The impact of interacting with AI in the workplace on employees' job and life satisfaction

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Dissertation written under the supervision professor
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Dissertation submitted in partial fulfillment of requirements for the MSc in Management with Specialization in Strategic Marketing at the Universidade Católica Portuguesa, April 3rd, 2024.

ABSTRACT

Title: The impact of interacting with AI in the workplace on employees' job and life satisfaction

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Given that AI is being implemented in the workplace, it is crucial to understand its impacts on employees' well-being. While previous research has focused on the negative consequences of AI related to stress and job insecurity, this thesis contributes to research by focusing on the positive implications. Thus, this research aims to investigate the impact of interacting with AI on employees' job and life satisfaction while considering their attitudes towards AI and applying the JD-R model. The proposed model was tested using a PLS-SEM analysis with 268 participants in a correlational research design. The results showed that interacting with AI is positively and directly correlated with job satisfaction and indirectly influences life satisfaction through the mediating role of job satisfaction. The same can be said about attitudes towards AI and job resources which are positively directly correlated with job satisfaction and indirectly with life satisfaction. No statistically significant effects regarding job demands were found. Moreover, none of the moderation effects of attitudes towards AI, job demands, and job resources could be supported. These findings provide valuable implications for organizations and practitioners seeking to implement AI in the workplace.

Keywords: artificial intelligence, workplace, attitudes towards AI, interaction with AI, job satisfaction, life satisfaction, job resources, job demands, JD-R model

SUMÁRIO

Título: O impacto da interação com a IA no local de trabalho na satisfação do trabalho e da vida dos funcionários

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Dado que a IA está sendo implementada no local de trabalho, é crucial entender seus impactos no bem-estar dos funcionários. Este estudo investiga a interação com a IA sobre a satisfação do trabalho e da vida dos funcionários, considerando suas atitudes em relação à IA, demandas de trabalho e recursos. O modelo proposto foi testado usando uma análise PLS-SEM com 268 participantes em um projeto de pesquisa correlacional. Os resultados mostraram que a interação com a IA está positivamente e diretamente correlacionada com a satisfação no trabalho e influenciam indiretamente a satisfacção na vida através do papel mediador da satisfacção no emprego. O mesmo pode ser dito sobre atitudes em relação à IA e aos recursos de emprego que estão positivamente diretamente correlacionados com a satisfação no trabalho e indiretamente com a satisfacção na vida. Não foram encontrados efeitos estatisticamente significativos relativamente às demandas de emprego. Além disso, nenhum dos efeitos de moderação das atitudes em relação à IA, demandas de emprego e recursos de emprego poderiam ser suportados. Essas descobertas fornecem implicações valiosas para organizações e profissionais que procuram implementar a IA no local de trabalho.

Palavras-chave: inteligência artificial, local de trabalho, atitudes em relação à IA, interação com a IA, satisfação com o trabalho, satisfeição com a vida, recursos de emprego, demandas de emprego Modelo JD-R

ACKNOWLEDGEMENTS

This thesis marks the end of my student life and time in Lisbon. The last 1.5 years were filled with moments of laughter with friends, dancing to techno at the Who the f*** is Henry? train station, drinking lots of Sangria and Somersby, eating Pastel de Nata, surfing and exploring the beaches and most of all learning and studying for all the different courses. I had an amazing time at Católica Lisbon, making memories and friendships that will hopefully last a lifetime, for which I am deeply grateful.

First of all, I wish to express my sincere appreciation to my supervisor Filipa regarding her continuous support and encouragement throughout the thesis process, from figuring out my topic, contemplating various research designs to the in-depth feedback of my drafts.

Secondly, I want to express my deepest gratitude to my mum, for supporting me financially and emotionally, and my sister for her motivational speeches that kept me going.

Thirdly, I want to thank my strategic marketing girlies Chica, Elana, Joana, and Sofia for being my core support at Católica, for suffering together through group projects and exams, for laughing and crying together, eating all the good food and providing emotional support and hugs 24/7.

Another big thank you goes out to Jill, who motivated me a lot during the last sprint of the thesis. Thank you for sitting with me for so many hours at the Starbucks on Langkawi, Malaysia until the baristas knew our names and orders by heart – thank you as well for the amazing drinks prepared by Ekmal to keep us going.

Last but not least, my heart goes out to the Lisbon Gang, for all the birthday dinners, parties, exploring Lisbon, the Algarve spring break,.. . Thank you Chica, Elana, Elena, Emma, Jasmin, Jill, Jojo, Jules, Linus, Mark, Mathieu, Robin, Sander, Sofia. I cannot wait for a reunion soon in Lisbon to graduate all together in November !!

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GLOSSARY

&	And
a	Cronbach’s alpha
AI	Artificial Intelligence
AIAS	AI Attitude Scale
AGI	Artificial General Intelligence
ANI	Artificial Narrow Intelligence
ASI	Artificial Super-Intelligence
AVE	Average Variance Extracted
ß	Beta-Coefficient (Regression Coeffiient)
CR	Composite Reliability
DV	Dependent Variable
DRM	Day Reconstruction Method
f2	Effect Size
JCQ	Job Content Questionnaire
JD-R	Job Demands-Resources
HAI	Human-Centered Artificial Intelligence
H1	Hypothesis 1 (2-7 respectively)
HRM	Human Resource Management
HTMT	Heterotrait-Monotrait ratio of correlations
IV	Independent Variable
M	Sample Mean
N	Total number of cases
NFI	Normed Fit Index
NHI	No-Human-Interaction
p	p-value
PLS-SEM	Partial least squares structural equation modelling
R2	R-squared; coefficient of determination; measure of variance explained
RPA	Robotic Process Automation
SD	Standard Deviation
SEM	Structural equation modelling
SES	Self-Esteem Scale
SRMR	Standardised Root Mean Square Residual
SWLS	Satisfaction with Life Scale

t	t-statistic (t-value)
VA	Virtual Assistant
WDRM	Work Day Reconstruction Method
$\chi 2$	Chi-square

1 INTRODUCTION

1.1 Topic Presentation

"In the future, I believe we will see more collaboration between humans and AI, with machines taking on tasks that are repetitive and mundane, freeing humans to focus on problem-solving, creativity, and empathy."

- Fei-Fei Li, Computer Scientist, and Co-Director of Stanford Institute for Human-Centered Artificial Intelligence (HAI).

Artificial Intelligence (AI) in the workplace indicates the beginning of a revolutionary era where human-machine collaboration is redefining the nature of work (Wang & Krishnan, 2020). The way businesses run and how employees interact with their jobs has undergone a profound transformation as a result of this transition (Lee et al, 2022). According to Fei-Fei Li, AI will enhance human labour rather than replace it, allowing people to overcome the constraints of monotonous work and focus more on creative, compassionate, and strategic endeavours (Dengel et al, 2021).

According to the World Economic Forum's "Future of Jobs Report 2020," it is projected that by 2025, automation and a new division of labor between people and machines will disrupt 85 million jobs worldwide in medium and large-sized enterprises across 15 industries and 26 economies. Over 50% of employers anticipate accelerating the automation of certain roles in their organisations, and over 80% of corporate executives are accelerating plans to implement innovative technologies and digitise work processes. However, it is expected that the robot revolution will create 97 million new jobs better suited to the new division of labor between humans, machines and algorithms (World Economic Forum, 2020). Moreover, the State of the Global Workplace 2022 report by Gallup revealed that 19% of workers globally are miserable and 60% feel emotionally detached at work, demonstrating the urgent need of exploring ways of enhancing job satisfaction and general well-being (Gallup, 2022). The level of stress employees feel at work has been steadily increasing over the past years as well, reaching record levels of 44% (Gallup, 2023).

Numerous advantages are linked to AI technologies, ranging from increased productivity, quicker and more precise outcomes, and a lower error rate at the process level to more successful and enhanced strategic outcomes at the organisational level (Davenport et al., 2020, Paschen et al., 2020). Evidence suggests that this is not always the case, even while AI has the ability to produce outcomes that are valued by organisations (Canhoto & Clear, 2020). Several businesses put time, money, and resources into artificial intelligence (AI), but they rarely see the results they had hoped for, leading them to declare AI projects a failure (Fountaine, McCarthy, & Saleh, 2019). As a survey of executives by BCG and MIT discovered, seven out of ten AI projects generated little impact and AI implementation plans dropped from 20% in 2019 to 4% in 2020 (The Economist, 2020). Similarly, in a study of senior managers working on 152 AI projects, Deloitte (2017) reports that 47% of respondents find it difficult to integrate AI with existing people, processes, and systems.

Thus, it is clear that in order for AI to be successful, employees must embrace, interact with, and integrate their behavior with AI systems (Glikson & Woolley, 2020, Lichtenthaler, 2018). The significance of AI and employee integration is clear, especially in practitioner literature and anecdotal evidence (Shrestha, Ben-Menahem, & von Krogh, 2019); yet the investigation of this integration is less developed in the management and organizational academic literature, with few AI related articles published in top management journals that are even "remotely connected" to people and work (Phan, Wright, & Lee, 2017). Moreover, much of the existing research on AI focuses on its technical application (e.g., Barrett, Oborn, Orlikowski, & Yates, 2012). Scholars have started to acknowledge the benefits and risks from the use of AI at work and the impact that smart computer-based technologies can have for people and organizations alike (Ibarra et al., 2018; Müller et al., 2020). Unlike prior technology, AI will have the capability to collaborate, learn from, and adapt to employee interactions (Davenport et al., 2020, Murray et al., 2020). Thus, to successfully bring and integrate AI into the organization, it is important to consider its social aspects. Given the increasing prevalence of AI systems in the workplace, it is crucial to understand how these systems impact job satisfaction (Huang & Rust, 2018). The way that work is done and the experiences that employees have at work might be drastically changed by incorporating AI technologies into various organisational processes. Gaining insight into the ways in which AI affects job satisfaction can be quite beneficial in analysing the changing nature of the contemporary workplace. Furthermore, job satisfaction is an important determinant in employee well-being, productivity, and retention (Abdullah, 2021). By examining the effects of AI on job satisfaction, businesses may better understand the opportunities and problems that come with implementing AI, which will help them create plans that will improve both employee happiness and overall business performance.

1.2 Problem Statement & Research Questions

The scope of this research is to explore how the interaction with AI in the workplace impacts employees' job satisfaction and to what extent it influences their life satisfaction. This problem statement substantiates itself into the following research questions:

RQ1: Does interacting with AI in the workplace affect employees' job satisfaction?

RQ2: Does interacting with AI in the workplace affect employees' life satisfaction?

RQ3: Do employees' attitudes towards AI impact their job and life satisfaction?

RQ4: How does interaction with AI in the workplace influence job satisfaction within the framework of the JD-R model, particularly when considering the moderating effects of perceived job demands and resources?

1.3 Academic & Managerial Relevance

Academically, this study contributes to the growing field of knowledge in HRM literature by exploring how workplace dynamics are evolving in the age of AI. Even though previous work has examined the influence of AI on organizational outcomes, a knowledge gap exists concerning the individual level, which this research wants to bridge (Pereira et al, 2023). This dissertation explores the emotional and social side of interacting with AI in the workplace, while previous research has concentrated on the technical aspects. Obtaining insights how AI is affecting job and life satisfaction will prove valuable for educational institutions and policymakers since they design curricula and policies that align with the demands of an AI-driven economy. Last but not least, this study offers an abundant setting for theoretical advancement by examining the complex relationships among artificial intelligence, job satisfaction, and general well-being.

This study provides managers and organisational leaders with a data-driven understanding of the effects of integrating AI in the workplace. Knowledge of the way AI may positively or negatively impact job satisfaction and work-life balance can inform decisions regarding AI

adoption and implementation strategies. Additionally, managers can utilise the findings to create employee-centric strategies that promote a more harmonious work environment.
For instance, identifying factors that improve job satisfaction and well-being in AI-assisted work environments can lead to targeted interventions, such as training programs or AI implementation adjustments. Moreover, businesses that put their workers' well-being first and successfully use AI to raise job satisfaction may find themselves at a competitive advantage. The results of a meta-analysis of 312 research studies conducted by Judge et al. (2001) indicated a significant and positive correlation between job satisfaction (a key component of employee happiness) and job performance. Thus, happier employees are typically more committed and productive, which may enhance organisational performance (Judge et al, 2001). Understanding the capabilities and limitations of AI also helps managers in strategically deploying AI tools to complement human skills, rather than solely automating jobs.

1.4 Research Methods

Primary data was collected through an online survey which was created using the platform Qualtrics and distributed via email and WhatsApp, social media channels including Instagram and Facebook, the professional networking sites LinkedIn, the survey sharing platform SurveyCircle, and the website Prolific to reach a wide variety of potential participants. This research consisted of a correlational research design, investigating whether there is a relationship between the interaction with AI and job and life satisfaction. The advantage of correlational research is that it is usually high in external validity, which means that the findings can be generalized to real life settings (Brewer & Crano, 2014). However, a downside is that the internal validity tends to be low, making it difficult to causally connect changes in one variable to changes in another variable (Brewer & Crano, 2014).

1.5 Structure

Following this introductory chapter, Chapter 2 consists of a literature review of the key research on AI, Applications of AI in the workplace, life satisfaction, and job satisfaction as well as the conceptual model. While the methodology and research design of the underlying study are explained in detail in Chapter 3, Chapter 4 provides a summary of the study's main analyses and results. These findings are further discussed in Chapter 5. Finally, Chapter 6 covers the main findings and answers the research questions, discusses theoretical and practical implications, the limitations of the study, and recommendations for future research.

2 LITERATURE REVIEW & CONCEPTUAL FRAMEWORK

This section presents an introduction and overview of AI and its applications in the workplace, addresses life satisfaction and job satisfaction, and explains the JD-R Model as the conceptual model a literature review on the topics related to the main research questions and purpose of the study.

2.1 Definition of Artifical Intelligence

The research field now known as AI was founded by McCarthy, Minsky, Newell, and Simon (Wang, 2019). AI, a term first coined by John McCarthy in 1956, is a multifaceted concept that has evolved significantly (McCarthy, 2006). Today, AI is defined as a system's capacity to comprehend and learn from external data and to achieve specific objectives through flexible adaptation (Feng et al., 2021). This entails employing computers to simulate human brain capabilities such as reasoning, identification, comprehension, learning, and problem-solving (Gu & Hua, 2021). Furthermore, AI can be understood as the creation of intelligent computer programmes and machines that can carry out creative tasks that are typically performed by humans, or as a collection of technological advancements that mimic human cognitive functions like self-learning and problem-solving without the need for predetermined algorithms (Batin & Turchin, 2017). There is no consensus on a universally accepted definition of AI, however, the EU has recently adopted a new definition that wishes to be relevant in the years to come, which defines AI as "An AI system is a machine-based system that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that [can] influence physical or virtual environments. Different AI systems vary in their levels of autonomy and adaptiveness after deployment." (OECD, 2019).

2.2 Types of Artifical Intelligence

The field of AI consists of numerous types of systems and technologies, each with distinctive capabilities and functions but can be categorized into narrow AI, general AI, and superintelligence (Batin & Turchin, 2017) which will be explored in more detail in this chapter.

Artificial Narrow Intelligence (ANI) is designed to perform a specific task or a set of closely related tasks and can thus be utilized in various fields (Manasa & Devi, 2022). Examples include the medical sector for image analysis and disease detection (Hosny et al., 2018), self-driving cars or the gaming technology (Spector & Ma, 2019).

Artificial General Intelligence (AGI) possesses a wider range of skills as the name might suggest. AGI describes systems capable of replicating human cognitive capacities as they can comprehend, learn, apply, and adapt intelligence to a variety of tasks (Manasa & Devi, 2022). While most applied systems used in organisations today are ANI, focusing on specific work-related tasks, AGI is being implemented increasingly as it is capable of handling complex and diverse data sets (Raj & Kos, 2022). Specifically in the workplace the application of AGI is beneficial to increase corporate efficiency and effectiveness through technology integration (Hamada & Kanai, 2021). Having said this, AI has the potential to fundamentally transform the workplace and how people work (Bednar & Welch, 2020).

Eventually, we could arrive at a "novel form of life" called Artificial Super-Intelligence (ASI) where AI might be able to create better AI systems than humans and AI will have surpassed humans in all aspects (Jiang et al., 2022).

2.3 Integration and Application of AI in the workplace

AI-based tools are not only being integrated into daily activities, but are also being implemented in various fields, including education, entertainment, healthcare, security, service, transportation, and the workplace (Frank et al. 2019; Stone et al., 2020).

Early applications of AI technology concentrated on automating repetitive, rule-based tasks such as data entry, scheduling, and basic customer care to improve efficiency. Administrative and routine tasks have been mostly taken over by robotic process automation (RPA) technology, enabling employees to focus on more complex and strategic tasks (Moraes et al., 2022). Over the past few years, AI technology has advanced to the point where it can now handle tasks that are getting progressively more complex. Machine learning algorithms have made it possible for systems to learn from data and get better over time without requiring explicit programming. As a result, there are now more possibilities to use AI in the workplace including personalised learning and development plans, sophisticated CRMs, and predictive analytics used in HR for hiring and retention (Pishgar et al., 2021).

HRM is one key area where AI is being used, and it is transforming the way how people are managed in the workplace (Böhmer & Schinnenburg, 2023). Research has shown that AI applications in the workplace have an impact on both job-related and well-being outcomes, demonstrating the wide-ranging effects of AI on employees (Yu et al., 2022). AI systems are utilised to facilitate data analysis and decision-making and are thus replacing traditional IT features in the workplace like Excel computations, to increase efficiency and productivity (Mirbabaie et al., 2021).

2.3.1 Opportunites of Artifical Intelligence

On the one hand, AI can be viewed as an opportunity. AI technologies can boost productivity across several organisational functions by optimising resource allocation, streamlining processes, and improving operational efficiency (Lu & Zheng, 2020). Furthermore, employees are assisted in the decision-making process and human-AI collaboration frees people from routine tasks, enabling them to embrace strong economic opportunities (Dellermann et al., 2019). According to a study, using AI in the form of computer-based support systems called virtual assistants (VAs) can help employees with work-related tasks as it is firstly, more efficient, and secondly, VAs decrease the workload for employees (Brachten et al., 2020).

2.3.2 Threats of Artifical Intelligence

On the other hand, AI can be viewed as a threat which might have a stronger effect on the perceptions of employees toward AI (Grundner & Neuhofer, 2021). For instance, a straightforward financial choice like cutting expenses by reducing the number of employees in a company could cause the underlying fear of being replaced by AI (Złotowski et al., 2017). Another topic involves ethical considerations, such as bias in AI algorithms and the repercussions of monitoring in the workplace (Samek et al., 2021; Rabe et al., 2023). Additionally, there is an increasing demand for new skills and abilities to effectively collaborate with AI, prompting concerns regarding workforce development and lifelong learning (Roche & Nicholas, 2017). Employees will need to adapt new skills and redefine employment responsibilities as AI moves beyond transactional tasks to more complex problem-solving roles (Ramchurn et al., 2021).

