The impact of (generative) AI in white-collar professions: An exploratory study about the impact of AI's automation potential on job security and job satisfaction

Jannis Röder

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Abstract

Title: The impact of (generative) AI in white-collar professions: An exploratory study about the impact of AI's automation potential on job security and job satisfaction

Author: Jannis Röder

This thesis explored how Generative Artificial Intelligence (GenAI) influences perceived job satisfaction and job security among white-collar workers. While prior studies had emphasized GenAI's potential to increase productivity and automate tasks, less is known about its psychological and motivational impact on employees. To address this gap, two complementary studies were conducted. Study 1 used qualitative interviews with 20 professionals across industries to examine which tasks were perceived as automatable and how workers experienced the growing presence of GenAI. The findings showed that routine cognitive tasks were widely seen as replaceable with positive impacts on job satisfaction, while interpersonal and strategic tasks are considered resistant to automation. Study 2 presented a survey of 189 white-collar employees. Regression analysis was used to assess predictors of job security and job satisfaction. Results indicated that perceived replacement likelihood was the strongest negative predictor of job security. In contrast, a positive attitude and high perceived organizational support were associated with greater job satisfaction. Emotion analysis further revealed widespread ambivalence, with many respondents expressing both optimism and concern. Together, the studies show that GenAI is not perceived as an outright threat or opportunity. Instead, its impact depended on task type, individual perceptions, and the organizational environment. These findings refined existing human response theories to automation and highlighted the need for thoughtful implementation strategies. Practical recommendations include transparent communication, effective change management, and support structures that promote psychological safety during GenAI integration.

Keywords: Generative Artificial Intelligence, white-collar workers, job satisfaction, job security, task automation, organizational readiness, Human-AI collaboration, perceived substitution risk

Resumo

Título: O impacto da IA (generativa) nas profissões de colarinho branco: Um estudo exploratório sobre o impacto do potencial de automatização da IA na segurança e satisfação no trabalho

Autor: Jannis Röder

Esta tese explorou como a Inteligência Artificial Generativa (GenAI) influenciou a satisfação e a perceção de segurança no emprego entre trabalhadores de colarinho branco. Embora estudos anteriores tenham destacado o potencial da GenAI para aumentar a produtividade e automatizar tarefas, sabe-se menos sobre o seu impacto psicológico e motivacional. Para colmatar esta lacuna, foram realizados dois estudos complementares. O Estudo 1 utilizou entrevistas com 20 profissionais de diferentes setores para identificar tarefas vistas como automatizáveis e como os trabalhadores experienciaram a crescente presença da GenAI. Os resultados mostraram que tarefas cognitivas de rotina foram amplamente consideradas substituíveis, com impactos positivos na satisfação, enquanto tarefas interpessoais e estratégicas foram vistas como resistentes à automatização. O Estudo 2 baseou-se num inquérito a 189 trabalhadores. A análise de regressão indicou que a perceção da probabilidade de substituição foi o fator negativo mais forte da segurança no emprego. Em contraste, uma atitude positiva e um elevado apoio organizacional foram associados a maior satisfação. A análise emocional revelou ambivalência generalizada, com muitos inquiridos a expressarem otimismo e preocupação. Em conjunto, os estudos mostraram que a GenAI não foi percecionada como uma ameaça ou oportunidade absoluta. O seu impacto depende do tipo de tarefa, das perceções individuais e do ambiente organizacional. Estas conclusões aperfeiçoaram teorias sobre a resposta humana à substituição tecnológica e sublinharam a importância de estratégias de implementação cuidadosas, como comunicação transparente, gestão da mudança eficaz e estruturas de apoio que promovam segurança psicológica.

Palavras-chave: Inteligência Artificial Generativa; trabalhadores de colarinho branco; satisfação no trabalho; segurança no emprego; automação de tarefas; prontidão organizacional; colaboração humano–IA; percepção de risco de substituição

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This thesis marks the final step of my academic journey and reflects not only months of dedicated research in an exciting and young area, but also the invaluable support I have received along the way.

First and foremost, I would like to express my sincere gratitude to Professor Cristina Mendonça, whose guidance, expertise and encouragement were essential throughout the entire process. Her thoughtful feedback consistently helped me sharpen my focus and elevate the quality of this work. I am also deeply thankful to my family and friends, who supported me with patience, optimism and understanding during this intense period.

Working on this thesis has been both intellectually challenging and rewarding. The topic – Generative AI's impact on white-collar work – is highly current and discussed across disciplines, yet it remains a relatively novel field of research. Its complexity relies in the many unresolved questions and nuanced dynamics it presents. I hope this work contributes, even in a small way, to the broader understanding of these emerging developments.

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List of Abbreviations

AI .... Artificial Intelligence
GenAI .... Generative Artificial Intelligence
JS .... Job Satisfaction
JSI .... Job Security Index
JSS .... Job Security Satisfaction
r .... Pearson correlation coefficient
RQ .... Research Question
VIF .... Variance Inflation Factor

1 Introduction

1.1 Opening Thought

Artificial intelligence (AI), the "imitation by computers of the intelligence inherent in humans" (Sheikh et al., 2023, p. 15), has recently received much attention across different disciplines and industries (Hyder et al., 2019). Through advancements in AI technologies, a broad set of economic and organizational opportunities has emerged (Comunale & Manera, 2024; Filippucci et al., 2024). Access to AI-generated recommendations can increase productivity, improve customer sentiment, and is associated with lower employee turnover (Brynjolfsson et al., 2023). In recent years, generative AI (GenAI) has received widespread attention across industries and the public sphere (Feuerriegel et al., 2024). It refers to computational technologies that generate novel and realistic content – such as text, images or audio – based on user prompts (Banh & Strobel, 2023). Researchers have forecasted that GenAI will affect both internal and external aspects of organizations (e.g., Kaplan & Haenlein, 2019; Noy & Zhang, 2023; Prasad & De, 2024; Zhang & Zhang, 2025). Within organizations, (Gen) AI allows both simple and complex tasks to be conducted faster, better, and at lower cost (Noy & Zhang, 2023). Externally, (Gen) AI influences the relationship between firms and their customers, other firms, and society (Kaplan & Haenlein, 2019).

1.2 Relevance of the topic

In recent years, advancements in AI have been largely driven by progress in GenAI applications, whose ability to produce synthetic data (Goyal & Mahmoud, 2024) offers substantial opportunities across various domains (e.g., Gozalo-Brizuela & Merchan, 2024; Sengar et al., 2024). For instance, GenAI enables collaborative work between AI and human workers in areas such as design, problem solving, creativity, music, art, literature, content creation, education, and healthcare (Sengar et al., 2024). According to a projection by Goldman Sachs, GenAI could raise global gross domestic product (GDP) by 7% and replace 300 million knowledge worker jobs (Goldman Sachs, 2023), exemplifying the technologies' extraordinary economic and social importance.

Due to the increased importance of (Gen) AI applications and their economic potential, a recent McKinsey study shows that 78% of the interviewed companies across different industries use AI in at least one business function (Singla et al., 2025). As shown by Acemoglu and Restrepo (2022), task automation and the resulting displacement does not only have an impact on wages, but also affects inequality, thus indicating socioeconomic implications (Acemoglu & Restrepo, 2022). While some researchers argue that (Gen) AI will substitute workers, thereby making firms more efficient and increasing valuations (e.g., Eisfeldt et al., 2024), others claim the use of (Gen) AI increases workers productivity and efficiency without necessarily replacing jobs (Noy & Zhang, 2023; Simkute et al., 2024). These days, the generative nature of AI tools has raised concerns about AI capabilities and potential negative effects on employment (e.g., Felten et al., 2023; Mitchell, 2023). GenAI, such as ChatGPT, are disruptive, as they complete tasks previously thought unrealizable by machines, for instance, writing essays or generating art that is indistinguishable from human work (AbuMusab, 2023).

1.3 Problem statement and research objective

(Gen) AI's ability to automize and support tasks across different occupations raises the machinery question, which is, the discussion around the potential substitution of human workforce by machines. The English economist Ricardo raised the machinery question first in 1821 (The Wall Street Journal, 2016), as previous industrial revolutions have caused the replacement of thousands of blue-collar workers (i.e., jobs that involve manual labor) by machines. Even though research regarding technology replacing human work is not novel (e.g., Brynjolfsson & Mcafee, 2012; Frey & Osborne, 2017; Nurski & Hoffmann, 2022), in times of (Gen) AI, for the first time, white-collar jobs (i.e., jobs that require more cognitive than manual work) instead of blue-collar workers seem to be subject to substitution (Chelliah, 2017). While the economic potential of (Gen) AI through efficiencies is well-studied, the impact on job satisfaction and job security is not reflected in many studies.

Some studies highlight potential negative impacts of GenAI, such as diminished autonomy in decision-making (Parent-Rocheleau & Parker, 2022a) and declines in job satisfaction and job security resulting from increased technology use (Brougham & Haar, 2020). In contrast, other research points to positive effects, including gains in productivity and efficiency (Brynjolfsson et al., 2023) and improved work-life balance for white-collar professionals (Chiong & Xie, 2024). However, few studies directly examine the specific effects of GenAI in this context (Ihensekien & Arimie, 2023). Given these mixed findings, this dissertation addresses the following general research question:

RQ: How does (Gen) AI impact white-collar workers' job satisfaction and job security?

To address the research gap, the central research question was divided into the following sub-questions:

RQ1: Which white-collar tasks are being automated by (Gen) AI and what are potential barriers for substitution?

RQ2: How do white-collar workers respond to the automation of specific tasks by (Gen) AI?

RQ3: How does the increasing use of (Gen) AI — and the potential automation of certain tasks — affect white-collar worker's perceived job security?

RQ4: To what extent does task automation by GenAI influence job satisfaction among white-collar workers?

1.4 Structure of the dissertation

While the introduction has outlined the topic, problem statement, and research question(s), the second chapter presents a structured literature review. It discusses the historical development and capabilities of GenAI, examines its substitution potentials, presents a task-based model, and explores the broader socioeconomic role of work. Furthermore, the foundations of job satisfaction, and job security as factors for motivation using Maslow's (1943) pyramid of needs and Herzberg's (1959) two factor theory are elaborated. The literature review builds the foundation for the development of the present research question(s). Chapters 3 and 4 present the two studies performed to answer the above-mentioned questions: First, interviews with white-collar workers are conducted to overview the potential tasks that are subject to substitution and gather first impressions of white-collar workers reaction to (Gen) AI usage, and their perceived substitution of tasks. The initial findings represent the basis for the second, survey-based quantitative analysis, in which the perceived replacement risk and the resulting effects on job security and job satisfaction are assessed — reflecting a mixed methods approach. In Chapter 5, the results are discussed considering the existing literature and both theoretical as well as practical implications are derived. The synthesis of results, limitations, and a presentation of further research potentials conclude the thesis.

2 Literature review

2.1 Artificial Intelligence

McCarthy is deemed the father of AI, as he originally brought up the term at the 1956 Summer Research Project (Y. Jiang et al., 2022). However, until now, there is no generally accepted definition of the concept, and numerous different definitions exist (Sheikh et al., 2023). In its broadest definition, AI is equated with algorithms, while in its strictest definition, AI stands for the imitation of human intelligence by computers (Sheikh et al., 2023). The High-Level Expert Group on AI of the European Commission defines AI as "systems that display intelligence behavior by analyzing their environment and taking actions — with some degree of autonomy — to achieve specific goals" (High-Level Expert Group on Artificial Intelligence, 2019, p.1). Another definition refers to AI as sophisticated algorithms that can learn from big data and use the knowledge to assist in practical applications (Darko et al., 2020). In the current thesis, the definition of Luan et al. (2020) is used, where AI is described as a collection of computer science methods that allow systems to carry out a variety of operations that would historically require human intellect, for instance, speech recognition, visual recognition, and decision making. The use of AI in the workplace can enhance productivity by enabling the rapid and accurate analysis of large volumes of data (Feuerriegel et al., 2024). As a result, AI systems are well suited to solving complex, nonlinear problems and can generate predictions and generalizations at high speed (Darko et al., 2020).

2.1.1 Historical development of AI

AI has received much attention across different disciplines and industries throughout the last years (Hyder et al., 2019). The period of modern AI started with McCarthy bringing up the term at the 1956 Dartmouth Summer Research Project on AI (Y. Jiang et al., 2022). Since its initial definition, research into AI has developed rapidly with achievements around machine learning, theorem proving, problem solving, natural language processing, and pattern recognition (Y. Jiang et al., 2022). Over the past decades, the rise of AI was driven by a significant increase in computing power and the availability of big data, which enabled the handling of highly complex tasks by the expansion of physical scales of AI-based systems (Y. Jiang et al., 2022; Russell &

Norvig, 2022). Due to advancements in both hardware and software technologies, the training periods of AI could be shortened from several months to days or hours (Y. Jiang et al., 2022). Another important factor that accelerated the development of GenAI was the cost of computational tasks. Nordhaus (2007) estimated the cost advantage by at least 1.7 trillion-fold between 1850 and 2006, with the most substantial reductions occurring over the past three decades, beginning with the increased availability of microprocessors in the 1970s. Nowadays, AI is assumed to have implications for any type of organization, both internally, and externally (Kaplan & Haenlein, 2019; Loureiro et al., 2021). Internally, AI allows a multitude of tasks to be conducted faster, better, and at lower cost (Filippucci et al., 2024), which will not only affect simple but also more complex tasks (Kaplan & Haenlein, 2019). Externally, AI has the potential to influence the relationship between firms and their customers, other firms, and society (Kaplan & Haenlein, 2019).

2.1.2 GenAI: Definition and applications

GenAI refers to computational techniques that generate new, meaningful content — such as images, text, or audio — from training data (Feuerriegel et al., 2024). Another definition of GenAI emphasizes its core function as the use of data, text, or images to generate new content in response to user prompts (Euchner, 2023). Examples of concrete applications include DALL-E2, GPT-4, Copilot, Jasper, and BingAI (Feuerriegel et al., 2024). Machine learning models — such as deep neural networks — are used in GenAI to create new data based on patterns they have learned (Feuerriegel et al., 2024). Systems such as ChatGPT or BingAI are powered by large language models, with their underlying machine learning algorithms trained on vast amounts of data and text. This enables them to predict the most likely next word or sentence in a text (Euchner, 2023). The model serves as a core component, that facilitates interaction, and application within a broader context. GenAI models play a central but incomplete role, as they require further fine-tuning for specific tasks through systems and applications (Feuerriegel et al., 2024).

