominant (Costa & McCrae, 1992, p. 244). Agreeableness implies being cooperative, tolerant, caring, and trustful (John & Srivastava, 1999, p. 30). Lastly, Neuroticism includes being worried, anxious, distressed, and insecure (Costa & McCrae, 1992, p. 244; Eysenck, 1998, p. 41).

The Big Five traits have been adopted and universally validated across various cultures and languages, making them a universal tool for the assessment of personality (e.g., Goldberg, 1990, p. 1223; McCrae & Costa, 1997, p. 514; Srivastava et al., 2015, p. 359; Soto, 2019, p. 722; Joshi et al., 2023, p. 2), including the use and acceptance of technologies (Schepman & Rodway, 2023, p. 2725). This is also true for the field of IS, where the impact of personality traits on ICT adoption and usage has been increasingly acknowledged in the last years (Hamari & Keronen, 2017; Liu & Campbell, 2017; Huang, 2019) and the Big Five were seen as an essential aid at capturing the essence of one’s personality (McElroy et al., 2007, p. 811). According to the findings of Chittaranjan et al. (2011, p. 35), individuals can be classified based on their scores across the five trait dimensions when using various ICTs. The gathered insights include a variety of contexts ranging from collaborative technologies (e.g., Devaraj et al., 2008), learning technologies (e.g., Barnett et al., 2015), and very recently also, AI (e.g., Kaya et al., 2022; Park & Woo, 2022; Riedl, 2022; Schepman & Rodway, 2023). The FFM has been regarded as a fundamental and comprehensive foundation for understanding this relationship, particularly in organizational settings where technology plays a crucial element (e.g., Nov & Ye, 2008; Tripathi et al., 2022).

Considering these insights, the relevance of the Big Five also extends to the realm of job crafting, where it has shown to be instrumental in understanding the relationship between personality traits and the subsequent job crafting behaviors (Peral & Geldenhuys, 2020, p. 4). Especially regarding the introduction of GenAI in the workplace, which represents a novel stimulus, varied responses based on individual traits can be expected. These traits might be decisive in determining how employees perceive and followingly interact with GenAI, influencing their attitudes and job crafting behaviors. According to the review of Schepman and Rodway (2023, p. 2725), it is essential to understand that the links between personality traits and particular technologies are context-dependent and cannot easily be generalized to new technologies. The authors further add that the role and type of technology are the main factors that significantly impact the way personality traits are related to it, as different ICT tools with different attributes support individual dispositions of drives and needs. Therefore, it is not possible to simply deduce the relationship between personality traits and GenAI. Building on previous research, which has shown that the role and type of technology significantly impact how personality relate to different ICT tools with varying attributes, this study aims to understand how the Big Five personality traits affect job crafting in the context of GenAI. This need for a more targeted investigation is especially emphasized after considering that, according to Park and Woo (2022, p. 69), scholars in the domain of human-computer interaction have primarily been focusing on selected traits – which also has caused inconsistent findings. Given the significant role played by the Big Five personality traits in the context of ICT, the objective of this research is to examine the relationship between these traits and the perceived job crafting behavior in the context of GenAI integrally. This is achieved by accounting for the complexity and contextual dependence of the associations found in previous studies, providing new insights into how individual differences in personality influence the adoption and integration of GenAI in job crafting practices.

#### Openness to Experience

Openness to experience, as already defined above, encompasses a receptivity to curiosity, creativity, and flexibility to change. Research has consistently shown that individuals who possess a strong inclination towards this trait tend to exhibit positive attitudes regarding new technologies (McElroy et al., 2007, p. 817; Svendsen et al., 2013, pp. 331–332) and are more willing to adopt innovative solutions (Park & Woo, 2022, p. 85). Further, it has been demonstrated that individuals high in openness often become early adopters and innovators in technology (Xu et al., 2016, p. 247) and thus play a central role in the success of its implementation (Rauschnabel et al., 2015, p. 642). This trait has shown significant correlations with the utilization of various ICTs (Joshi et al., 2023, p. 17), including “business and commerce,” “information-based,” and “career and education” applications (Joshi et al., 2023, p. 18), and has also extended to the realm of AI systems (Riedl, 2022, p. 2035; Schepman & Rodway, 2023, p. 2736). A possible reason for this is that their inherent curiosity and broad-mindedness relate to a solid drive to learn and engage in learning-oriented experiences (Major et al., 2006, p. 934; Payne et al., 2007, p. 140), which can hold significant relevance in scenarios where learning and adapting to new technological domains is particularly essential. In addition, this is paired with their motivation to explore novel experiences (DeYoung et al., 2007, p. 883) and their tendency to be more trusting toward unfamiliar means (Saef et al., 2019, p. 183). This, in turn, makes individuals more inclined to have positive cognitions and attitudes toward job-related technologies and their associated changes, whether them being positive or negative (Srivastava et al., 2015, p. 363; Tripathi et al., 2022, p. 1135). However, it is also important to note that some studies did not find any significant relationships between openness and technology usage (e.g., Terzis et al., 2012, p. 1994; Mark & Ganzach, 2014, p. 279; Xu et al., 2016, p. 253), indicating a more complex relationship possibly influenced by other factors such as personal innovativeness and prior experience with technology (Park & Woo, 2022, p. 84). Moreover, research has also found that openness to experience is a crucial factor in job crafting (Bell & Njoli, 2016, p. 4; M. Kim et al., 2019, p. 2), as it is closely associated with integral factors for job crafting behavior such as creativity and an open approach to job tasks (Baer & Oldham, 2006, p. 968; Tan et al., 2019, p. 116; W. Zhang et al., 2019, pp. 67–68). M. Kim et al. (2019, p. 2) further claim that individuals who exhibit a high degree of openness to experience tend to seek a broad range of opportunities and experiences. They typically prefer tasks that allow them to utilize various skills, involve a high level of task significance (i.e., impact on other members of the organization), and offer a sense of involvement in the entire project process (i.e., high task identity). According to Peral and Geldenhuys (2020, p. 9), individuals exhibiting high levels of this trait tend to be more engaged in task crafting behaviors, which involves adapting to their jobs' physical and cognitive aspects to better align them with their personal characteristics. Especially in the context of interacting with GenAI in the workplace, this propensity to adapt to new approaches and technologies could be a critical factor in discovering how white-collar employees approach job crafting. In light of these findings, the aim is to encapsulate the interaction effects of openness to experience utilizing GenAI concerning job crafting behavior within white-collar work environments. Ergo, the following hypothesis will be tested:

*H3a) The degree of Openness to Experience positively moderates the relationship between using GenAI and the perceived job crafting behavior among white-collar employees.*

This hypothesis is based on a synthesis of empirical research demonstrating the crucial role of openness to experience in the acceptance and innovative use of new technologies. The rationale for focusing on the moderating effect of openness to experience, particularly its positive moderation, is grounded in the trait's association with increased exploratory behavior, learning orientation, and adaptability in the face of change. These attributes are highly likely to magnify the advantages of GenAI in job crafting. By positing a positive moderation, the hypothesis thus suggests that individuals with higher levels of Openness are more inclined to utilize GenAI for job crafting.

#### Agreeableness

Continuing the exploration of the Big Five, the focus has now turned to the trait of agreeableness. As already described, individuals with this trait are characterized by attributes such as cooperativeness, trustfulness, and a general proclivity toward maintaining harmonious relationships. The relationship between sociality and functionality for agreeableness is rather complex, as it has been variedly associated with both positive and negative emotions (Park & Woo, 2022, p. 86). This means, in turn, that the relationship involved with technology acceptance and usage is not straightforward in nature, as demonstrated by several researchers who have conducted studies to investigate the relationship regarding the use of ICT. While some scholars have found that agreeableness is not a significant predictor of ICT use (e.g., Keller & Karau, 2013, p. 2498; Y. Kim et al., 2015, p. 144; Huang, 2019, p. 283), others have noted that it holds relevance in this regard (e.g., Benlian & Hess, 2010, pp. 10–11; Zhou & Lu, 2011, p. 555; Özbek et al., 2014, p. 548). A reason could be that agreeable individuals, known for their conflict-averse and risk-avoiding nature (Joshi et al., 2023, p. 5), tend to exhibit hesitancy towards the usage of technologies that carry inherent risks or disharmony (Timmermans & De Caluwé, 2017, p. 77; L. Zhang et al., 2017, p. 218). Further, it has been demonstrated that even though agreeableness is associated with a learning goal orientation (Payne et al., 2007, p. 136), it does not necessarily contribute to a stronger motivation to learn (Major et al., 2006, p. 932) or task performance, especially in situations where social interaction is weak (Barnett et al., 2015, p. 380). On the contrary, where technology design is aimed at promoting collaboration, agreeableness is positively linked to both perceived usefulness and effective usage (Devaraj et al., 2008, p. 101). This could suggest the fundamental importance of the context in which technology is introduced and furthermore have substantial effects on its perceived impact on social harmony. Connecting this to the setting of AI, according to Park and Woo (2022, p. 73) and Schepman and Rodway (2023, p. 2726), individuals with high levels of agreeableness feel positive attitudes towards AI because of their social compliance, tolerance, and inclination to view conflicts in a more positive light. Furthermore, Riedl (2022, p. 2030) found evidence of a positive relationship between agreeable individuals and trust in AI systems in nine papers. This has also been true for other types of ICTs in organizational contexts, such as ERP applications (Benlian & Hess, 2010, p. 10), where it seems that individuals are more likely to exhibit a higher degree of willingness to comply and collaborate when asked to interact with organizational ICTs (Devaraj et al., 2008, p. 98; Srivastava et al., 2015, p. 364). In terms of job crafting, Peral and Geldenhuys (2020, p. 9) revealed that employees who score high on agreeableness tend to engage in relational crafting, which involves modifying their job characteristics by increasing the frequency of social interactions at work. They further add that other scholars had already identified this positive interpersonal aspect of contextual performance (e.g., Organ & Ryan, 1995; Van Scotter & Motowidlo, 1996). Consequently, the context-dependent nature of agreeableness makes it a crucial interest in understanding the dynamics of GenAI utilization in job crafting. Given this background, the hypothesis for the trait of agreeableness in the context of GenAI utilization in job crafting is formulated as follows:

*H3b)* *The degree of Agreeableness positively moderates the relationship between using GenAI and the perceived job crafting behavior among white-collar employees.*

This hypothesis is derived from the understanding that agreeableness influences how individuals perceive and interact with technology, especially in contexts emphasizing collaboration and interpersonal harmony. Specifically, it states that higher levels of this trait will lead to enhanced use of GenAI for job crafting, given its association with positive attitudes towards AI and trust in AI systems. This use is expected to be particularly evident in enhancing relational aspects of work, where agreeable employees are likely to leverage GenAI to foster better communication, collaboration, and overall social harmony within their work environment.