2.4 Employees' Attitudes towards Artifical Intelligence

Perhaps for this reason, attitudes towards AI are not uniform. Depending on how employees perceive AI and weigh its advantages and disadvantages, employees may hold both positive and negative attitudes towards AI at the same time (Lichtenthaler, 2019). Employees' attitudes towards AI technology vary across industries. In the healthcare sector, nursing students who use AI health technologies extensively in clinical practice, for example, have more positive attitudes towards AI because of their expectations and experience with the technology (Kwak et al., 2022). Likewise, healthcare professionals have favourable views towards AI, indicating excitement and interest in AI as a diagnostic tool to improve pathology workflow quality and efficiency (Abdullah & Fakieh, 2020). On the contrary, more negative attitudes can be found in the hospitality industry, specifically towards humanlike robots as they are often perceived as a threat to human identity and uniqueness (Huang et al., 2021). In the business context, employees' attitudes towards AI may vary, with certain situations eliciting positive attitudes, particularly regarding technology acceptance and usability (Na et al., 2022). The acceptability of technology can be influenced by employees' attitudes towards AI; those with more positive attitudes are more likely to use the technology (Lee & Chang, 2011). On the contrary, some studies point out potential apprehension or negative attitudes towards AI. Chen (2022) referred to the so called no-human-interaction (NHI) attitude, which is defined by Lichtenthaler (2020) as a negative attitude toward engaging with artificial intelligence. Such, the hesitation to accept AI in the workplace can, for example, stem from concern of job displacement, because of the technology's power of substituting human labour (Lichtenthaler, 2019). But other concerns can play a role too. Loureiro et al. (2022), for instance, noted that human employees worry about AI taking away their interpersonal relationships at work.

2.4.1 Predictors of Attitudes

When evaluating predictors of AI attitudes, it is beneficial to include individual variations like technological readiness and openness to adapt. Previous research indicates that employees who are more technologically ready—that is, who are at ease and know how to use technology—are more likely to have positive attitudes towards AI (Chin et al., 2022). Additionally, organizational factors such as communication strategies and leadership support play a significant role in shaping employees' perceptions of AI (Chin et al., 2022). This aligns with studies that have explored the impact of organizational factors on innovation adoption (Damanpour & Schneider, 2006). Moreover, age seems to influence employees' acceptance of new technology, with younger employees generally being more receptive to technological advancements (Kashive et al., 2020).

Relatedness Issue

Exploring how employees perceive the relatedness of AI to their job tasks and responsibilities is crucial for understanding their acceptance of AI in the workplace (Presbitero & Teng-Calleja, 2023). Moreover, understanding how employees perceive the implementation of AI in the workplace can impact their job satisfaction, job security, and employability (Presbitero & Teng-

Calleja, 2023). Employees' perceptions of AI's transparency and usefulness can influence their trust in AI systems (Yu et al., 2023).

Familiarity

Familiarity and trust have a significant impact on employees’ attitudes towards AI. The study by Malik et al. on the impact of AI on employees in Industry 4.0-led organizations explores the effects of AI on originality, knowledge management, and creativity among employees (2021). Findings include both positive and negative impacts of the adoption of AI. On the one hand, the changes of digital transformations include information security, data privacy, and job risk as well as job insecurity, and even leading to technostress, negatively affecting employees. On the other hand, the introduction of AI in the workplace can lead to work-related flexibility and autonomy, creativity and innovation, and enhancement of job performance (Malik et al., 2022). Another study found that employees with familiarity and expertise with AI were more accepting and likely to support the autonomous applications in the experiment than those with a limited understanding of the technology (Horowitz et al., 2023).

Displacement fears

The AI identity threat in the workplace, indicating the potential psychological impact of AI on employees, can contribute to job displacement fears (Mirbabaie et al., 2021). Employees who perceive greater responsibilities and the heightened significance of their job roles are more likely to experience increased identity threat due to AI (Mirbabaie et al., 2021). This highlights the psychological implications of AI integration in organizations, emphasizing how employees view their roles and the potential concerns arising from AI technologies, such as fears of job displacement.

2.5 Subjective Well-being

In understanding the broader implications of workplace changes, specifically those driven by AI, it is crucial to explore the concept of subjective well-being and life satisfaction.

Diener et al. define subjective well-being as a person’s cognitive and affective evaluations of his or her life as a whole, including experiencing high levels of positive emotions, low levels of negative emotions, and a high life satisfaction (2002). The five item Satisfaction with Life Scale (SWLS) has been used extensively as a measure of the life satisfaction component of subjective well-being (Pavot & Diener, 2008) and is often employed to study life satisfaction and technology acceptance or AI (Jun et al., 2021). Therefore, in the context of this thesis it is vital to explore the concept of life satisfaction in more depth.

2.5.1 Life Satisfaction

Life satisfaction is defined as an individual's general evaluation and cognitive judgement of their life as a whole or over a certain period of time (Diener et al., 2002). It is a crucial part of subjective well-being and serves as a broad indicator of the quality of a person's life. The concept of life satisfaction is complex, consisting of multiple elements that influence people's general perception of wellbeing. Furthermore, life satisfaction is influenced by numerous areas of life including job, leisure, family, and health which each have mixed perception of satisfaction (Ferreira et al., 2020). It has been discovered that life satisfaction contains short-, moderate-, and long-term components that may be influenced by factors (Pavot & Diener, 2008).

The study of life satisfaction is crucial, particularly considering the modern workplace, as it both impacts and is influenced by social relationships, physical and mental health, work-life balance, and job performance (Rode, 2004). This interdependence emphasises how important it is to view life satisfaction within the broader context of people's experiences at work and their general well-being. In the age of AI, understanding life satisfaction becomes even more necessary. AI is unintentionally modifying work-life balance, career opportunities, and sense of job security for employees as it transforms employment structures, work processes, and organisational dynamics. These factors are all critical to an individual's life satisfaction.

2.6 Job Satisfaction

2.6.1 Definition of Job Satisfaction

Even though various definitions of job satisfaction exist, the one most widely used in organizational research is by Locke who define job satisfaction as “a pleasurable or positive emotional state resulting from the assessment of one's job or job experiences” (1969). This definition encompasses the emotional and subjective aspect of job satisfaction, reflecting the individual's perception and contentment derived from their work. However, others argue that job satisfaction does not only consist of positive feelings but also of the absence of negative feelings. Moreover, not only the psychological but also the environmental circumstances play a vital role. Thus, it might make more sense to consider job satisfaction as a multifaceted construct as it is influenced by numerous factors including the nature of work, pay, benefits, professional opportunities and relationships with colleagues and managers (Ravari et al., 2012).

2.6.2 How Job Satisfaction relates to Life Satisfaction

Job satisfaction is a factor that contributes significantly to life satisfaction and well-being as it plays a vital role in shaping individuals' overall happiness and contentment (Ray, 2021). According to Williams et al., job satisfaction is a key factor in determining how people view their overall quality of life, as well as how they feel about their experiences and emotional well-being (2017). People who are happier and more satisfied with their jobs also tend to be less stressed and have better psychological health, which adds to their overall sense of well-being (Tian et al., 2022). Moreover, BOZBAŞ and Gül discovered that the social aspect, including social support from colleagues, contributes to overall life satisfaction (2022). Within the educational context, self-esteem has proven to play a mediating role between teachers' job satisfaction and life satisfaction, highlighting a complex interplay between individual psychological factors and work-related satisfaction (Sarpkaya & Kirdök, 2019).

2.6.3 Previous Research on Job Satisfaction

The concept of job satisfaction has been extensively studied across various professions and contexts including work-life balance, job characteristics and automation. For instance, remote work and work-life balance has been a concept of interest specifically since the Covid-19 pandemic and has also been researched in the context of job satisfaction. In their research, Bellmann and Hübler did not find clear effects of remote work on job satisfaction, however, the impact on work–life balance is generally negative (2021). Moreover, employees working from home were found to be happier than those who want to work at home, job satisfaction is higher and work–life balance is not worse (Bellmann & Hübler, 2021). Karlita et al. also explored the influence of work-life balance on employee satisfaction and performance and highlighted the interconnectedness of personal well-being and job-related factors in their research (2020). Concerning the topic of automation, Schwabe and Castellacci (2020) found that 40% of the Norwegian workers in their sample think that their working tasks might be replaced by a machine and this fear of replacement leads to a lower job satisfaction. Specifically lower-skilled workers and routine tasks are at risk. Since ChatGPT and similar AI tools have been made publicly available in 2023 and used in various contexts, including the workplace (Jo & Park, 2023), it becomes clear to analyse the impact of integrating AI tools into the workplace and their effect on employees and their job satisfaction.

2.6.4 Predictors of Job Satisfaction

Previous research has demonstrated that job characteristics successfully predict job satisfaction (Thomas et al., 2004; Loher et al., 1985). Hackman and Oldham's (1976) job characteristics model has been widely applied for various job enrichment efforts. The model consists of five dimensions including skill variety, task identity, task significance, autonomy, and feedback that are linked with psychological stated which enrich a role and increase employee motivation, satisfaction, and performance (Loher et al., 1985). Another model often employed in the workplace to assess employee engagement or burnout is the Job Demands-Resources (JD-R) Model which assumes that job characteristics can be categorized as either job demands or job resources (Schaufeli & Bakker, 2004). The JD-R model will be explained in more detail in the Methodology section of this thesis.

2.6.5 Consequences of Job Satisfaction

Job satisfaction is a significant indicator of the quality of work life as it influences employee well-being, commitment, and performance (Moser & Schuler, 2004). It has been linked to organizational commitment and loyalty, with perceptions of a firm's ethics, values, and social responsiveness shaping employees' attitudes towards their job and the organization, with higher job satisfaction correlating with improved job loyalty and reduced turnover intentions (Waqas et al., 2014). Understanding the components of job satisfaction is essential for fostering a positive work environment as well as for designing effective personnel programs to engage and motivate employees (Rodríguez et al., 2017).

2.6.6 Variables interacting with Job Satisfaction

Common variables which contribute to job satisfaction or dissatisfaction are age, salary, work environment, recognition, and interpersonal relationships, among others (Pandita & Domnic, 2016). The following variables explained in more details are those relevant to this research. Various researchers have identified that there is a strong correlation between the age and the level of job satisfaction. Typically, young professionals show lower levels of job satisfaction, which increases with age as an employee moves to higher responsibility positions and along with promotions (Kacmar & Ferris, 1989).

Another important variable is gender which is commonly studied variable due to the previously gender based jobs and even today gender based discriminations are very common, leading often to higher stress levels and greater dissatisfaction among women. A study conducted by Marasinghe and Wijayaratne observed the role of gender on job satisfaction among university library professionals in Sri Lanka, considering the factors of work, co-workers, compensation, promotion, and supervision (2018). The findings indicate that the mean of job satisfaction of all parameters is higher for women, however, regarding supervision equal treatment of both both genders would lead to higher job satisfaction. Job Security is one of the most important aspects associated with job satisfaction (Pandita & Domnic, 2016). Supervision plays an important role in evaluating and enhancing the performance of each employee. Their role is to constantly monitor the workforce and provide feedback about their performance and are available. If these conditions are met, a positive correlation with job satisfaction can be observed (Churchill et al., 1976).

Ejiogu argues that interpersonal relationships are important for an employee's social and psychological well-being, which leads to his/her job satisfaction (1980). Overall, job satisfaction cannot be explained by one or two factors but rather is the interplay between a range of variables contributing either to job satisfaction or dissatisfaction. Generally, it can be assumed that employees who are satisfied with a greater number of job variables tend to show overall job satisfaction and vice versa (Pandita & Domnic, 2016).

With regards to the technological disruption, it is important to analyze the impact of automation and AI on employment. Brougham and Haar discovered that employees' perceived threat of technological disruption has a significant effect on job insecurity and turnover intentions (2020). The researchers argue that technology is able to complete various parts of jobs and many lines of work can be impacted by technology, likely leading to future automation, and could have vast number of employees suddenly out of work. Another longitudinal study of job insecurity found that high job insecurity affects employees' well-being, stress, job satisfaction and organizational efficiency (Kinnunen et al., 2000).

A recent study conducted by Jacobs et al. analysed how automatability impacts job satisfaction (2023). The research suggests that job satisfaction is impacted by the task content of automatable occupations. It highlights that occupations with higher automatability are less satisfying due to their lower requirement for originality, and this disparity in task composition between less and more automatable occupations differs based on educational level. Moreover, the study suggests that for lower-skilled workers, occupations with higher automatability entail more routine manual tasks, leading to a stronger negative association between automatability and job satisfaction within lower-educated labour market segments (Jacobs et al., 2023).

2.6.7 AI & Job Satisfaction

Recent AI research has concentrated on the technological understanding of AI adoption rather than the organisational problems connected with its implementation (Enholm et al., 2022). Although several studies have explored key factors in being able to leverage AI technology (Mikalef & Gupta, 2021) and identified research gaps (Dwivedi et al., 2021), there is still a lack of a comprehensive understanding of how AI is adopted and deployed in organisations. Potential societal impacts of AI, including the effects on mental health and social interaction, due to changes in the nature work and human-AI interaction, have not been a focus of research yet (Dwivedi et al., 2021). Furthermore, Bankins et al.'s multilevel review of AI in organisations highlighted the significance of workers' attitudes and perceptions towards AI and how these influence their responses to its use (2024). Future studies could potentially extend the application of the job demands-resources model (Demerouti et al., 2001). This model suggests that jobs are defined by two types of factors: resources (such as physical, psychological, and other aspects of the job that encourage achievement of goals and foster growth) and demands (including physical, psychological, and other aspects of the job that require effort and might result in negative outcomes like job overload and burnout). Thus, this thesis intends to close this research gap by uncovering the effects of AI interaction on employees' job and life satisfaction.

As mentioned in the previous chapter, AI technologies are being implemented into the workplace bringing along challenges as well as opportunities. AI has the potential to automate physically and psychologically demanding job tasks (Jetha et al., 2023). On the one hand, some studies have argued that automating routine tasks might lead to higher job satisfaction since automation leads to a decrease in the workload and employees are able to focus on more creative tasks (Stamate et al., 2021). On the other hand, employees job satisfaction can be negatively affected through performance pressure caused by AI and intensification of work. AI has the potential to increase efficiency and productivity with the effect that the pace of work to keep up with the AI increases for employees, resulting in a potentially higher business outcome but at the expense of the employees (Jetha et al., 2023). An increase AI implementation can further lead to loss of job autonomy with AI taking control over the performance of job tasks as well as stress and fear of employees to keep up with the pace of AI or else losing the job to AI (Howard, 2022). For instance, in the service industry, Loureiro et al. explored the impact of working with AI algorithms and agents on employee happiness and engagement (2023). The main findings were ambivalent; integrating AI in the workplace can generate stress and affect human well-being negatively, however it can also be a motivational factor instead of a concern, leading to increased productivity, reduced workload, decreased stress and anxiety, and heightened commitment (Loureiro et al., 2023). Yet again the results are not distinct, which might be due to the nature of different industries, the nature of the job or other reasons.

Organisations try to understand the influence of AI on humans, particularly how AI may be used in the workplace to interact with employees (Mirbabaie et al., 2021). Ghani et al. claim that implementing AI will benefit all workers indirectly and directly as AI evolves (2022). However, this requires companies to educate employees properly about the technology and its implications, so they are capable to adapt to the changing work environment, cultivate new skills, and effectively collaborate with AI technologies, contributing to improved job satisfaction and performance (Ghani et al., 2022).

2.7 Overview of Hypotheses

After reviewing the relevant literature, the following hypotheses can be derived, which are displayed in Figure 1.

Figure 1 Overview of Hypotheses

H1: Higher interaction with AI in the workplace leads to higher life satisfaction.

H2: Higher interaction with AI in the workplace leads to higher job satisfaction.

H3: Higher interaction with AI in the workplace leads to higher job satisfaction, which in turn leads to higher life satisfaction.

H4: Attitudes towards AI moderate the positive relationship between interaction with AI in the workplace and job satisfaction, such that the relationship is stronger when attitudes towards AI are more favourable.

H5: Attitudes towards AI moderate the positive relationship between interaction with AI in the workplace and life satisfaction, such that the relationship is stronger when attitudes towards AI are more favourable.

H6: Interaction with AI in the workplace leads to higher job satisfaction when job demands are perceived as low.

H7: Interaction with AI in the workplace leads to higher job satisfaction when job resources are perceived as high.

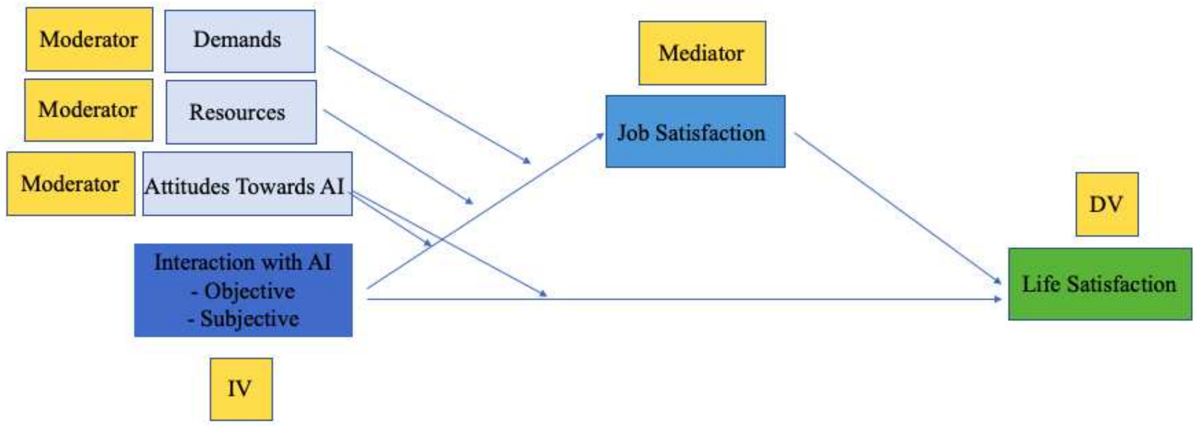
2.8 Conceptual Framework

To explore how interacting with AI in the workplace impacts employees' job and life satisfaction, I decided to apply the JD-R model which has been widely applied in research contexts concerning job satisfaction and well-being (Ahmad et al., 2020). The JD-R model has been widely applied in a number of organisations, prompting multiple studies and meta-analyses (Bakker et al., 2014; Bakker and Demerouti, 2017).

On the one side, job demands require both mental and physical effort and involve elements related to the physical, psychological, social, and organisational components of employment (Bakker & Demerouti, 2017). Workplace stress, work-family conflict, job insecurity, role ambiguity, conflict, task complexity, work overload, and pressure are examples of elements that contribute to job demands (Bakker & Demerouti, 2017). On the other side, job resources take the form of physical, psychological, and organisational environments that support the accomplishment of goals linked to the job (Bakker & Demerouti, 2017). Elements include workplace conditions and organisational support (Bakker & Demerouti, 2017).

Researchers have employed quantitative approaches to examine the effects of the JD-R model on work engagement and job satisfaction. Studies conducted by Awwad et al. (2022) and Manuaba & Hidayat (2019) have investigated the relationships within the JD-R model. They have looked at how job demands impact job satisfaction and how job demands and resources interact to predict work engagement. The idea of job crafting was incorporated into the JD-R theory by Bakker et al. (2014). They claimed that employees' proactive adaptations to their work anticipate future job demands and resources, which in turn affects work engagement and job satisfaction.

Figure 2 Proposed conceptual model



3 METHODOLOGY

The aim of this chapter is to describe how the proposed hypotheses were tested. First, the overall research strategy and design is outlined, followed by the procedure and a description of the participants. Moreover, details are given regarding the measurement of variables and applied scales.