GenAI applications enabled users to produce texts or images that are often indistinguishable from human work (Euchner, 2023; Kshetri et al., 2024). While AI capabilities were understood to be analytic in the past, GenAI gained the capability to perform content creation with creative and artistic elements (Feuerriegel et al., 2024). GenAI can be seen as a transformative engine, reshaping how we live and work with limitless possibilities in the workplace (Al Naqbi et al., 2024). It offers various use cases across a range of domains, including healthcare, education, and art, to support and accelerate content creation and enabling businesses to produce effective marketing materials (Al Naqbi et al., 2024). In education, GenAI enables personalized learning experiences, and the creation of innovative materials based on educational data (Mao et al., 2024). In medicine, it supports disease diagnosis and the delivery of healthcare services (Al Naqbi et al., 2024). More broadly, GenAI is reshaping how knowledge work is conducted across industries and business functions such as sales, marketing, operations, and software development. It is poised to transform roles and enhance performance (Chui et al., 2023). A practical example is the Abu Dhabi National Oil Company, which deployed AI-based automation to analyze and categorize rock samples, refine subsurface models, and improve decision-making in multi-billion-dollar field developments (Wamba-Taguimdje et al., 2020).

The progression of GenAI use cases emphasizes the importance of leveraging these technologies to enhance organizational performance (Singh et al., 2024). The ambition of GenAI usage is to increase efficiency across private, public, and governmental sectors worldwide, driving growing interest in its implementation (Al Naqbi et al., 2024). For example, GenAI can revolutionize customer self-service interactions, customer-agent interactions, and agent self-improvement (Chui et al., 2023). In addition to specific AI use cases across various business functions, GenAI is predicted to add value across the entire organization by transforming internal knowledge management systems (Alavi et al., 2024; Chui et al., 2023).

2.1.3 GenAI and its substitution potentials

GenAI systems are revolutionizing the way people work and communicate (Euchner, 2023; Feuerriegel et al., 2024). As demonstrated by various applications and use cases, (Gen) AI is expected to have a profound impact not solely on routine tasks but also on more complex, knowledge-intensive activities such as consulting, financial services, and law (Kaplan & Haenlein, 2019). A recent study by McKinsey & Company (Chui et al., 2023) highlights the potential of GenAI to automate tasks in occupations requiring higher levels of education. The study noted that GenAI is poised to transform knowledge work by automating activities that were previously considered relatively immune to automation. As a result, significant workforce transitions are necessary, where a quarter to a third of activities could change in the upcoming decade (Chui et al., 2023). The fact that higher-wage, white-collar occupations are at higher risk for automation is also supported by the work of Eloundou et al. (2023), who used task-level assessments to determine the technical feasibility of AI-driven substitution by Large Language Models. Consequently, 19% of US workers are employed in occupations where at least half of their tasks are exposed to potential substitution by AI models. Particularly, this affects tasks related to programming, writing and data analytics (Eloundou et al., 2023). The research of Felten et. al. (2023) supports the findings of white-collar occupations explicitly being more exposed to AI compared to other professions. Some researchers argue that productivity gains from (Gen) AI will not necessarily lead to the replacement of many office jobs (e.g., Brynjolfsson et al., 2023; Dillon et al., 2025; McKendrick, 2024), even though at least half of their tasks could be automated (McKendrick, 2024). As (Gen) AI takes over routine activities, workers are expected to shift into more active roles — such as advising, collaborating, and identifying new opportunities for AI support — rather than being replaced outright (McKendrick, 2024).

Another viewpoint on the evaluation of substitution potentials was presented by Arntz et al. (2016), who proposed the substitution potential is to be analyzed based on tasks, not occupations. They argue an occupation-based approach, as for example presented by Frey & Osborne (2013), would overestimate the substitution potentials of GenAI, not accounting for automatable and non-automatable tasks within a job (Arntz et al., 2016). Furthermore, the task-based analysis approach is supported by the work of Acemoglu & Restrepo (2018) and Webb (2020), who argue that analyzing the impact of automation and GenAI at the level of individual tasks — rather than entire occupations — provide a more accurate and nuanced understanding of technological substitution. Given the growing evidence that GenAI affects not only entire occupations but specific tasks within them, adopting a task-based analytical approach offers a more precise framework for assessing its impact — particularly in white-collar work.

2.2 Task model

In contrast with the occupation-based approach covered in the previous section, to study how (Gen) AI influences different types of tasks within white-collar jobs, the present thesis follows a task-based approach. For the elaboration of different categories of tasks, both the task model from Autor et al. (2003) and the task approach to labor markets from Autor (2013) are used in the present thesis. A task is defined as a unit of work activity that produces output (e.g., goods or services; Agrawal et al., 2019). Workers allocate their skills to different tasks depending on labor market price (Acemoglu & Autor, 2011). As the cost of symbolic data processing has declined, new economic incentives have emerged (Russell & Norvig, 2022), drawing increasing interest in AI integration across disciplines and industries (Hyder et al., 2019). Through advancements in AI technologies, a set of economic and organizational opportunities have emerged for employers to substitute information technology for expensive labor, but at the same time creates advantages for workers whose skills become increasingly productive as the price of computing power falls (Acemoglu & Autor, 2011). According to the research of Autor et al. (2003), the division of new tasks between humans and machines follows an economic logic: novel tasks are assigned first to workers as they are flexible and adaptive. Once they are formalized, according to this model, they can then be automized due to the economic cost advantage that machinery has over human labor. Whether they will be automized in practice is dependent on technological feasibility and economic cost (Autor et al., 2003). In the task model, the fundamental units of production are job tasks, that can be supplied either by domestic or foreign labor or capital (Autor, 2013).

Autor et al. (2003) distinguish between routine and non-routine tasks. In the different categories, cognitive, and manual tasks are separated. Routine cognitive tasks are defined as tasks that follow well-defined procedures and thus can be easily automated (Acemoglu & Autor, 2011; Autor et al., 2003; Frey & Osborne, 2017). Examples of these tasks are data entry, bookkeeping or cashier functions. Routine manual tasks require physical execution but are repetitive and structured, making them automatable, for example, factory assembly work or operating machines in predictable settings (Autor et al., 2003). Non-routine cognitive tasks are presented as activities that require problem-solving, analytical thinking or complex communication, for instance management, legal analysis or medical diagnosis. Finally, non-routine manual tasks are tasks requiring physical adaptability, dexterity or human interaction, making them hard to automate, for example, care work, construction or service roles (Autor et al., 2003).

For a task to be autonomously performed by computers, it must be sufficiently defined, as the machine potentially lacks flexibility or judgement (Autor et al., 2003). The framework of Agrawal et al. (2019) conceptualizes automation as an expansion of tasks that can be produced with capital. If financial funds are either sufficiently cheap or productive, automation leads to a substitution of capital for labor, resulting in the displacements of workers from the tasks being automated (Agrawal et al., 2019). In the current thesis, the distinction and differentiation between routine and non-routine cognitive tasks is used for both the qualitative and quantitative analysis. While the task-based approach provides a valuable framework for understanding how technological change reallocates labor across different task types, it remains equally important to consider the broader human consequences of these shifts. The following section therefore turns to the socioeconomic role of employment. It highlights how job loss influences mental health, personal development, and societal cohesion.

2.3 Socioeconomic role of the job

The role of employment in shaping well-being and life satisfaction has been extensively studied, which is illustrated by several key findings in the literature:

First, unemployment has consistently been linked to negative psychological outcomes. As shown in the meta-analysis of Paul & Moser (2009), unemployed individuals exhibit significantly more negative impacts, such as psychological distress, depression, or anxiety compared to employed individuals. Unemployment has been shown to reduce well-being more severely than divorce or marital separation (Clark & Oswald, 1994). Second, the negative effects were confirmed by Lucas et al. (2004), who found that even after re-employment individuals do not return to their pre-unemployment level of life satisfaction, indicating a long-term impact. Third, as the analysis of Winkelmann & Winkelmann (1998) showed, unemployment reduces life satisfaction significantly, even after controlling for individual fixed effects such as income, health, age and marital status, suggesting that the non-pecuniary costs of unemployment (i.e., those not related to the income loss) are much larger than the pecuniary costs. Fourth, job loss is a highly persistent negative shock to labor market outcomes. It depresses a worker's future wage and employment, resulting in large present value earning losses (Jarosch, 2023). Therefore, the unemployment rate receives widespread attention in economy and politics (Jarosch, 2023). Fifth, the negative effects concern not only the satisfaction of the affected person itself but also influences the worker's family due to increased stress and anxiety, which explains that also employed people suffer in periods with high unemployment (Björklund & Eriksson, 1998), underlining the societal impact of unemployment. The effects of unemployment on mental health have also been proven by a Nordic study, where the negative effects on mental health varied based on the type of unemployment (Björklund & Eriksson, 1998). While the detrimental effects of unemployment are substantial, it is equally important to consider the positive impacts that employment can have on an individual's mental health and overall well-being.

First, employment fosters self-reliance and leads to various positive outcomes, such as self-confidence, social recognition, and personal growth (Drake & Wallach, 2020). Second, the World Health Organization (2022) identifies employment as a crucial social determinant of health. Decent work provides individuals with a sense of purpose, achievement, and inclusion in a community, all of which are beneficial for mental health (World Health Organization, 2022).

Together, these findings underscore that employment plays a vital role not only in providing financial stability, but also in supporting psychological resilience, social integration, and long-term well-being. While employment supports well-being and social stability, the threat of losing one's job — known as job insecurity — can undermined many of these benefits and lead to significant psychological and behavioral consequences (e.g., Greenhalgh & Rosenblatt, 1984). The following section explores the definition, characteristics, and consequences of job insecurity in greater detail.

2.4 Job insecurity: Definition and determinants

Job insecurity refers to perceptions about employment conditions, specifically about losing job stability and continuity of the employment relationship with the organization (Bernardi et al., 2008). Two types of job insecurity are distinguished by Hellgren et al. (1999) and widely accepted (e.g., De Witte et al., 2010; Vander Elst et al., 2014): quantitative job insecurity, which refers to concerns about the continued existence of the job itself, and qualitative job insecurity, which involves perceived threats of lower quality in the employment relationship, for instance working condition or lack of career opportunities (Hellgren et al., 1999).

When it comes to the characteristics of job insecurity, first the belief that job insecurity is a subjective experience that results from individual perceptions and interpretations of the actual work environment is widely accepted among researchers (e.g., De Witte et al., 2015; Zheng et al., 2014). While some employees feel threatened even in the absence of objective reasons, others feel quite confident even when there is a real possibility that they will be dismissed (De Witte, 2005). Second, job insecurity involves uncertainty about the future, where the concrete future outcomes (i.e., to retain or lose the current job) are unclear and preparation for the outcome seems to be difficult, as the employees do not know whether actions are required. Thus, job insecurity is of an involuntary nature (Kausto et al., 2005; Sverke et al., 2002).

Finally, it involves a discrepancy between what employees wish for (certainty about the future in their current employment) and the actual outcome (feeling threatened with regards to the current job; De Witte et al., 2015).

Job insecurity has been a concern for most companies and academic research due to its critical implications for employee wellbeing, for example, economic stress is associated with serious mental and physical health complaints, burnout and emotional exhaustion (L. Jiang & Probst, 2017; Richter et al., 2014). Additionally, as shown by De Angelis et al. (2021), high levels of perceived job insecurity significantly increase the likelihood of experiencing conflicts between work and family demands, which underlines the role of job security for both private and personal life. The meta-analysis conducted by Sverke et al. (2002) revealed that job insecurity is significantly associated with employees' attitudes and behavioral orientations. In their research, job insecurity is negatively correlated with job satisfaction, trust, job involvement and positively correlated with employee's turnover intentions (Sverke et al., 2002). In addition, job insecurity, as it represents a source of anxiety, can be regarded as a source of stress, which results in ill health, depression, job exhaustion, and impaired self-rated health (Kausto et al., 2005).

Given the wide-ranging psychological and behavioral consequences of job insecurity, it is important to examine how these perceptions affect employee's overall experience at work, most notably their job satisfaction.

2.5 Job satisfaction: Definition and determinants

Job satisfaction is a broadly studied field within psychology and management studies and can be defined as "an affective reaction to one's job, resulting from the incumbent's comparison of actual outcomes with those that are desired" (Cranny, Smith & Stone, as cited in Weiss, 2002, p. 174). More recently, Weiss (2002) himself deconstructs job satisfaction into evaluations, beliefs and affective experiences — emphasizing job satisfaction includes both cognitive judgments and affective reactions towards different facets of the job (Weiss, 2002). As discussed by Faragher and colleagues (2005), the effects of job satisfaction have been consistently linked to outcomes for individuals and organizations. First, on an individual level, higher job satisfaction is associated with improved mental and physical health, including lower levels of anxiety, depression and burnout (Faragher et al., 2005). Second, on an organizational level, job satisfaction contributes to higher organizational commitment, lower turnover intentions and increased performance (Judge et al., 2000; Riketta, 2008).

Herzberg's (1959) two-factor theory represents a central theory within job satisfaction, where hygiene factors, which prevent dissatisfaction, and motivators, which actively contribute to satisfaction, are distinguished. According to this model, job satisfaction arises from intrinsic motivators such as recognition, responsibility, personal growth whereas dissatisfaction stems from extrinsic factors like salary and job security (Herzberg et al., 1959). Another important model in the field of job satisfaction is Hackman and Oldham's (1976) job characteristics model, which further elaborates that five core dimensions — skill, variety, task identity, task significance, autonomy, and feedback — lead to psychological states that contribute to internal motivation and satisfaction (Hackman & Oldham, 1976). Personality plays an important role within job satisfaction, where individuals with high levels of self-esteem, internal locus of control, and emotional stability tend to report greater satisfaction levels across various work contexts (Judge et al., 2000). These models highlight that job satisfaction is not solely determined by job characteristics but also by stable individual differences.

To understand the drivers behind job satisfaction and its variability across individuals, the following section introduces two foundational theories — Maslow's hierarchy of needs (Maslow, 1943, 1968) and Herzberg's two-factor theory (Herzberg et al., 1959) — that explain how different job-related factors influence job satisfaction and job security.

2.6 Motivational theories

2.6.1 Maslow's hierarchy of needs

Abraham Maslow developed the hierarchy model (1943, 1968), a framework that remains relevant today for understanding human motivation (Ballard, 2006). The hierarchy of needs theory emphasizes the importance of a work environment that enables individuals to fulfill their potential — an idea that remains highly relevant in today's organizational context (Setiawan et al., 2020). Maslow's hierarchy of needs remains one of the most iconic frameworks in management studies, illustrating the idea that human needs follow a hierarchical order (Bridgman et al., 2017). The theory continues to exert influence, with citations averaging over 200 per year well into the 21st century (Ballard, 2006).