#### Conscientiousness

Delving into the following trait, prior research has shown that individuals who score high on conscientiousness, characterized by attributes such as diligence, work ethic, and organizational skills, have a nuanced relationship with different kinds of ICTs. Conscientious individuals perceive time as a limited resource and have been observed to exhibit favorable attitudes towards technologies that can augment productivity and efficiency and please their need for achievement, thus indicating a positive relationship (e.g., Devaraj et al., 2008, p. 96; Barnett et al., 2015, p. 385). However, they may show hesitancy in regard to technologies perceived as aimless or unproductive (e.g., Landers & Lounsbury, 2006, p. 289; Joshi et al., 2023, p. 18). Their inclination in this regard can be demonstrated by the preference for utility-based applications (Lane, 2012, p. 259), work-related usage (Landers & Lounsbury, 2006, p. 289), or learning tools and assisted performance-enhancing activities (Terzis et al., 2012, p. 1993). This is in line with additional findings that have revealed that conscientious individuals are positively linked to higher learning motivation (Major et al., 2006, p. 934) and learning goal orientation (Payne et al., 2007, p. 140). Additionally, Srivastava et al. (2015, p. 364) found these individuals to accept technologies even if they were challenging or stress-causing, as long as they perceived the opportunity to improve their job performance. This understanding in the context of IS is essential to investigate the influence of GenAI subsequently. According to research by Park and Woo (2022, p. 86), conscientious individuals are likely to perceive AI systems as functionality-enhancing tools that augment work efficiency and task performance, which could be embedded in their inherent need for achievement and efficiency. On the flip side, negative attitudes toward AI have also been observed, as demonstrated by Schepman and Rodway (2023, p. 2735) and explained through the perspective of conscientious individuals who may view AI as an inherent threat to their job security and performance (Shank et al., 2019). Looking at the context of job crafting, it has been shown that conscientiousness plays a significant role in shaping how ICTs are used to enhance work roles and tasks. Peral and Geldenhuys (2020, p. 9) report that conscientious individuals are likely to utilize technologies to engage in task crafting behavior with the goal of improving task performance and enhancing personal growth. This, therefore, means a change in the physical aspects of their jobs that is more in line with their inherent individual characteristics, which has also been demonstrated by other scholars (Bell & Njoli, 2016, p. 8). Given the tendencies of conscientious people and the previous findings, the following hypothesis is posed:

*H3c) The degree of Conscientiousness positively moderates the relationship between using GenAI and the perceived job crafting behavior among white-collar employees.*

This hypothesis is rooted in the observed tendencies of conscientious individuals to favor technologies that align with their personal work ethics and productivity goals. Their inclination towards efficient, goal-oriented use of technology suggests that they are likely to adopt GenAI in ways that enhance their job performance. To be more concrete, the hypothesis states that higher levels of conscientiousness will lead to more enhanced use of GenAI regarding job crafting in order to improve task performance.

#### Extraversion

Extraverts, with their inherent characteristics of being socially engaging, energetic, and assertive, are involved in activities associated with forming positive relationships and facilitating interaction to attract social attention (Ashton et al., 2002, p. 250). In this context, it has been demonstrated that individuals who have a tendency towards extraversion are more likely to experience positive emotions towards social robots and new, in the sense of newly upcoming, technologies due to this inherent nature (Rice & Markey, 2009, p. 38; Qu et al., 2021, p. 2676; Park & Woo, 2022, p. 72). Yet again, focusing on the use of ICTs, according to Park and Woo (2022, p. 73), the nature of technology is pivotal in determining their attitudes. Various scholars have observed that technologies that promote social interaction are preferred by extraverts, as they derive pleasure from this interpersonal communication (Svendsen et al., 2013, p. 332; Sriyabhand & John, 2014, p. 84). According to Joshi et al. (2023, p. 19), this is probably a plausible reason for their preference for social networking and leisure applications. On the other side, it has also been made evident that those technologies that replace the social aspect generally tend to receive less enthusiasm (Barnett et al., 2015, p. 385). With respect to AI systems, both the findings from Park and Woo (2022, p. 85), as well as Schepman and Rodway (2023, p. 2735), presented a negative relationship between extraversion and attitudes toward AI. They related it to negative emotions and low functionality, possibly caused by a fear of replacement in routine tasks and a reduction in interpersonal communication. This was also supported by the findings of Barnett et al. (2015, p. 385). Combining these findings within the context of job crafting, it has been illustrated that extraverted individuals engage in relational crafting behavior (Peral & Geldenhuys, 2020, p. 9) and thereby adjust their job characteristics to their interpersonal needs of social interaction (Bell & Njoli, 2016, p. 9). Moreover, extraversion has been found to be a strong predictor of a diverse range of job-related tasks (Barnett et al., 2015, p. 380) and hence can be considered highly relevant to job tasks associated with learning (Barrick & Mount, 1991, p. 20). Given the characteristics and behaviors associated with extraversion, alongside their preference for ICTs that foster social interaction, the emergence of GenAI presents a nuanced challenge. Therefore, their fundamental nature of seeking pleasure in interpersonal communication could be disrupted in the workplace. Because of these dynamics, the following hypothesis is raised:

*H3d) The degree of Extraversion negatively moderates the relationship between using GenAI and the perceived job crafting behavior among white-collar employees.*

This hypothesis is predicated on the understanding that extraversion, by its very nature, emphasizes the value of direct, interpersonal interactions and deriving energy and satisfaction from such engagements. The introduction of GenAI, despite its potential to enhance certain job functions, may not fulfill the extravert's intrinsic need for social connectivity and may even be perceived as a barrier to such interactions. Therefore, while GenAI may offer numerous benefits in terms of efficiency and task optimization, its impact on the social aspects of job crafting – crucial to extraverted employees – may be limited or even hostile. For the specific experimental setting in this research project, it thus makes more sense that higher levels of extraversion lead to reduced efficacy of GenAI in facilitating job crafting behaviors predicated on interpersonal interactions – i.e., relational crafting.

#### Neuroticism

Exploring the impact of neuroticism, with its characteristics of having high levels of anxiety, stress, and emotional volatility, will lastly give the complete picture of the distinctive influence on individuals’ attitudes and interactions towards technologies. The role of neuroticism in shaping perceptions and behaviors regarding ICTs has been a focal point of scholars, resulting in a multifaced understanding of this trait (Joshi et al., 2023, p. 6). Bolger and Zuckerman (1995, p. 899) reported that for identical events, neurotic individuals tend to have a more pessimistic appraisal than their less neurotic counterparts. They justified this attitude with their higher level of sensitivity towards negative and stressful events. Hence, this predisposition towards negative emotionality makes them less receptive to new changes (DeYoung et al., 2007, p. 894), which followingly fosters resistance rather than acceptance (Barnett et al., 2015, p. 385). Based on the mentioned findings, it can be derived that individuals with high levels of neuroticism are more likely to approach technological advancements with a sense of heightened caution and wariness (Agyei et al., 2020, p. 5). This has also been argued by Schepman and Rodway (2023, p. 2726), who suggest that neuroticism can serve as a negative predictor, ergo indicating that neurotic individuals might exhibit more significant concerns regarding AI. This perspective is reinforced by findings across various technologies, where neuroticism is linked to apprehensions about innovative technologies that bear potential risks. Those findings include specific cases such as autonomous vehicles (Qu et al., 2021, p. 2671) or technology use in general (Devaraj et al., 2008, p. 101; Svendsen et al., 2013, p. 332; Barnett et al., 2015, p. 385). Hence, it is not unexpected that the presence of neuroticism can have an adverse impact on perceived usefulness and the behavioral intention to use as well as adopt various ICTs, as shown by multiple academics (e.g., Zhou & Lu, 2011, p. 555; Özbek et al., 2014, p. 549; Xu et al., 2016, p. 246; Camadan et al., 2018, p. 23). According to Tripathi et al. (2022, p. 1135), this is especially true for technological advancements in workplace settings. Consequently, the inherent wariness of higher levels of neuroticism exemplifies their cautious stance. In fact, studies have shown that people are often faced with feelings of threat or discomfort when communicating with AI (Liang & Lee, 2017, p. 381; Stein et al., 2019, pp. 79–80) and a lack of trust towards AI systems (Riedl, 2022, p. 2031). According to Devaraj et al. (2008, p. 97), such an attitude could cause less effective technological adaptations. When considering job crafting, the influence of neuroticism is again pronounced. Bell and Njoli (2016, p. 4) claim that individuals high in neuroticism may engage in job crafting as a way to cope with their emotional vulnerabilities, thereby modifying job tasks to align with their psychological needs and enabling them to better manage their emotions while at work. Given the nuanced understanding of the impact of neuroticism on the reception and interaction of an individual with technological analysis, the following hypothesis will be tested:

*H3e) The degree of Neuroticism negatively moderates the relationship between using GenAI and the perceived job crafting behavior among white-collar employees.*

The foundation of the negative moderation effect of this hypothesis is built upon the observed tendencies of individuals with high levels of neuroticism to exhibit a cautious approach toward new technologies, including GenAI. Their heightened sensitivity to negative and stressful events fosters resistance to change, influencing their perceptions of and attitudes toward innovative technologies that may carry potential risks. This cautious stance is further evidenced by the negative predictor role of neuroticism in technology adoption, suggesting that individuals high in this trait might display significant concerns regarding GenAI, impacting their behavioral intention to use and adopt it. In the context of job crafting, it is suggested that while neuroticism may drive particular forms of job crafting aimed at emotional regulation, its overall impact on leveraging GenAI for broader job crafting purposes could be constrained. Consequently, the proposed hypothesis articulates a specific directional effect of neuroticism on the utilization of GenAI in job crafting, positing that higher levels of neuroticism might limit the extent to which white-collar employees engage in innovative job crafting behaviors facilitated by GenAI.

# Methodology of the Research Approach

The methodology underpinning this thesis has been precisely designed to effectively shed light on GenAI on job crafting behaviors within white-collar professions. Anchored in a rigorous experimental framework, this chapter provides the foundation for the systematic approach employed in order to investigate the effects of GenAI tools, specifically ChatGPT, in reshaping job roles. The integration of a within-subject design allows not only to unveil the direct impacts of GenAI tool utilization on job crafting behavior but also helps to uncover the role of individual personality traits as critical moderators of this dynamic relationship. In the forthcoming sections, a comprehensive overview of the research design and approach, participants, data collections methodologies, and analytical strategies is provided. Doing so will contribute to the empirical insights that guide both theoretical advancement and practical application in the era of AI enabled workspaces.

## Research Design

The cornerstone of this research paper is the investigation into the differential impacts of GenAI on job crafting behavior, underscored by the moderating influence of personality traits, through a meticulously crafted experimental setting. A within-subject design was employed across three distinct conditions in order to be able to properly dissect the nuanced effect of the used GenAI tool, i.e. ChatGPT, as well as the influence of prompt engineering on two strategic thinking tasks. This design was selected to facilitate a controlled comparison of job crafting behaviors without or with the assistance of either ChatGPT, a prompting framework, or both, depending on the participant's assigned experimental condition. This enabled a clearer attribution of observed effects on the corresponding condition. The three conditions were organized in the following manner:

***Control Condition:*** All participants undertook the first strategic thinking task without any ChatGPT assistance, thereby establishing a baseline for job crafting behaviors in traditional work settings. Further, this ensured a mitigation of learning effects from the subsequent ChatGPT use.

***First Experimental Condition:*** This condition introduced ChatGPT as a supportive tool for completing the second strategic thinking task and enabled the examination of direct influences of GenAI on enhancing job crafting capabilities.

***Second Experimental Condition:*** The participants received both ChatGPT access and targeted guidance on prompt engineering before undertaking the second strategic thinking task. With this setup it was possible to specifically evaluate the added value of the structured prompt engineering framework in maximizing the effectiveness of GenAI tools on job crafting behaviors.