3.1 Research Strategy and Design

Previous research analysed the JD-R model and job satisfaction or AI in the workplace or work-related well-being and adopted different methods for their research purposes, ranging from a systematic literature review and outlook, a mixed-method approach using semi-structured interviews and a questionnaire analysing the data using structural equation modelling (SEM), and an online survey where the data was analysed using partial least square-structural equation modelling (PLS-SEM) (Bakker & Dermerouti, 2017; Loureiro et al., 2022). Since prior research mostly opted for a quantitative approach, I chose a quantitative methodology for data collection to gain insights into employees' perception of AI and its influence on their job and life satisfaction. Thus, I created an online survey via the platform Qualtrics to facilitate distribution and data gathering. Qualtrics is a user-friendly web-based data collection tool that allows users to design customized surveys (Howell et al., 2023). Using Qualtrics is consistent with current trends in academic data collection (Mharapara et al., 2022). Additionally, it has been demonstrated that Qualtrics offers high-quality data collection (Douglas et al., 2023).

I wanted the study to be set in a naturalistic setting to capture the complexity of real-world phenomena of employees' attitudes towards AI who interact with AI in their job. No controlled changes or stimuli were introduced, and no variables were manipulated. Even though this enhanced the external validity of the findings, there was limited control over extraneous variables, which made it challenging to establish causation. Non-experimental studies do not involve random assignment; thus, they may not be able to fully account for all potential variations among participants that might affect the relationship between my main variables of interest, leading to potential biases in the results (Heinsman & Shadish, 1996). Therefore, I included control variables, which will be explained in depth in section 3.4.5., to account for variations and isolating them impact of those from my main variables of interest to improve the internal validity of the study.

In line with prior research, I used PLS-SEM as it is a statistical technique that tests hypothesized relationships within a conceptual model by examining both direct and indirect effects (Al-Sharafi, 2022). Furthermore, PLS-SEM allows for the incorporation of mediation and moderation effects, which enables researchers to investigate the ways in which variables influence one another conditionally or through intermediary factors (Nazir et al., 2023). Since my conceptual model tested moderation and mediation effects, applying PLS-SEM seemed suitable for the underlying research.

3.2 Procedure

In order to test the hypotheses and the conceptual model, I created an English version of the online survey via Qualtrics and shared the link with employees of my personal and professional network via social media (Instagram and LinkedIn), WhatsApp, and via email. Moreover, I shared my survey on SurveyCircle, a platform with 2.5 million study participants that is free of charge and works on an "exchange basis" – you fill out other people's surveys to gain points putting you higher in the ranking and more likely for people to find you and fill out your survey. Additionally, to recruit even more professionals who interact with AI on a day-to-day basis, I recruited participants on the platform Prolific. Participants were awarded 7.58£ per hour for a survey lasting less than 10 minutes (median time: 4:45 min). Participants could voluntarily decide if they wanted to contribute to the study or not. Furthermore, the survey was only aimed at people currently interacting with AI daily in their workplace.

Once people opened the survey link, they were redirected to Qualtrics and a brief introduction was provided, informing participants about the purpose of this study, the duration as well as their guaranteed confidentiality and anonymity of their provided answers. After participants agreed to the informed consent, they were asked about their attitudes towards and given a definition of AI as well as some everyday life examples for clarification purposes. Next, a longer list of examples of AI applications in the workplace was provided, followed by an objective and subjective question asking about the number of interactions with AI about the previous day. The questions that followed were about the workplace specifically, addressing job demands and job resources. After that, participants agreed or disagreed to statements assessing self-esteem. Next, participants were asked to answer questions about their job satisfaction while keeping in mind their work alongside AI. Lastly, statements were shown about life satisfaction. Before debriefing and thanking participants for their participation, general demographic questions were presented regarding their age, their gender, their education, and employment status, as well as their English language skills. Additionally, an attention check was included, asking participants how much attention they paid when answering the questions. For a full description of the questions and the complete Qualtrics survey, see Appendix 1.

3.3 Participants

Between December 14th, 2023 and February 20th, 2024, a total of 303 responses were collected. I have a non-random sample as I chose convenience sampling by spreading my survey through my private and professional network, at least for the majority of the answers obtained. Furthermore, not everyone could answer this only survey, since it was aimed at people interacting with AI directly or indirectly in their workplace regardless of their position or industry. Analysing the responses, three responses were removed, as participants did not consent, another five were removed because the survey was previewed or tested, one response was omitted due to "paying little attention" to the survey, another nine responses had to be deleted since participants selected they are "extremely uncomfortable" with the English language, and another 17 did not complete the survey, leading to a total of 268 valid responses that were taken into consideration for further analysis.

In order to calculate the required sample size needed for my conceptual model, I employed the "10-times-rules" method that researchers frequently use to estimate the minimum sample size needed for PLS-SEM analysis (Hair et al., 2014). This method states that the minimum sample size for the underlying research model should be at least 10 times the maximum number of arrows pointing at any latent variable in the model (Hair et al., 2014). In my model this would result in a minimum sample size of 40 = 10 x 4 considering the direct and indirect relationships between the latent constructs. Since my final sample size is 268 participants, this rule is met.

1The total valid sample of 268 participants includes 138 women (51%) and 125 men (47%). Five participants (2%) decided to self-describe or preferred not to respond to this question. Their age ranged from 18 to 73 years old (M=33.76, SD=11.46) and 15% finished secondary education, 35% completed a bachelor's degree, 43% a master's degree and 5% a doctoral degree. Analysing the current employment status, 65% are employed, 7% work as freelancers, 13% working students, 10% are students and 2% are either looking for work or retired. For further details on the demographic descriptive statistics, refer to Appendix 2.

3.4 Measurement of Variables

The measures and corresponding scales (e.g., question items) were adapted from prior studies, and all the items were measured using a Likert-type scale from 1 (Strongly disagree) to 5 (Strongly agree). The measurement for the independent variable was the only exception – since I did not find a prior study testing the interaction of AI, I phrased the two questions in a similar style to the Work Day Reconstruction Method (WDRM).

3.4.1 Independent Variable

Interaction with AI (objective and subjective): The independent variable consisted of two questions; one was a scale variable asking about the number of times the participant had interacted with AI which he/she could indicate on a slider from 0 to 100 interactions. The second variable was ordinal and assessed how often the participant felt he/she interacted with AI. Both questions were self-developed and inspired by the Work Day Reconstruction Method (WDRM), which was adapted from the Day Reconstruction Method (DRM) to gain insights into individuals' daily activities, emotional experiences, and well-being in the workplace context (Gaucher, 2022).

3.4.2 Dependent Variable

Life Satisfaction: To assess life satisfaction as the dependent variable, I used the abbreviated three item version of the Satisfaction with life (SWL) scale. The original five item scale was introduced in 1985 and has been extensively used to assess the life satisfaction component of subjective well-being (Diener et al., 1985). Kjell and Diener proved that the three-item version yields as strong psychometric properties as the five-item scale and demonstrate measurement invariance across time and gender (2020).

3.4.3 Mediator Variable

Job Satisfaction: As demonstrated in section 2.6 of the Literature Review, job satisfaction has a significant impact on life satisfaction and well-being (Ray, 2021). The Satisfaction with Work scale, derived from the Satisfaction with Life Scale, is a reliable tool for assessing job satisfaction (Saks, 2006). Job satisfaction has been found to play a significant role in influencing organizational commitment, intention to quit, and other important outcomes (Saks, 2006). In the context of AI's influence on job satisfaction, it is essential to consider how AI tools and applications impact employees' satisfaction and job satisfaction (Nguyen & Malik, 2022). Therefore, participants were shown five items from the Satisfaction with Work scale with the introduction "When I work with AI…", connecting AI and job satisfaction.

3.4.4 Moderator Variables

Attitudes towards AI: Attitudes towards AI are crucial in shaping individuals' interactions with AI systems and technologies. The AI Attitude Scale (AIAS) is a valuable tool for assessing individuals' attitudes towards AI, focusing on the acceptance and willingness to use AI technologies in specific contexts (Grassini, 2023). Additionally, the scale assesses how these attitudes can impact the relationship between AI interaction and various variables of interest (Grassini, 2023). Furthermore, prior research has demonstrated that attitudes towards AI can act as a moderator variable, influencing outcomes in different contexts (Ciuchita et al., 2023). The scale included four items and was taken from research conducted by Grassini (2023). Before the AIAS was presented, participants were provided with a definition of AI as well as workplace applications from the OECD website for clarification purposes (Lane et al., 2023).

Job Demands & Job Resources: The JD-R model suggests that the interaction between job demands and job resources plays a crucial role in determining job strain and motivation levels (Xanthopoulou et al., 2007). To assess the JD-R model, five items were selected for each variable inspired by Karasek's Job Content Questionnaire (JCQ) to capture relevant aspects of job demands and resources across various work environments (Bouillon-Minois et al., 2023; Dutheil et al., 2022). Furthermore, as outlined by previous research, it is essential to consider both job demands and resources to understand their combined effects on employee well-being and performance (Crawford et al., 2010).

3.4.5 Control Variables

Control variables are essential in research studies to enhance accuracy and reliability of findings. Therefore, based on prior research I included variables such as self-esteem, age, gender, and education. According to Bernerth et al. the quality of research significantly improves when control variables are integrated into hypotheses, and when standard descriptive statistics and correlations are provided for these variables (2018).

Self-esteem: As discussed in section 2.6 of the literature review within “variables interacting with job satisfaction) self-esteem has been proven to play a mediating role between job and life satisfaction (Sarpkaya & Kirdök, 2019). In this research, self-esteem was assessed through five items adapted from the Rosenberg Self-Esteem Scale (SES) (Rosenberg 1965), disregarding the reverse items as the literature suggests that negatively oriented items have a minor impact on instrument quality but influence measurement model and path coefficients (Dueber et al. 2022). Similar to the rest of the survey, participants indicated on a 5-point Likert scale their disagreement (1) or agreement (5) with the statements.

Demographics: In line with previous studies, participants’ age, gender as well as their educational and employment status were included (Kacmar & Ferris, 1989). Age was collected in years. Gender was collected as either female, male, prefer not to say or other. Education was assessed asking participants to select their highest level of education ranging from less than secondary education up to doctoral degree, also offering the option “other” for participants to self-describe. Lastly, for employment type several options were provided, with the option to self-describe by selecting “other”.

4 RESULTS

The chapter will begin with describing the cleaning and preparation of the data, followed by a sample characterization using descriptive statistics. Afterwards, the PLS-SEM data analysis will be presented which was completed via the data analysis tool SmartPLS 4 to test the hypotheses.

4.1 Data Cleaning and Preparation

After pausing the data collection on Qualtrics, the data was exported as an SPSS file. The first step for the data analysis was to clean the data. Initially, a total of 303 responses were collected. Survey answers were removed from further analysis if they were previewed or tested by the researcher and if participants did not give consent to participate in the survey, failed to complete the survey, and did not pass the English level or attention check question, leaving 268 valid responses. Table 1 represents the final valid observations.

Table 1 Valid observations from the online survey

Observations	Number of Observations
Initial Observations	303
Preview/Testing	5
Failed Consent	3
English level too low	9
Failed Attention check	1
Incomplete responses	17
Total Valid Observations	**268**

4.2 Descriptive Statistics

In order to describe the sample, the demographic statistics were analysed using descriptive statistics in the data analysis tool SPSS and the overview can be found in Appendix 2. As mentioned in the methodology section, the participants were between the age of 18 to 73 (M = 33.76, SD = 11.49), 47% were male, 51% identified as female and 2% decided to self-describe or preferred not to reveal their gender. Regarding the level of education, 15% completed secondary education, 35% had a bachelor's degree, 43% hold a master's degree and 5% have a doctoral degree. Finally, 65% of participants are currently employed, 7% work as a freelancer, 1.5% are unemployed, 10% are students, 13% are working students and less than 1% is retired.

4.3 Data Analysis

After the data file was cleaned from any missing data points and simplified to only contain the questions and answers in numeric format, it was uploaded to SmartPLS 4, a data analysis tool suitable for complex structural models (Hair et al., 2012). I chose to use SmartPLS 4 as it is a balanced model well suited for data analysis using PLS-SEM according to researchers (Hair et al., 2012). Furthermore, SmartPLS requires smaller sample sizes than other tools and allows users to easily create complex models (Hair et al., 2014). As recommended by previous research, a two-step validation of PLS-SEM was carried out (Hair et al., 2019; Sarstedt et al., 2023). Considering the minimum required sample size as well as the data preparation, the measurement model was assessed considering the factor loadings, composite reliability (CR), and average variance extracted (AVE) (Hair et al., 2019). After determining the overall model fit, the structural model was evaluated. Therefore, path coefficients, standardised path coefficients, and associated statistical significance tests, were included. Lastly, the indirect effects were examined. an examination was conducted into the mediations, or indirect effects. Examining the hypotheses, bootstrapping resampling was conducted with a two-tailed test type, a significance level of .05, a percentile bootstrap as a confidence interval method, and 20,000 subsamples.

4.3.1 Assessment of reflective measurement model

A measurement model is a part of the general model that specifies latent constructs that are typically defined as reflective or formative (Hair et al., 2019). In formative constructs the arrows point from the indicators to the construct and each indicator represents important meaning for the construct, which means that changing or removing an indicator will change the meaning of the construct (Hair et al., 2019). On the contrary, in reflective constructs the arrows point from the construct to the indicators, and indicators can be adapted or removed as long as other indicators are representative of the construct (Hair et al., 2019). Since my underlying research model is reflective, the indicator loadings, cross-loadings, Cronbach's alpha (a) composite reliability (p) values were investigated to determine internal consistency reliability. To measure convergent validity, the AVE estimates were determined, and the Fornell-Larcker criterion and heterotrait-monotrait ratio of correlations (HTMT) were used to assess discriminant validity (Hanafiah, 2020).

4.3.1.1 Construct reliability and validity

Regarding the indicator loadings, prior research suggests to only include loadings above the threshold value of .708 to ensure item reliability (Hair et al., 2019). Consequently, five indicators (Q2_3 for the construct attitudes towards AI, Q5_4 and Q5_5 for the construct job demands, Q6_1 for the constructs job resources, and Q8_4 for the construct job satisfaction) were not considered appropriate in the initial model since the loadings were below .708 and excluded from the modified model. Considering the internal consistency reliability, Cronbach's alpha was investigated and deemed too low for the construct of job demands (e.g., below the threshold of .70) but all composite reliability values ranged from .70 to .90 and were considered "satisfactory to good" (Hair et al., 2019). The convergent validity was determined looking at the AVE, and items must be higher than .50 for a construct to be able to explain more than half of the variance of its measuring items, which was not the case for the construct of job demands with an AVE of .442 (Hair et al., 2019). An overview of the initial model can be found in Tables A-B in Appendix 3.

After removing these five constructs, the adjusted model demonstrated satisfactory values for all construct reliability and validity measurements. Subsequently, the discriminant validity, which assesses the extent of how a construct distinguishes itself from other constructs in the structural model, was examined with the Fornell and Larcker criterion (Fornell & Larcker, 1981). It states that each construct's AVE should be higher than its squared correlation with any other construct, which is the case for my model. Additionally, researchers have proposed to look at the HTMT values to assess discriminant validity as the HTMT can achieve higher specificity sensitivity rates compared to the cross-loadings and Fornell-Larcker criterion (Henseler et al., 2015). Looking at the HTMT in the modified model, all values are below .85, indicating no discriminant validity problems as well as no collinearity problems among the latent constructs. Finally, no issues were identified regarding the collinearity statistics for the outer model, as all VIF's were below 3.3 (Sarstedt et al., 2023). An overview of all relevant matrices and tables of the modified measurement model of the reflective constructs can be found in Appendix 4, Tables C-G.

4.3.1.2 Model Fit

Prior to examining the PLS-SEM structural model results, the model fit was examined. Several fit metrics are available with SMART PLS, including $\chi 2$ (Chi-square), squared Euclidean and geodesic distances, NFI (Normed Fit Index), and SRMR (Standardised Root Mean Square Residual). Nevertheless, since these metrics have not yet undergone a comprehensive examination, researchers ought to apply great caution when using them for PLS-SEM (Sarstedt et al., 2021). The SRMR was examined for the underlying model, which measures the difference between the correlation matrix that is actually observed and the correlation matrix that the model implies, acting as an absolute indication of the goodness-of-fit criterion (Becker et al., 2023). Hu & Bentler (1999) defined a satisfactory fit as a value less than 0.10 or 0.08 which this model is since the value of the saturated model is .061 and .072 for the estimated model. However, the NFI criteria, which stipulate that values above 0.9 and closer 1 imply a better fit could not be fully reached (NFI for the saturated model = 0.789; NFI for the estimated model = 0.782). Since there is no unanimous goodness-of-fit measure, I deemed the model fit as satisfactory for the continuation of assessing the structural model. For the overview of the model fit please refer to Table H in Appendix 4.

4.3.2 Assessment of the structural model

After this initial assessment and modification of the measurement model, the structural model was assessed by analysing the standard assessment criteria including collinearity, coefficient of determination (R2), the blindfolding-based cross-validated redundancy measure (Q2), as well as the statistical significance and relevance of the path coefficients as suggested by Hair et al. (2019). Please refer to Tables I-K in Appendix 5 for all relevant details.

4.3.2.1 Collinearity of the constructs

Before the structural relationships were assessed, collinearity was investigated to ensure that there is no bias in the results of the regression. Therefore, the VIF values were calculated with the latent variable scores of the predictor constructs. As demonstrated in Table L in Appendix 6, all VIF values of the inner model were below 3, meaning that no collinearity issues were detected among the predictor constructs (Hair et al., 2019).

4.3.2.2 Models explanatory and predictive power

Next, the R2 values of the endogenous constructs were assessed in order to measure the model's explanatory power (Sarstedt et al., 2021). R2 measures the variance explained by the endogenous constructs which reflects how much change in the dependent variables can be accounted for by the independent variables (Hair et al., 2019; Sarstedt et al., 2021). The closer the R2 value is to 1, the higher is the explanatory power and R2 values of .75, .05, and .25 are considered substantial, moderate, and weak (Hair et al., 2014). The R2 values for both job (R2 = .233) and life satisfaction (R2 = .126) were considered weak (see Table M in Appendix 6). Overall, the model explains 23.3% of the variation on job satisfaction and 12.6% of the variation on life satisfaction.