Maslow (1943) presents five layers of needs that must be met to achieve motivation and happiness. First are biological and physiological needs (e.g., air, food, and drink). The second layer composes safety needs: protection from elements, order, law, stability, followed by belongingness and love needs such as workgroup, family, or relationships. The fourth layer are esteem needs (e.g., self-esteem, achievement, mastery, independence, status). The last level compromises self-actualization needs: realizing personal potential, self-fulfillment, and seeking personal growth (Maslow, 1943). The different categories of needs must be satisfied following the hierarchical order. The aim and drive always shift to the next higher-order needs, which means, for example, a person cannot be motivated to achieve their sales targets when they have problems with their marriage (Setiawan et al., 2020).

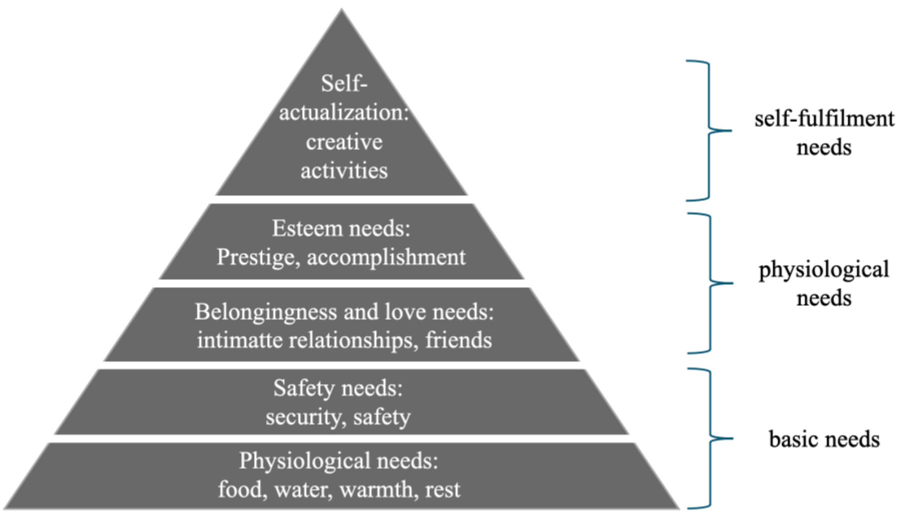

Figure 1: Maslow's hierarchy of needs, replicated based on (Maslow, 1943)

In the context of Maslow's (1943) theory, job security is a central determinant of employee motivation as part of safety needs. If job security is not met due to the fear of job loss, higher order needs cannot be fulfilled (Setiawan et al., 2020). Therefore, the concept of job security as factor for overall motivation is of central importance.

2.6.2 Herzberg's two factor motivational theory

Herzberg's (1959) two-factor model represents a key contribution to motivational theory. The model aimed to explain attitudes towards work and the experiences that employees in the organization reported during the survey (Herzberg et al., 1959). In the end, Herzberg was able to distinguish between motivation and hygiene factors. In his study, Herzberg was influenced by Maslow, McGregor, and Argyris and strived to isolate the elements that made people both happy, satisfied, unhappy and dissatisfied (Ihensekien & Arimie, 2023). Hygiene Factors are elements that prevent dissatisfaction, but do not necessarily increase job satisfaction, (e.g., salary, company policies or working conditions). In contrast, motivators are factors that lead to job satisfaction and motivation, such as achievement, recognition, and the work itself (Herzberg et al., 1959).

Company policy and administration, technical supervision, interpersonal connections with supervisors and peers, salary, personal life, and job security are examples of hygiene factors (Joseph, 2023). As exemplified by Ihensekien & Arimie (2023), the dimensions presented in Maslow's (1943) and Herzberg's (1959) foundational work correlate. For example, Maslow's theory helps to identify needs and motives, and Herzberg's provides insights into the goals and incentives that satisfied the needs (Hersey & Blanchard, 1969). As shown in the comparative research by Ihensekien & Arimie (2023), both theories are content theories assessing the needs of individuals and how managers can satisfy them to achieve organizational goals. However, both theories also mention that if the needs are not identified and met, this will lead to demotivation of employees. Additionally, the two theories indicate managers must provide an enabling work environment for employees to thrive and maximize their potential when working on organizational goals and objectives (Ihensekien & Arimie, 2023). Therefore, in relation to the research objective, when individuals fear job loss, the hygiene factor of job security is absent. This suggests that when hygiene factors such as job security are lacking, the resulting dissatisfaction may outweigh the positive effects of genuine motivators. As a result, perceived job insecurity suggests negative implications for employee motivation and organizational goals.

3 Study 1

3.1 Methodology

3.1.1 Research design

Mixed methods research capitalizes on the strengths of both quantitative and qualitative approaches, leading to more reliable and valid results (e.g., Johnson & Onwuegbuzie, 2004). By combining the ‘what’ (quantitative) with the ‘why’ (qualitative), it enables a more comprehensive understanding of the research questions (Bryman, 2006). The primary objective of Study 1 is to explore how white-collar workers perceive the use of (Gen) AI systems in their individual professional context, thereby addressing RQ1 and providing initial qualitative insights into RQ2. To achieve this, a series of qualitative expert interviews were conducted. In addition to capturing general attitudes and perceptions, the study used the task categories outlined by Autor and contributors (2003), to identify which categories of white-collar tasks are perceived as being most susceptible to GenAI substitution. While the task model developed by Autor and colleagues (2003) categorizes tasks based on their theoretical automatability, for instance, routine cognitive work, the interviews are used to assess whether such classifications align with subjective perception of substitution risk. This is essential, as there might be a significant gap between theoretical substitution potential(s) and the perceived risk of actual substitution, for example, when the company exhibits low GenAI integration overall. Furthermore, the interviews aim to capture the first insights into how (Gen) AI impacts the perception of job satisfaction and job security of white-collar workers along different professions.

The current qualitative study employed problem-centered interviews, a method primarily influenced by Witzel (1985), who introduced the form of open, semi-structured questioning within the boarder context of qualitative content analysis. The interview is focused on a specific problem, which the interviewer returns to during the interview, where the interviewee should be able to speak as freely as possible, and not be restricted in their answers (Witzel, 1985). A defining feature of this method is its flexibility and adaptability. Rather than relying on standardized instruments, the interview guide is tailored to the problem context and to the knowledge domain of the interview partner (Mayring, 2016). According to Witzel (1985), this format enables the step-by-step exploration and validation of insights within a real-world setting (Witzel, 1985). Two key advantages (Döringer, 2021) make it particularly well-suited to address the present RQ: First, the open format allows the interviewer to clarify misunderstandings in real time, ensuring that the intended meaning for each question is understood. Second, it supports the expression of subjective perspectives on certain topics and facilitates cognitive linkages/ associations during the interview process.

3.1.2 Participants

As white-collar jobs consist of a lot of different professions with various tasks and responsibilities (Abbott, 1988; Hopp et al., 2009) and the exposure to concrete GenAI use cases may vary based on profession and industry (e.g., Arntz et al., 2016; Felten et al., 2023), 20 participants were selected to represent a broad cross-section of white-collar professions. Participants were recruited via professional networks and LinkedIn, and no compensation for the interviews was provided. Information on gender, age, and employer was collected and anonymized to ensure confidentiality. According to (Hennink & Kaiser, 2022), in qualitative research, data saturation was achieved between 9 and 17 interviews, depending on the study's complexity and the homogeneity of the participant group. Other research suggests saturation occurs after 12 interviews (Guest et al., 2006), indicating the sample size of twenty should be sufficient to derive qualitative insights. The sample included 10 participants from industrial goods, four from financial services and insurance, two from apparel and fashion, as well as additional participants from consulting, hospitality and service, architecture and construction, and IT and digital services. This reflects a great variety of white-collar professions. Most interviewees had less than five years of practical work experience. The identification numbers assigned to participants (e.g., P1, P2) were randomized and do not reflect the sequence of the interviews.

3.1.3 Procedure

According to Mayring (2016), within interviews, the relationship of trust between the interviewer and the interviewee is an important benefit of the expert interview. Following the problem analysis and the development of guiding questions, a pilot phase involving 3 interviews was conducted. As no adjustments to the questionnaire were necessary, the main data collection proceeded, and the pilot interviews were included in the final sample.

In order to ensure validity and reliability, the research questions have been validated by independent peers to provide a more objective assessment of the questionnaire, as suggested by Barbour (2001). For the interviews, Mayring (2016) suggests three types of questions: exploratory questions, guideline questions and ad-hoc questions. In the beginning of the interview, a preamble serves as useful introduction into the research question and the purpose of the interview (Seidman, 2006). During the interview, follow-up questions were posed spontaneously to gain further insights (Rubin & Rubin, 2012). Following the suggestion of Mayring (2016), the interviews were recorded, and the material has been used for transcription. In the present study, all interviews were conducted remotely to increase the flexibility of scheduling and transcription. After the informed consent and the introduction, the content questions were posed with ad-hoc follow-up questions to clarify selected aspects in the interviews. As suggested by (Bolderston, 2012), triangulating qualitative findings enhances the credibility and depth of the research. In the present thesis, this has been achieved by integrating insights from a complementary quantitative study. The complete interview script and the access link to the transcripts can be found in Appendix 1.

The data collection for the qualitative part follows the process model described by Mayring (2016):

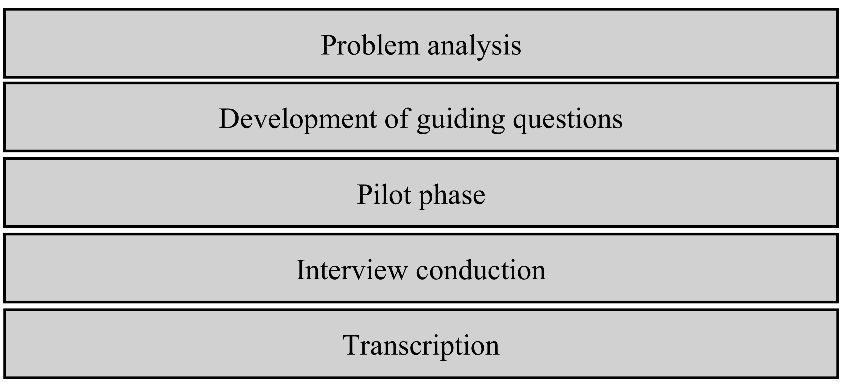

Figure 2: Process model of the problem-centered interview, replicated based on Mayring (2016)

3.1.4 Analysis procedure

To derive insights from the qualitative information, Mayring's (2016) method of qualitative content analysis is widely accepted and applied. It seeks to systematically reduce and summarize information in line with predefined research objectives (Döringer, 2021). One of the main strengths of qualitative content analysis, as emphasized by Kohlbacher (2006), is its ability to combine the methodological rigor of quantitative content analysis with the openness and contextual sensitivity of qualitative interpretation. This method is particularly well-suited to generating systematic and intersubjectively verifiable insights from textual data, as it preserves a close connection to the material and ensures transparency in the analytical process (Mayring, 2016). The integration enhances systematization in qualitative research, while supporting the generalizability of findings through theory-guided and rule-based procedures (Kohlbacher, 2006). In the present study, Mayring's approach to inductive category formation was applied by segmenting each interview transcript into coding units that captured coherent meanings relevant to the research question. Afterwards, the paraphrased statements were abstracted to a higher level of generality to allow categorization and then grouped into inductively developed categories that reflect recurring patterns. An internal review and revision of the developed system concluded the coding process (Belgrave & Seide, 2019; Mayring, 2000, 2016). The access link to the coding units can be found in Appendix 1.

3.2 Results

After having clarified the role, industry, position and main tasks of participants, drawing on Autor's (2003) task model, participants were first asked to describe the structured, routine tasks they perform in their daily work and to assess the extent to which these tasks may be susceptible to substitution by (Gen) AI. Nine participants (P2-6, P8, P13, P15, P17) believed that a high degree of task structure was typically associated with a high proportion of routine activities. However, some experts pointed out that certain white-collar roles - such as those of a sales engineer, marketing manager, or senior product owner – appeared to involve highly structured tasks without necessarily being repetitive. In addition, participants whose roles included manual components (e.g., P1, P4, P9) argued that a high share of routine tasks did not necessarily imply a greater susceptibility to AI substitution, as they viewed the manual aspect of their work as core and less automatable.

Second, the experts were asked regarding AI usage and experience, where opinions varied notably. Nine experts reported regularly using AI systems – often adapted to their company context – including GenAI tools (P6, P7, P11, P12, P14, P15, P17, P18, P20). In contrast, eight experts described their use as moderate (P1, P3, P5, P8-10, P16, P19). Interestingly, P3 and P12 mentioned they had attempted to integrate GenAI into their workflows but found the outputs unsatisfactory, which led to frustration and a subsequent decline in usage. Thus, organizational maturity seems to vary significantly across industries and organizations. One frequently mentioned reason for the varying penetration of GenAI across white-collar professions was concerns around data protection. Although the participants perceived the theoretical use cases as significant, they reported actual usage and implementation remained low or even absent (P2, P4, P5, P13, P16).

Third, the participants were asked to identify non-replaceable elements of their work. Many participants believed that the primary safeguard against automation was the necessity of human interaction (P1-P6, P9, P11-P17, P20). For example, P5, a sales agent at a luxury hotel, described guest interactions as critical, noting that they "add a personal touch to the guest experience" and constitute essential service touchpoints. Similarly, P17, a technical buyer, highlighted the role of human trust in negotiations, stating, "I think human trust will still be very important in the long term." These reflections illustrate a shared perception that communication is not supplementary but rather central to the job, protecting it from GenAI substitution.

The fourth interview question focused on future prospects of GenAI and its implications for job security. Several experts expected GenAI to change the nature of roles within their field without reducing the overall number of jobs. Participants 1, 6, 7, and 19 believed that, while job profiles may shift significantly, the total volume of employment would likely remain stable. Only one participant (P14) anticipated an increase in job opportunities due to GenAI, citing their involvement in a company focused on AI development as the basis for this view. In contrast, ten experts explicitly stated that they expected (Gen) AI to reduce the number of job opportunities in their domain. This represented the majority opinion, although views overall remained mixed. Participants 5, 11, 12, and 17 identified administrative and repetitive tasks as particularly vulnerable to automation. In addition, P16 pointed out that creative roles in marketing could also face substitution or downsizing as (Gen) AI advances in content production and ideation.

Fifth, regarding general attitudes toward (Gen)AI in the workplace, most interviewees expressed a positive outlook. Several experts, including P1 and P12, anticipated notable efficiency gains from its implementation. Many interviewees described a shift away from repetitive tasks – often viewed as low value and minimally rewarding – toward more strategic and intellectually engaging responsibilities. This transition, they argued, would likely enhance job satisfaction by allowing more time for meaningful tasks aligned with their core professional interests. However, a few experts emphasized that (Gen) AI carries both positive and negative implications. For instance, Participant 5 highlighted the dual nature of (Gen) AI integration, acknowledging potential benefits while also expressing concern about the risk of job displacement. Participant 7 shared a nuanced perspective, suggesting that even if GenAI leads to efficiency gains, it may not enhance overall job satisfaction. This expert anticipated that some of the tasks replacing the automated ones might also be low in value. Unlike those tasks, new responsibilities could not be delegated to an algorithm.