To guarantee a successful implementation, a great attention to detail was maintained. The experiment was designed to last approximately 50 minutes, with each task having a 12-minute timeframe. This ensured focused engagement and limited fatigue. It is important to note that each participant was compensated with 20 Swiss Francs, with an additional incentive of 15 Swiss Francs awarded to 10% ones who demonstrated the most innovative solutions. This was verified with a measure that calculated how significantly their solutions diverged from ChatGPT’s output. Implementing a compensation strategy was not only to renumerate participants for their time but also to simulate a more authentic work environment and ultimately fostering genuine effort and creativity in task completion. Before starting the experiment, the participants were initially briefed about the goals, procedure, and potential challenges. Following their informed consent, they proceeded to a pre-survey capturing demographic details, work-related aspects, AI literacy and general attitudes toward AI as well as personality traits. Controlling for the last two variables is essential to isolate the effects of GenAI accurately. These factors can significantly impact the ability to effectively use and adopt as well as percept and engage with GenAI tools. This will in turn, aid in ensuring that the results reflect its true impact. Due to the within-subject design and with the goal of augmenting the validity of the findings, after the completion of the pre-survey, the order of control and experimental tasks was randomized for each participant. This decision addressed potential order effects, ensuring that any observed differences in job crafting behavior could be attributed more confidently to the manipulations rather than to the sequence in which the tasks were presented. Therefore, this ensured an unbiased examination of the impact of completing the task without utilizing ChatGPT, with ChatGPT alone, and with ChatGPT along with the prompt engineering framework. An important sidenote regarding the second experimental condition is that the participants were only exposed once to the prompting framework. This allowed for consistent circumstances, mitigated variability, and subsequently increased the reliability of the findings. Following each of the conditions, participants reflected on their autonomy and competence needs level and job crafting behavior through a post survey. Attention checks and suspicion probes were incorporated to validate the integrity of responses and to assess memory span, concluding with a comprehensive debriefing session (Abbey & Meloy, 2017, p. 68). Further, a manipulation check was conducted following each task with the aim to ascertain participants’ comprehension of the implemented manipulation. This ensured a further level of integrity of experimental manipulations and reliability of resultant data (Hauser et al., 2018, p. 6; Kane & Barabas, 2019, p. 247). A critical element in executing this experiment was the integration of all components into a single platform, which was developed and refined by the University of Kassel. Through a reconfiguration and adaptation specifically implemented for this study, a seamless and distraction-minimized experience was ensured for the participants. Finally, the controlled conditions of this experimental setting ensured consistency by mitigating effects of external variables and thus emphasizing the intrinsic capabilities of ChatGPT and the effectiveness of prompt engineering.

## Participants

In the pursuit of understanding the impact of GenAI tools on job crafting, a cohort of 30 participants was targeted from the student pool of a prominent public university in Switzerland, the University of St. Gallen. The recruitment was strategically conducted through the Behavior Lab of the university. The targeted sampling ensured a structured and controlled process while meeting the selection criteria, which were carefully defined in advance. Eligible participants were required to have a minimum of six months of work experience and either currently or previously having at least a part-time employment status. Additionally, a profound understanding of the German language was deemed essential for engaging with the questions and ChatGPT. The aim of this selection process was to closely replicate the demographic of white-collar professionals who are likely to interact with GenAI tools int their work context. The familiarity of the selected cohort with professional work environments, coupled with their academic engagement, positions them as an ideal proxy for a nuanced examination in this research context. Furthermore, the experiment was conducted within the facility of the Behavior Lab and hence allowed for a standardized and replicable setting to simulate the necessary workspace. A plausible challenge to consider is that the selected students may not accurately represent the broader population of white-collar employees due to their concurrent academic commitments and potentially limited industry exposure. The selection, however, is justified by the need of studying a population that is not only adept at navigating new technologies but also stands at the cusp of entering full-time employment. This makes them highly relevant for understanding future workplace dynamics. Moreover, their academic background provides a unique lens through which the implications of GenAI on job crafting can be explored. In addition to the in-lab experiment, the same experiment was conducted using the online platform Prolific. Using exactly the same experimental design and requirements, an additional cohort of 82 participants was assembled, bringing the total number of participants to 112. This dual setting approach enhanced the study's robustness and breadth first of all, by accessing a broader demographic, potentially also including individuals with different levels of academic but also professional background and experience than just those typically found at the university. This diversity helped in generalizing the findings across a wider population. Second of all, using multiple settings mitigated the risk of contextual biases, thereby enhancing the reliability of the results (Andrade, 2018, p. 498). The last benefit of this combination regards the validity of the data sample. Through the laboratory setting, the internal validity was enhanced due to its controlled environment and minimized disruptions (Bortz & Döring, 2006, p. 520). On the other side, the online setting allowed for more realistic conditions, thus increasing the ecological validity of the findings (Andrade, 2018, p. 499; Webster Jr. & Sell, 2014, p. 193). Implementing this combination therefore, offered to obtain results that hold under strict experimental conditions but also reflect real-world applicability.

## Instruments for the Data Collection

The subsequent sub-chapters present and discuss the instruments used for the collection of data during the research experiment. This involves the specifically crafted strategic thinking tasks and the selected scales and variables, with their corresponding changes. Each instrument was chosen based on its ability to contribute to the overarching research objectives while ensuring methodological rigor and ultimately strengthening the scientific foundation.

### Strategic Thinking Tasks

To assess the influence of GenAI, two strategic thinking tasks were employed, designed to stimulate high job demand scenarios. These tasks were meant to be integral to an executive assistant’s role and consequently crafted to necessitate advanced executive functioning skills (Basharpoor et al., 2021), thereby inducing intellectual demand that mirrors real-world professional challenges. As stated above, the experiment was conducted entirely in German, with each session lasting approximately 50 minutes, with a 12-minute duration allocated for each task. The first task required participants to devise a comprehensive week-long communication strategy to integrate sustainability as a core value across the company. The second task involved creating a concept for a memorable one-day event for executives to discuss digital transformation. Both tasks aimed to foster strategic thinking, demanding creativity, problem-solving, and conceptualization skills akin to those required in high-level corporate environments. The complete tasks can be found in **APPENDIX XYZ**. The tasks were assigned randomly to either the control condition or one of the experimental conditions.

To ensure the tasks’ similarity in complexity and suitability for strategic thinking, a quantitative pre-test with 14 participants was conducted before the actual experiment by SOURCE **(cite Eva, Mahei et al.)** (TABLE X). Adjustments were made based on feedback to refine task clarity and execution expectations, emphasizing the development of conceptual solutions within a specified solution format, as well as including a time limit. TABLE X provides an overview of the adjustments. The task design was underpinned by Webb’s (1997) depth of knowledge concept, which aimed at assuring equal structure and word count to eliminate complexity differences and promote strategic thinking. Ultimately, through the strategic use of those tasks in a controlled laboratory setting, the collection of precise data on participants job crafting behavior through the use of GenAI was allowed.

### Measurements

***Job Crafting Scale:*** An adapted version of the Job Crafting Scale by Tims et al. (2012) was used to measure the job crafting behavior. The scale’s adaptation and translation into German were undertaken to specifically tailor the instrument to the research context, while still maintaining its integrity, cultural relevance, and linguistic accuracy. Further, the focus was selectively placed on the two dimensions “increasing structural job resources” (IStR) and “decreasing hindering job demands” (HRJD). This is justified as these dimensions directly address the central aim of the study, i.e., how GenAI tools as new job resources enhance or impede the strategic modification of job roles and demands within a technology-infused job environment. The participants reported their engagement in job crafting behaviors on a 5-point Likert scale. Choosing this scale was justified due to its strong psychometric properties, including reliability and validity across various settings and significant Cronbach’s alpha values (Petrou et al., 2012, p. 1126; Tims et al., 2012, p. 177). This ensured an accurate assessment of job crafting and was supported by the scale’s proven multidimensionality in dissecting the complex nature of job crafting across various cultures and contexts (e.g., Eguchi et al., 2016; Sora et al., 2018).

***The Big Five Personality Traits:*** The personality traits were assessed using the “Kurzversion des Big Five Inventory” (BFI-K) by Rammstedt and John (2005), on the same 5 point Likert scale as well. This scale is a succinct measure that concisely yet effectively captures the broad dimensions of personality. The selection of the BFI-K was predicated on its established reliability and the efficiency it brings to large-scale studies without compromising on depth of the personality assessment (Rammstedt & John, 2005, p. 196). Its extensive verification process supports its application in diverse research settings and substantial structural, convergent, and external validity (Rammstedt & John, 2007, p. 209). Those robust psychometric properties offered accurate personality profiling and a nuanced understanding of the personality’s impact on job crafting behavior.

***Basic Psychological Needs:*** To measure the autonomy and competence needs level of the participants, the "Basic Psychological Needs in Physical Education Scale" (BPN-PE) by Vlachopoulos et al. (2011) was applied, which was first adapted for workplace and then translated into German. While originally it has been developed for educational contexts, its theoretical foundations in the SDT made it still a valuable instrument to assess psychological needs in professional work settings. To affirm its robustness and consistency, the psychometric integrity of the scale has been validated through rigorous evaluations, encompassing analyses of internal consistency, measurement invariance across genders, and nomological validity (Vlachopoulos et al., 2011, pp. 272–273). The choice for this scale was further supported by extensive research which validates its effectiveness in diverse cultural contexts, supporting its adaptability (e.g., Cagas & Hassandra, 2014; Menéndez Santurio & Fernández-Río, 2018).

***Control Variables:*** A set of control variables, including age, gender, academic degree, employment status, AI literacy, and attitudes towards AI were measured during the experiment. AI literacy was measured using the “Meta AI Literacy Scale” (MAILS) developed by Carolus et al. (2023), which offered a comprehensive assessment of the understanding and the competencies of individuals related to AI. The scale was developed to comprehensively assess the understanding, application, and ethical thoughts, along with psychological competencies like problem-solving or learning regarding AI (Carolus et al., 2023, p. 10). Grounded in substantial AI literacy literature, it allowed for a multidimensional approach that could be adapted to various professional and educational needs. The MAILS is made up of the constructs “Use”, “Knowledge”, “Detection”, and “Ethic.” To examine how well the participants operationalize AI tools in job crafting scenarios, only the constructs “Use” and “Knowledge” were utilized. Thereby, “Use” evaluates practical application skills and “Knowledge” assesses understanding of AI functionalities. Those made up the two vital components to assess the immediate impact and effective utilization. The reason for the exclusion of “Detection” and “Ethic” was rooted in the concentration of the practical competencies. As the participants were explicitly instructed to use ChatGPT, the question of detecting and ethically classifying GenAI tools becomes less relevant. Complementing this, a shortened and translated version of the “General Attitudes towards Artificial Intelligence Scale” (GAAIS) by Schepman and Rodway (2020) was utilized to capture the attitudes towards AI. This scale permitted to capture the influence of general – positive or negative – perceptions of AI. The GAAIS demonstrated strong psychometric properties, including convergent and discriminant validity when comparing it against existing technology attitudes measures (Schepman & Rodway, 2020, p. 11). Further research by Schepman and Rodway (2023) confirms its reliability while exploring the relationship with personality traits and (dis-)trust. The MAILS and GAAIS were essential elements for isolating and controlling for the specific effects of GenAI tools on job crafting, whit their selection being rooted in the need for robust and validated effectiveness in capturing the relevant data for this research context.

## Ethical Considerations

The experiment adhered strictly to ethical guidelines and was only conducted with the approval of the university's ethics committee. All participants provided informed consent and understood the research's purpose, procedures, and potential challenges. Both in the laboratory of the university and online via Prolific, anonymity was ensured, and participant rights were respected throughout the whole process. Adhering to ethical compliance, participants were briefed about the goals and procedure of the study and needed to first read and then sign a declaration of consent and voluntariness. This form detailed the study's nature, the voluntary participation and ability to withdraw at any time without consequences, potential risks like psychological discomfort, and data privacy measures. The latter was maintained rigorously by storing personal data separately from research data, which were anonymized before analysis to prevent identification. Integrating these ethical research practices ensured the participant’s privacy and integrity but also strengthened the research's validity and reliability through credible and ethically obtained data.