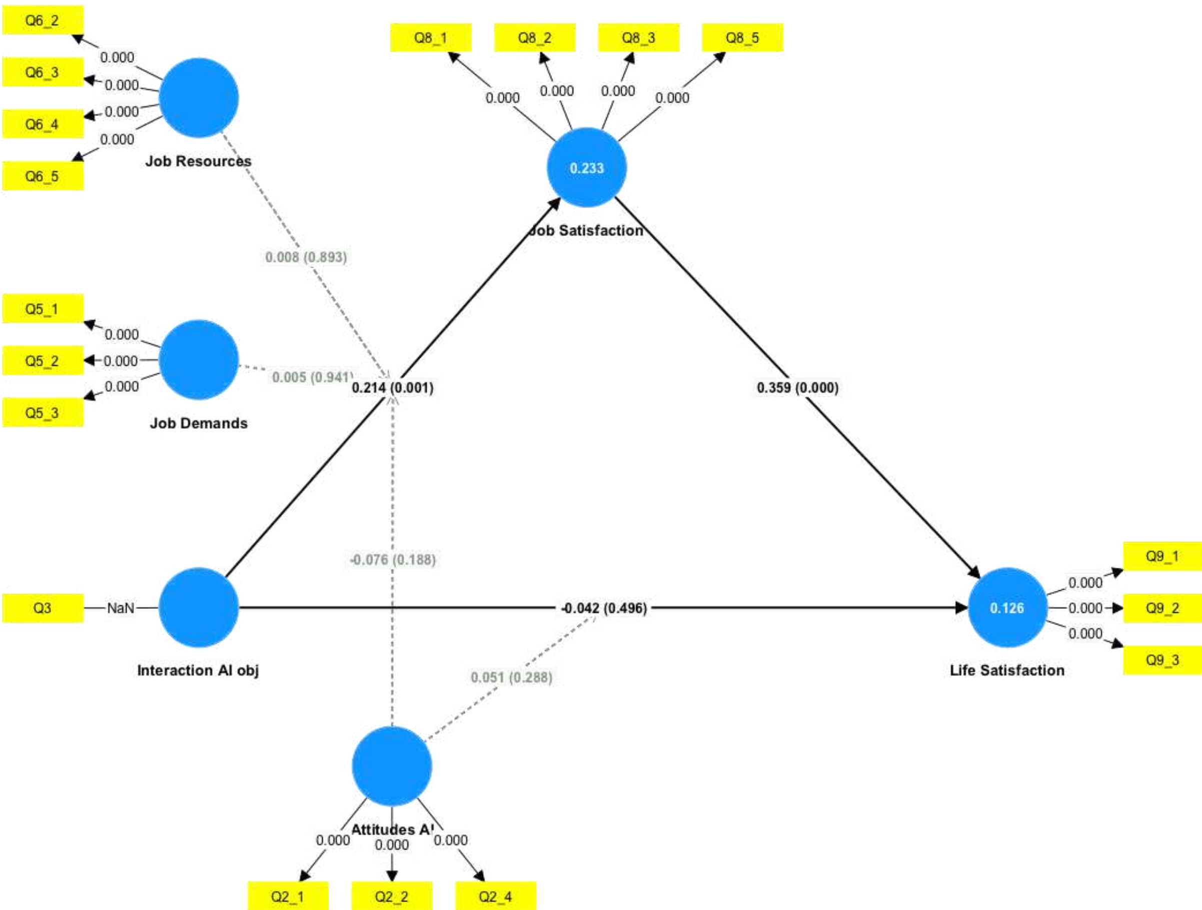
Additionally, the effect sizes (f2) were calculated, which represents the impact of each independent variable on the dependent variable, or in other words, the strength of the relationship between latent variables (Sarstedt et al., 2021). According to Cohen, effect size values below .02 indicate that there is no effect, .02, .15 and .35 illustrate a small, medium and high effect (1988). As demonstrated in the following Table 2, for most variables there is no effect, a small effect exists for attitudes towards AI on job satisfaction, interaction with AI (objective) on job satisfaction and job resources on job satisfaction. A close to medium effect size can be identified with job satisfaction on life satisfaction.

Table 2 F-square list

Direct effects	f-square
Attitudes AI -> Job Satisfaction	0.096
Attitudes AI -> Life Satisfaction	0
Interaction AI obj -> Job Satisfaction	0.051
Interaction AI obj -> Life Satisfaction	0.002
Job Demands -> Job Satisfaction	0.011
Job Resources -> Job Satisfaction	0.068
Job Satisfaction -> Life Satisfaction	0.122
Attitudes AI x Interaction AI obj -> Job Satisfaction	0.008
Attitudes AI x Interaction AI obj -> Life Satisfaction	0.004
Job Resources x Interaction AI obj -> Job Satisfaction	0
Job Demands x Interaction AI obj -> Job Satisfaction	0

4.3.2.3 Hypothesis testing – statistical significance and relevance of path coefficients

Figure 3 Structural Model with path estimates and p-values (objective)



*Note: *p-values are displayed in the brackets after the respective path coefficients (= Beta-Coefficients)*

The bootstrapping process was used to determine the statistical significance (p-values) and relevance of the route coefficients, which represent the strength of the effect, as shown in Figure

3 (Hair et al., 2019). For an effect to be considered significant, Hair et al. (2019) state that the p-values must be below the.05 threshold and the path coefficients' significance values typically range from -1 to +1. Figure B in Appendix 6 displays the comprehensive structural model with all path coefficients, including the indicator variables.

First, the direct effects were analysed (as shown in Table 4), which represent the immediate influence that one variable has on another variable in the model (Becker et al., 2023). A statistically significant positive effect of interaction with AI on job satisfaction (**H2**: ß = .214, t = 3.433, p = .001) and a statistically significant positive effect of job satisfaction on life satisfaction (ß = .359, t = 5.456, p = .000) was revealed. The effect of job satisfaction on life satisfaction is stronger than interaction with AI on job satisfaction. This shows that H2 was supported. However, the effect of interaction with AI on life satisfaction was not found to be significant (H1: ß = -.042, t = .681, p = .496) and thus, H1 was not supported.

Table 3 Direct effects – Hypothesis testing

Direct effects	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Attitudes AI -> Job Satisfaction	0.285	0.287	0.062	4.617	0
Attitudes AI -> Life Satisfaction	-0.004	-0.001	0.067	0.058	0.954
Interaction AI obj -> Job Satisfaction	0.214	0.2	0.062	3.433	0.001
Interaction AI obj -> Life Satisfaction	-0.042	-0.044	0.062	0.681	0.496
Job Demands -> Job Satisfaction	0.095	0.108	0.057	1.673	0.094
Job Resources -> Job Satisfaction	0.236	0.245	0.061	3.877	0
Job Satisfaction -> Life Satisfaction	0.359	0.36	0.066	5.456	0
Attitudes AI x Interaction AI obj -> Job Satisfaction	-0.076	-0.074	0.058	1.317	0.188
Attitudes AI x Interaction AI obj -> Life Satisfaction	0.051	0.055	0.048	1.062	0.288
Job Resources x Interaction AI obj -> Job Satisfaction	0.008	0.017	0.061	0.134	0.893
Job Demands x Interaction AI obj -> Job Satisfaction	0.005	0.011	0.063	0.075	0.941

Secondly, the indirect effects were examined (found in Table 5), which occur when one variable does not affect another variable immediately but operates through other variables in the model (e.g., mediation) (Becker et al., 2023). The indirect effect for interaction with AI on life satisfaction, being mediated by job satisfaction is statistically significant and has a positive effect (**H3**: ß = .077, t = 3.01, p = .003), indicating support for H3.

Table 4 Indirect effects – Hypothesis testing

Total Indirect effects	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Attitudes AI -> Life Satisfaction	0.102	0.103	0.029	3.539	0
Interaction AI obj -> Life Satisfaction	0.077	0.072	0.026	3.01	0.003
Job Demands -> Life Satisfaction	0.034	0.038	0.021	1.603	0.109
Job Resources -> Life Satisfaction	0.085	0.089	0.03	2.869	0.004
Attitudes AI x Interaction AI obj -> Life Satisfaction	-0.027	-0.027	0.022	1.246	0.213
Job Resources x Interaction AI obj -> Life Satisfaction	0.003	0.006	0.022	0.132	0.895
Job Demands x Interaction AI obj -> Life Satisfaction	0.002	0.005	0.023	0.073	0.942

Thirdly, the interaction effects were analysed (refer to Table 6), which reflect moderation, where the effect of one variable on another is moderated upon the value of a third variable

(Becker et al., 2023). For the moderation effects both the direct effects as well as the total effects were analysed, to not only see the immediate influence that one variable has on another variable but to also assess the total influence of one variable on another, accounting for both direct and mediated effects. Regarding Attitudes towards AI, both the interaction effect with interaction with AI on job satisfaction (H4: ß = -.076, t = 1.317, p = .188) as well as life satisfaction (H5: ß = .051, t = 1.062, p = .288) was not found to be significant. Continuing the analysis with job demands (H6: ß = .005, t = .075, p = .941) and job resources (H7: ß = .008, t = .134, p = .893) acting as moderators between the interaction with AI and job satisfaction, no statistically significant interaction effect could be found. Overall, none of the moderating hypotheses (H4, H5, H6 and H7) were supported.

Table 5 Total effects – Hypothesis testing

Total effects	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Attitudes AI -> Job Satisfaction	0.285	0.287	0.062	4.617	0
Attitudes AI -> Life Satisfaction	0.098	0.103	0.072	1.373	0.17
Interaction AI obj -> Job Satisfaction	0.214	0.2	0.062	3.433	0.001
Interaction AI obj -> Life Satisfaction	0.034	0.028	0.064	0.54	0.589
Job Demands -> Job Satisfaction	0.095	0.108	0.057	1.673	0.094
Job Demands -> Life Satisfaction	0.034	0.038	0.021	1.603	0.109
Job Resources -> Job Satisfaction	0.236	0.245	0.061	3.877	0
Job Resources -> Life Satisfaction	0.085	0.089	0.03	2.869	0.004
Job Satisfaction -> Life Satisfaction	0.359	0.36	0.066	5.456	0
Attitudes AI x Interaction AI obj -> Job Satisfaction	-0.076	-0.074	0.058	1.317	0.188
Attitudes AI x Interaction AI obj -> Life Satisfaction	0.023	0.028	0.06	0.388	0.698
Job Resources x Interaction AI obj -> Job Satisfaction	0.008	0.017	0.061	0.134	0.893
Job Resources x Interaction AI obj -> Life Satisfaction	0.003	0.006	0.022	0.132	0.895
Job Demands x Interaction AI obj -> Job Satisfaction	0.005	0.011	0.063	0.075	0.941
Job Demands x Interaction AI obj -> Life Satisfaction	0.002	0.005	0.023	0.073	0.942

Additional results were identified, apart from the analysis of the hypothesis testing. Regarding the direct effects, there is a statistically significant positive effect of attitudes towards AI on job satisfaction (ß = .285, t = 4.617, p = .000) and a statistically significant positive effect of job resources on job satisfaction (ß = .236, t = 3.877, p = .000). This further holds true when analysing the indirecte effects: Looking at the specific indirect effects, there is a statistically significant positive effect for the influence of attitudes on life satisfaction mediated through job satisfaction (ß = .102, t = 3.539, p = .000) as well as the impact of job resources on life satisfaction mediated through job satisfaction (ß = .085, t = 2.869, p = .004). Lastly, assessing the total effects attitudes towards AI influence job satisfaction in a statistically significant positive way (ß = .285, t = 4.617, p = .000) and job resources affect job and life satisfaction in a statistcially significant positive way (ß = .236, t = 3.877, p = .000; ß = .085, t = 2.869, p = .004) .These results can be found in Tables 4 – 7.

Table 6 Specific Indirect effects – Hypothesis testing

Specific Indirect Effects	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Attitudes AI -> Job Satisfaction -> Life Satisfaction	0.102	0.103	0.029	3.539	0
Interaction AI obj -> Job Satisfaction -> Life Satisfaction	0.077	0.072	0.026	3.01	0.003
Job Demands -> Job Satisfaction -> Life Satisfaction	0.034	0.038	0.021	1.603	0.109
Job Resources -> Job Satisfaction -> Life Satisfaction	0.085	0.089	0.03	2.869	0.004
Attitudes AI x Interaction AI obj -> Job Satisfaction -> Life Satisfaction	-0.027	-0.027	0.022	1.246	0.213
Job Resources x Interaction AI obj -> Job Satisfaction -> Life Satisfaction	0.003	0.006	0.022	0.132	0.895
Job Demands x Interaction AI obj -> Job Satisfaction -> Life Satisfaction	0.002	0.005	0.023	0.073	0.942

For simplification purposes, the hypothesis testing was analyzed in detail for the objective interaction with AI but the structural model regarding subjective interaction with AI has also been created and calculated with PLS-SEM. An overview with the detailed path coefficients and p-values can be found in Appendix 7 Figure C. In a nutshell, results remained largely similar to the structural model addressing the objective interaction with AI. There were slight differences regarding the strength of the path coefficients as well as the p-values. The biggest difference was for the direct effect between interaction with AI and job satisfaction as this effect was only marginally statistically significant (ß = .112, p = .066) in comparison to the objective interaction with AI model, where it was fully statistically significant (ß = .214, p = .001).

The full overview of the hypothesis support can be found in Table 3.

Table 7 Hypotheses analysis

Hypothesis analysis					
Total effect			Direct effect		
H1: Interaction AI obj -> Life satisfaction			H1: Interaction AI obj -> Life satisfaction		
ß	*t*	*p*	ß	*t*	*p*
0.034	0.54	0.589	-0.042	0.681	0.496
Total effect			Direct effect		
H2: Interaction AI obj -> Job satisfaction			H2: Interaction AI obj -> Job satisfaction		
ß	*t*	*p*	ß	*t*	*p*
0.214	3.433	0.001	0.214	3.433	0.001
Indirect effects on Life Satisfaction					
H3: Interaction AI obj -> Job satisfaction -> Life satisfaction					
ß		*t*		*p*	
0.077		3.01		0.003	
Total Interaction effect			Direct Interaction effect		
H4: Attitudes AI x Interaction AI obj -> Job Satisfaction			H4: Attitudes AI x Interaction AI obj -> Job Satisfaction		
ß	*t*	*p*	ß	*t*	*p*
-0.076	1.317	0.188	-0.076	1.317	0.188
Total Interaction effect			Direct Interaction effect		
H5: Attitudes AI x Interaction AI obj -> Life Satisfaction			H5: Attitudes AI x Interaction AI obj -> Life Satisfaction		
ß	*t*	*p*	ß	*t*	*p*
0.023	0.388	0.698	0.051	1.062	0.288
Total Interaction effect			Direct Interaction effect		
H6: Job Demands x Interaction AI obj -> Job Satisfaction			H6: Job Demands x Interaction AI obj -> Job Satisfaction		
ß	*t*	*p*	ß	*t*	*p*
0.005	0.075	0.941	0.005	0.075	0.941
Total Interaction effect			Direct Interaction effect		
H7: Job Resources x Interaction AI obj -> Job Satisfaction			H7: Job Resources x Interaction AI obj -> Job Satisfaction		
ß	*t*	*p*	ß	*t*	*p*
0.008	0.134	0.893	0.008	0.134	0.893

Note: ß = Beta-Coefficient; t = t-value; p = p-value; SD = Standard Deviation

4.3.3 Exploratory Analyses

In addition to the primary analysis, the suggested conceptual model was refined to account for the effects of age, gender, education, and self-esteem on life satisfaction. Despite the addition of these control variables to the original proposed model, the results stayed mostly the same, some values improved or worsened but nothing changed with regards of being statistically significant. Assessing the control variables, age, gender, and education did not have a statistically significant effect on life satisfaction. However, self-esteem had a strong positive statistically significant effect on life satisfaction (ß = .542, t = 10.12, p = .000). In Appendix 7, Figure C represents the structural model including control variables with path coefficients and p-values, and Table N show the respective direct and indirect effects of the exploratory analyses. The same holds for the analysis conducted of the structural model regarding the subjective interaction with AI and the results can be found in Appendix 7, Figure D.

5 DISCUSSION

The underlying research sought to investigate the interaction with AI and its impact on employees' job and life satisfaction. PLS-SEM was applied as the statistical method to explore the structural relationships between the variables. The research model investigated whether interacting with AI leads to higher job satisfaction as well as life satisfaction and how attitudes towards AI, job demands, and job resources moderate this relationship.

The results indicated that interacting with AI in the workplace significantly and positively impacts job satisfaction, supporting **H2**. Furthermore, job satisfaction does have a significant and positive influence on life satisfaction, which is in line with previous research (Rode, 2004). Additionally, the study found that job satisfaction mediated the relationship between interacting with AI in the workplace and life satisfaction, thus supporting **H3**. Interestingly, no support was found for H1, which proposed that interacting with AI would impact life satisfaction. The p-value was not statistically significant, but if it had been, a negative impact could have been observed between interacting with AI and life satisfaction. Maybe if a simple model had been run to test the effect of the IV on the DV there would have been a statistically significant effect. There may be additional factors at play that influence the relationship between interacting with AI and life satisfaction that were not considered in this research model. Further research is needed to fully understand the impact of AI on life satisfaction in the workplace. As proposed by previous researchers, there is a complex interplay of AI in the workplace that can have both positive and negative effects on employee well-being (Loureiro et al., 2022).

Additional variables that were included in the structural model and that acted as moderators were attitudes towards AI, job demands, and job resources. When assessing their influence on job satisfaction and life satisfaction, different results were found, considering if the direct effect of the variable was measured or if the interaction effect was measured. Attitudes towards AI influenced job satisfaction directly and influenced life satisfaction indirectly through the mediating role of job satisfaction in a positive way. However, when considering the interaction effect with interaction with AI, the relationship between attitudes towards AI and job as well as life satisfaction was found to be more complex, and thus, H4 and H5 could not be supported. The results of the study suggested that attitudes towards AI may not have a straightforward impact on job and life satisfaction. Moving on to job demands, no statistically significant relationships were found, regardless of whether assessing the direct, indirect, or interaction effects, and therefore, H6 was not supported. This suggests that either job demands do not play a significant role in the relationship between interacting with AI and job and life satisfaction, that the question design was insufficient or not appropriate, or other factors may be at play. Surprisingly, the outcomes of job resources support a variety of conclusions. In this research model, job resources have a significant and positive direct effect on job satisfaction and an indirect effect on life satisfaction, mediated through job satisfaction. These results suggest that job resources are crucial in enhancing employees' overall well-being. Nonetheless, when assessing the effect in combination with interacting with AI, no statistically significant interaction effects are observed, and hence, no support was found for H7. Thus, it might be interesting to analyse this relationship further to discover if there is truthfully no impact in regard to interacting with AI or if there are other factors at play that were not considered, such as question development or assessment rubrics. To conclude, although attitudes towards AI and job resources do significantly and positively influence job and life satisfaction when measured independently, no interaction effects can be found, and H4, H5, H6, and H7 cannot be supported.

Upon reflection, there could be several improvements in the methodology of this study, which would have allowed me to gather more information to test the hypotheses. First, the questionnaire design might have had a greater number of questions to assess the interaction with AI. This would have enabled a more thorough examination of participants' experiences and perspectives. Second, the survey should have either included a question regarding the industry a person works in, a list of industries to choose from, or been directed towards a specific industry to gather more specific and meaningful data. Since survey participants had the option to leave feedback at the end of the survey, the feedback suggested that participants thought similarly about the differences in use and interaction with AI across different industries and positions. Furthermore, additional feedback was received concerning the job satisfaction question. A number of respondents expressed confusion regarding the formulation of the question itself, as the satisfaction with work scale was not utilised in isolation, as was the case in previous studies. Instead, it was combined with the statement, "When I work with AI..." This introduced an extra level of complexity to the responses and was likely unsuitable for statement 1 (Q8_1), "I feel close to people at work."

In sum, this research sheds light on whether interacting with AI influences employees' job and life satisfaction. According to the findings, interacting with AI increases employees' job satisfaction, which in turn increases life satisfaction when job satisfaction is higher.

