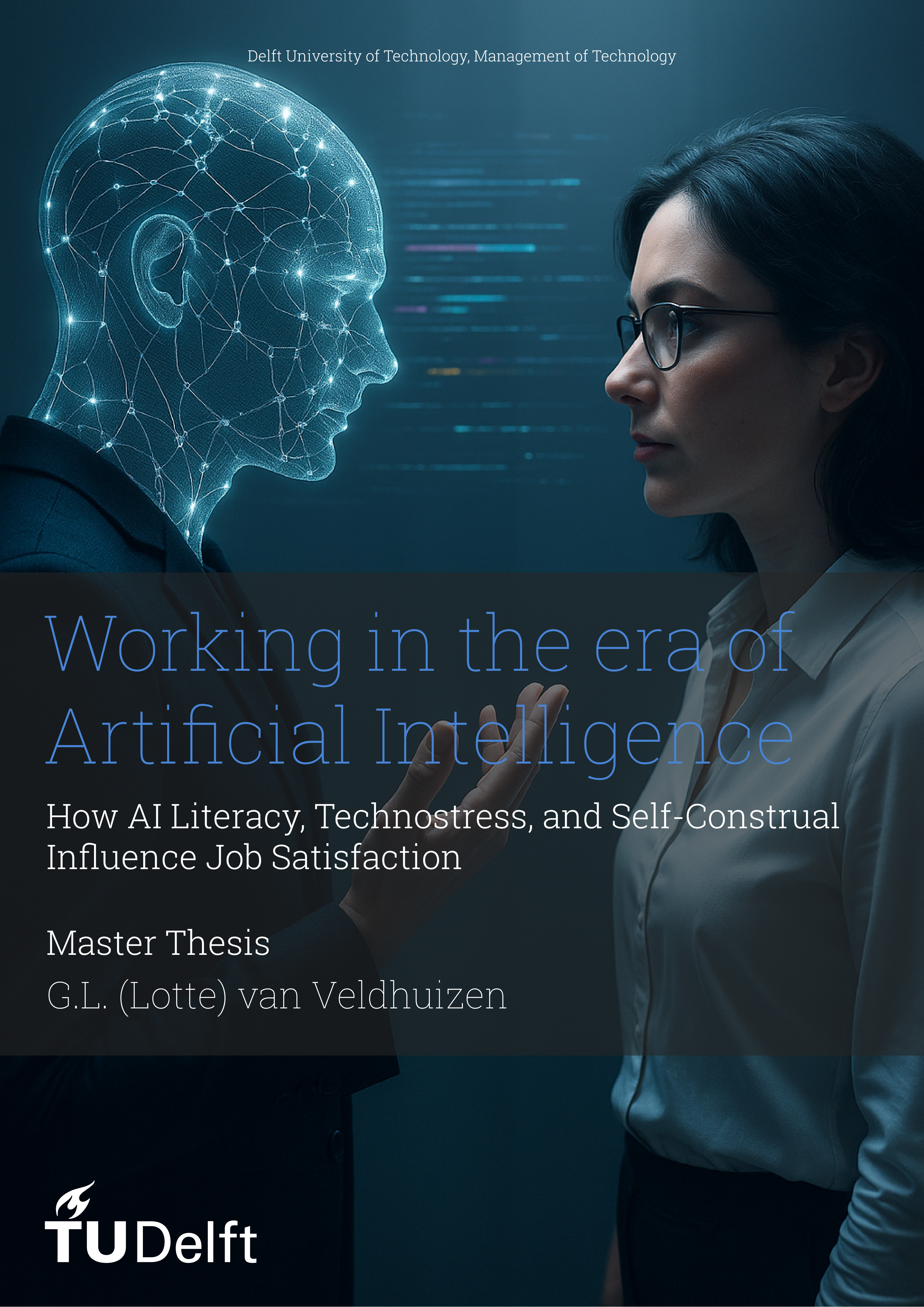

Delft University of Technology, Management of Technology

Working in the era of Artificial Intelligence

How AI Literacy, Technostress, and Self-Construal Influence Job Satisfaction

Master Thesis

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TU Delft

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How AI Literacy, Technostress, and Self-Construal Influence Job Satisfaction

by

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TU Delft

Preface

I want to start this preface by thanking my first supervisor, Sander, for all the valuable insights, the clear feedback, and for always being willing to help and guide when I needed it. Without this support, I would not have been able to write this thesis. Additionally, many thanks to my second supervisor, Neelke, who provided me with valuable feedback during the meetings. I really took it to heart, and I can say that I learned a lot about the writing process.