Question six focused on the perception of job opportunities in their field. Although several experts acknowledged the potential of AI to support routine tasks, nine reported that GenAI had no significant impact on employment prospects in their respective fields. This perspective was particularly common among those whose roles included manual components (P1, P4) or relied heavily on interpersonal exchanges. Experts working in sales and purchasing (P2, P15, P20) emphasized that ongoing interaction with business partners represented a substantial portion of their daily responsibilities — an aspect they did not believe could be effectively delegated to an algorithm.

Sevenths, regarding the impact of (Gen) AI usage on job satisfaction, several experts reported limited impact on (Gen) AI on their job satisfaction. Participant 3 and 11 attributed this to the restricted use of AI tools in their current work environment. Others, such as P15, indicated that their motivation to work was primarily driven by factors unrelated to areas affected by (Gen) AI – particularly interpersonal relationships, which they considered central to their job satisfaction. In terms of job security, most experts acknowledged the potential for efficiency gains and a possible reduction in the number of jobs within their fields.

Question eight asked participants about changes they had observed in job requirements because of (Gen) AI usage. Most experts reported not having observed any changes in job requirements (P2-4, P6, P8, P10, P12, P13, P16-19), while others described moderate changes (P1, P5, P7, P9, P11, P20). These observations suggest that, despite its theoretical potential, (Gen) AI has not yet widely replaced routine tasks in practice. Interviewees attribute this to limited technical maturity and insufficient organizational readiness, leaving key conditions for large-scale substitution unmet. In question nine, participants were asked to assess the impact of GenAI on their own employability, where the majority reported a low perceived threat (P1, P3-P6, P10-P12, P15-P17, P20). This sense of stability stemmed from various factors. For example, Expert 4 attributed their confidence to a strong educational background. P6 cited severe understaffing in their industry, which limited any immediate efficiency gains from lay-offs. Participants 12 and 16 referred to the low maturity of (Gen) AI integration within their specific organizational contexts. They believed that this diminished the relevance of (Gen) AI for their current roles.

Question 10 focused on measures organizations should take to prepare for AI-related transitions, where many experts emphasized the importance of active change management. P2 described it as "one of the most important factors […] and a major contributor to success of the implementation." Several experts underscored the role of clear, transparent communication as central to managing change effectively (P6, P8, P10, P15, P19). In addition, training and enablement emerged as recurring theme. Participants 3, 4, 6, 7, 11, 12, 13, 15, and 18 identified targeted upskilling as critical component to ensuring that GenAI tools could be adopted and integrated meaningfully into daily workflows. As Expert 6 emphasized, the effectiveness of GenAI depends heavily on how it is introduced and used by staff. "For example, we recently got a new tool, but no one knew how to use it. That's unfortunate because […] if people don't understand it, it's a waste of resources", they explained. Several experts also addressed the need for structural adjustments in response to AI integration. Three interviewees discussed organizational restructuring as a necessary step, with management taking responsibility for guiding change processes. P13, for instance, highlighted the possibility of reducing workforce size and consolidating responsibilities, stating that "[…] one person could take over two or three departments instead of one". At the same time, experts expressed caution about over-reliance on GenAI. P6 warned against hasty or unplanned implementation, observing that "[…] it shouldn't happen too fast or without a plan, because once you start depending on AI, you're also vulnerable if your whole workflow depends on one AI […]". These reflections suggest that, while (Gen) AI presents opportunities for efficiency and structural change, its deployment must be deliberate and supported by organizational readiness to avoid new forms of risk.

4 Study 2

4.1 Methodology

4.1.1 Research design

After exploring the first qualitative results on white-collar worker's view on (Gen) AI usage, the purpose of Study 2 was to quantitatively investigate how (Gen) AI usage and implementation in white-collar jobs impacts job satisfaction and job security as factors for motivation and well-being. To this end, a cross-sectional survey study was designed to quantitatively address RQ2, as well as to examine RQ3 and RQ4.

First, respondents were asked to allocate their work time across different categories which were deductively developed based on the aggregated insights from Study 1. In the second section of the survey, participants reported their current use of AI tools in their working environment, including the primary purpose of usage and the perceived relevance of (Gen) AI to their role. For example, if (Gen) AI is primarily used for simple data entry, but the participant's role consists mainly of interpersonal communication, their perceived risk of replacement may be low — even if such tasks are theoretically automatable according to task-based models that discuss the degree of automatability (Autor et al., 2003; Frey & Osborne, 2013, 2017). Further items assessed the participant's attitudes and general perceptions towards (Gen) AI, for instance the perceived capabilities of the systems in practice. Perceptions may diverge from theoretical capabilities due to limitations in implementation or organizational readiness for (Gen) AI systems, as highlighted in Study1. The qualitative findings indicate that white-collar workers view organizational support and effective change management as crucial for the successful implementation of (Gen) AI. The role of perceived organizational support influencing outcomes such as job security or job satisfaction could also been shown by previous studies (e.g.,Hngoi et al., 2024; Maan et al., 2020; Thevanes & Saranraj, 2018), even though the overall research design and settings were different from the present thesis. Accordingly, this study will also examine perceived organizational support through quantitative methods, testing its moderating influence on job security and job satisfaction via a moderation analysis. Finally, to assess the perceived susceptibility of work tasks to automation, participants were asked to estimate the proportion of routine cognitive and non-routine cognitive work that could be performed by (Gen) AI. This distinction, derived from the task model (Autor et al., 2003), enables a more differentiated analysis of potential job disruption. The complete survey questionnaire can be found in Appendix 2.

4.1.2 Participants

Participants for Study 2 were recruited through an online Qualtrics survey distributed via professional networks, social media platforms such as LinkedIn, and the online research platform Prolific. For the participants recruited via Prolific, a compensation of 0.8 £ was offered. The sample was restricted to individuals currently employed in white-collar roles. To ensure eligibility, the survey began with a screening question explicitly asking whether respondents were currently working in a white-collar job; only those who confirmed were permitted to continue. A power analysis was conducted to determine the required sample size for detecting a single regression coefficient in a linear multiple regression with 8 predictors. The analysis assumed a two-tailed test, $\alpha = .05$, power = .95, and a medium effect size ($f^2 = .15$). In addition, the commonly cited rule of thumb of at least 20 participants per predictor (Maxwell, 2000) suggests a minimum of 160 participants for a model with eight predictors and one interaction term to test moderation. Data collection concluded upon reaching this predetermined target. The final sample of valid responses from white-collar professionals satisfies both the power analysis requirement and the rule-of-thumb guideline. Between March 31 and April 6, a total of 263 valid responses were collected. Of these, 189 passed the sanity check, confirming that the participants were currently employed in white-collar professions and had completed all required questions. This led to a final sample of 189 white-collar workers (54.0 % female, 43.9 % male, 2.0% other) aged between 18 and 61 ($M = 29.20$, $SD = 7.97$). The complete descriptive statistics can be found in Appendix 3.

4.1.3 Procedure

After accessing the online survey through Qualtrics and accepting the informed consent, participants were screened using a control question to confirm current employment in a white-collar occupation. Based on pre-tests and the informed consent statement, the survey required approximately 8 minutes to complete. Responses were anonymous and no personal identifiers were collected. Demographic variables — such as age, gender, industry, and exposure to AI — were collected to characterize the sample and enable subgroup analysis. The introductory block was followed by questions on usage and perception of (Gen) AI, task susceptibility to (Gen) AI, and the impact of GenAI on job security and job satisfaction. Afterwards the perceived organizational maturity was assessed. In the end of the survey, participants were asked which emotions they associate with the increased (Gen) AI usage in their jobs.

4.1.4 Main variables

To enhance scale reliability and maintain participant attentiveness, the scales included a mix of positively and negatively worded statements. To assess the concrete impacts of (Gen) AI, validated scale items were used to measure job security (Bazzoli & Probst, 2021; Probst, 2003) and job satisfaction (Brayfield & Rothe, 1951; Faragher et al., 2005). The primary advantage of using standardized, pre-validated instruments in this study is that their reliability and validity have been extensively established (Hyman et al., 2006), ensuring methodological rigor while also saving time in the instrument development. Except for the emotion analysis, the following variables have been assessed using a 5-point Likert scale (1 = Strongly disagree, 5 = Strongly agree).

Job security: The first main outcome variable was the job security index, a validated measure of job security. First, job security consists of two factors (Probst, 2003): the Job Security Index (JSI) and Job Security Satisfaction (JSS). The JSI is a series of adjectives that addresses the expected continuance and stability of one's job, for example "stable" (Probst, 2003). The JSS, in turn, captures affective reactions regarding level of job securities, for example "positive" (Probst, 2003). Both scales consist of 9 adjectives, of which positive and negative statements are intermixed (Probst, 2003). Due to participant burden and survey space constraints, in practice, shorter scales are often-times used to assess psychological constructs (Fisher et al., 2015). While the original scale has been widely validated, a more recent version of the JSI and JSS scales includes fewer items, thereby reducing criterion contamination while avoiding the limitations associated with single-item measures (Bazzoli & Probst, 2021). To measure job security, three adjectives from the reduced JSI and JSS scales were selected from the reduced job security scale developed by Bazzoli and Probst (2021), compromising two negatively and four positively worded items. Both scales were introduced with the statement "Considering the impact of (Generative) AI in my industry,…". The adjectives of JSI and JSS were incorporated into sentences to restrict their scope to the impact of (Gen) AI, for example "I think the future of my employment is stable" for the JSI.

Job satisfaction: The second main outcome variable was job satisfaction. For the assessment of job satisfaction (JS), five items were selected from the scale developed by (Brayfield & Rothe, 1951), which has been widely used and validated in subsequent research (e.g., Faragher et al., 2005; Judge et al., 2000). In the current thesis, the same five items as in Judge et al. (2000), for example “I find real enjoyment in my work”, were introduced with the statement “Considering the impact of (Generative) AI in my industry,…”.

Attitude towards AI: An important predictor variable is attitude towards AI. Two positive and two negative items about the participants attitude towards AI were included in the questionnaire. Among the positive items, the interest of incorporating (Gen) AI systems into daily routines and the usefulness of (Gen) AI application have been assessed. With regards to the negative items, the participants were asked for their agreement to the statements that AI is being used unethically and whether they believe (Gen) AI systems are dangerous.

AI-impact: A second important predictor included the items (Gen) AI usage, the likelihood of (Gen) AI to change the role and the perceived individual relevance of (Gen) AI in the job context. After asking participants to allocate the time spent on different activities, they were asked whether they have already used (Gen) AI in their work context using four frequency categories (e.g., 1 = Yes, regularly,…). Another question in the context of AI impact was the likelihood of (Gen) AI to change their role. Participants were asked to indicate their agreement to the statement “(Gen) AI is likely to significantly change my role in the next 5 years.”. The question was added to address the limited implementation of GenAI applications identified in Study 1. Furthermore, participants were asked how relevant they consider (Gen) AI to be in the context of their current job responsibilities using a 5-point scale (e.g., 1 = Not relevant at all). The items have been aggregated to an AI-impact index.

Degree of organizational support: Expert interviews in Study 1 highlighted the importance of organizational support in managing role shifts and enabling effective change. To assess perceived organizational support as a potential moderator, participants were asked to respond to the statement: “My organization has put in a lot of effort to effectively support white-collar workers in adapting well to (Gen) AI”. In addition, participants were invited to suggest specific actions organizations should take to address white-collar workers’ concerns about GenAI.

GenAI Opportunities: As confirmed by Study 1, attitudes toward GenAI are often marked by ambivalence — an observation that aligns with broader research findings. While many view it as a tool for innovation and efficiency, concerns about job loss, privacy and misinformation remain widespread (Alessandro et al., 2024; Mahmoud et al., 2025; Miyazaki et al., 2024). Therefore, the quantitative survey included an item to assess participants’ interpretation of

GenAI's capabilities. Specifically, respondents were asked to indicate their agreement with the statement: "I think GenAI creates more job opportunities than efficiencies", capturing whether they primarily perceived GenAI as a source of new opportunities or as a tool for enhancing efficiency.

Emotions: An important exploratory variable were the emotions of participants regarding (Gen) AI usage and its impact. They were assessed by asking participants to enter concrete emotions at the end of the survey. As a first step of data cleaning, the emotions mentioned were categorized into positive and negative emotions according to the NRC Word-Emotion Association Lexicon developed by Mohammad & Turney (2010, 2013). However, some emotions or associations could not be found in Mohammed and Turney's dictionary. They were reviewed manually and deemed neutral in most cases. Examples of neutral emotions were "neutral", "not sure", "okay", "no emotions".

4.1.5 Covariates

All covariate items, except for demographics, were assessed using a 5-Point Likert Scale (1 = Strongly disagree, 5 = Strongly agree) with the negative elements being reverse-coded for the analysis.

Replacement, routine tasks: As the analysis of the interviews in Study 1 revealed, white-collar workers' belief in (Gen) AI's capabilities to effectively support routine tasks is of great importance for the perceived impact on job satisfaction and job security. Additionally, it is of interest to see whether the perceptions of white-collar workers confirm the differentiation between routine and non-routine tasks proposed by Autor et al., (2003). The perceived replacement susceptibility was assessed using the positively framed statement "I believe (Gen) AI is well suited to replace routine tasks".

Replacement, non-routine tasks: As the first study showed, the perceived capabilities of (Gen) AI varied based on industry, use cases, and organizations. Reasons for the variance included data protection concerns or integration of (Gen) AI systems into company specific IT environments. Similarly to routine tasks, the perceived replacement capability was assessed using the statement "I believe (Gen) AI is well suited to replace non-routine tasks".

Demographics: Following previous research, demographic data (age, gender, work experience) were included in the regression to analyze potential differences in job security and job satisfaction between demographic groups. For example, the interviews in Study 1 pointed at generational differences in how people perceive the impact of (Gen) AI on job security.

Apart from the main variables and covariates, a few informative variables have been assessed in the survey, for example the primary effect that (Gen) AI affects the work of participants a scale from 1 to 5 (e.g., 1 = Automates routine tasks, 2 = Improves decision making, see Appendix 2 for all answer options). Additionally, as the first study revealed, the type of work matters in the context of susceptibility of technological replacement (replacement likelihood). Therefore, the amount of work done in different categories (routine work, human judgement, communication, creativity) as well as the frequency of (Gen) AI usage have been assessed. These variables were not part of the regression model but rather served as informative variables to understand the sample.