Nonetheless, the additional influence of attitudes towards AI, job demands, and job resources was not proven to be statistically significant in relation to interacting with AI and its influence on job and life satisfaction.

6 CONCLUSIONS AND LIMITATIONS

This study assessed whether interacting with AI has a significant impact on job and life satisfaction. Moreover, additional factors, including attitudes towards AI, job demands, and job resources, were included in the analysis to provide a comprehensive understanding of the relationship. Quantitative research was conducted in the form of an online questionnaire created with Qualtrics, and 303 responses were collected. Subsequently, the data was analysed by conducting PLS-SEM via the data analysis programme SmartPLS 4, by creating and assessing the reflective measurement model, the structural model, and exploratory analyses.

6.1 Main Findings & Conclusions

RQ1: Does interacting with AI in the workplace affect employees' job satisfaction?

This study found that interacting with AI in the workplace has a positive impact on employees' job satisfaction. Further analysis revealed that this positive impact was particularly significant for employees who had more frequent interactions with AI in their daily tasks. Overall, these results indicate that implementing AI in the workplace can increase employee job satisfaction.

RQ2: Does interacting with AI in the workplace affect employees' life satisfaction?

The findings suggest ambiguous outcomes. The coefficient from the PLS-SEM model failed to achieve statistically significant results regarding the direct relationship between interacting with AI in the workplace and employees' life satisfaction, meaning that interacting with AI does not have a direct influence on life satisfaction. Looking at the model, if the p-value were significant, it would even suggest a negative relationship between the two variables. However, the results support a moderated relationship, meaning that employees interacting with AI who experience higher job satisfaction also reported higher life satisfaction. This suggests that while the direct relationship may not be significant, there may still be a positive impact on employees' overall well-being when they feel more at ease with AI technology.

RQ3: Do employees' attitudes towards AI impact their job and life satisfaction?

There is a two-fold answer to this question. In general, the results indicated that attitudes towards AI have a positive impact on job satisfaction and influence life satisfaction indirectly through the mediating role of job satisfaction. However, in light of the hypothesis and considering attitudes towards AI as a moderator, the results were not statistically significant. Thus, in this research model, it could not be verified whether employees' attitudes towards AI impact their job and life satisfaction. In conclusion, the results of the study suggested that attitudes towards AI may not have a straightforward impact on job and life satisfaction.

RQ4: How does interaction with AI in the workplace influence job satisfaction within the framework of the JD-R model, particularly when considering the moderating effects of perceived job demands and resources?

The findings show no evidence of a significant relationship between interaction with AI in the workplace and job satisfaction within the framework of the JD-R model. When analysing the effects of the variables separately, the findings are still not statistically relevant for job demands. However, job resources have a significant and positive effect on job satisfaction as well as on life satisfaction, indicating that job resources contribute positively to both work and personal life outcomes. Therefore, even though the moderated relationship of the JD-R model could not be confirmed, job resources still have a beneficial impact on overall well-being.

6.2 Managerial / Academic Implications

Academically, this research contributes to the emerging literature on AI-technology integration in the workplace (Pereira et al., 2023). Research has been conducted in various fields, ranging from multilevel reviews of AI in organizations (Bankins et al., 2024), to multi-country studies regarding technological disruption and employment (Brougham & Haar, 2020), to AI’s impact on work stress and job insecurity (Ghani et al., 2022). While previous work has addressed the impact of AI on employees’ well-being and more often burnout and stress, this study wants to contribute to research by focusing on the positive side of AI. Academically, this work is one of the first to use the JD-R model as the underlying model to test the interaction with AI on job and life satisfaction and thus offers relevant insights. Even though the structural model did not offer statistically significant support for the moderated effects of job demands and job resources and their impact on interacting with AI on job and life satisfaction, job resources were indeed supported to have a positive impact on job and life satisfaction. Future research should investigate these effects further by applying the JD-R framework with more questions to find stronger effects.

This study offers managers and organizational leaders a data-driven understanding of the impacts of implementing artificial intelligence in the workplace. The results of the study showed that employees who work with AI generally report an increase in job satisfaction, which in turn can contribute to a higher life satisfaction. Understanding the potential effects of AI on job satisfaction and life satisfaction can help managers make more informed decisions about implementing AI in the workplace and create strategies to ensure a smooth transition for their teams. This can ultimately lead to a more positive and productive work environment.

6.3 Limitations / Future Research

Despite the insights provided by this study, there are several limitations to consider. First, the data was mostly collected through a non-probability sampling technique, which was reasonable given the time and resource constraints, however it led to a non-representative sample. As the survey was addressed to anyone interacting with AI in the workplace regardless of the industry or position, this limits the generalizability of the results, as people who work extensively with AI may have different experiences and attitudes to those who are less involved with AI. Future studies should rather target a specific industry or industries where AI is prevalently employed or focus on specific positions associated with high AI usage to better capture the impacts of AI in the workplace.

Another limitation of this research arises regarding the research design. It is possible that important concepts or variables were not sufficiently addressed, which could affect the internal validity of the results. Regarding job demands and resources the questions chosen only reflected some aspects but did not include all questions from the original scales, which could have led to biased results. Future studies should therefore be carefully planned and consider the length of the questionnaire and the scope of topics covered to create a more comprehensive and meaningful data set. Furthermore, the wording of the question assessing interaction with AI must be viewed critically. As this question was self-formulated, there is a possibility that it was not clear or meaningful enough to capture the desired information. Future studies could therefore use standardised questionnaires or validated measurement tools to increase the reliability and validity of the data collected.

Finally, it would have been interesting to not only touch on some aspects of job and life satisfaction but to go into more depth on how AI affects employees in their day-to-day working lives. Future research could employ the complete satisfaction with work scale or other appropriate scales that measure more extensive aspects of job satisfaction. This would provide a more comprehensive understanding of the impact of AI on employee well-being.

REFERENCE LIST

Abdullah, R., & Fakieh, B. (2020). Health Care Employees' Perceptions of the Use of Artificial Intelligence Applications: Survey Study. *Journal of Medical Internet Research*, *22*(5), e17620. https://doi.org/10.2196/17620

Ahmad, J., Saffardin, S. F., & Teoh, K. B. (2020). How does job demands and job resources affect work engagement towards burnout? The case of penang preschool. *International Journal of Innovation, Creativity and Change*, *12*(5), 283–293. https://doi.org/10.37200/ijpr/v24i2/pr200490

Al-Sharafi, M. A., Al-Emran, M., Iranmanesh, M., Al-Qaysi, N., Iahad, N. A., & Arpaci, I. (2023). Understanding the impact of knowledge management factors on the sustainable use of AI-based chatbots for educational purposes using a hybrid SEM-ANN approach. *Interactive Learning Environments*, *31*(10), 7491–7510. https://doi.org/10.1080/10494820.2022.2075014

Arslan, A., Cooper, C., Khan, Z., Golgeci, I., & Ali, I. (2022). Artificial intelligence and human workers interaction at team level: a conceptual assessment of the challenges and potential HRM strategies. *International Journal of Manpower*, *43*(1), 75–88. https://doi.org/10.1108/IJM-01-2021-0052

Awwad, R. I., Aljuhmani, H. Y., & Hamdan, S. (2022). Examining the Relationships Between Frontline Bank Employees' Job Demands and Job Satisfaction: A Mediated Moderation Model. *SAGE Open*, *12*(1), 215824402210798. https://doi.org/10.1177/21582440221079880

Bakker, A. B., & Demerouti, E. (2017). Job demands–resources theory: Taking stock and looking forward. *Journal of Occupational Health Psychology*, *22*(3), 273–285. https://doi.org/10.1037/ocp0000056

Bakker, A. B., Demerouti, E., & Sanz-Vergel, A. I. (2014). Burnout and Work Engagement: The JD–R Approach. *Annual Review of Organizational Psychology and Organizational Behavior*, *1*(1), 389–411. https://doi.org/10.1146/annurev-orgpsych-031413-091235

Bankins, S., Ocampo, A. C., Marrone, M., Restubog, S. L. D., & Woo, S. E. (2024). A multilevel review of artificial intelligence in organizations: Implications for organizational behavior research and practice. *Journal of Organizational Behavior*, *45*(2), 159–182. https://doi.org/10.1002/job.2735

Batin, M., Turchin, A., Markov, S., Zhila, A., & Denkenberger, D. (2017). Artificial Intelligence in Life Extension: from Deep Learning to Superintelligence. In *Informatica* (Vol. 41). http://scienceagainstaging.com/https://www.ibm.com/watson/http://allfed.info/

Becker, J.-M., Cheah, J.-H., Gholamzade, R., Ringle, C. M., & Sarstedt, M. (2023). PLS-SEM's most wanted guidance. *International Journal of Contemporary Hospitality Management*, *35*(1), 321–346. https://doi.org/10.1108/IJCHM-04-2022-0474

Bednar, P. M., & Welch, C. (2020). Socio-Technical Perspectives on Smart Working: Creating Meaningful and Sustainable Systems. *Information Systems Frontiers*, *22*(2), 281–298. https://doi.org/10.1007/s10796-019-09921-1

Bellmann, L., & Hübler, O. (2021). Working from home, job satisfaction and work–life balance – robust or heterogeneous links? *International Journal of Manpower*, *42*(3), 424–441. https://doi.org/10.1108/IJM-10-2019-0458

Bernerth, J. B., Cole, M. S., Taylor, E. C., & Walker, H. J. (2018). Control Variables in Leadership Research: A Qualitative and Quantitative Review. *Journal of Management*, *44*(1), 131–160. https://doi.org/10.1177/0149206317690586

Böhmer, N., & Schinnenburg, H. (2023). Critical exploration of AI-driven HRM to build up organizational capabilities. *Employee Relations: The International Journal*, *45*(5), 1057–1082. https://doi.org/10.1108/ER-04-2022-0202

Bouillon-Minois, J.-B., Trousselard, M., Mulliez, A., Adeyemi, O. J., Schmidt, J., Thivel, D., Ugbolue, U. C., Borel, M., Moustafa, F., Vallet, G. T., Clinchamps, M., Zak, M., Occelli, C., & Dutheil, F. (2023). A cross-sectional study to assess job strain of emergency healthcare workers by Karasek questionnaire: The SEEK study. *Frontiers in Psychiatry*, *13*. https://doi.org/10.3389/fpsyt.2022.1043110

BOZBAŞ, A., & GÜL, T. (2022). Correlationship between job and life satisfaction: A research on occupational characteristics. *Journal of Tourism Leisure and Hospitality*, *4*(1), 1–13. https://doi.org/10.48119/toleho.1037497

Brachten, F., Brünker, F., Frick, N. R. J., Ross, B., & Stieglitz, S. (2020). On the ability of virtual agents to decrease cognitive load: an experimental study. *Information Systems and E-Business Management*, *18*(2), 187–207. https://doi.org/10.1007/s10257-020-00471-7

Brougham, D., & Haar, J. (2020). Technological disruption and employment: The influence on job insecurity and turnover intentions: A multi-country study. *Technological Forecasting and Social Change*, *161*, 120276. https://doi.org/10.1016/j.techfore.2020.120276

Chen, S.-H. (Ava), Tzeng, S.-Y., Tham, A., & Chu, P.-X. (2021). Hospitality services in the post COVID-19 era: Are we ready for high-tech and no touch service delivery in smart hotels? *Journal of Hospitality Marketing & Management*, *30*(8), 905–928. https://doi.org/10.1080/19368623.2021.1916669

Chin, J.-H., Do, C., & Kim, M. (2022). How to Increase Sport Facility Users' Intention to Use AI Fitness Services: Based on the Technology Adoption Model. *International Journal of Environmental Research and Public Health*, *19*(21), 14453. https://doi.org/10.3390/ijerph192114453

Churchill, G. A., Ford, N. M., & Walker, O. C. (1976). Organizational Climate and Job Satisfaction in the Salesforce. *Journal of Marketing Research*, *13*(4), 323–332. https://doi.org/10.1177/002224377601300401

Ciuchita, R., Gummerus, J. K., Holmlund, M., & Linhart, E. L. (2023). Programmatic advertising in online retailing: consumer perceptions and future avenues. *Journal of Service Management*, *34*(2), 231–255. https://doi.org/10.1108/JOSM-06-2021-0238

Cohen, J. (1988). Set Correlation and Contingency Tables. *Applied Psychological Measurement*, *12*(4), 425–434. https://doi.org/10.1177/014662168801200410

Crawford, E. R., LePine, J. A., & Rich, B. L. (2010). Linking job demands and resources to employee engagement and burnout: A theoretical extension and meta-analytic test. *Journal of Applied Psychology*, *95*(5), 834–848. https://doi.org/10.1037/a0019364

Damanpour, F., & Schneider, M. (2006). Phases of the Adoption of Innovation in Organizations: Effects of Environment, Organization and Top Managers [1]. *British Journal of Management*, *17*(3), 215–236. https://doi.org/10.1111/j.1467-8551.2006.00498.x

Dellermann, D., Ebel, P., Söllner, M., & Leimeister, J. M. (2019). Hybrid Intelligence. *Business & Information Systems Engineering*, *61*(5), 637–643. https://doi.org/10.1007/s12599-019-00595-2

Demerouti, E., Bakker, A. B., Nachreiner, F., & Schaufeli, W. B. (2001). The job demands-resources model of burnout. *Journal of Applied Psychology*, *86*(3), 499–512. https://doi.org/10.1037/0021-9010.86.3.499

Diener, E., Emmons, R. A., Larsen, R. J., & Griffin, S. (1985). The Satisfaction With Life Scale. *Journal of Personality Assessment*, *49*(1), 71–75. https://doi.org/10.1207/s15327752jpa4901_13

Diener, E., Lucas, R. E., & Oishi, S. (2002). *Subjective well-being: The science of happiness and life satisfaction.* (S. J. Lopez & C. R. Snyder, Eds.; 2nd ed.).

Douglas, B. D., Ewell, P. J., & Brauer, M. (2023). Data quality in online human-subjects research: Comparisons between MTurk, Prolific, CloudResearch, Qualtrics, and SONA. *PLOS ONE*, *18*(3), e0279720. https://doi.org/10.1371/journal.pone.0279720

Dueber, D. M., Toland, M. D., Lingat, J. E., Love, A. M. A., Qiu, C., Wu, R., & Brown, A. v. (2022). To Reverse Item Orientation or Not to Reverse Item Orientation, That Is the Question. *Assessment*, *29*(7), 1422–1440. https://doi.org/10.1177/10731911211017635

Dutheil, F., Pereira, B., Bouillon-Minois, J.-B., Clinchamps, M., Brousses, G., Dewavrin, S., Cornet, T., Mermillod, M., Mondillon, L., Baker, J. S., Schmidt, J., Moustafa, F., & Lanhers, C. (2022). Validation of Visual Analogue Scales of job demand and job control at the workplace: a cross-sectional study. *BMJ Open*, *12*(3), e046403. https://doi.org/10.1136/bmjopen-2020-046403

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., … Williams, M. D. (2021). Artificial

Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, *57*, 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Ejiogu, A. M. (1980). When Innovations are External to the Realities and Needs of an Organization: Problems of Educational Innovations in the Developing Countries. *Journal of Curriculum Studies*, *12*(2), 161–166. https://doi.org/10.1080/0022027800120208

Enholm, I. M., Papagiannidis, E., Mikalef, P., & Krogstie, J. (2022). Artificial Intelligence and Business Value: a Literature Review. *Information Systems Frontiers*, *24*(5), 1709–1734. https://doi.org/10.1007/s10796-021-10186-w

F. Hair Jr, J., Sarstedt, M., Hopkins, L., & G. Kuppelwieser, V. (2014). Partial least squares structural equation modeling (PLS-SEM). *European Business Review*, *26*(2), 106–121. https://doi.org/10.1108/EBR-10-2013-0128

Ferreira, P., Gabriel, C., Faria, S., Rodrigues, P., & Sousa Pereira, M. (2020). What if Employees Brought Their Life to Work? The Relation of Life Satisfaction and Work Engagement. *Sustainability*, *12*(7), 2743. https://doi.org/10.3390/su12072743

Fornell, C., & Larcker, D. F. (1981). Structural Equation Models with Unobservable Variables and Measurement Error: Algebra and Statistics. *Journal of Marketing Research*, *18*(3), 382–388. https://doi.org/10.1177/002224378101800313

Frank, A. G., Dalenogare, L. S., & Ayala, N. F. (2019). Industry 4.0 technologies: Implementation patterns in manufacturing companies. *International Journal of Production Economics*, *210*, 15–26. https://doi.org/10.1016/j.ijpe.2019.01.004

Gaucher, R. (2022). The Work Day Reconstruction Method: an adaptation of the Day Reconstruction Method to the work setting. *Quality & Quantity*, *56*(6), 4487–4509. https://doi.org/10.1007/s11135-021-01290-9

Ghani, B., Memon, K. R., Han, H., Ariza-Montes, A., & Arjona-Fuentes, J. M. (2022). Work stress, technological changes, and job insecurity in the retail organization context. *Frontiers in Psychology*, *13*. https://doi.org/10.3389/fpsyg.2022.918065

Grassini, S. (2023). Development and validation of the AI attitude scale (AIAS-4): a brief measure of general attitude toward artificial intelligence. *Frontiers in Psychology*, *14*. https://doi.org/10.3389/fpsyg.2023.1191628

Grundner, L., & Neuhofer, B. (2021). The bright and dark sides of artificial intelligence: A futures perspective on tourist destination experiences. *Journal of Destination Marketing & Management*, *19*, 100511. https://doi.org/10.1016/j.jdmm.2020.100511

Gu, Y., & Hua, L. (2021). A Novel Smart Motor Imagery Intention Human-Computer Interaction Model Using Extreme Learning Machine and EEG Signals. *Frontiers in Neuroscience*, *15*. https://doi.org/10.3389/fnins.2021.685119

Hair, J. F., Howard, M. C., & Nitzl, C. (2020). Assessing measurement model quality in PLS-SEM using confirmatory composite analysis. *Journal of Business Research*, *109*, 101–110. https://doi.org/10.1016/j.jbusres.2019.11.069

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Hair, J. F., Sarstedt, M., Ringle, C. M., & Mena, J. A. (2012). An assessment of the use of partial least squares structural equation modeling in marketing research. *Journal of the Academy of Marketing Science*, *40*(3), 414–433. https://doi.org/10.1007/s11747-011-0261-6

Hamada, H. T., & Kanai, R. (2022). *AI agents for facilitating social interactions and wellbeing*.