This thesis marks the end of my seven years as a student. On the one hand, I am very excited about graduating, but on the other hand, it also feels a bit strange. Every year since 2018, my life has been pre-determined in the sense that I knew I was going to be studying. I started at the Amsterdam University of Applied Sciences studying Aviation Engineering, followed by a summer of mathematics to be eligible for TU Delft's premaster's program Management of Technology. It is funny how this time flew by, whereas in the moment, it feels like a very long road ahead. The master's program in Delft has brought me so much, with a semester in Munich being the most memorable of all. Munich has given me many new international friends, to whom I still speak every other day and, hopefully, will continue to do so in the future.

This brings me to my family, that has continuously supported me while writing this and throughout my whole student time. I especially want to thank my parents and sister for always believing in me. Every time I would come up with a new idea, they were the ones rooting for me. Additionally, I would like to express my gratitude to my mentor at KLM Engineering and Maintenance for the insightful conversations and career guidance. These discussions have greatly shaped my time as a student and helped me gain clarity about the direction I want to take in life. I also want to give a special thanks to my boyfriend, who has read many pieces of this thesis over and over again in order to give me feedback on it. Thank you for dealing with my sometimes unjustified annoyance because I was stressed. Also, a special thanks to my good friend Donna-Tinke, with whom I often studied this last year, both in Delft and in Munich, and who always found a way to make me laugh until crying. I am also grateful to my friends back in Amsterdam, for always reminding me of the importance of friendship and who have made Amsterdam my hometown. Finally, many thanks to my snowboard friends, who showed me that real stress is meant to be felt when hitting a rail on a snowboard rather than behind a desk writing a thesis, something that truly helped to take the edge off it.

To summarize this preface for those who do not have time to read it: Thank you!

G.L. (Lotte) van Veldhuizen
Delft, October 2025

Abstract

Although job satisfaction is generally stable, AI-induced organizational changes are pressuring job satisfaction. Prior research shows contradictory findings: some suggest that AI literacy boosts productivity and someone's self-esteem, while others argue that it increases one's awareness of AI's threats to the nature of work and career perspectives. Understanding this tension is crucial, considering that job satisfaction underpins both employee well-being and organizational performance. This thesis assumes an inverted-U relationship between AI literacy and job satisfaction, with technostress as the mechanism driving the decline. Additionally, as AI develops increasingly human-like features, technostress may vary depending on self-construal: independent orientations are suggested to amplify technostress, while interdependent orientations may buffer it. While the inverted-U was expected, this study specifically examines the potential decreasing effect, testing technostress as the mediating mechanism in a linear regression model. Data was collected through a survey from 106 employees in the Dutch professional services industry. AI literacy showed no direct effect on job satisfaction but indirectly reduced it through reduced technostress, challenging the expected inverted-U relationship. Self-construal did not moderate this AI literacy's effects on technostress. This thesis contributes to the inconsistent findings of AI literacy's effects on job satisfaction and shows that AI literacy reduces technostress and acts as a protective resource rather than a liability, challenging the idea of an inverted-U relationship with job satisfaction. However, the small sample, cross-sectional design, and self-reported AI literacy may limit the findings, highlighting the need for longitudinal studies with larger samples.

Executive Summary

This thesis investigates the effects of AI literacy on job satisfaction mediated by technostress. It additionally researches if self-construal amplifies or absorbs the effects of AI-literacy-induced technostress. AI literacy is conceptualized as an employee's AI usage, evaluation, and awareness, while technostress is defined as anxiety triggered by technologies. Individuals with higher levels of interdependent self-construal are guided by values that emphasize the collective; they define themselves in relation to their group and prioritize collective over personal goals. By contrast, independent self-construal is characterized by autonomy and the prioritization of personal goals. Hence, given AI's human-like features, individuals with independent self-construal are expected to perceive AI as a threat, whereas those with interdependent self-construal are more likely to view it as a valuable team member. Where the former is expected to amplify technostress, and the latter to weaken technostress.