4.2 Results

4.2.1 Scale assessment

To assess the internal consistency of the scales used in this study, Cronbach's α was calculated for each construct, as recommended by Tavakol & Dennick (2011). According to Bland & Altman (1997), α values above .70 are generally considered acceptable, while Gliem & Gliem (2003) argue that an α value of .60 or higher may be sufficient for newly developed scales or exploratory research. First, with regards to job security, since not all items of the original scale have been used, a factor analysis was conducted following the methodology presented by Field (2009). Using an eigenvalue cut-off of 1, the analysis identified three components, with the third component marginally exceeding the threshold. The pattern matrix (see Appendix 4) revealed a clear distinction between component 1 (Job security) and component 2 (Job security satisfaction). Additionally, a reliability test was conducted, resulting in a Cronbach's α of .87 (See Appendix 4 for full factor analysis). With regards to job satisfaction, as the categorical analysis revealed a clear pattern, supporting the grouping of items into a single factor, the reliability analysis yielded a Cronbach's α of .85. For the construct measuring perceived AI impact, the reliability analysis yielded a Cronbach's α of .64. Although slightly below the conventional threshold, the scale was retained, as all items consistently reflect dimensions of how (Gen) AI affects the work environment. Finally, the attitude towards AI scale included negatively phrased items, which were reverse coded prior to analysis. The resulting Cronbach's α of .69 indicates acceptable internal consistency for exploratory purposes, though results should be interpreted with caution.

4.2.2 Descriptive statistics

To understand how GenAI might influence job satisfaction and job security, it is important to first examine how white-collar workers allocate their time across different task types and how they perceive (Gen) AI's role in their daily work. The average task distribution (see Appendix 4 for full results) shows that white-collar roles in the sample was primarily composed of routine tasks ($M = 29.5\%$), followed closely by human judgement and problem solving ($M = 26.8\%$) and communication ($M = 25.8\%$). Regarding the perception of GenAI use cases, responses clustered around two dominant functions: supporting complex tasks ($M = 29.6\%$) and automating routine tasks ($M = 28.6\%$; see Appendix 4 for frequencies of all perceptions). These perceptions align with the reported task distribution, suggesting that participants recognize both (Gen) AI's potential to augment analytical work and its capability to automate repetitive activities. Notably, 21.7% of respondents indicated that GenAI supports creative tasks, highlighting that the technology was also perceived as relevant for higher-order cognitive tasks.

Descriptive statistics (see Appendix 3 for full results) show that most participants believed GenAI is well-suited to replace routine-cognitive tasks in their profession (M = 3.89, SD = 1.04), whereas the perceived capability of GenAI to replace non-routine cognitive tasks was considerably lower (M = 2.69, SD = 1.21). A paired samples t-test revealed a statistically significant difference between these two judgments, $t(188) = 11.31$, $p < .001$, $r = .17$.

As a final survey question, participants were asked to report their emotions regarding GenAI in the workplace. The analysis reveals a high degree of ambivalence on GenAI perceptions. Of the 189 participants, 169 provided emotional responses. Among these, 34.9% reported only positive emotions, while just 11.1% expressed purely negative ones. Notably, nearly half of participants reported mixed emotions, indicating both optimism and concern. This points to an emerging but complex emotional landscape surrounding the integration of GenAI in white-collar professions.

4.2.3 Bivariate correlations

Regarding bivariate correlations, and focusing on the main variables in Study 2, several significant correlations emerged. Job satisfaction was positively associated with job security ($r = .40$, $p < .001$) and with positive attitudes toward GenAI (r = .24, p < .001), but negatively associated with replacement likelihood ($r = –.47$, $p < .001$). Perceiving a stronger impact of AI was positively related to believing that AI creates more opportunities than efficiencies ($r = .34$, $p < .001$) and to experiencing stronger organizational support for AI ($r = .40$, $p < .001$). The complete bivariate correlation table is presented in Appendix 4.

4.2.4 Main analysis

To assess the impact of GenAI on job security and job satisfaction, two multiple stepwise regression analyses were conducted. Demographic variables were included only in the final step to examine potential differences based on age, gender, or country of residence. The first regression focused on predictors of job security. Perceived replacement likelihood, belief in GenAI as an opportunity creator (GenAI opportunities), and attitude towards (Gen) AI were entered as predictors. The final model explained 27% of the variance in job security. Perceived replacement likelihood was negatively associated with job security ($b = -0.32$, $p < .001$), while a stronger belief that GenAI creates more opportunities than efficiencies ($b = 0.12$, $p < .001$) as well as the attitude towards (Gen) AI ($b = 0.15$, $p < .001$) were positively associated with job security. The second regression analysis examined predictors of job satisfaction. The final model explained 23% of the variance in job satisfaction. A positive general attitude toward GenAI ($b = 0.26$, $p < .001$) and degree of organizational support ($b = 0.15$, $p = <.001$) were positive predictors of job satisfaction, while replacement likelihood ($b = -0.14$, $p = .002$) was a negative predictor. These results suggest that, while fear of replacement reduces job satisfaction, a supportive organizational environment and a positive disposition toward GenAI may increase job satisfaction.

Moderation analyses were conducted to examine whether perceived organizational support moderates the relationship between perceived replacement likelihood and two outcomes: job security and job satisfaction. The perceived degree of support was measured using a 5-point Likert scale. In moderation, the percentile method was used to define high, median and low levels of perceived support. For job security, the interaction between replacement likelihood and support was statistically significant ($b = 0.09$, $p = .007$). Simple slope analysis showed that at low (16^{th} percentile, $b = -0.42$, $p < .001$) and median (50^{th} percentile, $b = -0.33$, $p < .001$) levels of support, higher perceived replacement likelihood significantly predicted lower job security. At high support (84^{th} percentile), the effect was weaker but remained statistically significant ($b = -0.15$, $p = .046$). The pattern is visualized in the simple slope (Figure 3).

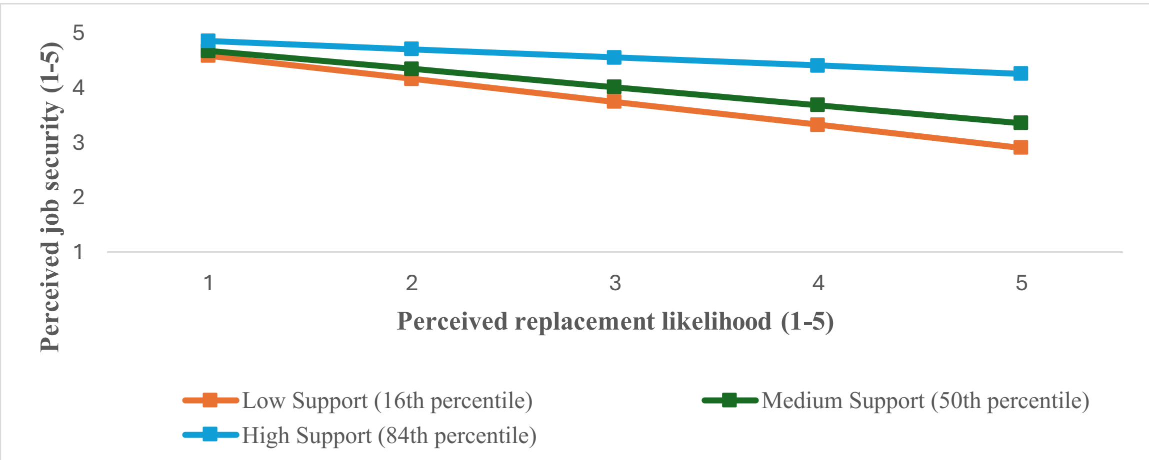

Figure 3: Interaction between perceived replacement likelihood and support

With regards to job satisfaction, the interaction between perceived replacement likelihood and organizational support was not significant ($b = 0.06$, $p = .056$). Multicollinearity was not a concern in either model (all VIF values < 1.3). The full results for both regressions and moderations are presented in Appendix 5.

5 Discussion

5.1 Research findings

Study 1 revealed that participants across different white-collar professions perceived that routine-cognitive tasks (e.g., data entry, documentation) are most likely to be substituted by GenAI, which confirms theoretical assumptions (e.g., Kaplan & Haenlein, 2019; McKendrick, 2024). However, interpersonal tasks, particularly those involving negotiation, collaboration, or customer-facing interactions are widely regarded as non-substitutable due to their reliance on emotional intelligence. Experts from different industries were interviewed, where the threat of substitution varied greatly across industries and organizational readiness for GenAI implementation. Some professions showcased low substitution concerns due to the human-centric nature of the work, while others already recognized there will be less jobs in their position.

The perceived threat of substitution and general attitude towards AI furthermore varied by role and organizational maturity. The perceived substitution seems to be moderated by organizational GenAI maturity, as in contexts with limited AI integration or strong data privacy concerns, even automatable tasks are currently not substituted. White-collar workers in client facing roles, e.g., hospitality, procurement, or sales expressed greater confidence in job continuity due to the centrality of human interaction in their work. While most experts expressed positive attitudes towards GenAI, especially when it reduces low-value work and enables shift to more strategic or creative tasks, some participants were concerned that new tasks replacing routine tasks may not be more fulfilling. Interestingly, most participants have not reported strong perceived threats to their own job security, even when acknowledging broader workforce impacts. This is attributed to factors such as skill level, sector-specific demand, and lack of current GenAI deployment. With regards to necessary actions, the interviewed experts highlighted the critical role of change management, training and leadership in mitigating GenAI related fears, accompanied with clear communication.

Study 2 expanded upon the qualitative insights. Stepwise regression analysis demonstrated that the perceived likelihood of task replacement was the most robust negative predictor of job security. The second strongest predictor was the belief that GenAI will generate opportunities rather than merely drive efficiencies. Additionally, the general attitude influences the perceived job security positively. These results elucidate RQ3 regarding the impact of GenAI on job security. The finding that perceived replacement likelihood strongly reduces job security suggests that displacement fears may undermine workers' sense of stability. However, participants who believed that GenAI will create new opportunities reported higher levels of job security. Additionally, the attitude towards GenAI was positively associated with job security. For job satisfaction, three key predictors emerged: attitude toward GenAI, higher perceived organizational support, and lower perceived replacement likelihood. These findings indicate that while fear of replacement reduces job satisfaction, favorable affective responses to GenAI and supportive change management environments may buffer against negative impacts. Additionally, the attitude towards (Gen) AI seems to have a significant impact on how it influences both job security and job satisfaction.

The emotion analysis further illustrates the ambivalence reported in Study 1. Approximately half of the participants expressed both positive and negative emotions in response to GenAI, reflecting emotional dissonance. This supports Parent-Rochelau and Parker’s (2022) research, which posits that AI systems evoke both enthusiasm for innovation and anxiety about control, competence, and job relevance. Finally, the differentiation between routine and non-routine cognitive task replacement capacity was empirically confirmed: participants rated routine tasks as significantly more vulnerable than non-routine tasks. This pattern aligns with prior findings by Chui et al. (2023) and Eloundou et al. (2023), further highlighting the task-specific nature of GenAI’s perceived impact.

5.2 Implications

This study contributes to the theoretical understanding and offers actionable guidance for managing GenAI’s integration in white-collar professions. Theoretically, the findings refine models of technological change, work motivation, and job insecurity. First, by combining qualitative and quantitative evidence, the study refines task-based models (e.g., Autor et al., 2003), suggesting that perceived substitutability depends not only on technical feasibility, but also on organizational maturity and task framing. Technically automatable tasks remain untouched if constrained by legal or data protection concerns. The persistent distinction between routine and non-routine cognitive tasks remains central to workers' perceptions of technological substitutability.

Second, the thesis adapts motivation theory to GenAI introductions demonstrating how GenAI influences both hygiene and motivation factors. In line with Herzberg's (1959) two-factor theory, GenAI was seen to reduce dissatisfaction when automating routine tasks and to enhance motivation when enabling focus on creative, strategic, or interpersonal work. Simultaneously, perceived job insecurity — rooted in fears of replacement — emerged as barrier to job satisfaction, in line with Maslow's (1943) hierarchy, which positions safety as a precondition for higher level needs (i.e., fulfillment and growth). This underscores the importance of psychological needs in shaping the experience of technological change within white-collar professions.

Third, ambivalence in emotional responses aligns with literature that frames technological change as both a source of anxiety and opportunity (Parent-Rocheleau & Parker, 2022). Importantly, this study reinforces a sociotechnical perspective on GenAI adoption: Employees evaluate (Gen) AI systems not only based on capability but also the ecosystem of support — including leadership, training, and communication — that accompanies implementation. Finally, this work contributes to the body of literature specifically addressing GenAI in white-collar professions. While prior research has focused extensively on either the economic potential of GenAI or its role in automation (e.g., (Chui et al., 2023; Frey & Osborne, 2017), fewer studies have empirically examined how GenAI is perceived by white-collar workers in terms of its psychological and professional implications. By integrating qualitative and quantitative findings, this research offers a more granular understanding of how GenAI is influencing the white-collar professions and provides a foundation for future theoretical development in the field of Human-AI collaboration.

From a managerial standpoint, the findings point to clear priorities. First, in consideration of the expert interviews, managers must recognize the task-specific nature of GenAI substitution fears and address them with clear, role-tailored communication. Study 2 demonstrated that the perceived likelihood of task replacement is the strongest negative predictor of job security. This aligns with the conceptualization of job insecurity as subjective and context dependent. Consequently, leaders must address uncertainty proactively by framing GenAI as a tool for augmentation rather than substitution. Communication strategies should emphasize long-term workforce stability and provide a realistic picture of the GenAI strategy (De Witte et al., 2015). Second, as the results of the quantitative analysis showed, the perceived replacement likelihood lowers job satisfaction and job security. Thus, organizations should assess which tasks can be automated or replaced and use this to guide human-AI role balancing, potentially redefining specific roles (Acemoglu & Restrepo, 2022). With the redesigning of job roles, human-centric strengths can be emphasized. The qualitative interviews revealed that workers welcomed GenAI when it enabled them to shift focus from repetitive, low-value tasks to more strategic, interpersonal, or creative work. This finding is supported by Herzberg's (1959) two-factor theory, suggesting that removing dissatisfiers (i.e., routine tasks) and enhancing motivators (i.e., autonomy, meaningful work) can boost satisfaction. Job audits should be conducted to identify automation opportunities and reallocate time toward tasks that rely on human judgement, empathy, and creative thinking.

Third, organizations need to invest in AI readiness and support of implementation. Participants often pointed to poor integration as a key barrier to realizing GenAI's potential. Even with high automation potential, actual usage was limited by weak implementation or data protection concerns. Thus, seamless integration and trust-building trainings are essential for a successful implementation.