## Data Preparation and Descriptive Statistics

The initial phase of the data preparation involved a thorough cleaning and feature engineering process to ensure high quality and integrity of the data. The raw dataset was initially inspected for completeness and consistencies. Anomalies and participants with incomplete responses, for example due to technical problems or incorrect conduction of the experiment, were systematically identified. This step also included the verification of the built-in attention and manipulation checks. Those problematic entries in addition to several non-essential columns (i.e., timestamps and metadata) were removed and excluded from subsequent analyses. At this point it is worth mentioning that the data quality for the controlled laboratory environment was of a higher degree than for the online environment. To further align with the analytical needs, the dataset underwent additional transformations. Responses recorded on the Likert scale were mapped and converted from text-based to numerical values onto a scale from 1 for the lowest to 5 for the highest. In order to successfully address the randomization of the experimental design, the entries for the corresponding control and experimental conditions were conditionally allocated based on the sequence of execution. Categorical variables such as gender and education level were transformed into binary dummy variables to facilitate the upcoming quantitative analysis. Further, new features were created by calculating mean values from the sets of related items (MacKenzie et al., 2011, p. 298) for constructs such as AI Literacy, Attitudes towards AI, Big Five Personality Traits, and Job Crafting. Finally, the fully cleaned and merged dataset contained 68 rows, i.e., participants, and 53 columns. The performed operations were a crucial foundation for the successive analytical steps.

Upon cleaning and structuring the dataset, descriptive statistical analyses were performed to explore and examine the central variables of interest, thereby providing preliminary insights into the demographic distributions and initial tendencies. As already mentioned, the participant pool consisted of 68 individuals, whereby 48 (70.6%) were male and 20 (29.4%) females, thus showing a predominance in males. The age ranged from 18 to 71 years with a mean age of 29.6 years and standard deviation of 10.25 years, suggesting a broad representation. Most of the participants had a significant employment status, indicated by the mean of 59.25% (SD = 36.59%). **(IMAGES)** The educational background varied widely, though a significant proportion had an above average education level and held a Bachelor's (30.88%) or Master's degree (26.47%), indicating a sample that fits the description of a white-collar employee in relation to the education. Regarding the randomization and allocation into the two experimental conditions, the data showed an evenly distributed sample. This confirmed the effectiveness of the randomization process, which is critical to the internal validity, and it also ensured a robust comparative analysis between the conditions. Looking at the means for the key constructs related to job crafting and self-determination in **IMAGE X**, highlighted variable impacts in how participants perceived the impact of GenAI usage. Notably, the job crafting score for JC2HRJD in the experimental condition already showed a higher mean compared to the control condition. Lastly, Shapiro-Wilk tests indicated non-normal distributions for all the constructs, except for IStR in the control and experimental condition. This guided the choice in using non-parametric tests (Shapiro & Wilk, 1965, p. 591). All the insights derived from these preliminary analyses set a foundation for the subsequent hypothesis testing.

# Results

This chapter delineates the validation and analysis of the integral constructs and hypotheses of this study. The sub-chapter 4.1, "Validation of Constructs," systematically examines the validity and reliability of the constructs through Confirmatory Factor Analysis (CFA), thereby ensuring that each construct is accurately represented by the data. Following this, sub-chapter 4.2, "Analysis of Hypotheses," delves into the empirical investigation of the proposed hypotheses. Utilizing a range of statistical tools, this section thoroughly assesses the impact of GenAI on job crafting behaviors, as well as the moderating effects of personality traits. This provides a comprehensive statistical analysis of the underlying theoretical frameworks. This structured approach fortifies and enriches the findings and understanding of the hypotheses, setting stage for intriguing insights and discussions.

## Validation of Constructs

To confirm the validity and reliability of used constructs, CFA was employed using the “lavaan” package in R. Prior to the CFA, the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy was calculated to justify factor analysis. The overall averaged adequacy for all constructs was 0.7, indicating a sufficient applicability. This was coupled with Bartlett’s Test of Sphericity, which strongly rejected the null hypothesis and thus demonstrated that the overall correlation matrix is significantly different from an identity matrix. Those results support suitability of factor analysis for the dataset, paving the way for the specification of separate CFA models for each set of constructs related to AI Literacy, Attitudes towards AI, Big Five Personality Traits, and Job Crafting. Each construct was modeled as a latent variable indicated by survey items that were presumed to be its manifest variables. Given the Shapiro-Wilk test indicated deviations from normality, Maximum Likelihood estimation (MLR) with robust standard errors was applied to mitigate for it. Each model was estimated was estimated and evaluated based on several fit indices, such as Chi-square Test of Model Fit (χ² p > 0.05), Comparative Fit Index (CFI > 0.95), Tucker-Lewis Index (TLI > 0.95), Root Mean Square Error of Approximation (RMSEA < 0.05), and Standardized Root Mean Square Residual (SRMR < 0.05). Internal consistency was evaluated using Cronbach's Alpha (α > 0.7) and Composite Reliability (CR > 0.7) for each construct, and convergent validity through Average Variance Extracted (AVE > 0.5). The following sections will describe the results of the CFA for each construct, starting with the ones for the control variables and ending with the fundamental ones, i.e., the Big Five and Job Crafting constructs.

Both AI literacy constructs (“AILiteracy\_Use” and “AILiteracy\_Kno”) suggested a generally good fit with the χ² p-values being above 0.05, as well as CFI and TLI values being above 0.90, demonstrating that the hypothesized model captures the data's structure effectively. The RMSEA of 0.088, though slightly above the preferred threshold, was still within an acceptable range, showing reasonable approximation errors. The factor loadings were significant, especially for “AILiteracy\_Use”, indicating strong representations of constructs by items. Reliability measures, i.e., α and CR, were above the thresholds for both constructs and hence suggested adequate internal consistency. However, the AVE for “AILiteracy\_Kno” was below 0.5, highlighting potential issues in convergent validity. Continuing with the CFA for the positive (“P\_GAT”) and negative (“N\_GAT”) general attitudes towards AI, the Chi-square, CFI, TLI, and RMSEA collectively demonstrated a very good fit considering their corresponding thresholds. Factor loadings were substantial across both constructs, affirming that the items effectively captured the latent variables. The reliability and AVE of "P\_GAT" were found to be good, while the ones of "N\_GAT" were both slightly below the thresholds. Proceeding with the Big Five model (“NEO\_A”, “NEO\_C”, “NEO\_E”, “NEO\_N”, “NEO\_O”) two items needed to be removed due to inadequate influence related to a possible misinterpretation in the translation. The CFA indices presented a predominantly good fit measure, with CFI and TLI being very near to the threshold and RMSEA within an acceptable limit. Overall, this suggested a satisfactory model fit. The factor loadings varied, with some items showing very strong and some weak loadings. This was also true for reliability and AVE, which displayed good measures for “NEO\_E”, “NEO\_O”, and “NEO\_N”, but poorer ones for “NEO\_A” and “NEO\_C”. Concluding with the job crafting constructs, the CFA was conducted twice to examine the fit for the control condition (“JC1\_IStR” and “JC1\_HRJD”) and experimental condition (“JC2\_IStR” and “JC2\_HRJD”). Both constructs for JC1 displayed an excellent fit with high CFI and TLI and an RMSEA close to zero. Factor loadings were generally high, demonstrating a strong representation of the items. Further, good internal consistency and composite reliability values were identified, as well as AVE values reflecting satisfactory convergent validity. The second measurement point, JC2, also showed an excellent model fit with strong factor loadings for almost all items. The internal consistency was slightly lower than in JC1 but still within a good range. The AVE values for JC2 constructs were adequate, confirming sufficient convergent validity. Summing up, the conducted CFA provided a comprehensive evaluation of the measurement models. While most constructs demonstrated good fit and reliability, this is not the case for every construct and needs to be taken into consideration when discussing the results.

## Analysis of Hypotheses

The statistical analyses to test the proposed hypotheses were conducted in R using different statistical procedures. After the generation of summary statistics, it was essential to conduct a visual analysis for the important variables to obtain a first idea of data distribution and mean scores. **Figure X** offers a visual representation of this step. To assess hypothesis H1, which posits that the integration of GenAI as a primary ICT tool enhances perceived job crafting behavior, it was important ensuring the appropriateness of the data. As already mentioned before, the Shapiro-Wilk test was employed to evaluate the normality of data distributions for job crafting scores, specifically JC1IStR and JC2IStR, which confirmed normality and thus the suitability of parametric tests. Conversely, for JC1HRJD and JC2HRJD, the distribution did not meet the normality criteria, necessitating the application of non-parametric tests for these variables. Ergo, both test types were used to be on the safe side and ensure robustness. Levene's Test for homogeneity of variances was conducted to ascertain the homogeneity of variances across the control and experimental groups. This was an important prerequisite for the reliability of subsequent t-tests. The results indicated no significant differences in variances, which permitted the use of paired sample t-tests and its normality robust counterpart without adjustments for unequal variances. Therefore, The primary analytical method involved paired sample t-test, comparing job crafting scores between the two conditions, i.e., the control condition without and the experimental condition with GenAI assistance. Additionally, non-parametric Wilcoxon Signed-Rank Tests were conducted to validate the findings from the parametric tests, ensuring normality-robust findings. To quantitatively measure the magnitude of GenAI’s effect on job crafting, Cohen’s d was calculated for each comparison, providing a standardized measure of effect size, more specifically the magnitude of difference between the control and experimental condition (Cohen, 1988, p. 27). The paired sample t-tests indicated statistically significant differences in both job crafting behaviors when participants utilized GenAI tools. This means, that the p-values for IStR (p = 0.02) and HRJD (p = 0.00) were below the threshold p-value of 0.05, therefore underlining the difference between control and experimental condition and therefore an effect of the experimental condition on job crafting behaviors. The non-parametric Wilcoxon Signed-Rank Tests corroborated these findings, with significant test statistics (p < 0.05) for both constructs and thus supporting those across different statistical assumptions about data distribution. Finally, measuring the effect sizes utilizing Cohen’s d showed an effect of 0.30 for IStR and 1.12 for HRJD, indicating medium to large effects respectively. These empirical results collectively affirm Hypothesis H1, demonstrating that the integration of GenAI as a primary ICT tool significantly enhances perceived job crafting behaviors among white-collar employees.

🡪Image with consolidated findings

For hypotheses H2a and H2b, which explore the effect of GenAI on the satisfaction of autonomy and competence needs respectively, it was also vital to start with visual inspections to explore the relationship and distributions of the autonomy and competence scores in the control and experimental condition. Given the non-normal distribution of the data (Shapiro-Wilk p < 0.05), it was also appropriate to consider both parametric and non-parametric tests to ensure credible findings. Therefore, paired sample t-tests were initially conducted and then compared to Wilcoxon Signed-Rank Tests. Performing Levene's Test for homogeneity of variances also showed no significant differences, consequently not needing any changes for the chosen tests. The paired t-test revealed a statistically significant decrease (p = 0.03) in autonomy need scores from pre- to post-intervention with GenAI assistance, highlighted by the negative t-value of the test. Conversely, competence need scores significantly increased (p = 0.02) in the experimental condition, suggesting an improvement following the intervention. The Wilcoxon tests supported these findings, confirming a significant decrease in autonomy (p = 0.04) and an increase in competence (p = 0.02) need levels. Cohen’s d demonstrated medium effect sizes of -0.27 for autonomy and 0.29 for competence. The statistical analysis conducted to assess Hypothesis H2a revealed critical insights into the effects of GenAI on the satisfaction of autonomy needs among white-collar employees engaged in strategic thinking tasks. Despite the initial expectation that GenAI would enhance autonomy, test results indicated a statistically significant decline in perceived autonomy among participants, contrary to the hypothesis. Given these insights, H2a is not supported and in consequence the integration of GenAI as a primary ICT tool in this context did not enhance the satisfaction of autonomy needs. In contrast to the results for autonomy, the analysis for Hypothesis H2b provided supportive evidence regarding the impact of GenAI on competence needs. The significant empirical evidence confirms H2b and therefore, the integration of GenAI as a primary ICT tool in completing strategic thinking tasks effectively enhanced the satisfaction of competence needs.