Hanafiah, M. H. (2020). Formative Vs. Reflective Measurement Model: Guidelines for Structural Equation Modeling Research. *International Journal of Analysis and Applications*. https://doi.org/10.28924/2291-8639-18-2020-876

Heinsman, D. T., & Shadish, W. R. (1996). Assignment methods in experimentation: When do nonrandomized experiments approximate answers from randomized experiments? *Psychological Methods*, *1*(2), 154–169. https://doi.org/10.1037/1082-989X.1.2.154

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Horowitz, M. C., Kahn, L., Macdonald, J., & Schneider, J. (2023). Adopting AI: how familiarity breeds both trust and contempt. *AI & SOCIETY*. https://doi.org/10.1007/s00146-023-01666-5

Hosny, A., Parmar, C., Quackenbush, J., Schwartz, L. H., & Aerts, H. J. W. L. (2018). Artificial intelligence in radiology. *Nature Reviews Cancer*, *18*(8), 500–510. https://doi.org/10.1038/s41568-018-0016-5

Howard, S. K., Swist, T., Gasevic, D., Bartimote, K., Knight, S., Gulson, K., Apps, T., Peloche, J., Hutchinson, N., & Selwyn, N. (2022). Educational data journeys: Where are we going, what are we taking and making for AI? *Computers and Education: Artificial Intelligence*, *3*, 100073. https://doi.org/10.1016/j.caeai.2022.100073

Howell, P., Aryal, A., & Wu, C. (2023). Web-Based Patient Recommender Systems for Preventive Care: Protocol for Empirical Research Propositions. *JMIR Research Protocols*, *12*, e43316. https://doi.org/10.2196/43316

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, *6*(1), 1–55. https://doi.org/10.1080/10705519909540118

Huang, M.-H., & Rust, R. T. (2021). Engaged to a Robot? The Role of AI in Service. *Journal of Service Research*, *24*(1), 30–41. https://doi.org/10.1177/1094670520902266

Jacobs, A., Verhofstadt, E., & van Ootegem, L. (2023). Unravelling the Link between Automatability and Job Satisfaction. *Journal of Labor Research*, *44*(3–4), 199–227. https://doi.org/10.1007/s12122-023-09346-5

Jetha, A., Bakhtari, H., Rosella, L. C., Gignac, M. A. M., Biswas, A., Shahidi, F. v., Smith, B. T., Smith, M. J., Mustard, C., Khan, N., Arrandale, V. H., Loewen, P. J., Zuberi, D., Dennerlein, J. T., Bonaccio, S., Wu, N., Irvin, E., & Smith, P. M. (2023). Artificial intelligence and the work–health interface: A research agenda for a technologically transforming world of work. *American Journal of Industrial Medicine*, *66*(10), 815–830. https://doi.org/10.1002/ajim.23517

Jiang, Y., Li, X., Luo, H., Yin, S., & Kaynak, O. (2022). Quo vadis artificial intelligence? *Discover Artificial Intelligence*, *2*(1), 4. https://doi.org/10.1007/s44163-022-00022-8

Jo, H., & Park, D.-H. (2023). AI in the Workplace: Examining the Effects of ChatGPT on Information Support and Knowledge Acquisition. *International Journal of Human–Computer Interaction*, 1–16. https://doi.org/10.1080/10447318.2023.2278283

Jun, J. S., Lee, K. H., & Roh, S. (2021). Technology acceptance, social support, and life satisfaction among rural American Indian Elders. *Journal of Ethnic & Cultural Diversity in Social Work*, *30*(5), 398–412. https://doi.org/10.1080/15313204.2019.1702606

Kacmar, K. M., & Ferris, G. R. (1989a). Theoretical and methodological considerations in the age-job satisfaction relationship. *Journal of Applied Psychology*, *74*(2), 201–207. https://doi.org/10.1037/0021-9010.74.2.201

Kacmar, K. M., & Ferris, G. R. (1989b). Theoretical and methodological considerations in the age-job satisfaction relationship. *Journal of Applied Psychology*, *74*(2), 201–207. https://doi.org/10.1037/0021-9010.74.2.201

Karlita, I. V., Surati, S., & Suryatni, M. (2020). The Effect of Job Characteristics and Work Life Balance on Performance through Job Satisfaction as Interverning Variables (Studies on Female Partners on Gojek Services in Mataram City). *International Journal of Multicultural and Multireligious Understanding*, *7*(11), 145. https://doi.org/10.18415/ijmmu.v7i11.2161

Kashive, N., Powale, L., & Kashive, K. (2020). Understanding user perception toward artificial intelligence (AI) enabled e-learning. *The International Journal of Information and Learning Technology*, *38*(1), 1–19. https://doi.org/10.1108/IJILT-05-2020-0090

Kinnunen, U., Mauno, S., N�tti, J., & Happonen, M. (2000). Organizational antecedents and outcomes of job insecurity: a longitudinal study in three organizations in Finland. *Journal of*

Organizational Behavior, *21*(4), 443–459. https://doi.org/10.1002/(SICI)1099-1379(200006)21:4<443::AID-JOB24>3.0.CO;2-N

Kjell, O. N. E., & Diener, E. (2021). Abbreviated Three-Item Versions of the Satisfaction with Life Scale and the Harmony in Life Scale Yield as Strong Psychometric Properties as the Original Scales. *Journal of Personality Assessment*, *103*(2), 183–194. https://doi.org/10.1080/00223891.2020.1737093

Kwak, Y., Seo, Y. H., & Ahn, J.-W. (2022). Nursing students' intent to use AI-based healthcare technology: Path analysis using the unified theory of acceptance and use of technology. *Nurse Education Today*, *119*, 105541. https://doi.org/10.1016/j.nedt.2022.105541

Lane, M., Williams, M., & Broecke, S. (2023). *The impact of AI on the workplace: Main findings from the OECD AI surveys of employers and workers*.

Lee, H.-H., & Chang, E. (2011). Consumer Attitudes Toward Online Mass Customization: An Application of Extended Technology Acceptance Model. *Journal of Computer-Mediated Communication*, *16*(2), 171–200. https://doi.org/10.1111/j.1083-6101.2010.01530.x

Lichtenthaler, U. (2019). An Intelligence-Based View of Firm Performance: Profiting from Artificial Intelligence. *Journal of Innovation Management*, *7*(1), 7–20. https://doi.org/10.24840/2183-0606_007.001_0002

Locke, E. A. (1969). What is job satisfaction? *Organizational Behavior and Human Performance*, *4*(4), 309–336. https://doi.org/10.1016/0030-5073(69)90013-0

Loher, B. T., Noe, R. A., Moeller, N. L., & Fitzgerald, M. P. (1985). A meta-analysis of the relation of job characteristics to job satisfaction. *Journal of Applied Psychology*, *70*(2), 280–289. https://doi.org/10.1037/0021-9010.70.2.280

Loureiro, S. M. C., Bilro, R. G., & Neto, D. (2023). Working with AI: can stress bring happiness? *Service Business*, *17*(1), 233–255. https://doi.org/10.1007/s11628-022-00514-8

Loureiro, S. M. C., Guerreiro, J., & Han, H. (2022). Past, present, and future of pro-environmental behavior in tourism and hospitality: a text-mining approach. *Journal of Sustainable Tourism*, *30*(1), 258–278. https://doi.org/10.1080/09669582.2021.1875477

Lu, Y., & Zheng, X. (2020). 6G: A survey on technologies, scenarios, challenges, and the related issues. *Journal of Industrial Information Integration*, *19*, 100158. https://doi.org/10.1016/j.jii.2020.100158

Malik, P. K., Sharma, R., Singh, R., Gehlot, A., Satapathy, S. C., Alnumay, W. S., Pelusi, D., Ghosh, U., & Nayak, J. (2021). Industrial Internet of Things and its Applications in Industry 4.0: State of The Art. *Computer Communications*, *166*, 125–139. https://doi.org/10.1016/j.comcom.2020.11.016

Manuaba, I. A. K. A., & Hidayat, A. E. (2019). Increasing the Engagement of Millennials: Finding Autonomy and Salience in High Workload. *Proceedings of the 2nd International Conference on Intervention and Applied Psychology (ICIAP 2018)*. https://doi.org/10.2991/iciap-18.2019.71

Marasinghe, M. P. L. R., & Wijayaratne, A. (2018). The Impact of Gender Differences on Job Satisfaction of University Library Professionals. *Journal of the University Librarians Association of Sri Lanka*, *21*(2), 1–20. https://doi.org/10.4038/jula.v21i2.7905

McCarthy, J., Minsky, M. L., Rochester, N., & Shannon, C. E. (2006). *A Proposal for the Dartmouth Summer Research Project on Artificial Intelligence*.

Mharapara, T. L., Cooper-Thomas, H. D., Stadler, M., & Hutchison, A. (2022). Comparing models of follower outcomes: destructive and constructive leader behavior. *Leadership & Organization Development Journal*, *43*(7), 1140–1155. https://doi.org/10.1108/LODJ-10-2021-0488

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management*, *58*(3), 103434. https://doi.org/10.1016/j.im.2021.103434

Mirbabaie, M., Stieglitz, S., Brünker, F., Hofeditz, L., Ross, B., & Frick, N. R. J. (2021). Understanding Collaboration with Virtual Assistants – The Role of Social Identity and the Extended Self. *Business & Information Systems Engineering*, *63*(1), 21–37. https://doi.org/10.1007/s12599-020-00672-x

Monteith, S., Glenn, T., Geddes, J., Whybrow, P. C., & Bauer, M. (2022). Commercial Use of Emotion Artificial Intelligence (AI): Implications for Psychiatry. *Current Psychiatry Reports*, *24*(3), 203–211. https://doi.org/10.1007/s11920-022-01330-7

Moraes, C. H. V. de, Scolimoski, J., Lambert-Torres, G., Santini, M., Dias, A. L. A., Guerra, F. A., Pedretti, A., & Ramos, M. P. (2022). Robotic Process Automation and Machine Learning: a Systematic Review. *Brazilian Archives of Biology and Technology*, *65*. https://doi.org/10.1590/1678-4324-2022220096

Moser, K., & Schuler, H. (2004). Is Involvement a Suppressor of the Job Satisfaction–Life Satisfaction Relationship? [1]. *Journal of Applied Social Psychology*, *34*(11), 2377–2388. https://doi.org/10.1111/j.1559-1816.2004.tb01982.x

Na, S., Heo, S., Han, S., Shin, Y., & Roh, Y. (2022). Acceptance Model of Artificial Intelligence (AI)-Based Technologies in Construction Firms: Applying the Technology Acceptance Model (TAM) in Combination with the Technology–Organisation–Environment (TOE) Framework. *Buildings*, *12*(2), 90. https://doi.org/10.3390/buildings12020090

Nazir, S., Khadim, S., Ali Asadullah, M., & Syed, N. (2023). Exploring the influence of artificial intelligence technology on consumer repurchase intention: The mediation and moderation approach. *Technology in Society*, *72*, 102190. https://doi.org/10.1016/j.techsoc.2022.102190

Nguyen, T.-M., & Malik, A. (2022). Impact of knowledge sharing on employees' service quality: the moderating role of artificial intelligence. *International Marketing Review*, *39*(3), 482–508. https://doi.org/10.1108/IMR-02-2021-0078

OECD. (2019). *Scoping the OECD AI Principles*.

Pandita, R., & Domnic, J. (2016). Variables of Job Satisfaction: A Review Study with Special Reference to LIS Professionals. *International Journal of Information Dissemination and Technology*, *6*(4), 258–267.

Pavot, W., & Diener, E. (2008). The Satisfaction With Life Scale and the emerging construct of life satisfaction. *The Journal of Positive Psychology*, *3*(2), 137–152. https://doi.org/10.1080/17439760701756946

Pereira, V., Hadjielias, E., Christofi, M., & Vrontis, D. (2023). A systematic literature review on the impact of artificial intelligence on workplace outcomes: A multi-process perspective. *Human Resource Management Review*, *33*(1), 100857. https://doi.org/10.1016/j.hrmr.2021.100857

Pishgar, M., Issa, S. F., Sietsema, M., Pratap, P., & Darabi, H. (2021). REDECA: A Novel Framework to Review Artificial Intelligence and Its Applications in Occupational Safety and Health. *International Journal of Environmental Research and Public Health*, *18*(13), 6705. https://doi.org/10.3390/ijerph18136705

Presbitero, A., & Teng-Calleja, M. (2023). Job attitudes and career behaviors relating to employees' perceived incorporation of artificial intelligence in the workplace: a career self-management perspective. *Personnel Review*, *52*(4), 1169–1187. https://doi.org/10.1108/PR-02-2021-0103

R., M., & Jayanthila Devi, A. (2022). Amazon's Artificial Intelligence in Retail Novelty - Case Study. *International Journal of Case Studies in Business, IT, and Education*, 787–804. https://doi.org/10.47992/IJCSBE.2581.6942.0233

Rabe, A., Kreinsen, M., Grospietsch, F., & Schulz, S. (2023). How to Deal with Students' Conceptions: Conceptual Change Texts on Artificial Intelligence. *Proceedings of the 18th WiPSCE Conference on Primary and Secondary Computing Education Research*, 1–2. https://doi.org/10.1145/3605468.3609781

Raj, R., & Kos, A. (2022). A Comprehensive Study of Mobile Robot: History, Developments, Applications, and Future Research Perspectives. *Applied Sciences*, *12*(14), 6951. https://doi.org/10.3390/app12146951

Ramchurn, S. D., Stein, S., & Jennings, N. R. (2021). *Trustworthy human-AI partnerships*. https://doi.org/10.1016/j.isci

Ravari, A., Mirzaei, T., Kazemi, M., & Jamalizadeh, A. (2012). Job satisfaction as a multidimensional concept: A systematic review study. *Journal of Occupational Health and Epidemiology*, *1*(2), 95–102. https://doi.org/10.18869/acadpub.johe.1.2.95

RAY, T. K. (2021a). Work related well-being is associated with individual subjective well-being. *Industrial Health*, *60*(3), 2021–0122. https://doi.org/10.2486/indhealth.2021-0122

RAY, T. K. (2021b). Work related well-being is associated with individual subjective well-being. *Industrial Health*, *60*(3), 2021–0122. https://doi.org/10.2486/indhealth.2021-0122

Roche, A., & Nicholas, R. (2017). Workforce development: An important paradigm shift for the alcohol and other drugs sector. *Drugs: Education, Prevention and Policy*, *24*(6), 443–454. https://doi.org/10.1080/09687637.2016.1262823

Rode, J. C. (2004). Job satisfaction and life satisfaction revisited: A longitudinal test of an integrated model. *Human Relations*, *57*(9), 1205–1230. https://doi.org/10.1177/0018726704047143

Rodríguez, D., van Landeghem, H., Lasio, V., & Buyens, D. (2017). Determinants of job satisfaction in a lean environment. *International Journal of Lean Six Sigma*, *8*(2), 134–152. https://doi.org/10.1108/IJLSS-01-2016-0002

Rosenberg, M. (1965). Rosenberg self-esteem scale (RSE). *Measures Package*, *61*(52), 1–18.

Saks, A. M. (2006). Antecedents and consequences of employee engagement. *Journal of Managerial Psychology*, *21*(7), 600–619. https://doi.org/10.1108/02683940610690169

Samek, W., Montavon, G., Lapuschkin, S., Anders, C. J., & Muller, K.-R. (2021). Explaining Deep Neural Networks and Beyond: A Review of Methods and Applications. *Proceedings of the IEEE*, *109*(3), 247–278. https://doi.org/10.1109/JPROC.2021.3060483

Sarpkaya, A., & Kırdök, O. (2019a). The Mediating Role of Self-Esteem in Understanding Relationship between Teachers' Job Satisfaction and Life Satisfaction. *Acta Didactica Napocensia*, *12*(1), 213–224. https://doi.org/10.24193/adn.12.1.16

Sarpkaya, A., & Kırdök, O. (2019b). The Mediating Role of Self-Esteem in Understanding Relationship between Teachers' Job Satisfaction and Life Satisfaction. *Acta Didactica Napocensia*, *12*(1), 213–224. https://doi.org/10.24193/adn.12.1.16

Sarstedt, M., Hair, J. F., & Ringle, C. M. (2023). "PLS-SEM: indeed a silver bullet" – retrospective observations and recent advances. *Journal of Marketing Theory and Practice*, *31*(3), 261–275. https://doi.org/10.1080/10696679.2022.2056488

Sarstedt, M., Ringle, C. M., & Hair, J. F. (2022). Partial Least Squares Structural Equation Modeling. In *Handbook of Market Research* (pp. 587–632). Springer International Publishing. https://doi.org/10.1007/978-3-319-57413-4_15

Schaufeli, W. B., & Bakker, A. B. (2004). Job demands, job resources, and their relationship with burnout and engagement: a multi-sample study. *Journal of Organizational Behavior*, *25*(3), 293–315. https://doi.org/10.1002/job.248

Schwabe, H., & Castellacci, F. (2020). Automation, workers' skills and job satisfaction. *PLOS ONE*, *15*(11), e0242929. https://doi.org/10.1371/journal.pone.0242929

Spector, J. M., & Ma, S. (2019). Inquiry and critical thinking skills for the next generation: from artificial intelligence back to human intelligence. *Smart Learning Environments*, *6*(1), 8. https://doi.org/10.1186/s40561-019-0088-z

Stamate, A. N., Sauvé, G., & Denis, P. L. (2021). The rise of the machines and how they impact workers' psychological health: An empirical study. *Human Behavior and Emerging Technologies*, *3*(5), 942–955. https://doi.org/10.1002/hbe2.315

Stone, M., Aravopoulou, E., Ekinci, Y., Evans, G., Hobbs, M., Labib, A., Laughlin, P., Machtynger, J., & Machtynger, L. (2020). Artificial intelligence (AI) in strategic marketing decision-making: a research agenda. *The Bottom Line*, *33*(2), 183–200. https://doi.org/10.1108/BL-03-2020-0022

Sun, F., Lu, Q., Feng, S., & Zhang, T. (2021). Flexible Artificial Sensory Systems Based on Neuromorphic Devices. *ACS Nano*, *15*(3), 3875–3899. https://doi.org/10.1021/acsnano.0c10049

Thomas, A., Buboltz, W. C., & Winkelspecht, C. S. (2004). JOB CHARACTERISTICS AND PERSONALITY AS PREDICTORS OF JOB SATISFACTION. *Organizational Analysis*, *12*(2), 205–219. https://doi.org/10.1108/eb028993

Tian, J., Yu, H., & Austin, L. (2022). The Effect of Physical Activity on Anxiety: The Mediating Role of Subjective Well-Being and the Moderating Role of Gender. *Psychology Research and Behavior Management*, *Volume 15*, 3167–3178. https://doi.org/10.2147/PRBM.S384707

Wang, P. (2019). On Defining Artificial Intelligence. *Journal of Artificial General Intelligence*, *10*(2), 1–37. https://doi.org/10.2478/jagi-2019-0002

Waqas, A., Bashir, U., Sattar, M. F., Abdullah, H. M., Hussain, I., Anjum, W., Aftab Ali, M., & Arshad, R. (2014). Factors Influencing Job Satisfaction and Its Impact on Job Loyalty. *International Journal of Learning and Development*, *4*(2). https://doi.org/10.5296/ijld.v4i2.6095

Williams, P., Kern, M. L., & Waters, L. (2017). The Role and Reprocessing of Attitudes in Fostering Employee Work Happiness: An Intervention Study. *Frontiers in Psychology*, *8*. https://doi.org/10.3389/fpsyg.2017.00028

Xanthopoulou, D., Bakker, A. B., Demerouti, E., & Schaufeli, W. B. (2007). The role of personal resources in the job demands-resources model. *International Journal of Stress Management*, *14*(2), 121–141. https://doi.org/10.1037/1072-5245.14.2.121

Yu, L., & Li, Y. (2022). Artificial Intelligence Decision-Making Transparency and Employees' Trust: The Parallel Multiple Mediating Effect of Effectiveness and Discomfort. *Behavioral Sciences*, *12*(5), 127. https://doi.org/10.3390/bs12050127

Yu, X., Xu, S., & Ashton, M. (2023). Antecedents and outcomes of artificial intelligence adoption and application in the workplace: the socio-technical system theory perspective. *Information Technology & People*, *36*(1), 454–474. https://doi.org/10.1108/ITP-04-2021-0254

Zhao, J., Wu, M., Zhou, L., Wang, X., & Jia, J. (2022). Cognitive psychology-based artificial intelligence review. *Frontiers in Neuroscience*, *16*. https://doi.org/10.3389/fnins.2022.1024316

Zhu, Y., Gao, T., Fan, L., Huang, S., Edmonds, M., Liu, H., Gao, F., Zhang, C., Qi, S., Wu, Y. N., Tenenbaum, J. B., & Zhu, S.-C. (2020). Dark, Beyond Deep: A Paradigm Shift to Cognitive AI with Humanlike Common Sense. *Engineering*, *6*(3), 310–345. https://doi.org/10.1016/j.eng.2020.01.011

Złotowski, J., Yogeeswaran, K., & Bartneck, C. (2017). Can we control it? Autonomous robots threaten human identity, uniqueness, safety, and resources. *International Journal of Human-Computer Studies*, *100*, 48–54. https://doi.org/10.1016/j.ijhcs.2016.12.008

APPENDICES

Appendix 1: Qualtrics Survey

Intro

Welcome and thank you for taking your time to participate in this study!