Data was collected through a survey given out to 106 professionals employed in the service industry, a sector highly exposed to AI-driven transformation. Researching the effects of AI literacy on job satisfaction is important as AI is increasingly getting adopted within businesses. Most research underlines AI's ability to take over repetitive tasks and increase productivity, thereby stimulating job satisfaction. Yet, with AI adopting more human-like capabilities and executing tasks at an accelerated pace, which poses a threat to employees. Employees with greater knowledge of AI's capabilities may experience increased pressure, which can trigger anxiety and, in turn, reduce job satisfaction. It is thus important to investigate how AI literacy is affecting employees during times of AI-induced business transformations, both to maintain employee well-being, and to indirectly support organizational performance. Hence, this thesis aims to answer the following research question:

To what extent does AI literacy in the professional services sector affect job satisfaction, to what degree is this effect mediated by technostress, and how much is technostress moderated by self-construal theory?

Contrary to expectations, the findings indicate that AI literacy does not directly affect job satisfaction. Instead, it reduces technostress, which in turn negatively impacts job satisfaction. Hence, this study suggests that AI literacy indirectly enhances job satisfaction through its reducing effect on technostress. Although self-construal was expected to either absorb or amplify technostress in light of AI's increasingly human-like capabilities, no such moderating effects were found. However, interdependent self-construal showed a direct increasing effect on technostress, suggesting that those prioritizing collective goals and social belonging are generally more sensitive to technology-induced stress. Additionally, the study also confirms that self-construal is not necessarily culturally bound. This research was conducted among professionals employed in the Dutch professional services sector, and no rigid separation between independent and interdependent self-construal was uncovered. This also reveals a possible reason for the lack of moderating effects: people possess both traits, and it is less rigid than initially assumed. Nonetheless, these results require careful consideration: within this study, AI literacy is a self-reported measure, and people can overestimate their AI knowledge. As a result, they may be objectively less aware of AI's potential and its implications for their jobs than they subjectively perceive.

Based on these findings, this thesis suggests the following measures for managers in the professional services sector to sustain job satisfaction during organizational changes driven by the adoption of Artificial Intelligence:

- **Invest in AI literacy training**: The diffusion of innovation theory by Rogers (2003) suggests that adoption of technologies is stimulated when uncertainty is reduced. It is therefore argued that AI literacy training should focus on reducing uncertainty and therefore focus on five aspects established by Rogers cited by Sahin (2006):
    1. Highlight AI's relative advantage compared to the status quo by focusing on its benefits and hereby introducing it as a supportive rather than a threatening tool.
    2. Demonstrate compatibility of AI to existing values and needs by demonstrating how AI can contribute to employees' needs and wants.
    3. Reduce complexity through practical AI training and user-friendly tools.
    4. Enable trialability by allowing employees to experiment with the technologies and hereby open the possibility for feedback before organizational-wide implementation. This could potentially be organized using work groups of motivated individuals.
    5. Promote AI adoption by introducing promoters who are trusted peers in an organization.
- **Monitor employees' AI skills**: employees might overestimate their AI literacy, which could affect their position compared to AI. For organizations seeking to introduce or expand AI applications, it is therefore essential to ensure that employees are genuinely prepared to avoid heightened technostress, resistance to change, and reduced job satisfaction, thereby supporting both employee well-being and successful AI adoption.

In conclusion, AI literacy functions as a tool to reduce technostress and thereby indirectly increase job satisfaction. However, managers must be cautious when introducing AI; employees might overestimate their skills or be unaware of AI's potential to take over their daily tasks, and sudden changes could increase technostress. Hence, focusing on AI literacy training will secure an understanding of AI among employees, reducing technostress and uncertainty, and thereby retaining employee well-being in times of AI-induced organizational change, which is expected to increase in the coming years within the professional services sector.