🡪Image with consolidated findings

To assess the moderation effects of the Big Five personality traits in hypotheses H3a-e on the interaction between GenAI use and the analyzed job crafting dimensions, IStR and HRJD, a covariance-based structural equation modeling (CB-SEM) approach was employed. Using this approach is appropriate as for several reasons. Current research from Dash and Paul (2021, p. 8) illustrates that CB-SEM excels in factor-based models, where latent constructs are assumed to cause the observed measure. Furthermore, Reinartz et al. (2009, p. 341) demonstrate that it is well-regarded for its parameter accuracy and its ability to provide comprehensive fit indices to test theorized relationships. This approach included the development of two distinct models for each construct, allowing for a more nuanced analysis of how personality moderated the use of GenAI under the realm of job crafting. Prior to the construction of the models for the main hypotheses, a preliminary analysis was essential to determine whether the introduction of a prompting framework influenced job crafting behaviors differently across two experimental conditions. Understanding this was crucial for deciding whether to analyze the participant pool as a whole or as separate groups in the subsequent SEM analyses. Welch’s t-tests for unequal variances were hence conducted to assess the impact of the prompting framework, i.e., the difference between the first and second experimental condition. For IStR as well as for HRJD, both p-values exceeded the threshold, indicating no statistically significant differences in mean job crafting scores between participants who used the prompting framework and those who did not. Given the absence of significant difference in job crafting scores, it was deemed appropriate to treat the participant pool as a whole and thus maximize statistical power and generalizability. In order to properly examine the effects, it is good practice to specify two models (**source)**. The initial model served as a baseline and included the direct effects of the integration of GenAI and the five personality traits, as well as a set of control variables, such as age, gender, employment status, educational level, AI literacy, and attitudes towards AI. This model is crucial for understanding the direct relationships between the independent variables and dependent variable and provides a clear, uncontaminated reference point to assess the main effects and of the primary relationships and establish baseline model fit indices. Building upon this foundation, the second model introduced interaction terms between each personality trait and the job crafting scores derived from the experimental conditions (JC2\_IStR and JC2\_HRJD) to enable the investigation of potential moderation effects. This allows to understand the full complexity of relationships among variables and further helps to control for Type I errors that might arise from fitting overly complex models (Green & Babyak, 1997, p. 41; McCoach et al., 2007, p. 463). The chosen procedure was based on the work of Lin et al. (2010), who advocate the "Double Mean Centering" approach as a robust method to handle potential multicollinearity concerns between the main effects and the interaction terms. As a result, double mean centering was used to generate the interaction variables. Furthermore, both models were estimated using the MLR (maximum likelihood with robust standard errors) to accommodate non-normality and provide more reliable inference (King & Roberts, 2015, p. 160). **The model specification below** illustrates the definition of two latent variables, “JobCraftingControl” and “JobCraftingExp”, each indicated by their corresponding job crafting scores (JC1IStR or JC1HRJD for control and JC2IStR or JC2HRJD for experimental). The direct predictors include the five personality traits along with the aforementioned control variables. The moderation effects are tested with the interaction terms, one for each personality trait.

🡪Model here

Having outlined the methodologies adopted for this analysis, the attention is turned to the outcomes of the models. Both baseline models for IStR and HRJD converged normally and showed good fit indices, with the chi-square p-value and the CFI and TLI being above the threshold of 0.95, RMSEA not exceeding 0.07 and SRMR being below 0.05. The introduction of interaction terms in the complete model for both IStR and HRJD resulted in slight decreases in fit indices, reflecting the increased complexity and strain on the model. Despite this, the fit indices remained within very good ranges of their corresponding thresholds. CFI and TLI values were still above the threshold for both models, reinforcing the appropriate fit. SRMR values were still very good (p < 0.05) while RMSEA was acceptable for IStR (p = 0.068) but above the threshold for HRJD (p = 0.113). A reason for this slight misfit could be explained by the added complexity. Building on the understanding of the model fits provides a good foundation for subsequent findings. Starting with the IStR model, several control variables significantly predict job crafting in the experimental condition, notably “AILiteracyUse”, “AILiteracyKno”, “PGAT”, age and educational variables, reflecting the role of individual differences in literacy and educational background on job crafting. More importantly, significant positive moderation effects were found for “JC2IStR.NEOA” (β = 0.585, p = 0.000) and “JC2IStR.NEOO” (β = 0. 673, p = 0.010), indicating that Agreeableness and Openness significantly modulate the impact of the experimental condition on job crafting. The positive coefficients suggest enhancing effects: higher degrees of Agreeableness and Openness amplify the positive impact of GenAI utilization on job crafting behaviors, specifically for enhancing structural job resources. In the HRJD mode, most control variables, except age and “NGAT”, do not significantly contribute to the prediction of job crafting in the experimental condition. More notable are the significant interaction terms, which show positive moderation effects for “JC2HRJD.NEOE” (β = 0.898, p = 0.040) and “JC2HRJD.NEON” (β = 0.508, p = 0.004). Similar to the IStR model, a positive coefficient represents reinforcing effects and in consequence advocates that participants having a higher degree of Extraversion and Neuroticism are more likely to harness GenAI to mitigate hindering job demands.

🡪Findings here

Summing up, the findings revealed a diverse array of results. The SEM analysis for the IStR model revealed significant positive moderation effects of Openness to Experience on the relationship between GenAI usage and perceived job crafting behavior. This suggests that individuals with higher levels of Openness tend to utilize GenAI more effectively to enhance structural job resources, supporting H3a for the IStR dimension. However, no significant effects were observed in the HRJD model, indicating that the hypothesis is only partially supported when considering both dimensions of job crafting. Similar findings are true for Agreeableness, which showed a significant positive moderation effect for the IStR dimension but no significant influence in the HRJD model. Ergo, H3b is also partially supported, affirming the positive impact in one job crafting dimension but not in both. In relation to Conscientiousness, the analysis did not yield significant interaction effects in either the IStR or HRJD model. Therefore, H3c is not supported, indicating that Conscientiousness does not modify the impact of GenAI on either increasing structural resources or hindering job demands. Contrary to initial predictions of a negative moderation, the HRJD model indicated a significant positive moderation effect of Extraversion on reducing hindering job demands through GenAI use. Accordingly, this indicates that more extraverted individuals might leverage GenAI more effectively in this context. On the other side, no significant effects were found in the IStR model, leading to a rejection of H3d. Similarly, the HRJD model showed an unexpected positive moderation effect for Neuroticism, implying that higher levels of Neuroticism might lead to greater use of GenAI to mitigate hindering job demands. This positive coefficient contradicts the hypothesized negative effect and, like the previous traits, did not manifest in the IStR model. Therefore, H3e is also not supported.

🡪Summary image of all hypotheses

# Discussion

This chapter delves into the implications of integrating GenAI within white-collar work settings, focusing on both theoretical and practical impacts. Sub-chapter 5.1, “Discussion of Findings” discusses and integrates the empirical insights with the theoretical frameworks to outline how GenAI reshapes job demands and resources, particularly depending on the individual’s degree of personality traits. The resulting theoretical implications of this discussion are then elaborated in sub-chapter 5.2, “Theoretical Implications” and demonstrate which essential contributions were made. Following this, sub-chapter 5.3, “Managerial Implications,” translates these insights into practical implications for different stakeholders, while providing recommendations tailored to align personal and organizational goals. Lastly, sub-chapter 5.4, “Limitations and Future Research,” transparently acknowledges the study’s limitations and based on this, maps out directions for future research. This structured approach enables a critical reflection of the role of GenAI-enabled job crafting for white-collar employees.

## Discussion of Findings

Introducing the discussion with hypothesis H1 allows to elaborate the baseline of the role of GenAI in enabling white-collar employees to craft their jobs. The statistical findings support this hypothesis and thus suggest that the integration of GenAI tools within the workplace can contribute to the enhancement of job crafting behaviors. This aligns optimally with the JD-R model, which advocates that job crafting occurs by balancing job demands and resources to enhance work engagement and personal work outcomes (Tims et al., 2012, p. 174). Hereby, it is essential to note that GenAI tools serve as dynamic resources which, unlike static resources, can actively transform the work environment by enabling the employees to alter the landscape of job demands and resource (Petrou et al., 2012, p. 1122; Tims & Bakker, 2010, p. 5). Reviewing the results demonstrates that the use of GenAI in the experimental condition leads to an increase in both IStR and HRJD. This is an important finding as it positions GenAI in a twofold manner. On the one hand, the IStR dimension involves efforts to enhance the quality and quantity of structural job resources to an employee (Tims et al., 2012, p. 176). The significant positive effects, therefore, suggest that GenAI effectively permits to access and create new resources that support and facilitate work tasks. According to Bakker & Demerouti (Bakker & Demerouti, 2007, p. 311), the role of such enhanced resources is crucial in the JD-R model, as it improves employee’s engagement and productivity. On the other hand, the HRJD dimensions entails endeavors to decrease aspects of the job that impede productivity and well-being (Tims et al., 2012, p. 175). As demonstrated by the positive findings, in this case GenAI not only adds resources but also plays a vital role in mitigating job demands, which aligns with the JD-R model’s assertation that reduction in job demands can alleviate stress and enhance job satisfaction, fostering a more productive work environment (Demerouti, 2014, p. 237). Hence, particularly considering the large observed effect size (add Cohen’s d), it underscores GenAI’s transformative potential in redefining job roles and its expectations. Examining this from a broader perspective, it is crucial to relate this twofold effect to the underlying capabilities of GenAI. Previous IS-research already highlighted that specific ICT are able to influence job crafting resources (M. M. Li et al., 2022, pp. 3–4). GenAI, however, is unlike conventional ICT tools, and with its sophisticated abilities to understand, generate, and execute complex task that traditionally required significant human input (Lim et al., 2023, p. 2), it is able to extend the capabilities and can act both as an enabler of structural resource enhancement, or as a facilitator for reducing hindering job demands. Therefore, employees might use GenAI to allow them, for example, to focus on higher-value activities, thereby enriching their job roles or to streamline and reduce the frequency of manual-intensive tasks, which reduces the cognitive burdens and alters the requirements of the job (Tims et al., 2013, p. 237). These results conclusively, extend the theoretical propositions within the JD-R model by demonstrating that GenAI not only serves as a static tool but actively transforms the job crafting landscape. This, in turn, enables employees to better align their jobs with both their personal and organizational goals, which is consistent with research emphasizing the importance of ICT in facilitating job crafting and enhancing the overall quality of work life (Bruning & Campion, 2018, p. 517; Mukherjee & Dhar, 2023, p. 1271).