I, Olivia Metzger, am conducting this survey as part of my Master's thesis at the Católica Lisbon School of Business and Economics under the supervision of Dr. Filipa de Almeida. The purpose of this survey is to investigate the **interaction with artificial intelligence (AI) at the workplace**.

Your participation holds significant value for my research and takes around **5 minutes** to complete. All answers will be treated **confidentially** and **anonymously** and the data collected will be used for research purposes only. I kindly ask you to answer the survey in one go, without interruptions.

If you have any questions or comments please do not hesitate to contact me:
s-ometzger@ucp.pt

Do you consent to participate in this study?

- ○ Yes, I consent
- ○ No, I do not consent

Attitudes towards AI

Artificial **I**ntelligence - or **AI** in short - is what enables smart computer programs and machines to carry out tasks that would typically require human intelligence. This includes learning from data, making decisions based on information, solving complex problems, understanding and responding to language, recognizing patterns, and adapting to new situations.

Some examples where AI can be found in your everyday life include:

- Siri, Alexa and other smart assistants,
- Netflix or YouTube recommendations, and
- Self-driving cars

To begin, I would like to learn more about **your attitudes towards AI.**

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
I believe that AI will improve my life	O	O	O	O	O
I believe that AI will improve my work	O	O	O	O	O
I think I will use AI technology in the future	O	O	O	O	O
I think AI technology is positive for humanity	O	O	O	O	O

Interaction with AI at work

Next, I would like to learn more about **your interaction with AI at your workplace**.

<u>Some examples where AI Can be found in the workplace include:</u>

1. Customer Service: AI-powered chatbots and virtual assistants that can handle customer requests, provide product information and offer support
2. Human Resources: Automated screening of job applications, chatbots for HR-related requests, AI-driven employee engagements tools
3. Marketing and Sales: AI tools to optimize marketing campaigns, personalize customer experiences, to analyze sales data for better targeting potential customers
4. Manufacturing and Logistics: Software that predicts prices and demands, AI that can tell when machines should be serviced, robots that use cameras to check items for flaws
5. Data Analysis and Decision Making: AI algorithms to analyze large sets of data, generating insights, making predictions and guiding decision making

6. Finance: Robo-advisors, chatbots used for customer service, fraud detection software
7. Healthcare: AI tools for analysing medical images, diagnosing diseases and personalizing patient care plans
8. Creative Industries: AI-driven content creation tools for writing, graphic design and music production
9. Code Generation: AI that helps developers write code, either by analyzing a code-base or generating code itself (GitHub CoPilot, Replit Code LLM, etc)

Your interaction with AI at your workplace might include using these technologies directly, working in environments enhanced by these technologies, or making decisions influenced by insights provided by AI systems.

Keeping this information in mind, please refer to the following questions.

Thinking back to **yesterday**, can you recall and count the number of times you used AI-enabled tools or systems during your workday? Please consider each separate interaction with AI in software, tools for data analysis, customer service bots, etc.
Example: You use ChatGPT to help you out with your code and it gives you one line. You then ask it something else and it gives you another line. This counts as 2 interactions.

	0	20	40	60	80	100	
0 times							

Reflecting on your workday **yesterday**, how often do you feel you interacted with AI-enabled tools or services?

- Very little
- A bit
- A moderate amount
- A lot
- Almost constantly

Job Demands and Resources

Now, I would like to learn more about **how you experience your workplace**.

	Never	Sometimes	About half the time	Most of the time	Always
My job requires me to work very fast	○	○	○	○	○
My job requires me to work very hard	○	○	○	○	○
I need a lot of effort in my job	○	○	○	○	○
I have enough time to do my tasks	○	○	○	○	○
I have conflicts in the team	○	○	○	○	○

Now, I would like to learn more about **how you experience your workplace**.

	Never	Sometimes	About half the time	Most of the time	Always
I get on well with my co-workers	○	○	○	○	○
I can ask my co-workers for help if necessary	○	○	○	○	○
My co-workers understand if I have a bad day	○	○	○	○	○
I get on well with my supervisors	○	○	○	○	○
I can ask my supervisors for help if necessary	○	○	○	○	○

Self-Esteem

Now, I would like to learn more about **how you view yourself**.

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
I take a positive attitude toward myself	○	○	○	○	○
I feel that I have a number of good skills	○	○	○	○	○
I am able to do things as well as most other people	○	○	○	○	○
I feel that I am a person of worth	○	○	○	○	○
Overall, I am satisfied with myself	○	○	○	○	○

Job Satisfaction

Please answer the questions below keeping in mind **your work alongside AI.**

When I work with AI, ...

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
... I feel close to people at work	○	○	○	○	○
... I feel good about working at the company	○	○	○	○	○
... I feel secure about my job	○	○	○	○	○
... I believe management is concerned about me	○	○	○	○	○
... I am satisfied with my job overall	○	○	○	○	○

Life Satisfaction

Lastly, please answer the questions below about **how satisfied you are with your life.**

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
In most ways my life is close to my ideal	○	○	○	○	○
The conditions of my life are excellent	○	○	○	○	○
I am satisfied with my life	○	○	○	○	○

Demographic Questions

Thank you for your answers!

To end, I kindly ask you to answer a few demographic questions.

How old are you?

[ ]

How do you describe yourself?

○ Male
○ Female
○ Non-binary / third gender
○ [ ] Prefer to self-describe
○ Prefer not to say

What is your highest level of education?

- Less than Secondary education
- Secondary education
- Bachelor's Degree
- Master's Degree
- Doctoral Degree
- Other

What is your current employment status?

- Employed
- Freelancer
- Unemployed
- Student
- Working Student
- Retired
- Other

How comfortable are you with the English language?

- Extremely uncomfortable
- Somewhat uncomfortable
- Neither comfortable nor uncomfortable
- Somewhat comfortable
- Extremely comfortable

How much attention did you pay during this survey?

- None at all
- A little
- A moderate amount
- A lot

○ A great deal

Do you have any comments you would like to share with the researcher? If so, please write them in the box below. Otherwise, just leave blank

Debriefing

Thank you for your participation in this study. In this study I actually wanted to find out how interacting with AI affects satisfaction with work and in broader terms satisfaction with life. My hypothesis is that interacting more with AI leads to higher satisfaction with work and higher overall life satisfaction. However, other factors play into this as well, which is why I asked you about your attitude towards AI, questions about how you view yourself (self-esteem) as well as your workplace (job demands and resources). I did not disclose the full goal of the tasks you were exposed to as doing so would render the results of the current study not informative.

For any comments or questions please contact: s-ometzger@ucp.pt

Appendix 2: Demographic profile of participants

Age

	N	Minimum	Maximum	Mean	Std. Deviation
How old are you?	268	18	73	33.76	11.485
Valid N (listwise)	268				

Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	125	46.6	46.6	46.6
	Female	138	51.5	51.5	98.1
	Prefer to self-describe	3	1.1	1.1	99.3
	Prefer not to say	2	.7	.7	100.0
	Total	268	100.0	100.0	

Highest level of Education

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Secondary education	40	14.9	14.9	14.9
	Bachelor's Degree	94	35.1	35.1	50.0
	Master's Degree	114	42.5	42.5	92.5
	Doctoral Degree	13	4.9	4.9	97.4
	Other	7	2.6	2.6	100.0
	Total	268	100.0	100.0	

Current Employment Status

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Employed	174	64.9	64.9	64.9
	Freelancer	19	7.1	7.1	72.0
	Unemployed	4	1.5	1.5	73.5
	Student	27	10.1	10.1	83.6
	Working Student	35	13.1	13.1	96.6
	Retired	1	.4	.4	97.0
	Other	8	3.0	3.0	100.0
	Total	268	100.0	100.0	

Appendix 3: Modification Process to improve construct reliability and validity

Table A Initial factor cross-loadings analysis of constructs

	Attitudes AI	Interaction AI obj	Job Demands	Job Resources	Job Satisfaction	Life Satisfaction	Attitudes AI x Interaction AI obj	Job Resources x Interaction AI obj	Job Demands x Interaction AI obj
Q2_1	**0.883**	0.089	0.067	0.172	0.322	0.129	0.114	0.102	0.187
Q2_2	**0.855**	0.135	0.063	0.219	0.289	0.139	0.032	0.087	0.153
Q2_3	**0.649**	0.121	0.097	0.11	0.209	0.104	-0.031	0.084	0.064
Q2_4	**0.782**	0.189	0.091	0.131	0.315	0.056	0.11	0.136	0.146
Q3	0.165	**1**	0.171	-0.044	0.26	0.054	0.137	0.043	0.318
Q5_1	0.069	0.189	**0.843**	0.019	0.131	0.065	0.136	0.023	0.035
Q5_2	0.09	0.077	**0.89**	0.011	0.131	-0.009	0.139	0.131	0.035
Q5_3	0.103	0.109	**0.808**	-0.01	0.093	0.004	0.181	0.097	0.037
Q5_4	-0.024	0.082	**-0.14**	0.198	0.054	0.117	-0.018	0.032	0.14
Q5_5	-0.014	0.095	**0.193**	-0.41	0.019	-0.063	0.035	0.079	0.184
Q6_1	0.17	0.028	-0.032	**0.675**	0.179	0.272	0.014	-0.161	-0.033
Q6_2	0.134	-0.05	0.043	**0.775**	0.181	0.269	0.108	0.004	0.088
Q6_3	0.114	-0.053	-0.019	**0.732**	0.199	0.174	0.094	-0.04	0.014
Q6_4	0.113	-0.026	0.002	**0.72**	0.188	0.287	0.04	-0.025	0.164
Q6_5	0.201	-0.053	0.065	**0.79**	0.246	0.249	0.155	0.014	0.124
Q8_1	0.218	0.168	0.22	0.204	**0.713**	0.166	0.02	0.122	0.123
Q8_2	0.368	0.259	0.061	0.219	**0.84**	0.318	0.12	0.151	0.168
Q8_3	0.242	0.134	0.187	0.224	**0.726**	0.22	0.017	-0.038	0.078
Q8_4	0.047	0.153	0.023	0.065	**0.309**	0.092	0.166	0.074	0.155
Q8_5	0.296	0.207	0.074	0.215	**0.835**	0.357	-0.043	-0.026	0.054
Q9_1	0.098	0.055	0.014	0.269	0.345	**0.91**	0.024	0.032	0.114
Q9_2	0.146	0.037	0.094	0.329	0.302	**0.846**	0.109	-0.028	0.094
Q9_3	0.113	0.049	0.004	0.293	0.267	**0.883**	0.038	0.011	0.12
Attitudes AI x Interaction AI obj	0.079	0.137	0.176	0.117	0.056	0.064	**1**	0.339	0.353
Job Resources x Interaction AI obj	0.129	0.043	0.109	-0.05	0.074	0.007	0.339	**1**	0.271
Job Demands x Interaction AI obj	0.179	0.318	0.079	0.101	0.148	0.124	0.353	0.271	**1**

Table B Initial Construct reliability overview

Construct	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	AVE
Attitudes AI	0.805	0.827	0.873	0.636
Job Demands	0.444	0.702	0.707	0.442
Job Resources	0.793	0.802	0.857	0.547
Job Satisfaction	0.735	0.814	0.826	0.507
Life Satisfaction	0.855	0.867	0.911	0.775

Appendix 4: Measurement model for reflective constructs and model fit

Table C Factor cross-loadings analysis of constructs after modification

	Attitudes AI	Interaction AI obj	Job Demands	Job Resources	Job Satisfaction	Life Satisfaction	Attitudes AI x Interaction AI obj	Job Resources x Interaction AI obj	Job Demands x Interaction AI obj
Q2_1	**0.897**	0.089	0.081	0.167	0.326	0.13	0.125	0.11	0.19
Q2_2	**0.868**	0.135	0.06	0.198	0.296	0.139	0.048	0.098	0.156
Q2_4	**0.813**	0.189	0.086	0.126	0.317	0.056	0.121	0.142	0.156
Q3	0.158	**1**	0.145	-0.06	0.25	0.054	0.123	0.035	0.302
Q5_1	0.066	0.189	**0.849**	0.025	0.126	0.065	0.14	0.035	0.01
Q5_2	0.073	0.077	**0.904**	0.015	0.132	-0.009	0.14	0.156	0.009
Q5_3	0.092	0.109	**0.833**	0.003	0.106	0.005	0.187	0.115	0.001
Q6_2	0.135	-0.05	0.033	**0.783**	0.19	0.269	0.088	0.041	0.076
Q6_3	0.132	-0.053	-0.041	**0.741**	0.192	0.174	0.096	-0.02	0.02
Q6_4	0.095	-0.026	0.019	**0.705**	0.185	0.287	0.048	0.008	0.161
Q6_5	0.207	-0.053	0.037	**0.845**	0.252	0.25	0.145	0.05	0.117
Q8_1	0.226	0.168	0.211	0.205	**0.718**	0.166	0.01	0.088	0.101
Q8_2	0.353	0.259	0.047	0.208	**0.831**	0.318	0.101	0.147	0.177
Q8_3	0.255	0.134	0.178	0.219	**0.744**	0.22	0.009	-0.058	0.062
Q8_5	0.292	0.207	0.054	0.221	**0.843**	0.357	-0.051	-0.047	0.047
Q9_1	0.103	0.055	-0.006	0.247	0.339	**0.908**	0.017	0.04	0.104
Q9_2	0.13	0.037	0.086	0.32	0.305	**0.848**	0.112	-0.007	0.097
Q9_3	0.102	0.049	-0.019	0.271	0.269	**0.883**	0.033	0.032	0.115
Attitudes AI x Interaction AI obj	0.115	0.123	0.178	0.127	0.024	0.061	**1**	0.35	0.373
Job Resources x Interaction AI obj	0.135	0.035	0.119	0.028	0.044	0.025	0.35	**1**	0.318
Job Demands x Interaction AI obj	0.196	0.302	0.008	0.123	0.126	0.119	0.373	0.318	**1**

Table D Construct reliability overview after modification

Construct	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	AVE
Attitudes AI	0.823	0.826	0.895	0.739
Job Demands	0.828	0.838	0.897	0.744
Job Resources	0.771	0.789	0.853	0.593
Job Satisfaction	0.794	0.813	0.865	0.617
Life Satisfaction	0.855	0.864	0.912	0.775

Discriminant validity:

Table E Fornell-Larcker criterion after modification

Fornell-Larcker	Attitudes AI	Interaction AI obj	Job Demands	Job Resources	Job Satisfaction	Life Satisfaction
Attitudes AI	**0.86**					
Interaction AI obj	0.158	**1**				
Job Demands	0.088	0.145	**0.863**			
Job Resources	0.191	-0.06	0.018	**0.77**		
Job Satisfaction	0.364	0.25	0.141	0.269	**0.786**	
Life Satisfaction	0.127	0.054	0.024	0.316	0.349	**0.88**

Table F HTMT analysis of constructs after modification

HTMT	Attitudes AI	Interaction AI obj	Job Demands	Job Resources	Job Satisfaction	Life Satisfaction	Attitudes AI x Interaction AI obj	Job Resources x Interaction AI obj	Job Demands x Interaction AI obj
Attitudes AI									
Interaction AI obj	0.177								
Job Demands	0.108	0.159							
Job Resources	0.232	0.067	0.054						
Job Satisfaction	0.444	0.274	0.201	0.343					
Life Satisfaction	0.15	0.058	0.072	0.394	0.406				
Attitudes AI x Interaction AI obj	0.126	0.123	0.199	0.14	0.061	0.066			
Job Resources x Interaction AI obj	0.15	0.035	0.13	0.044	0.121	0.033	0.35		
Job Demands x Interaction AI obj	0.215	0.302	0.009	0.139	0.138	0.129	0.373	0.318	

Table G Collinearity (VIF) Outer Model <u>after</u> modification

Collinearity (VIF) Outer model	VIF
Q2_1	2.286
Q2_2	2.095
Q2_4	1.58
Q3	1
Q5_1	1.759
Q5_2	2.312
Q5_3	1.889
Q6_2	1.669
Q6_3	1.482
Q6_4	1.379
Q6_5	1.732
Q8_1	1.462
Q8_2	1.778
Q8_3	1.526
Q8_5	1.883
Q9_1	2.531
Q9_2	1.775
Q9_3	2.488
Job Resources x Interaction AI obj	1
Attitudes AI x Interaction AI obj	1
Job Demands x Interaction AI obj	1

Table H Model fit <u>after</u> modification

Model fit measures	Saturated model	Estimated model
SRMR	0.061	0.072
d_ULS	0.639	0.893
d_G	0.242	0.253
Chi-square	396.209	409.109
NFI	0.789	0.782

Note: SRMR = Standardized Root Mean Square Residual; d_ULS = squared Euclidean distance; d_G = geodesic distance; $\chi 2$ = Chi-square; NFI = Normed Fit Index

Appendix 5: Assessment of the structural model

Table I Collinearity Statistics (VIF) – Inner Model – Matrix

Construct	Attitudes AI	Interaction AI obj	Job Demands	Job Resources	Job Satisfaction	Life Satisfaction	Attitudes AI x Interaction AI obj	Job Resources x Interaction AI obj	Job Demands x Interaction AI obj
Attitudes AI					1.101	1.172			
Interaction AI obj					1.165	1.086			
Job Demands					1.073				
Job Resources					1.073				
Job Satisfaction						1.208			
Life Satisfaction									
Attitudes AI x Interaction AI obj					1.294	1.027			
Job Resources x Interaction AI obj					1.222				
Job Demands x Interaction AI obj					1.379				