Contents

1 Introduction

Job satisfaction is often understood as someone's subjective evaluation of their job (Spector, 1985), and it particularly aims to capture the degree to which someone enjoys their profession (Lent and Brown, 2006). It was found to be the most researched topic in behavioral science (Spector, 1985), and its importance is underlined by its effect on employee well-being, which is found to directly enhance organizational performance (Lent and Brown, 2006). Although often regarded as relatively stable, job satisfaction has been repeatedly revisited by scholars, as it tends to become more volatile when organizations undergo cultural or technological transformations (Spagnoli et al., 2012). This sensitivity to business transformations and their implications for organizational performance is particularly salient in the current context of Artificial Intelligence (AI). It was found that more than 70% of all employees predict changes in their jobs within the next 2 years as a result of AI (Mayer et al., 2025). Mckinsey Explainers (2022) underlines this by referring to the present as the fourth industrial revolution, in which AI plays a central role. Their research shows that the skills demanded from workers are changing: the demand for technological skills such as coding will increase by more than 50%, the demand for complex cognitive skills are expected to rise by 33%, and the need for social and emotionally skilled workers is anticipated to grow by 30%. Hence, AI is transforming businesses and employee's skillsets and thereby destabilizing job satisfaction. This thesis argues that AI's actual impact on employees' job satisfaction does not solely depend on an organization's AI adoption rates. Rather, this thesis suggests that someone's AI literacy (AI usage, AI awareness, and AI evaluation rates) provides a more accurate indicator of AI's actual impact on job satisfaction. Hence, this study examines the effects of AI literacy on job satisfaction.

This thesis focuses on employees in the professional services industry. This sector is among the most heavily impacted by AI: Singla et al. (2025) found that at least 80% of professional services companies use AI in at least one business function, such as marketing and sales, product and service development, IT, and knowledge management. Such adoption not only transforms business processes but also influences workforce structures, particularly in service operations, where 48% of organizations anticipate a reduction in headcount, compared to only 33% anticipating an increase (Singla et al., 2025). More broadly, about 47% of US professions are at risk due to computerization, and many of these jobs are high-paying middle-class jobs in the service sector (Frey and Osborne, 2017), including accountants, market research analysts, customer service, sales staff, and office/administration workers (Brougham and Haar, 2018). By contrast, occupations that mostly rely on practical, manual, or interpersonal skills, such as plumbing, construction, or nursing, are assumed to be less vulnerable to AI-driven substitution (Autor, 2015). Given this high exposure to AI in knowledge work, the professional services industry provides a particularly relevant context to research how AI literacy affects job satisfaction.

However, studies examining AI literacy in relation to job satisfaction present mixed results. AI is rapidly developing, and its ability to automate repetitive tasks, generate code, and even function as a customer service employee (Kraus et al., 2021) (Bernard, 2023), makes AI a widely discussed phenomenon within many organizations. Cabello (2023), Bhargava et al. (2021), and Hemmer et al. (2023) found that increased AI usage eliminates low-value tasks, shifting employees' work toward more expertise-focused activities. This, alongside AI's rapid task conduction, may lead to heightened productivity and increased efficiency, enhancing someone's work confidence and subsequently their job satisfaction (Korteling et al., 2021). In contrast, Ai (2024) found that awareness about AI's functionalities and increasing human-like capabilities may result in employees questioning the relevance of their skills, leaving them feeling underappreciated and experiencing a heightened fear of job layoffs. Job layoffs, often referred to as job insecurity, is known to directly lower job satisfaction (Brougham and Haar, 2018). AI literacy can thus function in two ways: it may boost job satisfaction by improving efficacy, or it may lower it by shifting employees' career outlook.

This inconsistency in the literature suggests the possible existence of an inverted-U relationship between AI literacy and job satisfaction. Where AI literacy may initially increase someone's job satisfaction by enhanced productivity, it is suggested to decline after a certain point due to increased awareness of its potential threats. This decline remains unexplored, and this research argues that technostress, referring to any negative emotion such as increased insecurity and uncertainty induced by new technology, is the underlying mechanism decreasing job satisfaction (Chuang et al., 2025). Additionally, Zhao et al. (2025) found that self-construal influences how individuals interpret AI output: those with independent self-construal tend to be more reflective, whereas those being interdependent are showing more dependent behavior. Above this, research suggests that individuals with an independent self-construal place greater value on autonomy and personal goals, whereas those with higher levels of interdependent self-construal emphasize collective goals and group decision-making. As AI is getting more advanced and is increasingly developing its human-like features, interdependents may perceive AI as a team player, and independents as an intruder. Where the former is likely to absorb technostress, and the latter to amplify technostress. Traditionally, self-construal theory was understood as culturally determined. However, more recent research shows that it is far less rigid and can vary across individuals (Califf et al., 2020).