Lastly, psychological safety must be supported throughout the transformation process. Drawing on Maslow's (1943) hierarchy of needs, job security constitutes a foundational layer upon which higher-order motivation depends. This is consistent with dedicated research on job security, suggesting that job insecurity is associated with adverse mental health outcomes, including anxiety, depression, and burnout (Faragher et al., 2005; L. Jiang & Probst, 2017; Sverke et al., 2002). Moreover, job insecurity negatively impacts family life and long-term life satisfaction (De Angelis et al., 2021; Lucas et al., 2004). Given these wide-ranging effects, leaders should establish participatory change processes and ensure that restructuring efforts are paced, inclusive, and anchored in employee well-being. Therefore, implementation strategies should be tailored to the nature of work, as occupation-based frameworks may be limited. Automation potential and GenAI relevance varied significantly by task type. Thus, managers should segment functions by their dominant task profiles, e.g., routine/ non-routine, task, communication, or human judgement and adjust their deployment, support and messaging accordingly. Employees feel more secure and satisfied when enabled to use GenAI effectively.

In the end, firms should combine GenAI deployment with upskilling programs to empower employees and shift from low value to more strategic work. Where AI usage is limited or ineffective, frustration and disillusionment can reduce engagement. Expectation management, and the investment in robust systems with the clear definition of use cases can mitigate this risk.

5.3 Limitations and further research

While the present thesis offers valuable insights into the perceived impact of GenAI on job satisfaction and job security among white-collar professions, several limitations must be acknowledged with regards to the interpretation of results and future research. First, the qualitative study is limited by the demographic composition of its sample. Most of the 20 experts were between 25 and 35 years old, meaning that perspectives from older generations — who may experience and evaluate technological change differently — are underrepresented. Prior research suggests that older generations exhibit different attitudes towards new technologies, (e.g., Charness & Boot, 2009; Lee & Coughlin, 2014) and thus may exhibit different reactions towards GenAI implementation. Even though the stereotypes that older adults fear or reject technology could not be supported by some studies (e.g., Mitzner et al., 2010, 2018), including a more diverse age range in future studies could help capture generational differences in GenAI-related attitudes and perceived risks. Second, while Study 1 included participants from different industries and professional backgrounds, the number of interviews per industry was too small to allow for sector-specific analysis. Given the variation and heterogeneity in (Gen) AI adoption and task structures across sectors, future research should consider an industry focused approach, for example by focusing the analysis to industries, functions (i.e., only office and administrative support) or countries/ regions that exhibit a high substantiality towards AI substitutions (Frey & Osborne, 2013).

Third, although the interviews revealed important differences in how participants assess the substitution potential of tasks, the findings are based on self-reported perceptions. The perceptions may diverge from actual task exposure or organizational readiness. Therefore, future studies could complement the analysis by either extended assessments on perceived organizational readiness or independent expert evaluations on actual organizational readiness. Fourth, the quantitative study is not able to capture the dynamic evolution of GenAI-related attitudes. As GenAI evolves, further improvements and capabilities that can automate a broader set of tasks are expected (e.g., Eloundou et al., 2023), which may lead to changes in perceptions of job security and job satisfaction. A longitudinal study design would be interesting to capture these changes and identify longer-term patterns, as the integration of GenAI into business processes and tasks is, at least for some organizations, in the very beginning.

Finally, while the survey captured basic indicators of GenAI relevance and usage, it did not include direct measures of organizational maturity. Further research should aim to operationalize organizational maturity more systematically, potentially including variables on integration level, leadership support, and internal communications. Lastly, although the final survey sample ($N = 189$) met the statistical requirement for regression analysis, it was not large enough to allow for subgroup regressions based on profession, industry, or region. Such analysis would have enabled a more granular understanding of the variation in job satisfaction and job security.

6 Conclusion

This thesis explored how generative AI (GenAI) influences job satisfaction and job security among white-collar professionals, integrating qualitative and quantitative insights to examine both individual perceptions and organizational dynamics. The findings highlight that the impact of GenAI is not determined solely by technological capabilities or task characteristics but is significantly shaped by how workers interpret these changes and how organizations manage their implementation. While routine cognitive tasks are perceived as most susceptible to automation, roles involving interpersonal communication and human judgment are seen as more resistant. However, the perception of replacement risk varies considerably based on industry context, AI maturity, and organizational readiness. Study 1 emphasized the importance of leadership, change management, and transparent communication in shaping employee acceptance. Study 2 confirmed that perceived replacement likelihood is a strong negative predictor of both job satisfaction and job security. Importantly, perceived organizational support moderates the effect on job security: high levels of support reduce the negative impact of replacement fears. These results suggest that GenAI implementation should not be viewed as a purely technical process. Instead, it represents a broader organizational shift that requires human-centered strategies. Whether GenAI is seen as a threat, or an opportunity depends on how organizations support their employees throughout the transition. Ultimately, successful adoption hinges not just on what GenAI can automate, but on how people are prepared and empowered to work with it.

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Appendix

Appendix 1: Qualitative Analysis – Interview Script & Transcripts

Access Link to the full interview transcripts and coding units:
https://www.icloud.com/iclouddrive/09arlQ8lf18JsOstjlfnpyjIw

Section 1: Background information

- Could you briefly describe your current role and industry? Also, how many years of experience do you have in this field?
- What are the key responsibilities in your current position?
- Could you provide an overview of the main tasks you perform daily/weekly?

Section 2: Categories of tasks & potential AI influence

1) Which of the tasks follow a structured method (i.e., tasks that follow the same sequence)
   a. How much of your daily work consists of repetitive or routine tasks? (i.e. repetitive tasks (filling in standardized templates, creating standardized reports)
2) Have you already experienced any form of AI integration in your job? If so, to what extent? Can you provide some examples?
3) Which of your tasks do you think could be automated by AI? Why? And which tasks do you think could be partially automated, even if not fully? Why?
4) Which tasks do you think cannot be effectively automated? What are the barriers?
   a. Are there particular tasks you feel more positive about? And more negative about?
   b. How do you feel about the potential of AI to take over some aspects of your work? What aspects of your work do you feel more positive about? What aspects do you feel more negative about?
5) How do you feel about AI assisting humans in tasks in your field?
6) Do you think AI will primarily enhance or reduce job opportunities in your industry? Why?

Section 3: Impact on job security and job satisfaction

7) Do you think AI could positively or negatively affect how satisfied you are with your job? Why and in which areas? i.e. more time for creative work, less administrative
8) Have you noticed any changes in the skill requirements for your job due to AI advancements? How do you feel about these changes?
9) How do you think this increase in AI use impacts your employability? Do you think it will affect how likely you are to lose your current job? How so? And do you think it impacts how likely you are to get a new job if you need to? How so?
10) What measures do you think employees or organizations should take to adapt to AI-driven changes in the workplace?

Section 4: Final reflections

11) Is there anything else you would like to add regarding the role of AI in white-collar jobs?

Appendix 2: Quantitative Survey

Informed consent

Welcome and thank you for considering participating in this survey on the impact of (Generative) Artificial Intelligence on white-collar jobs. I, Jannis Röder, am conducting this survey as part of my Master Thesis at Católica Lisbon School of Business and Economics, under the supervision of Cristina Mendonça. The study consists of answering questions regarding your job and feelings and thoughts related to AI. The survey will take about 7-8 minutes to complete. Your participation will contribute to research in the area of automation and the future workplace. The potential side effects of this study are similar to those applicable to looking at a computer screen for circa 8 minutes (e.g., for instance, fatigue). In the end, you will learn more about the scientific research. All responses will be kept strictly confidential and are anonymous. This means that it will not be possible to link your responses to your identity. The data collected will be used for research purposes only and may be presented in my thesis or disseminated in academic journals, always in an aggregated form, never about any individual response. We ask you to take the study in one go, without interruptions. Please answer as honestly as possible. You may change your mind and drop out at any point of the study during its completion. If you have any questions about this study, please email Jannis Röder (s-jaroder@ucp.pt) .

Participation confirmation

Do you wish to participate?

- ☐ Yes (1)
- ☐ No (2)

Sanity check – currently employed in a white-collar profession

Q1 This study explores the impact of (Generative) AI on white-collar professions. White-collar jobs are typically defined as non-manual roles that involve administrative, managerial, or clerical tasks. These positions are characterized by **intellectual rather than physical labor** and are commonly found in sectors such as government, consulting, academia, accounting, and legal services. Are you currently employed in a **"white-collar"** job?

- ☐ Yes (1)
- ☐ No (2)

Block 1 – Demographics

Q2 Please insert your age as a number.

____

Q3 What is your gender?

- ☐ Male (1)
- ☐ Female (2)
- ☐ Other (3) ____
- ☐ Prefer not to say (4)

Q4 Which country are you from?

▼ Germany (1) ... Poland (55)

Q5 What is your highest level of education?

- ☐ High school diploma (1)
- ☐ Bachelor's degree (2)
- ☐ Master's degree (3)
- ☐ Doctorate/ PhD (4)

Other (please specify) (5)

Q4 Which industry do you primarily work in?

- ☐ Finance (1)
- ☐ Healthcare (2)
- ☐ Legal Services (3)
- ☐ Marketing & Advertising (4)
- ☐ IT & Software development (5)
- ☐ Consulting (6)
- ☐ Industrial Goods (e.g., Automotive, Aerospace) (7)
- ☐ Education and Research (8)

Other (please specify) (9)

Q5 How many years of experience do you have?

- ☐ <1 year (1)
- ☐ 1-5 years (2)
- ☐ 6-10 years (3)
- ☐ 11-20 years (4)
- ☐ 20+ years (5)

Q6 What is your current job function?

- ☐ Management/ Leadership (1)
- ☐ Technical Specialist (e.g., IT, engineering) (2)
- ☐ Administrative/ Support/ Analyst (3)
- ☐ Customer facing role (e.g., Sales, client management, customer service) (4)

Other (please specify) (5)

Block 2 – Tasks and (Gen) AI Usage and attitude

Q7 Please allocate 100% across the following categories based on how your work activities are distributed in your current role.

- ☐ Routine work (e.g., meeting minutes, summaries, translations, standardized reports) : _____(1)
- ☐ Human judgement and problem solving : _______ (2)
- ☐ Communication (e.g., participance in meetings, e-mails, phone-calls) : _______ (3)
- ☐ Creativity : _______ (4)
- ☐ Other (please specify) : _______ (5)
- ☐ Total : ________

Q8 Have you already used (Generative) AI in your work?

- ▢ Yes, regularly (1)
- ▢ Yes, occasionally (2)
- ▢ No, not yet (3)
- ▢ No, and I have no interest using it (4)

Display this question:
If Have you already used (Generative) AI in your work? = Yes, regularly
Or Have you already used (Generative) AI in your work? = Yes, occassionally

Q9 If you have used (Generative) AI, what was the primary purpose of your usage? (Select all that apply)

- ▢ Writing and content creation (1)
- ▢ Data analysis and reporting (2)
- ▢ Coding and software development (3)
- ▢ Customer support or communication (4)
- ▢ Process automation (5)
- ▢ Brainstorming and idea generation (6)
- ▢ Other (please specify) (7)

Q10 How relevant do you consider (Generative) AI to be in the context of your current job responsibilities?

- ▢ Not relevant at all (1)
- ▢ Slightly relevant (2)
- ▢ Moderately relevant (3)
- ▢ Very relevant (4)
- ▢ Extremely relevant (5)

Q11 I am interested in incorporating (Generative) AI systems into my daily routines.

- ▢ Strongly disagree (1)
- ▢ Somewhat disagree (2)
- ▢ Neither agree nor disagree (3)
- ▢ Somewhat agree (4)
- ▢ Strongly agree (5)

Q12 I believe (Generative) AI has useful applications in everyday life and work.

- ▢ Strongly disagree (1)
- ▢ Somewhat disagree (2)
- ▢ Neither agree nor disagree (3)
- ▢ Somewhat agree (4)
- ▢ Strongly agree (5)

Q13 I think (Generative) AI is dangerous.

- ▢ Strongly disagree (1)
- ▢ Somewhat disagree (2)
- ▢ Neither agree nor disagree (3)
- ▢ Somewhat agree (4)
- ▢ Strongly agree (5)

Q14 Organizations use (Generative) AI unethically.

- ▢ Strongly disagree (1)
- ▢ Somewhat disagree (2)
- ▢ Neither agree nor disagree (3)
- ▢ Somewhat agree (4)
- ▢ Strongly agree (5)

Q15 What is the primary way (Generative) AI affects your work?

- ▢ Automates routine tasks (1)
- ▢ Improves decision making (2)
- ▢ Supports creative tasks (3)
- ▢ Helps with complex tasks (4)
- ▢ Has no noticeable impact (5)

Q16 (Generative) AI is likely to significantly change my role in the next 5 years

- ▢ Strongly disagree (1)
- ▢ Somewhat disagree (2)
- ▢ Neither agree nor disagree (3)
- ▢ Somewhat agree (4)
- ▢ Strongly agree (5)

Q17 I believe (Generative) AI is well suited to replace routine cognitive tasks in my profession (e.g., data entry, drafting, repetitive e-mails, reviewing documents, ...)

- ▢ Strongly disagree (1)
- ▢ Somewhat disagree (2)
- ▢ Neither agree nor disagree (3)
- ▢ Somewhat agree (4)
- ▢ Strongly agree (5)

Q18 I believe (Generative) AI is well suited to replace non-routine cognitive tasks in my profession (e.g., strategic decision making, creative problem solving,...)

- ▢ Strongly disagree (1)
- ▢ Somewhat disagree (2)
- ▢ Neither agree nor disagree (3)
- ▢ Somewhat agree (4)
- ▢ Strongly agree (5)

Q19 There is a high likelihood of white-collar workers to being replaced by (Generative) AI in my industry.

- ▢ Strongly disagree (1)
- ▢ Somewhat disagree (2)
- ▢ Neither agree nor disagree (3)
- ▢ Somewhat agree (4)
- ▢ Strongly agree (5)

Block 3 – Impact of (Gen) AI on job satisfaction & job security
Q20 Considering the impact of (Generative) AI in my industry...

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
I think the future of my employment is stable. (1)	○	○	○	○	○
I think the future of my employment is sure. (2)	○	○	○	○	○
I think the future of my employment is unpredictable. (3)	○	○	○	○	○
I think the future of my employment is positive. (4)	○	○	○	○	○
it is upsetting how little job security I have. (5)	○	○	○	○	○
I think the future of my employment looks optimistic (6)	○	○	○	○	○

Q21 Considering the impact of (Generative) AI in my industry,...

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
my job makes me feel fairly satisfied. (2)	○	○	○	○	○
my job makes me feel enthusiastic about work at most days. (3)	○	○	○	○	○
each workday seems like it will never end. (4)	○	○	○	○	○
I find real enjoyment in my work. (5)	○	○	○	○	○
my job feels unpleasant. (6)	○	○	○	○	○

Q22 (Generative) AI will create more job opportunities than efficiencies.

- ▢ Strongly disagree (1)
- ▢ Somewhat disagree (2)
- ▢ Neither agree nor disagree (3)
- ▢ Somewhat agree (4)
- ▢ Strongly agree (5)

Q23 What are the top 3 emotions that you associate with the increased use of (Generative) AI in your workplace?