Having established the significant role of GenAI in enabling job crafting through the examined dimensions, the focus now shifts to hypotheses H2a and H2b, which are centered around autonomy and competence of the SDT, two fundamental psychological needs influencing motivation, engagement, and well-being (Gagné & Deci, 2005, p. 337; Bergdahl et al., 2023, p. 3). Autonomy, in this context, refers to the degree of control and agency that employees experience in their work (Deci & Ryan, 2000, p. 231). The expectation was that using GenAI, for example by automating routine tasks and providing data-driven insights, would enhance employees' autonomy and thus enable them to make more informed independent decisions (Petrou et al., 2012, p. 1123; Sekiguchi et al., 2017, p. 474). Contrary to expectations, the statistical analysis revealed a significant decrease in autonomy need scores following the integration of GenAI (Cohen's d = -0.27). This suggests that while GenAI may have provided support in task execution (Bergdahl et al., 2023, p. 10), it possibly constrained the perceived control or choice over their work processes, leading to a decrease in perceived autonomy. This decrease in autonomy scores thus paints a more complex picture that warrants further discussion. One plausible explanation is that while GenAI can execute tasks autonomously, it may also standardize certain decisions or procedures, thus limiting employees' scope for exercising personal judgment or creativity – key components of autonomy (Petrou et al., 2012, p. 1135; Slemp et al., 2015, p. 10). This standardization could constrain employees' ability to tailor their work processes, reducing the perceived autonomy (Nolan & Highhouse, 2014, p. 341). Strongly connected to this is the perceived control, as the automatization of tasks inevitably means a reduction of an employee's direct involvement in these processes, leading to a diminished sense of control over the outcome. This goes strictly against the concept of autonomy, as defined by Deci & Ryan (2000, p. 231). Furthermore, increased reliance on GenAI might also lead to a feeling of dependence for task completion on these tools, thereby potentially undermining their sense of self-efficacy (Shu et al., 2011, p. 935). This outcome challenges the assumption that technological advancement invariably enhances job autonomy. Instead, it suggests that the nature of the technology and the context in which it is implemented play crucial roles in determining its impact. Another possible explanation for this outcome is related to the constraints of the experimental design. Autonomy refers not only to the freedom to make choices but also to the quality and range of those choices (Deci & Ryan, 2000, p. 234; Slemp et al., 2015, p. 3). In the context of the experiment, although participants were free to decide how to use ChatGPT, the mandatory nature of its usage could have restricted the perceived autonomy. This in turn, might have led to a feeling of control over their actions, which is contrary to the principle of autonomy. Research confirms this argument, demonstrating that external compulsion diminishes the sense of control and choice, leading to a reduction in perceived autonomy (Grell & Rau, 2010, p. 27) and ultimately to lower intrinsic motivation (Jacobsen et al., 2014, p. 801) and job satisfaction (Padmanabhan, 2021, p. 5).

Turning the attention to competence in hypothesis H2b, which refers to an individual's need to feel effective and capable within their work environment (Deci & Ryan, 2000, p. 231), it was hypothesized that the use of GenAI would lead to an enhancement of this need. The results supported this hypothesis, with a significant increase in competence need scores following the introduction of GenAI (Cohen’s d = 0.29). This indicates that GenAI tools likely had a positive contribution to the participant’s perceptions of skills and effectiveness, thereby potentially boosting their confidence and perceived efficacy (Bergdahl et al., 2023, p. 3; Gagné & Deci, 2005, p. 337). This is consistent with SDT’s emphasis on the importance of competence for fostering intrinsic motivation and engagement (Deci & Ryan, 2002, p. 14). The positive impact of GenAI on competence aligns with previous research suggesting that appropriate technological support can enhance employees' ability to meet job demands, thereby increasing their sense of competence (Karaca et al., 2023, p. 8). It therefore illustrates that when GenAI tools are perceived as enhancing one’s ability to perform job tasks effectively, they can significantly boost the psychological need for competence. Moreover, it also highlights the potential of GenAI to act as a powerful enabler in the workplace, fostering a sense of mastery and personal growth, but also allowing for quicker learning cycles and adjustment through the instant feedback provided by GenAI tools, which consequently could enhance perceived competence as well.

After having discussed the implications of the first and second hypothesis, attention now shifts to explore the potential insights offered by hypotheses H3a-H3e, delving deeper into the interplay between personality traits and job crafting behavior. Starting with H3a, which focuses on Openness to Experience, a trait encompassing intellect, imagination, and curiosity (Costa & McCrae, 1992, p. 244), is integral to job crafting because it influences how individuals perceive and interact with their environment. This includes the adoption and usage of newly introduced technologies (McElroy et al., 2007, p. 817; Xu et al., 2016, p. 247). Therefore, the findings of the moderation analysis are intuitive. The significant positive moderation effects on the IStR dimension insinuate that individuals with a higher degree of openness are more likely to leverage GenAI to enhance structural resources. This observation aligns with the findings of Rudolph et al. (2017, p. 129), who have similarly noted these tendencies (towards a more productivity enhancing form of job crafting) for a different contextual setting. In consequence, this positively impacts their job crafting behaviors. Academics already linked openness to greater acceptance and utilization of new technologies (Rauschnabel et al., 2015, p. 642; Svendsen et al., 2013, p. 332), including positive emotions toward AI (Park & Woo, 2022, p. 85), thereby underlining the willingness but also the capability of integrating novel ICTs (Joshi et al., 2023, p. 18; Park & Woo, 2022, p. 85), as it aligns more closely with their cognitive flexibility (DeYoung et al., 2007, p. 883; Srivastava et al., 2015, p. 363) and their needs for creativity, novelty, variety in their work (Tan et al., 2019, p. 116; W. Zhang et al., 2019, pp. 67–68). This enhanced perception could lead to more effective job crafting by expanding the resources available for job role and task modification. This aligns with their predisposition towards using innovative solutions to increase the richness of their job resources, thus effectively enhancing the structural resources to enable the job crafting behavior. However, just as exciting is also the insignificant moderation effect on the HRJD dimension. This posits that individuals high in openness may be more pronounced in activities that involve expanding capabilities and resources rather than reducing barriers or constraints. A possible explanation of this might be due to the primary orientation of openness toward towards exploration and expansion (DeYoung et al., 2007, p. 883; M. Kim et al., 2019, p. 2; Saef et al., 2019, p. 183) rather than reduction or simplification of tasks. The result would be diminished interests or perceived benefits in using GenAI to reduce job demands. Therefore, expanding their capabilities could overshadow the potential uses of GenAI as a tool for simplifying tasks or mitigating stressors.

A similar pattern of findings can be seen for Agreeableness in H3b, which is characterized by traits such as cooperativeness, compliance trust, altruism, and a general propensity toward maintaining harmonious interpersonal relationships (John & Srivastava, 1999, p. 30). The positive moderation of agreeableness on the IStR dimensions suggests that agreeable individuals may facilitate a more effective utilization of GenAI tools that enhance structural job resources. Even though the JD-R model categorizes physical tools as well as interpersonal relationships both as kinds of job resources (Tims et al., 2012, p. 174), caution is needed not to imply that agreeableness drives the use of GenAI to strengthen communication and collaboration, as this is measured by a different job crafting dimension which was not measured due to the individual task completion demanded by experimental design. However, this could mean that agreeable individuals might leverage GenAI tools to indirectly enhance their social environment by first improving their structural job conditions. For example, by increasing their job autonomy and opportunities for development, agreeable individuals may create environments where cooperative and harmonious interactions are more likely to occur, even though these interactions were not directly measured as part of the social job resources. Those structural changes initiated through job crafting are perfectly in line with the definition of the IStR dimension (Bakker & Demerouti, 2014, p. 18; Tims et al., 2012, pp. 174–175) and have also been observed by academics (Rudolph et al., 2017, p. 129). The importance of such social contextual settings for agreeable individuals was also investigated by various researchers (Devaraj et al., 2008, p. 101; Joshi et al., 2023, p. 18). Therefore, by using GenAI to bolster these resources, a significant enhancement of their work environment can be achieved, aligning with their natural tendencies to seek out and maintain interpersonal harmony and social norms (Park & Woo, 2022, p. 86). In contrast, no significant moderation effect war observed for HRJD, indicating a negligible impact in reducing job demands. Tracing this back to the risk-averse and conflict-avoidant characteristics of agreeableness implies a potential reluctance to engage in activities that require confrontational change or cause instability (Timmermans & De Caluwé, 2017, p. 77; L. Zhang et al., 2017, p. 218), such as significantly altering established procedures or reducing existing job demands, which may involve negotiation or conflict. Hence, this might orient individuals towards leveraging GenAI to add value rather than to subtract difficulties.

Transitioning to the discussion of hypothesis H3c, it becomes notable that the findings for conscientiousness diverge from the other as the sole ones without significant outcomes. On this ground, it is important to discuss whether this aligns with the nature of conscientious individuals or, despite the thorough research efforts, if it may be attributed to the quality of the data. Characterized by traits like organization, diligence, and reliability, consciousness influences behaviors in structured settings and drives individuals towards systematic and goal-oriented actions (Costa & McCrae, 1992, p. 245). This is the reason that, in the context of job crafting, it was hypothesized that individuals with a high degree of conscientiousness would engage in behaviors to enhance their maximize efficiency and achieve better alignment with their work goals. Supporting this were the characteristics of GenAI, which, for example, offer efficient automation of tasks and optimization of time management, thus theoretically appealing to the conscientious worker's desire for order and productivity. One potential interpretation for the missing positive moderation could be due to the nature of GenAI itself. The output of ChatGPT is, by design, not very structured, particularly variable, and not predictable (Dwivedi et al., 2023, p. 3; Lim et al., 2023, p. 2). This, subsequently, contradicts with their need for control and predictability in their work process (Barnett et al., 2015, p. 385; Landers & Lounsbury, 2006, p. 289) and deters them from depending on these tools, ergo not enhancing their job crafting behaviors to increase structural resources or reduce hindering job demands as expected. Further, their cautious approach to new technologies (Joshi et al., 2023, p. 18; Landers & Lounsbury, 2006, p. 289) may inhibit spontaneous or flexible interactions with GenAI, limiting its perceived utility in their job crafting processes. Alternatively, switching angle to the data quality, another potential explanation for the insignificant findings regarding conscientiousness and its impact on job crafting behaviors could relate to the measurement of the construct itself. The measures used to assess conscientiousness exhibited less than satisfactory AVE, as well as reliability (Cronbach’s alpha and Composite Reliability), in comparison to most of the other traits. This needs to be taken into account, as it could distort the true effect of conscientiousness on the use of GenAI. Further investigations are required on that ground.