Thus, this thesis investigates AI literacy's potential negative effects on job satisfaction by analyzing whether higher levels of AI literacy lead to increased technostress, and whether self-construal amplifies or reduces this stress, ultimately decreasing job satisfaction. By examining whether AI literacy reduces job satisfaction through technostress, this study helps explain the contradictions in existing literature and offers organizations in the professional services industry insights into managing AI-driven transformations, and whether employees' self-construal should be considered when introducing AI. By analyzing these differences in technostress across independent and interdependent self-construals in the Dutch context, this study also contributes to the debate on whether self-construal is culturally fixed or varies across individuals within a single culture. In other words, this thesis tests a moderated mediation model of AI literacy on job satisfaction mediated by technostress, and moderated by self-construal. Hence, this study contributes to understanding the potential negative effects of AI literacy while also offering organizations guidance on how to sustain employee job satisfaction during AI-driven organizational change, thereby supporting both well-being and organizational performance. Accordingly, this thesis aims to answer the following research question:

To what extent does AI literacy in the professional services sector affect job satisfaction, to what degree is this effect mediated by technostress, and how much is technostress moderated by self-construal theory?

2 Theoretical Framework

This study examines how AI literacy influences employees' job satisfaction through technostress while also including individual differences in self-perception using the self-construal theory. Job satisfaction is conceptualized as a multi-dimensional construct that reflects someone's evaluation of their work, including different facets such as career prospects, relationships with colleagues and supervisors, and task variety. Although generally stable over time, technological transformations, like AI adoption in organizations, are reshaping work in ways that may undermine job satisfaction through increased stress and insecurity (Spagnoli et al., 2012).

Because of AI's ability to perform tasks such as article writing, prototype development, generating call scripts, assisting with coding, and supporting customer interactions through self-service chatbots, it is being increasingly adopted by organizations (Bernard, 2023). However, it is assumed that studying the actual effects of AI on employees' job satisfaction requires a more detailed measure than its adoption rate. Hence, this thesis suggests AI literacy (AI usage, AI awareness, and AI evaluation rates) as a more sophisticated measure.

Literature researching the effects of AI on job satisfaction show contradicting results. Some studies found that AI usage raises employees' productivity levels and efficiency. Meaning, those who often use AI showed increased confidence levels due to higher task performance (Hemmer et al., 2023). On the other hand, Rodríguez et al. (2023) found a positive relationship with technostress. Specifically, awareness of AI's capacity to perform human tasks may undermine employees' self-esteem, leaving them feeling less competent and valued in their professional roles (Ai, 2024). When users perceive AI as capable of performing tasks autonomously and efficiently, and become increasingly aware of its human-like qualities that may surpass their own abilities, their anxiety can intensify (Zhang and Tong, 2025). Similarly, Zhao et al. (2025) suggested that the higher someone's awareness of AI's capabilities, the more one compares themselves to it. This may lead to increased pressure on employees to update their skills, while AI might limit expertise development opportunities, leading to increased role ambiguity and anxiety (Ragu-Nathan et al., 2008). Such consequences can disrupt career planning and undermine professional fulfillment (Brougham and Haar, 2018), ultimately reducing job satisfaction (Spagnoli et al., 2012).

The contradicting results in the literature suggest that the effects of AI literacy may follow an inverted-U pattern: while moderate levels of literacy enhance efficacy and confidence, greater awareness of AI's disruptive potential drives down job satisfaction. This thesis argues that technostress may be the underlying mechanism driving down job satisfaction. Considering that higher AI literacy increases employees' awareness of AI's rapid advancements and human-like capabilities, it can induce technostress creators such as insecurity, overload, complexity, and uncertainty. These stressors may undermine employees' skill confidence and their future career prospects, ultimately reducing job satisfaction (Zhang and Tong, 2025) (Chuang et al., 2025). Meaning, higher levels of AI literacy increase technostress, which negatively influences an employee's job satisfaction.