- ▢ Emotion 1 (4) ____
- ▢ Emotion 2 (5) ____
- ▢ Emotion 3 (6) ____

Q24 My organization has put in a lot of effort to effectively supporting white-collar workers in adapting well to (Generative) AI.

- ▢ Strongly disagree (1)
- ▢ Somewhat disagree (2)
- ▢ Neither agree nor disagree (3)
- ▢ Somewhat agree (4)
- ▢ Strongly agree (5)

Q25 What steps do you think your organization should take to address potential fears of white-collar workers about (Generative) AI?

____

End of Survey text

Thank you for your participation in this study. In this study we want to study how (Generative) AI influences the perception of job security and job satisfaction across white-collar workers as it is the first technological revolution that potentially threatens their jobs if Generative AI can be used for creative, bureaucratic and administrative work. Thank you for your time!

Appendix 3: Population Statistics, Descriptive Statistics, Bivariate Correlation

		Frequency	Percent
ORIGIN	Germany	54	28.6
	Portugal	7	3.7
	Angola	4	2.1
	Armenia	1	.5
	Australia	1	.5
	Austria	10	5.3
	Botswana	15	7.9
	Bulgaria	2	1.1
	Cameroon	1	.5
	Canada	1	.5
	China	3	1.6
	Colombia	1	.5
	Cuba	1	.5
	Czech Republic	3	1.6
	Denmark	2	1.1
	Egypt	1	.5
	Ethiopia	1	.5
	France	3	1.6
	Switzerland	3	1.6
	Netherlands	2	1.1
	Italy	6	3.2
	Spain	1	.5
	United Kingdom	26	13.8
	United States	14	7.4
	Canada	1	.5
	Poland	8	4.2
	South Africa	13	6.9
FUNCTION	Management/ Leadership	48	25.4
	Technical Specialist (e.g., IT, engineering)	30	15.9
	Administrative/ Support/ Analyst	75	39.7
	Customer facing role (e.g., Sales, client management, customer service)	23	12.2
	Other (please specify)	13	6.9
EXPERIENCE	<1 year	26	13.8
	1-5 years	100	52.9
	6-10 years	33	17.5
	11-20 years	16	8.5
	20+ years	14	7.4

		Frequency	Percent
SECTOR	Finance	32	16.9
	Healthcare	16	8.5
	Legal Services	12	6.3
	Marketing & Advertising	16	8.5
	IT & Software development	29	15.3
	Consulting	25	13.2
	Industrial Goods (e.g., Automotive, Aerospace)	10	5.3
	Education and Research	25	13.2
	Other (please specify)	24	12.7
EDUCATION	High school diploma	16	8.5
	Bachelor's degree	92	48.7
	Master's degree	65	34.4
	Doctorate/ PhD	11	5.8
	Other (please specify)	5	2.6
Gender	Male	83	43.9
	Female	102	54.0
	Other	4	2.1

Descriptive Statistics

	N	Minimum	Maximum	M	SD
Age	189	18	61	29.20	7.97
Job Security Index	189	1.00	5.00	3.54	.88
Job Satisfaction	189	1.00	5.00	3.66	.82
Attitude towards AI	189	1.25	5.00	3.52	.79
AI-impact index	189	1.33	5.00	3.77	.80
(Generative) AI will create more job opportunities than efficiencies.	189	1.00	5.00	2.86	1.13
Replacement-Likelihood	189	1.00	5.00	3.10	1.21
Replacement, routine tasks	189	1.00	5.00	3.89	1.04
Replacement, non-routine tasks	189	1.00	5.00	2.69	1.22
Degree of support	186	1.00	5.00	3.10	1.31
What is the primary way (Generative) AI affects your work?	188	1.00	5.00	2.78	1.36
Time distribution – routine tasks	189	.00	100.00	29.49	19.40
Time distribution - Human judgement and problem solving	189	.00	97.00	26.79	15.11
Time distribution - Communication	189	.00	100.00	25.80	15.08
Time distribution - Creativity	189	.00	60.00	16.06	12.78
Time distribution - Other	189	.00	40.00	1.86	6.57
(Gen) AI primary purpose: Writing and content creation	120	1.00	1.00	1.00	.00
(Gen) AI primary purpose: Data analysis and reporting	80	1.00	1.00	1.00	.00
(Gen) AI primary purpose: Coding and software development	45	1.00	1.00	1.00	.00
(Gen) AI primary purpose: Customer support or communication	60	1.00	1.00	1.00	.00
(Gen) AI primary purpose: Process automation	40	1.00	1.00	1.00	.00
(Gen) AI primary purpose: Brainstorming and idea generation	109	1.00	1.00	1.00	.00

Table of frequencies – Impact of GenAI on the job

		Frequency	Percent
Valid	Automates routine tasks	54	28.6
	Improves decision making	21	11.1
	Supports creative tasks	41	21.7
	Helps with complex tasks	56	29.6
	Has no noticeable impact	16	8.5
Total		189	100.0

Bivariate correlation table

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.
1. Job Security	1	.40**	.24**	-.02	.24**	-.47**	-.03	.03	.07	-.12	.03	-.19*	.09	.05	-.08	-.08	-.08
2. Job Satisfaction	.40**	1	.38**	.16*	.13	-.23**	.12	.08	.34**	-.01	.03	-.04	.08	-.01	.07	-.01	-.18*
3. AI attitude	.24**	.38**	1	.46**	.34**	-.13	.34**	.23**	.41**	-.01	-.13	.00	.11	-.18*	.16*	-.14	-.22**
4. AI impact	-.02	.16*	.46**	1	.17*	.21**	.37**	.32**	.40**	.06	-.09	-.05	.07	-.11	.21**	-.06	-.18*
5. Opportunities > efficiencies	.24**	.13	.34**	.17*	1	-.11	.11	.23**	.23**	.08	-.11	.11	.07	-.10	.12	-.03	-.15*
6. Replacement likelihood	-.47**	-.23**	-.13	.21**	-.11	1	.04	.21**	.05	.04	-.08	.04	-.01	-.04	.11	.14	-.03
7. Replacement, routine tasks	-.03	.12	.34**	.37**	.11	.04	1	.17*	.22**	.05	-.09	-.09	.11	-.15*	.17*	-.14	-.08
8. Replacement, non-routine tasks	.03	.08	.23**	.32**	.23**	.21**	.17*	1	.18*	.00	-.10	.06	-.0.09	-.01	.12	.11	-.21**
9. Degree of Support	.07	.34**	.41**	.40**	.23**	.05	.22**	.18*	1	-.13	.01	.14	.12	-.09	.04	.04	-.14
10. Age	-.12	-.01	-.01	.06	.08	.04	.05	.00	-.13	1	-.01	.19*	.16*	.06	.75**	-.05	-.19**

11. Gender	.03	.03	-.13	-.09	-.11	-.08	-.09	-.10	.01	-.01	1	.15*	.18*	.07	-.01	.17*	.03
12. Origin	-.19*	-.04	.00	-.05	.11	.04	-.09	.06	.14	.19*	.15*	1	.08	.04	.17*	.08	-.09
13. Education	.09	.08	.11	.07	.07	-.01	.11	-.09	.12	.16*	.18*	.08	1	.08	.16*	.10	-.09
14. Industry	.05	-.01	-.18*	-.11	-.10	-.04	-.15*	-.01	-.09	.06	.07	.04	.08	1	.00	.15*	.06
15. Experience (y)	-.08	.07	.16*	.21**	.12	.11	.17*	.12	.04	.75**	-.01	.17*	.16*	.00	1	-.07	-.37**
16. EffGenAI-Work	-.08	-.01	-.14	-.06	-.03	.14	-.14	.11	.04	-.05	.17*	.09	.10	.15*	-.07	1	-.06
17. Job function	-.08	-.18*	-.22**	-.18*	-.15*	-.03	-.08	-.21**	-.14	-.19**	.03	-.10	-.09	.06	-.37**	-.06	1

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Note: EffGenAIWork = Perceived effect of GenAI on the work

Appendix 4: Factor analysis

Correlation Matrix

		1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.
Correlation	1. JSI_neg1R	1.00	0.60	0.50	0.47	0.41	0.41	0.19	0.04	0.12	0.21	0.16
	2. JSS_neg2R	0.60	1.00	0.45	0.53	0.41	0.43	0.25	0.14	0.16	0.26	0.30
	3. JSI_pos2	0.50	0.45	1.00	0.76	0.51	0.60	0.38	0.32	0.38	0.16	0.23
	4. JSI_pos1	0.47	0.53	0.76	1.00	0.51	0.68	0.32	0.23	0.27	0.10	0.24
	5. JSS_pos4	0.41	0.41	0.51	0.51	1.00	0.73	0.40	0.39	0.31	0.20	0.19
	6. JSS_pos3	0.41	0.43	0.60	0.68	0.73	1.00	0.34	0.21	0.33	0.09	0.21
	7. JS_pos1	0.19	0.25	0.38	0.32	0.40	0.34	1.00	0.70	0.63	0.35	0.59
	8. JS_pos2	0.04	0.14	0.32	0.23	0.39	0.21	0.70	1.00	0.71	0.37	0.58
	9. JS_pos3	0.12	0.16	0.38	0.27	0.31	0.33	0.63	0.71	1.00	0.34	0.59
	10. JS_neg1R	0.21	0.26	0.16	0.10	0.20	0.09	0.35	0.37	0.34	1.00	0.45
	11. JS_neg2R	0.16	0.30	0.23	0.24	0.19	0.21	0.59	0.58	0.59	0.45	1.00

a. Determinant = .002

Eigenvalues

Total Variance Explained

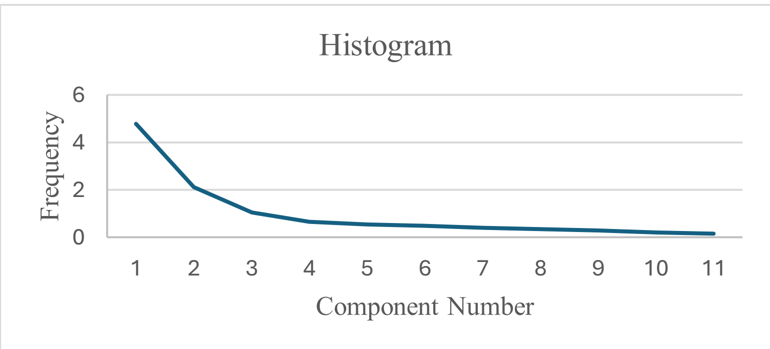
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	4.78	43.45	43.45	4.78	43.45	43.45	3.80
2	2.11	19.20	62.65	2.11	19.20	62.65	3.44
3	1.05	9.55	72.20	1.05	9.55	72.20	1.97
4	0.66	6.04	78.24				
5	0.54	4.91	83.15				
6	0.48	4.34	87.49				
7	0.39	3.55	91.04				
8	0.35	3.21	94.25				
9	0.28	2.52	96.77				
10	0.20	1.86	98.63				
11	0.15	1.38	100.00				

Extraction Method: Principal Component Analysis.
a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.809
Bartlett's Test of Sphericity	Approx. Chi-Square	1041.47
	df	55
	Sig.	<.001

Frequency



Pattern Matrix

	Component		
	1	2	3
JSI_neg1R	0.48	−0.19	0.63
JSS_neg2R	0.43	−0.07	0.66
JSI_pos2	0.78	0.13	0.08
JSI_pos1	0.83	0.02	0.10
JSS_pos4	0.74	0.18	−0.03
JSS_pos3	0.88	0.07	−0.07
JS_pos1	0.21	0.78	−0.01
JS_pos2	0.09	0.89	−0.12
JS_pos3	0.16	0.83	−0.10
JS_neg1R	−0.25	0.47	0.64
JS_neg2R	−0.08	0.75	0.30

Appendix 5: Regression and moderation

Regression 1, Dependent Variable: Job Security Index

Variables Entered/Removed

Model	Variables Entered	Variables Removed	Method
1	Replacement_Likelihood	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
2	GenAIOpportunities	.	
3	Attitude_MEAN	.	

a. Dependent Variable: Job security mean

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics
					R Square Change
1	.47a	.22	.21	.78	.22
2	.50b	.25	.25	.76	.04
3	.52c	.27	.26	.76	.02

a. Predictors: (Constant), Replacement_Likelihood, b. Predictors: (Constant), Replacement_Likelihood, GenAIOpportunities

c. Predictors: (Constant), Replacement_Likelihood, GenAIOpportunities, Attitude_MEAN

d. Dependent Variable: Job security mean

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	30.96	1	30.96	50.81	<.001b
	Residual	112.12	184	.61		
	Total	143.08	185			
2	Regression	36.19	2	18.10	30.98	<.001c
	Residual	106.89	183	.58		
	Total	143.08	185			
3	Regression	38.54	3	12.85	22.36	<.001d
	Residual	104.54	182	.57		
	Total	143.08	185			

a. Dependent Variable: Job security mean, b. Predictors: (Constant), Replacement_Likelihood

c. Predictors: (Constant), Replacement_Likelihood, GenAIOpportunities

d. Predictors: (Constant), Replacement_Likelihood, GenAIOpportunities, Attitude_MEAN

		Unstandardized Coefficients		St. Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	4.59	.16		29.01	<.001
	Replacement_Likelihood	-.34	.05	-.47	-7.13	<.001
2	(Constant)	4.12	.22		18.53	<.001
	Replacement_Likelihood	-.32	.05	-.45	-6.92	<.001
	GenAIOpportunities	.15	.05	.19	2.99	.003
3	(Constant)	3.65	.32		11.49	<.001
	Replacement_Likelihood	-.32	.05	-.43	-6.74	<.001
	GenAIOpportunities	.12	.05	.15	2.17	.031
	Attitude_MEAN	.15	.07	.14	2.02	.045

Excluded Variables

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics		
						Tolerance	VIF	Min. Tolerance
1	Gender	-.01b	-.18	.86	-.01	.99	1.01	.99
	Age	-.10b	-1.47	.14	-.11	1.00	1.00	1.00
	Origin	.04b	.64	.53	.05	.99	1.01	.99
	Education	.08b	1.28	.20	.09	1.00	1.00	1.00
	Industry	.03b	.48	.63	.04	1.00	1.00	1.00
	Experience (y)	-.03b	-.38	.70	-.03	.99	1.01	.99
	Function	-.10b	-1.46	.15	-.11	1.00	1.00	1.00
	Attitude_MEAN	.19b	2.88	.00	.21	.98	1.02	.98
	AI impact index	.09b	1.29	.20	.10	.96	1.05	.96
	GenAIOpportunities	.19b	2.99	.00	.22	.99	1.01	.99
	Replacement, routine tasks	-.01b	-.18	.86	-.01	1.00	1.00	1.00
	Replacement, non-routine tasks	.13b	1.92	.06	.14	.96	1.04	.96
	Degree of support	.10b	1.49	.14	.11	1,00	1.00	1,00
2	Gender	.01c	.16	.87	.01	.98	1.02	.98
	Age	-.11c	-1.78	.08	-.13	.99	1.01	.98
	Origin	.02c	.33	.74	.02	.98	1.02	.98
	Education	.07c	1.11	.27	.08	1,00	1.01	.98
	Industry	.05c	.80	.43	.06	.99	1.01	.98
	Experience (y)	-.05c	-.80	.43	-.06	.97	1.03	.97
	Function	-.07c	-1.04	.30	-.08	.98	1.03	.97
	Attitude_MEAN	.14c	2.02	.05	.15	.87	1.14	.87
	AI impact index	.05c	.72	.47	.05	.91	1.09	.92