Delving into the last two hypotheses takes a fascinating turn, presenting counterintuitive findings. Contrary to the expectations of a negative effect assumed in H3d, extraversion showed a significant positive moderation effect on HRJD, indicating that more extraverted individuals might leverage GenAI more adequately in contexts that decrease hindering job demands. In the background of the JD-R model, this means a proactive adjustment of job demands and resources in response to perceived stressors and opportunities, and can include both emotional (i.e., collaborating with people) and mental (i.e., employing cognitive assets.) job demands (Tims et al., 2012, p. 176), which are particularly significant in knowledge-work. This result can be better understood by considering the sociable, energetic, and proactive nature of extraverts. The positive impact of extraversion on the reduction of hindering job demands subsequently posits that GenAI might be seen as a tool to manage overwhelming cognitive demands more effectively. Instead of the hypothesized concerns of diminishing human interaction and consequently their social engagement, extraverts could be leveraging GenAI to optimize their interactions and alleviate the stress associated with hindering demands, for example by automating routine mental tasks, and thus focusing more on meaningful and engaging aspects of their work. This in turn, aligns with the broader narrative in the JD-R model about enhancing job engagement and well-being by effectively managing job demands. These findings, contrary to the view that extraverts reject GenAI because of its potential to replace interpersonal interactions, imply that the unique abilities of GenAI might be valued for how they can reduce burdensome demands. This then, allows them to reshape their job demands in a way that aligns with their social and professional goals, i.e., craft their jobs. Looking at GenAI through the eyes of an extrovert from this perspective, paints a different picture and allows to make sense of the positive moderation effect. This assertion finds also support in scientific literature, where studies have identified the preference of extraverts toward technologies that either facilitate or maintain social interaction (Sriyabhand & John, 2014, p. 84; Svendsen et al., 2013, p. 332), often utilizing such tools to reduce stressors related to interpersonal demands (Srivastava et al., 2015, p. 365), which in turn increases the likelihood of them engaging in job crafting activities (Bell & Njoli, 2016, p. 9). Reinforcing this notion, the findings of Park and Woo (2022, p. 85) demonstrate that extraverts generally do not hold negative attitudes toward the social dimension of AI. At this point, the remaining question is the lack of a positive moderation effect on IStR. A potential explanation could be that extraverts may not perceive the same level of benefit or necessity in expanding structural resources because their work satisfaction and effectiveness often stem more from dynamic social interactions than from the autonomous or varied nature of tasks. Supporting of this are the findings of Ashton et al. (2002, p. 250), stating that extraverts prioritize and derive energy from external stimuli, which in the workplace translates to a greater focus on the social aspects of their roles. In other words, for extraverts, this optimization seems to skew towards enhancing interpersonal interactions rather than modifying the structural aspects of their jobs. Therefore, the absence of a significant effect on increasing structural job resources is not entirely surprising but rather indicative of the alignment of their job crafting efforts with their personality-driven needs and preferences.

Drawing parallels to the preceding hypothesis, the findings for neuroticism in H3e offer a compelling continuation of this discussion. Characterized by traits like anxiety, moodiness, and worry (Costa & McCrae, 1992, p. 244; Eysenck, 1998, p. 41), individuals with a high degree of neuroticism are typically associated with a more negative perception of workplace changes (DeYoung et al., 2007, p. 894; Tripathi et al., 2022, p. 1135), as well as a heightened caution (Agyei et al., 2020, p. 5) and response to stress (Bolger & Zuckerman, 1995, p. 899), which is also the reason for the hypothesized negative moderation effect between using GenAI and perceived job crafting behavior. The counterintuitive positive moderation in HRJD suggests a need to reconsider the traditional view of neuroticism solely as a detractor (e.g., Barnett et al., 2015, p. 385; Gori et al., 2021, p. 13) within technological contexts. Complementing this perspective, Park and Woo (2022, p. 85) and Schepman and Rodway (2023, p. 2736), revealed that neurotic individuals do not invariably hold negative attitudes toward AI. It may be, that in certain conditions, the heightened sensitivity of neurotic individuals to environmental stressors makes them more likely to utilize GenAI tools to effectively manage and mitigate these workplace stressors, aligning with the JD-R model's emphasis on balancing demands and resources. Similar remarks have been made by Bell and Njoli (2016, p. 4), who claim that neurotic individuals engage in job crafting in order to cope with their emotional vulnerabilities, thereby modifying their job tasks to align context, with their psychological needs and enabling them to better manage their emotions. Further, outside of an ICT context, Rudolph et al. (2017, p. 129) also observed a positive relationship between neuroticism and decreasing hindering job demands. This could be interpreted as neurotic individuals finding a valuable resource in GenAI by counteracting their usual stress responses associated with the cognitive and emotional load of exhausting tasks to cope with their typically higher sensitivity to job demands. As already observed by various academics (Henshall et al., 2022, p. 10; Kulkarni et al., 2023, p. 101; Weerasekara et al., 2022, pp. 11–12) the use of ICTs can act as a coping mechanism, providing more control and acting as a buffer against (job-related) stressors. In the case of GenAI, for example, by automating routine and stressful tasks, thereby offering a sense of security and stability. Considering these findings from this point of view also provides a more comprehensible explanation for the significant influence on the HRJD dimension rather than the IStR dimensions. Neurotic individuals are less likely to seek enhancement in structural resources due to their risk-averse nature, focusing instead on alleviating existing stressors (Devaraj et al., 2008, p. 97) rather than pursuing growth opportunities (Barnett et al., 2015, p. 385; DeYoung et al., 2007, p. 894). This aligns with the results showing no significant effect of neuroticism on increasing structural resources, which involve seeking new challenges and responsibilities – actions potentially perceived as risky or stress-inducing by those high in neuroticism.

## Theoretical Implications

Concluding and synthesizing the discussion of the findings, the theoretical contributions of this research are multifaceted and pivotal, particularly in the context of the evolving digital workspace characterized by the integration of GenAI tools. The implications of GenAI on job crafting within the framework of the JD-R model explored in this study extend the current understanding of how dynamic technological tools can be operationalized to enhance work environments. Moreover, integrating the FFM of personality provides nuanced insights into the interaction between individual personality traits and the use of GenAI in workplace, a previously new and unexplored relation. Firstly, this research contributes to the JD-R model by demonstrating how GenAI serves as a dynamic and transformative job resource rather than a static tool. The findings illustrate that GenAI can significantly alter the balance between job demands and resources, supporting the notion that technological advancements are not merely facilitative but can actively redefine job crafting processes and behaviors (e.g., M. M. Li et al., 2022, p. 12; Mukherjee & Dhar, 2023, p. 1271; Tarafdar et al., 2022, p. 729). By showing how GenAI can be used to both increase structural resources and reduce hindering job demands, the study aligns with and extends the JD-R model's utility in explaining the interaction between technology and job crafting dynamics. Secondly, the research advances the understanding of SDT in the context of technological workplace integrations. The mixed findings on autonomy and competence needs – where autonomy unexpectedly decreased, while competence increased – highlight the complex relationship between technology use and the fulfillment of core psychological needs (Deci & Ryan, 2000, p. 228). These results prompt a reevaluation of how GenAI impact employees' perceptions of control and effectiveness, suggesting that the nature of technological implementation and the specific functionalities of such tools can differentially influence the satisfaction of these needs, as well as their indirect effects on satisfaction, well-being, and productivity. Finally, incorporating personality traits into the analysis of job crafting behaviors addresses a notable gap in existing research. The moderation analyses conducted for each of the Big Five personality traits offer compelling insights into how individual differences influence the GenAI-enabled job crafting. The findings that traits such as openness to experience and agreeableness enhance the use of GenAI by increasing structural resources, while extraversion and neuroticism influence the reduction of hindering job demands, underscore the nuanced ways in which personality can affect interactions with this new kind of technology. Particularly the counterintuitive moderation effects of the last two traits enrich the discourse on personality trait and technology use by challenging traditional assumptions about the negative impacts of certain traits on technology adoption. These insights, conversely, highlight the potential for GenAI to serve as a coping mechanism, helping them manage job demands like workplace stressors or social and cognitive demands. Overall, this research study directly addresses the research question and thus significantly contributes to the theoretical understanding of job crafting behavior of white-collar employees in the age of GenAI, by integrating robust theoretical frameworks and hence offering a comprehensive view that bridges individual traits, psychological needs, and technological impacts with organizational settings.

## Managerial Implications

Alongside the theoretical contributions, there are also some practical implications for various stakeholders that should be considered, as they provide actionable insights to help leverage GenAI effectively within the contemporary work settings. Starting with white-collar employees, it has been deemed essential to understand the interaction between their personality traits and their use of GenAI tools in the context of job crafting. Having highlighted that different traits influence specific job crafting dimensions is a crucial asset, as being aware of these dynamics can be used to harness GenAI tools more effectively in order to tailor the work environments to the personal strengths and professional needs of the employees. For instance, employees high in openness might seek opportunities to use GenAI as a structural resource for creative problem-solving or innovating work processes, while those high in neuroticism could use to minimize job stressors that typically heighten their job dissatisfaction or mental strain. Given the varying moderation effects of personality-driven GenAI use on the different job crafting dimensions, communication and implementation should be personalized to address specific concerns and highlight relevant benefits.

These insights can also be applied at a higher level, proving invaluable from the standpoint of organizational perspective. Firstly, by integrating GenAI tools that align with the job crafting preferences facilitated by employees' personality traits, organizations can improve job design. Leveraging these tools to redesign job roles not only enhances job satisfaction and employee engagement (e.g., Lazazzara et al., 2020, p. 3; Petrou et al., 2012, p. 1136; Tims et al., 2013, pp. 236–237), but could also optimize human resources in talent management, training, and development. Understanding which traits influence the effective use of GenAI in job crafting and its underlying dimensions is vital for organizations to tailor training programs that enhance the skills needed to use those tools effectively and sustain job crafting behaviors. Fostering a culture that supports the use of GenAI in a manner that complements the natural characteristics and strengths of their workforce is beneficial for all the affected parties. Additionally, recognizing the role of GenAI in modifying job resources and demands can help managers make more informed decisions about technology implementation strategies that minimize resistance and maximize acceptance. Such strategies are particularly relevant in managing and mitigating the negative perceptions that may arise from the implementation of GenAI in an organization, and hence smoothing the transition and integration of those tools into everyday work processes.

Finally, it is also relevant to highlight implications at a societal level because they contribute to the future of work, shaped by the advancing implementation of GenAI. As job crafting becomes an increasingly important part of how individuals align their professional lives with their personal identities and values, understanding how personality affect the ability of job crafting behaviors through the use of GenAI can guide the development of ethical standards and practices. These insights can used by policymakers for the deployment of GenAI in the workplace.

## Limitations and Future Research

In this section, the potential limitations for the general applicability of this study are examined. An understanding of these, not only situates the study within the appropriate academic context, but also lays a foundation for future research directions. A principal focus should be on the methodological constraints. The main experimental design for this study, a within-subject design, while beneficial for its statistical power and efficiency in controlling for individual differences (Charness et al., 2012, p. 2), it also introduces some limitations that may affect the interpretation of the results. Primarily, a within-subject design is prone to carryover effects (Greenwald, 1976, p. 318), where the experiences from the control conditions could have influenced the responses in the subsequent experimental conditions. Such effects could be attributed to practice and sequence influences that could potentially lead to artificial alterations in job crafting behavior. Furthermore, an additional drawback in the experimental design could be attributed to the time constraints for the task completion. The 12-minute timeframe provided a maximum limit, yet the absence of a minimum requirement may have led some participants to rush through tasks using GenAI, without genuinely engaging with them. This could have potentially skewed the data towards superficial interaction. Although a standardization of task durations could mitigate this pacing issue (Dell’Acqua et al., 2023, pp. 7–8), it might also lead to participant discomfort or disengagement, thus impacting task performance and outcomes. Compounding the design concerns are the challenges inherent in the measurement of complex constructs such as job crafting, AI Literacy, and personality traits. The reliance on self-reported measures is quite susceptible to biases like social desirability and response tendencies (Van de Mortel, 2008, p. 46), which in turn could have negatively influenced the validity of the measurements. As already mentioned in sub-chapter 4.1, an optimal fit could not be achieved for all constructs. Especially AI literacy knowledge within the AI literacy scale, as well as the traits of agreeableness and conscientiousness in the NEO scale could have enhanced the difficulty of capturing the nuanced effects. It is thus imperative to transparently state this and engage in a discussion regarding its potential reasons. One possible explanation could be attributed to translation inaccuracies in converting items from English to German, which may have led to misinterpretations affecting construct validity (Pérez, 2009, p. 1544). An additional impairing element could also be the length of the survey. The mean time for the task was **time from descriptive statistics**, which could have been fatiguing for some participants, potentially leading to hurried responses or opinions. On the bright side however, it should be also considered that the scales were not developed during this study, but rather, have undergone extensive usage and testing by numerous academics (see chapter 3.3.2). In light of all those aspects, there is thus still a compelling reason to consider that those constructs are applicable and reliable, despite its imperfect validity. Increasing the sample size to ensure that the scales better fit the constructs could lead to more accurate and reliable findings.