Table J R-square Overview

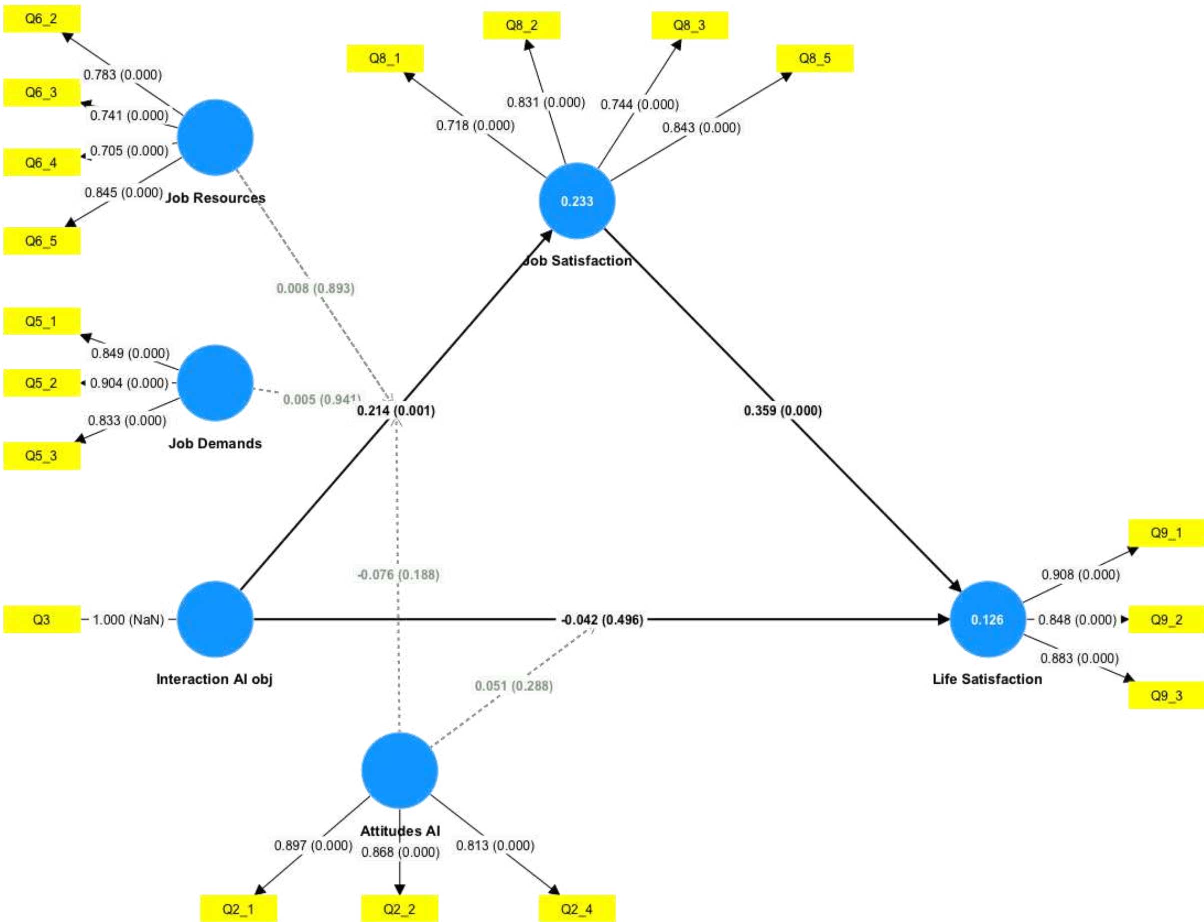
Construct	R-square	R-square adjusted
Job Satisfaction	0.233	0.213
Life Satisfaction	0.126	0.113

Table K F-square Matrix

Construct	Attitudes AI	Interaction AI obj	Job Demands	Job Resources	Job Satisfaction	Life Satisfaction	Attitudes AI x Interaction AI obj	Job Resources x Interaction AI obj	Job Demands x Interaction AI obj
Attitudes AI					0.096	0			
Interaction AI obj					0.051	0.002			
Job Demands					0.011				
Job Resources					0.068				
Job Satisfaction						0.122			
Life Satisfaction									
Attitudes AI x Interaction AI obj					0.008	0.004			
Job Resources x Interaction AI obj					0				
Job Demands x Interaction AI obj					0				

Appendix 6: Hypothesis Testing

Figure A Detailed structural Model with path estimates and p-values (objective)



*Note: *p-values are displayed in the brackets after the respective path coefficients (= Beta-Coefficients)*

Table L Path-Coefficients (Direct effects)

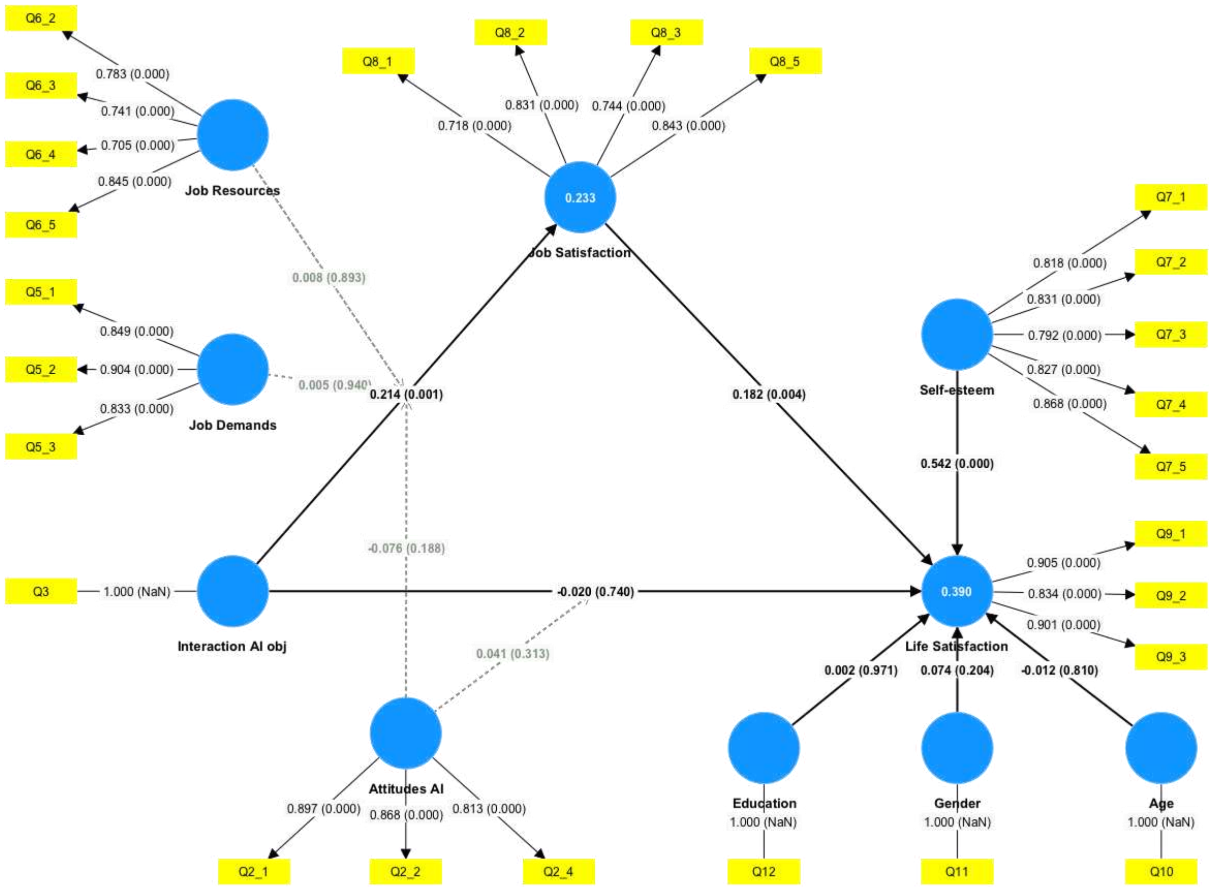
Direct effect	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Attitudes AI -> Job Satisfaction	0.285	0.287	0.062	4.617	0
Attitudes AI -> Life Satisfaction	-0.004	-0.001	0.067	0.058	0.954
Interaction AI obj -> Job Satisfaction	0.214	0.2	0.062	3.433	0.001
Interaction AI obj -> Life Satisfaction	-0.042	-0.044	0.062	0.681	0.496
Job Demands -> Job Satisfaction	0.095	0.108	0.057	1.673	0.094
Job Resources -> Job Satisfaction	0.236	0.245	0.061	3.877	0
Job Satisfaction -> Life Satisfaction	0.359	0.36	0.066	5.456	0
Attitudes AI x Interaction AI obj -> Job Satisfaction	-0.076	-0.074	0.058	1.317	0.188
Attitudes AI x Interaction AI obj -> Life Satisfaction	0.051	0.055	0.048	1.062	0.288
Job Resources x Interaction AI obj -> Job Satisfaction	0.008	0.017	0.061	0.134	0.893
Job Demands x Interaction AI obj -> Job Satisfaction	0.005	0.011	0.063	0.075	0.941

Table M Support of structural model assessment hypothesis

Hypothesis	Supported
H1: Higher interaction with AI in the workplace leads to higher life satisfaction	Not Supported
H2: Higher interaction with AI in the workplace leads to higher job satisfaction	Supported
H3: Higher interaction with AI in the workplace leads to higher job satisfaction, which in turn leads to higher life satisfaction	Supported
H4: Attitudes towards AI moderate the positive relationship between interaction with AI in the workplace and job satisfaction, such that the relationship is stronger when attitudes towards AI are more favourable	Not Supported
H5: Attitudes towards AI moderate the positive relationship between interaction with AI in the workplace and life satisfaction, such that the relationship is stronger when attitudes towards AI are more favourable	Not Supported
H6: Interaction with AI in the workplace leads to higher job satisfaction when job demands are perceived as low	Not Supported
H7: Interaction with AI in the workplace leads to higher job satisfaction when job resources are perceived as high	Not Supported

Appendix 7: Exploratory Analyses

Figure B Structural Model including control variables with path estimates and p-values (objective)



*Note: *p-values are displayed in the brackets after the respective path coefficients (= Beta-Coefficients)*

Table N Path-Coefficients <u>including control variables</u> (Direct effects)

Direct effect	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Age -> Life Satisfaction	-0.012	-0.011	0.051	0.24	0.81
Attitudes AI -> Job Satisfaction	0.285	0.288	0.062	4.619	0
Attitudes AI -> Life Satisfaction	-0.025	-0.025	0.059	0.434	0.664
Education -> Life Satisfaction	0.002	0.002	0.053	0.036	0.971
Gender -> Life Satisfaction	0.074	0.073	0.058	1.271	0.204
Interaction AI obj -> Job Satisfaction	0.214	0.201	0.062	3.433	0.001
Interaction AI obj -> Life Satisfaction	-0.02	-0.02	0.059	0.332	0.74
Job Demands -> Job Satisfaction	0.095	0.108	0.057	1.67	0.095
Job Resources -> Job Satisfaction	0.236	0.245	0.061	3.876	0
Job Satisfaction -> Life Satisfaction	0.182	0.182	0.062	2.92	0.004
Self-esteem -> Life Satisfaction	0.542	0.544	0.054	10.12	0
Attitudes AI x Interaction AI obj -> Job Satisfaction	-0.076	-0.074	0.058	1.315	0.188
Attitudes AI x Interaction AI obj -> Life Satisfaction	0.041	0.042	0.04	1.009	0.313
Job Resources x Interaction AI obj -> Job Satisfaction	0.008	0.017	0.061	0.135	0.893
Job Demands x Interaction AI obj -> Job Satisfaction	0.005	0.011	0.063	0.075	0.94

Figure C <u>Detailed</u> structural Model with path estimates and p-values (subjective)

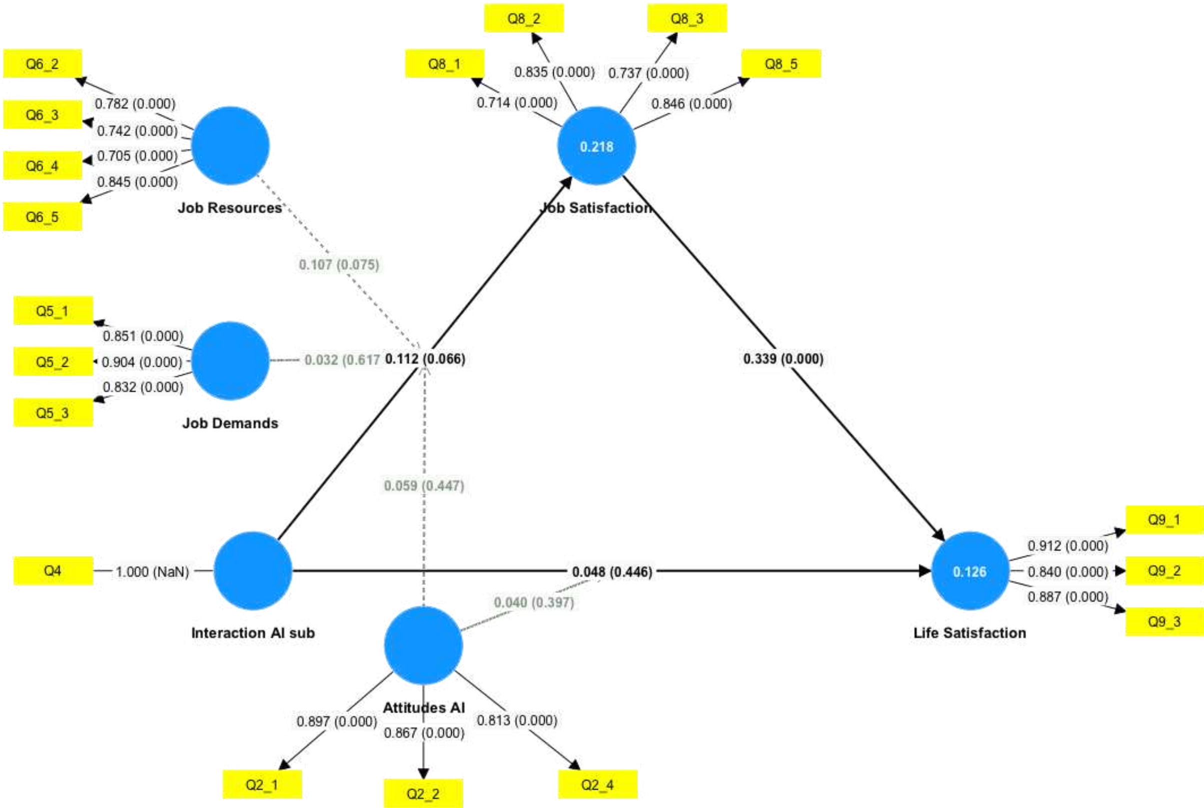
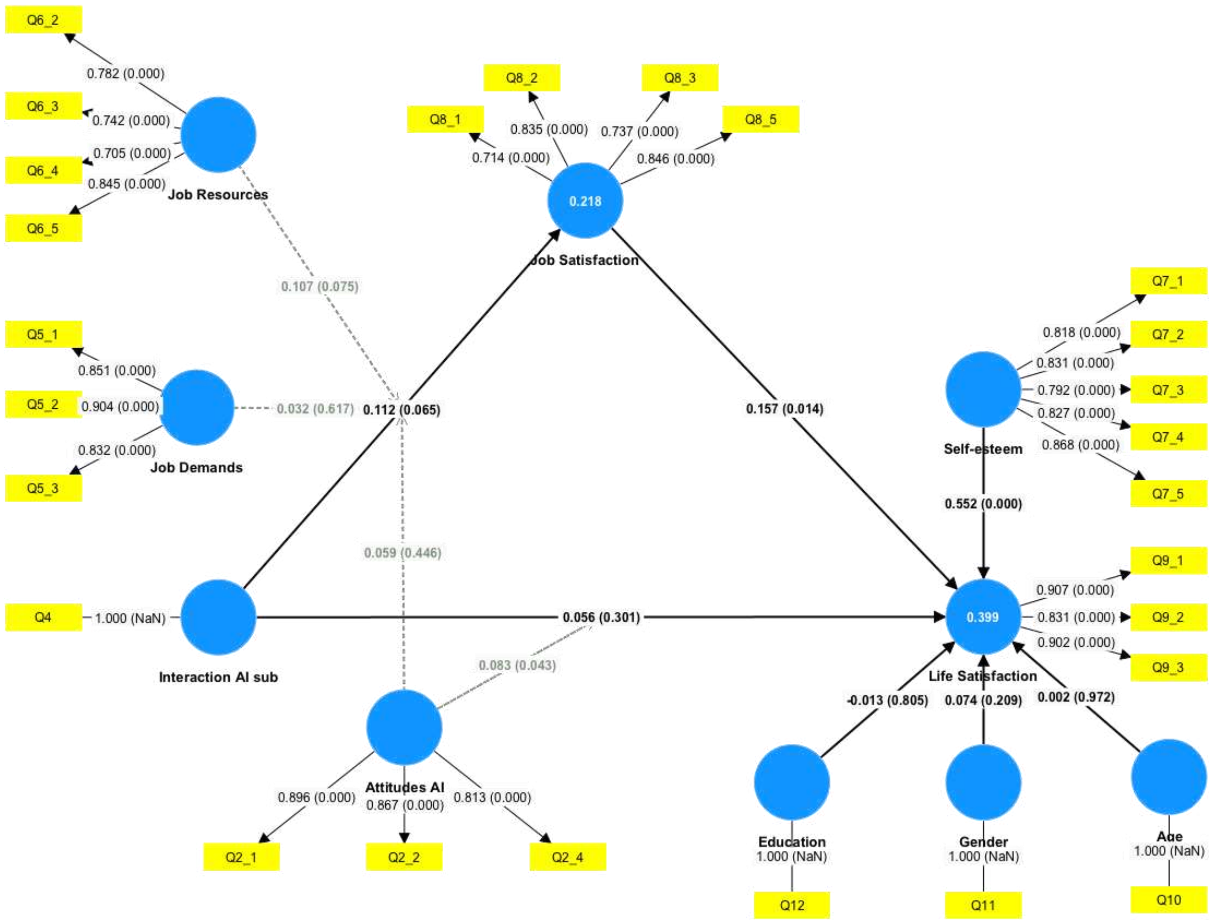


Figure D Structural Model <u>including control variables</u> with path estimates and p-values (subjective)


Q6_2
0.782 (0.000)
Q6_3
0.742 (0.000)
Q6_4
0.705 (0.000)
0.845 (0.000)
Q6_5
Job Resources
Q8_1
Q8_2
Q8_3
Q8_5
0.835 (0.000)
0.737 (0.000)
0.714 (0.000)
0.846 (0.000)
0.218
Job Satisfaction
0.107 (0.075)
Q5_1
0.851 (0.000)
Q5_2
0.904 (0.000)
0.032 (0.617)
0.112 (0.065)
0.832 (0.000)
Job Demands
Q5_3
0.157 (0.014)
Q7_1
0.818 (0.000)
Q7_2
0.831 (0.000)
Q7_3
0.792 (0.000)
0.827 (0.000)
Q7_4
0.868 (0.000)
Self-esteem
Q7_5
0.552 (0.000)
0.059 (0.446)
Q4
1.000 (NaN)
Interaction AI sub
0.056 (0.301)
0.083 (0.043)
Q9_1
0.907 (0.000)
0.399
Q9_2
0.831 (0.000)
0.902 (0.000)
Q9_3
Life Satisfaction
-0.013 (0.805)
0.074 (0.209)
0.002 (0.972)
Attitudes AI
0.896 (0.000)
0.867 (0.000)
0.813 (0.000)
Q2_1
Q2_2
Q2_4
Education
1.000 (NaN)
Q12
Gender
1.000 (NaN)
Q11
Age
1.000 (NaN)
Q10