	Replacement, routine tasks	-.03c	-.53	.60	-.04	.99	1.02	.98
	Replacement, non-routine tasks	.08c	1.23	.22	.09	.90	1.12	.90
	Degree of support	.06c	.83	.41	.06	.94	1.06	.93
3	Gender	.03d	.40	.69	.03	.97	1.03	.86
	Age	-.11d	-1.72	.09	-.13	.99	1.01	.87
	Origin	.02d	.26	.79	.02	.98	1.02	.87
	Education	.06d	.94	.35	.07	.99	1.01	.87
	Industry	.07d	1.15	.25	.09	.96	1.04	.85
	Experience (y)	-.07d	-1.10	.27	-.08	.95	1.05	.86
	Function	-.04d	-.67	.50	-.05	.94	1.07	.84
	Attitude_MEAN	-.02d	-.27	.79	-.02	.71	1.41	.70
	AI impact index	-.09d	-1.29	.20	-.10	.88	1.14	.78
	GenAIOpportunities	.06d	.86	.39	.06	.86	1.16	.84
	Replacement, routine tasks	.01d	.09	.93	.01	.81	1.24	.75

a. Dependent Variable: Job security mean, b. Predictors in the Model: (Constant), Replacement_Likelihood

c. Predictors in the Model: (Constant), Replacement_Likelihood, GenAIOpportunities

d. Predictors in the Model: (Constant), Replacement_Likelihood, GenAIOpportunities, Attitude_MEAN

Collinearity Diagnostics

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions			
				(Constant)	Repl. Likelihood	GenAIOpportunities	Attitude_MEAN
1	1	1.93	1.00	.03	.03		
	2	.07	5.35	.97	.97		
2	1	2.81	1.00	.01	.02	.02	
	2	.15	4.39	.00	.44	.46	
	3	.04	8.19	.99	.55	.53	
3	1	3.77	1.00	.00	.01	.01	.00
	2	.15	4.99	.00	.50	.29	.01
	3	.06	7.67	.06	.27	.70	.23
	4	.02	13.79	.93	.22	.00	.76

Regression 2, job satisfaction

Variables Entered/Removed

Model	Variables Entered	Variables Removed	Method
1	Attitude_MEAN	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
2	DegreeofSupport	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
3	Replacement_Likelihood	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).

a. Dependent Variable: JS mean

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.38a	.15	.14	.76	.15	31.24	1	181	<.001
2	.43b	.19	.18	.74	.04	8.91	1	180	.003
3	.48c	.23	.22	.72	.04	9.53	1	179	.002

a. Predictors: (Constant), Attitude_MEAN, DegreeofSupport, Replacement_Likelihood, b. Dependent Variable: JS mean

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	17.87	1	17.87	31.24	<.001[b]
	Residual	103.57	181	0.57		
	Total	121.45	182			
2	Regression	22.76	2	11.38	20.76	<.001[c]
	Residual	98.69	180	.55		
	Total	121.45	182			
3	Regression	27.75	3	9.25	17.67	<.001[d]
	Residual	93.70	179	0.52		
	Total	121.45	182			

a. Predictors: (Constant), Attitude_MEAN, DegreeofSupport, Replacement_Likelihood, b. Dependent Variable: JS mean

		B	Std. Error	Beta			Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	2.27	0.26		8.87	<.001					
	Attitude towards AI	0.40	0.07	0.38	5.59	<.001	0.38	0.38	0.38	1.00	1.00
2	(Constant)	2.17	0.25		8.61	<.001					
	Attitude towards AI	0.30	0.08	0.29	3.97	<.001	0.38	0.28	0.27	0.83	1.20
	Degree of support	0.14	0.05	0.22	2.99	0.003	0.34	0.22	0.20	0.83	1.20
3	(Constant)	2.69	0.30		9.02	<.001					
	Attitude towards AI	0.26	0.08	0.26	3.50	<.001	0.38	0.25	0.23	0.81	1.24

Degree of support	0.15	0.05	0.25	3.39	<.001	0.34	0.25	0.22	0.82	1.22
Replacement-Likelihood	−0.14	0.05	−0.21	−3.09	0.002	−0.23	−0.23	−0.20	0.97	1.03

Excluded Variables

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance	VIF	Minimum Tolerance
1	Age	−0.01[b]	−0.08	0.94	−0.01	1.00	1.00	1.00
	AI impact index	−0.02[b]	−0.30	0.77	−0.02	0.79	1.28	0.79
	GenAIOpportunities	0.00[b]	0.03	0.98	0.00	0.88	1.13	0.88
	Replacement-Likelihood	−0.18[b]	−2.63	0.01	−0.19	0.98	1.02	0.98
	Replacement, routine tasks	−0.01[b]	−0.11	0.91	−0.01	0.88	1.13	0.88
	Replacement, non-routine tasks	−0.01[b]	−0.17	0.87	−0.01	0.95	1.06	0.95
	Degree of support	0.22[b]	2.99	0.00	0.22	0.83	1.20	0.83
	Gender	0.09[b]	1.24	0.22	0.09	0.98	1.02	0.98
	Origin	−0.04[b]	−0.62	0.53	−0.05	1.00	1.00	1.00
	Industry	0.06[b]	0.87	0.39	0.07	0.97	1.03	0.97
	Experience (y)	0.01[b]	0.19	0.85	0.01	0.98	1.03	0.98
	Function	−0.10[b]	−1.41	0.16	−0.10	0.95	1.05	0.95
2	Age	0.02[c]	0.35	0.73	0.03	0.98	1.02	0.81
	AI impact index	−0.09[c]	−1.13	0.26	−0.08	0.73	1.37	0.72
	GenAIOpportunities	−0.02[c]	−0.28	0.78	−0.02	0.87	1.14	0.77
	Replacemen-Likelihood	−0.21[c]	−3.09	0.00	−0.23	0.97	1.03	0.81
	Replacement, routine tasks	−0.03[c]	−0.40	0.69	−0.03	0.88	1.14	0.76

	Replacement, non-routine tasks	−0.03[c]	−0.46	0.64	−0.03	0.94	1.07	0.81
	Degree of support	0.07[c]	1.07	0.29	0.08	0.98	1.02	0.81
	Gender	−0.08[c]	−1.11	0.27	−0.08	0.98	1.02	0.81
	Origin	0.06[c]	0.94	0.35	0.07	0.97	1.03	0.81
	Industry	0.02[c]	0.29	0.77	0.02	0.97	1.03	0.81
	Experience (y)	−0.09[c]	−1.28	0.20	−0.10	0.95	1.06	0.80
3	Age	0.04[d]	0.54	0.59	0.04	0.98	1.02	0.80
	AI impact index	−0.02[d]	−0.27	0.79	−0.02	0.67	1.50	0.67
	GenAIOpportunities	−0.04[d]	−0.53	0.60	−0.04	0.87	1.15	0.75
	Replacemen-Likelihood	−0.01[d]	−0.15	0.88	−0.01	0.87	1.15	0.74
	Replacement, routine tasks	0.02[d]	0.26	0.79	0.02	0.89	1.13	0.77
	Replacement, non-routine tasks	0.05[d]	0.76	0.45	0.06	0.97	1.04	0.79
	Degree of support	−0.07[d]	−1.06	0.29	−0.08	0.98	1.03	0.80
	Gender	0.05[d]	0.77	0.44	0.06	0.96	1.04	0.79
	Origin	0.05[d]	0.73	0.47	0.06	0.96	1.05	0.78
	Industry	−0.10[d]	−1.49	0.14	−0.11	0.94	1.06	0.78

a. Dependent Variable: JS mean, b. Predictors in the Model (Constant), Attitude_MEAN, DegreeofSupport, Replacement_Likelihood

Collinearity Diagnostics

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions			
				(Constant)	Attitude_MEAN	DegreeofSupport	Replacement_Likelihood
1	1	1.98	1.00	0.01	0.01		
	2	0.02	9.03	0.99	0.99		
2	1	2.89	1.00	0.01	0.00	0.01	
	2	0.09	5.69	0.12	0.05	0.94	
	3	0.02	11.11	0.87	0.95	0.05	
3	1	3.77	1.00	0.00	0.00	0.01	0.01
	2	0.14	5.19	0.00	0.01	0.33	0.52
	3	0.08	7.05	0.08	0.14	0.62	0.25
	4	0.02	14.03	0.91	0.84	0.04	0.22

a. Dependent Variable: JS mean

Moderation Analysis, JSI (Job Security)

Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

Written by Andrew F. Hayes, Ph.D.   www.afhayes.com
Documentation available in Hayes (2022). www.guilford.com/p/hayes3

****
Model : 1
Y : JSI_Mean
X : Repl_lik
W : Support

Covariates:
AI_Imp Origin Gender Age Exp Func Industry Educ GAIOpps Act_Rout
AI_Att

Sample
Size: 183

****
OUTCOME VARIABLE:
JSI_Mean

R	R^2	MSE	F	df_1	df_2	p
.6167	.3803	.5194	7.3636	14	168	< .001

Model	coeff	se	t	P	LLCI	UCLI
constant	4.7138	0.6155	7.6582	< .001	3.4986	5.9289
Repl_lik	-0.6046	0.1203	-5.0237	< .001	-0.8421	-0.3670
Support	-0.2439	0.1132	-2.1545	.033	-0.4673	-0.0204
Int_1	0.0908	0.0334	2.7187	.007	0.0249	0.1567
AI_Imp	-0.0169	0.0852	-1.1983	.843	-0.1851	0.1513
Origin	-0.0081	0.0024	-3.3258	.001	-0.0129	-0.0033
Gender	0.0196	0.1063	1.1841	.854	-0.1902	0.2293
Age	-0.0107	0.0107	-1.0033	.317	-0.0318	0.0104
Exp	0.0146	0.0833	1.1749	.861	-0.1499	0.1790
Func	-0.0536	0.0497	-1.0789	.282	-0.1517	0.0445
Industry	0.0250	0.0200	1.2504	.213	-0.0145	0.0645
Educ	0.0619	0.0674	0.9191	.359	-0.0711	0.1949
GAIOpps	0.1493	0.0516	2.8909	.004	0.0473	0.2512
Act_Rout	0.0028	0.0029	0.9748	.331	-0.0029	0.0086
AI_Att	0.1289	0.0866	1.4879	.139	-0.0421	0.3000

Product terms key:
Int_1 : Repl_lik x Support

Test(s) of highest order unconditional interaction(s):

R^2 change	F	df_1	df_2	p
.0273	7.3912	1	168	.007

Focal predict: Repl_lik (X)
Mod var: Support (W)

Conditional effects of the focal predictor at values of the moderator(s):

Support	Effect	se	t	p	LLCI	ULCI
2.0000	-0.4230	0.0652	-6.4843	< .001	-0.5518	-0.2942
3.0000	-0.3322	0.0499	-6.6620	< .001	-0.4307	-0.2338
5.0000	-0.1507	0.0751	-2.0065	.046	-0.2989	-0.0024

**************** ANALYSIS NOTES AND ERRORS *****************
Level of confidence for all confidence intervals in output: 95.0000

W values in conditional tables are the 16th, 50th, and 84th percentiles.

------ END MATRIX -----

Moderation Analysis, JS (Job Satisfaction)
Run MATRIX procedure:
***************** PROCESS Procedure for SPSS Version 4.2 *****************
Written by Andrew F. Hayes, Ph.D. www.afhayes.com
Documentation available in Hayes (2022). www.guilford.com/p/hayes3

****
Model : 1
Y : JS_MEAN
X : Repl_lik
W : Support
Covariates:
AI_Imp Origin Gender Age Exp Func Industry Educ GAIOpps Act_Rout
AI_Att

Sample
Size: 183
****
OUTCOME VARIABLE: JS_MEAN

Model Summary

R	R^2	MSE	F	df_1	df_2	p
.5805	.3370	.4745	6.0983	14	168	< .001

Model

	coeff	se	t	p	LLCI	ULCI
constant	39.2220	0.5883	66.6710	< .001	27.6080	50.8360
Repl_lik	-0.2793	0.1150	-24.2810	.016	-0.5064	-0.0522
Support	-0.0166	0.1082	-0.1539	.878	-0.2302	0.1969
Int_1	0.0614	0.0319	19.2460	.056	-0.0016	0.1244
AI_Imp	-0.1002	0.0814	-12.3040	.220	-0.2609	0.0606
Origin	-0.0040	0.0023	-17.3600	.084	-0.0086	0.0006
Gender	0.0428	0.1016	0.4211	.674	-0.1577	0.2433
Age	0.0011	0.0102	0.1077	.914	-0.0190	0.0212
Exp	0.0035	0.0796	0.0444	.965	-0.1536	0.1607
Func	-0.0695	0.0475	-14.6360	.145	-0.1632	0.0242
Industry	0.0105	0.0191	0.5499	.583	-0.0272	0.0482
Educ	0.0154	0.0644	0.2385	.812	-0.1117	0.1425
GAIOpps	-0.0217	0.0494	-0.4405	.660	-0.1192	0.0757
Act_Rout	-0.0108	0.0028	-38.6760	< .001	-0.0163	-0.0053
AI_Att	0.2601	0.0828	31.4130	.002	0.0966	0.4236

Product terms key:
Int_1 : Repl_lik x Support

Test(s) of highest order unconditional interaction(s):

R^2 change	F	df_1	df_2	p
.0146	3.7040	1	168	.056

Focal predict: Repl_lik (X)
Mod var: Support (W)

Conditional effects of the focal predictor at values of the moderator(s):

Support	Effect	se	t	p	LLCI	ULCI
2.0000	-0.1564	0.0623	-25.0920	.013	-0.2795	-0.0334
3.0000	-0.0950	0.0477	-19.9370	.048	-0.1891	-0.0009
5.0000	0.0278	0.0718	0.3875	.699	-0.1139	0.1695

***************** ANALYSIS NOTES AND ERRORS ******************
Level of confidence for all confidence intervals in output: 95.0000

W values in conditional tables are the 16th, 50th, and 84th percentiles.------ END MATRIX