Moving forward, a different facet of limitations revolves around the generalizability of its findings. The participant sample, specifically drawn from the DACH region, restricts the generalizability of findings across varied global workforces, industries, and cultural contexts. Joshi et al. (2023, p. 7) have found that the impact of ICTs on job crafting behaviors exhibited notable variability, contingent on where and how it was implemented within work processes. Such variability suggests that the effects of GenAI cannot be interpreted as uniform across all job functions, industries, or organizational size and culture (Petrou et al., 2017, p. 79). Furthermore, the acceptance and effectiveness of ICTs are influenced by a range of factors including subjective norms (Belanche et al., 2019, p. 1420), cultural contexts (Sindermann et al., 2021, p. 117), and voluntariness of use (Schlachter et al., 2018, p. 838). These factors can significantly affect how white-collar employees engage with and benefit from GenAI, hence it may have also altered the outcomes observed in the experimental setting. Lastly, the exploration of the moderating role of personality traits is more complex than depicted. Individuals are probably made up of a lot more than five personality traits, which further influence each other to paint a big picture. The interaction of complex and multi-dimensional personality traits presents a dynamic that may not be fully captured by the Big Five model alone (McAdams, 1992, p. 335).

While certain limitations were identified, it is essential to acknowledge the importance of an iterative process. Ergo, building upon these insights and the groundwork laid in this study, there remain intriguing opportunities for future research. Among those, one promising direction involves the need for longitudinal research to track how white-collar job crafting behaviors evolve as employees adapt to and integrate GenAI tools into their daily work routines. Invaluable insights into the long-term effects would be gained, which in turn, shed light on the sustainability and reliability. Moreover, incorporating cross-cultural perspectives could enrich the comprehension of how diverse cultural norms and interconnected industrial practices shape the utilization of GenAI in terms of job crafting behavior. In doing so, we aim to address the current limitations concerning generalizability. Related to this, future research should also include multigroup SEM to observe how various demographic groups, such as different genders, ages, or educational backgrounds, uniquely respond to the introduction of GenAI and subsequently potentially revealing the differential impacts that could guide more nuanced implementation strategies. Additionally, exploring how job crafting varies for different job functions and professional fields could identify more specific and effective managerial implications across diverse organizational landscapes. (Complementing the within-subject design with a mixed-method approach would fuse the depth of qualitative insights with the breadth of quantitative data, thereby enriching the generalizability and richness of findings.) Furthermore, this study did not examine two job crafting dimensions from the JD-R model and one psychological need from the SDT model due to the setting of the experimental design. Integrating the dimensions of “Increasing Social Job Resources” – enhancing social support and coaching from supervisors or peers – and “Increasing Challenging Job Demands” – seeking out new challenges that stimulate learning and personal growth – from the JD-R (Tims et al., 2012), as well as the dimension “Relatedness” – the need for connection and interaction with others – from SDT (Deci & Ryan, 2000) could provide a more complete and comprehensive understanding of job crafting dynamics. To those dimensions in the study, a more suitable experimental setting that incorporates the opportunity for collaboration with peers would be necessary. Though potentially challenging to implement, gaining insights into collaboration and its impact on job crafting behaviors would significantly enrich the study.

Another promising avenue for future research lies in in integrating the job crafting models of Tims et al. (2012) and Wrzesniewski and Dutton (2001), as well as expand the through the lens of SDT from Deci and Ryan (2000). Trying to map those construct perfectly will not be possible in a few sentences, but rather calls for a dedicated exploration. Nevertheless, the following table gives a high-level overview, illustrating the interrelation between these constructs:

|  |  |  |  |
| --- | --- | --- | --- |
| Tims et al.  (2012) | Wrzesniewski and Dutton (2001) | Deci and Ryan (2000) | Reason |
| Increasing  Structural  Job Resources | Task Crafting | Autonomy | Enhancing job structure increases autonomy by allowing employees control over their tasks and work conditions. |
| Increasing Social Job Resources | Relational  Crafting | Relatedness | Improving social resources enhances relationships at work, fulfilling the need for connectedness. |
| Increasing  Challenging  Job Demands | Task Crafting | Competence | Seeking new challenges aligns with task crafting, promoting growth and meeting the need for competence. |
| Decreasing  Hindering  Job Demands | *Cognitive  Crafting* ***(only indirectly)*** | Autonomy | Reducing negative job demands alleviates stress and enhances autonomy, potentially supporting cognitive crafting by changing how tasks are perceived. |

Focusing again on our specific content, it is noticeable that while the JD-R model of Tims et al. (2012) provides a structured approach to understand how job resources and demands are navigated by using GenAI, it may not fully capture the individual’s subjective and intrinsic modifications emphasized by Wrzesniewski and Dutton’s (2001) approach. Especially because of the missing direct alternative for the dimension of cognitive crafting, the internal, individualized focus might me not adequately represented in this study (Tims et al., 2022, p. 55). Future research should hence explore how these two models can be synthesized or contrasted to provide a more holistic view of how GenAI, but also ICTs in general, reshape job crafting across both structural and cognitive dimensions. This approach would enable a comprehensive exploration of not only how job resources and demands are modified but also how these modifications are – qualitatively – perceived and internalized by employees. Additionally, this should be combined with a more in-depth exploration of the role of different personality facets. Research concerning the levels or combinations of personality traits and its influence on GenAI-enabled job crafting behavior can provide highly interesting insights into deployment strategies to better fit individual differences. Lastly, this could be augmented by exploring how GenAI is used in the first place, an aspect overlooked in this study. Particularly, investigating what changes in usage patterns or usage processes are associated with the influence of GenAI on job crafting behaviors is intriguing. This includes examining how individuals with varying personality traits affect not only the frequency and intensity of use but also the different kind of work styles while using it. For instance: do individuals high in openness perceive greater structural resources solely because they frequently utilize GenAI to accomplish their tasks, or do they enhance interaction quality by integrating it into their daily routines, possibly resulting in a more profound and strategic utilization? Conversely, what implications does a high degree of neuroticism hold in this regard? Such studies would provide a deeper understanding of the dynamic relationship between technology use and job crafting activities. In conclusion, these proposed directions for future research underscore the complexity of integrating GenAI into workplace practices and the multifaceted nature of job crafting behaviors. By addressing these areas, future studies can enrich our understanding of the interplay between technology and individual agency in crafting jobs, ultimately contributing to more effective and satisfying work environments.

# Conclusion

In today’s rapidly evolving white-collar professions, the integration of GenAI tools, such as ChatGPT, is in the process of transforming how work is conducted while potentially fostering unprecedented levels of creativity, efficiency, and productivity. This research sought to understand how specific personality traits of white-collar employees moderate the relationship between the use of GenAI tools and job crafting behaviors. This addresses a critical research gap in current IS-related literature. To achieve this, a randomized within-subject design was implemented, involving a completion of a strategic thinking task under three conditions: a control condition with no ChatGPT assistance, a first experimental condition with ChatGPT assistance, and a second experimental condition with both ChatGPT assistance and a framework explaining how to adequately prompt. Before each condition, AI literacy, attitudes towards AI, and the Big Five personality traits were measured. After each condition, the participants self-assessed their job crafting behaviors – specifically, increasing structural resources and decreasing hindering job demands – as well as their levels of autonomy and competence. The findings revealed that the use of ChatGPT significantly enhanced both job crafting dimensions, indicating that GenAI facilitates proactive modifications through the increase of structural resources or the reduction of challenging job demands. Findings for autonomy and competence were more nuanced, with an increase in perceived competence and a decrease in perceived autonomy. Relating this back to the capabilities of GenAI and the experimental design this indicated that the nature of the technology and the implementation context play crucial roles in determining its impact. The core question of the study could also be answered, yielding insights to the moderation effects of the Big Five personality traits. Hereby, openness to experience and agreeableness had a positive moderation effect on increasing structural resources, while extraversion and neuroticism showed a more complex dynamic by positively moderating decreasing hindering job demands. Especially the last two findings, initially hypothesized to have a negative effect, revealed counterintuitive but finings highly interesting findings. Justifying these moderation effects through the lens of behavioral tendencies, coupled with the unique capabilities of GenAI resulted in a fruitful discussion that laid the groundwork for future research. In summary, valuable insights into the influence of personality traits and the transformative potential of GenAI in reshaping job roles were underscored and should be considered by organizations to better tailor their implementation of GenAI strategies in workplace-settings.

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Appendix

**Appendix A**

Task 1:

**Bitte lösen Sie die folgende Aufgabe**

Es ist Freitagnachmittag, die Vorgesetzte Ihres Chefs kommt auf Sie zu und fragt Sie, ob sie spontan für ein Vorstandsmeeting aushelfen können.

Entwickeln Sie eine umfassende, **einwöchige Kommunikationsstrategie zur Einführung** von **Nachhaltigkeit als Kernwert** im gesamten Unternehmen.

Die Aufgabe soll in Form eines schriftlichen One-Pagers gelöst werden.

Sie haben 12 Minuten Zeit.

**Zielsetzung**

* Das Engagement des Unternehmens für Nachhaltigkeit gegenüber allen Mitarbeitenden, Stakeholdern und der Öffentlichkeit soll klar zum Ausdruck bringen.
* Die Strategie soll zu einem tieferen Verständnisses von Nachhaltigkeit und ihrer Bedeutung bei den Mitarbeitern beitragen.
* Die Umsetzung der Nachhaltigkeitsprinzipien soll in konkrete Maßnahmen und Initiativen in allen Abteilungen und Betrieben umgesetzt werden können.

***Die folgenden Fragen können helfen:***

* Welche Ziele werden mit der Strategie verfolgt?
* Wer ist das Zielpublikum?
* Welche Themen wären für die Mitarbeitenden am relevantesten und interessantesten?
* Welche Art von Erfahrung sollen die Mitarbeitenden machen?

Task 2:

**Bitte lösen Sie die folgende Aufgabe**

Es ist Freitagnachmittag, die Vorgesetzte Ihres Chefs kommt auf Sie zu und fragt Sie, ob sie spontan für ein Vorstandsmeeting aushelfen können.

Entwickeln Sie ein Konzept für eine denkwürdige **eintägige Veranstaltung** für Führungskräfte, um die **digitale Transformation** zu diskutieren.

Die Aufgabe soll in Form eines schriftlichen One-Pagers gelöst werden.

Sie haben 12 Minuten Zeit.

**Zielsetzung:**

* Erstellen Sie eine Veranstaltung, die sowohl informativ als auch unterhaltsam ist, bei der Führungskräfte etwas über die digitale Transformation erfahren und sich miteinander austauschen können.
* Die Teilnehmenden sollen inspiriert und darüber informiert werden, wie die neue Technologie der generativen KI ihr Geschäftsmodell beeinflusst.

***Die folgenden Fragen können helfen:***

* Wer ist das Zielpublikum?
* Welche Themen wären für die Führungskräfte am relevantesten und interessantesten?
* Welche Art von Erfahrung sollen die Führungskräfte machen?

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