Additionally, because individuals differ in their values and characteristics, the extent to which AI literacy induces technostress likely depends on personal perceptions of these developments. Self-construal theory, which explains how people define themselves in relation to others, is particularly relevant given AI's increasingly human-like features. It may determine whether employees see AI as a threatening competitor that amplifies technostress or as a supportive partner that aligns with their goals. Independents, who value self-development, personal goals, and autonomy, may perceive AI as undermining these values and thus experience heightened technostress. In contrast, interdependents, who emphasize collaboration and collective decision-making (Zhao et al., 2025), may view AI as a complementary tool that helps reduce technostress.

Additionally, individuals differ in their values and characteristics, the extent to which AI literacy induces technostress likely depends on personal values and perceptions of these developments. Self-construal theory, which explains how people define themselves in relation to others, is particularly relevant given AI's increasingly human-like features. It may shape whether employees perceive AI as a threatening competitor that amplifies technostress, or as a team player that reduces technostress. Independents, who value self-development, personal goals pursuit, and autonomy, may perceive AI as undermining these values and thus experience heightened technostress. In contrast, interdependents, who emphasize collaboration and collective decision-making, may view AI as a complementary tool that helps absorbing technostress (Zhao et al., 2025).

In conclusion, this research argues that AI literacy reduces job satisfaction through its increasing effects on technostress, and technostress is moderated by independent, or interdependent self-construal. In other words, a moderated mediation model is predicted. See Figure 2.1 for a visualization of the suggested conceptual framework.

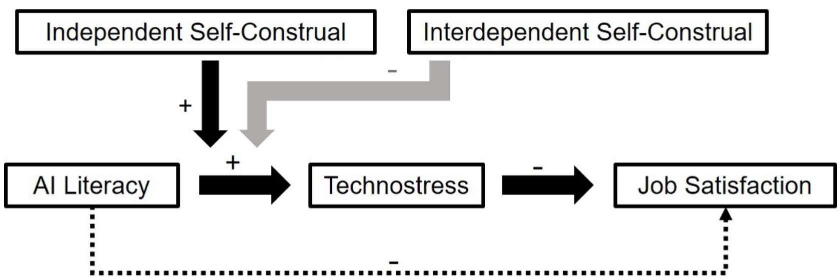

Figure 2.1: Conceptual framework: visualizing AI literacy, technostress, job satisfaction, and moderating role of self-construal

2.1. Job Satisfaction

This research defines job satisfaction as a representation of an employee's evaluative feelings towards a job (Spector, 1985). Considering that job satisfaction is a multi-dimensional construct, this study focuses on the three facets that are assumed to be most relevant in times of technological transformation: promotion opportunities, contingent rewards, and the nature of work. These facets are considered most important as AI has the potential to replace employees and impact the nature of work and thereby an employee's perceived feelings of recognition. Finally, job satisfaction is treated as the dependent variable; hence, this thesis does not include the effects of job satisfaction on organizational success.

Job satisfaction was identified as the most researched topic in behavioral science in 1997 (Spector, 1997), and in 2009, Bryman and Buchanan (2009) reported more than 5,500 published studies on job satisfaction. Searching the term "job satisfaction" in databases such as Scopus, provides you with 84,000 results, which underlines its sustained academic interest. Beyond academic relevance, job satisfaction also has ethical and practical importance. Ethically, it reflects an employee's well-being and their right to be treated respectfully at work. Practically, job satisfaction functions as an indicator of organizational performance: an employee's job satisfaction often influences organizational functioning and success (Spector, 1997).

Although job satisfaction appears to be stable over time, research by Spagnoli et al. (2012) found instabilities as soon as organizations changed. Organizational change refers to the transformation of structure, culture, or technology within an institution. More specifically, it is defined as the "process that is activated by an organization in order to respond to a resolute need for development" (Gomes, 2009). For instance, the accelerated adoption of Microsoft Teams during the COVID-19 pandemic made in-person meetings largely redundant and shifted conventional work practices from on-site interactions to hybrid ways of working. Research by Fry Gunn Building and Nicholas Bloom (n.d.) demonstrated that while some employees preferred having multiple work-from-home days, others favored fewer or none. This implies that during COVID, when employees had no choice between working from home or in the office, some experienced increased job satisfaction, while others did not. This perception might depend on one's perceived levels of technological understanding, stress levels, values, and character, and it illustrates that job satisfaction among employees responds to technological changes within organizations, highlighting its dynamic nature. Naturally, given that 70% of employees expect changes in their work within the next two years (Mayer et al., 2025), and AI's rapid developments, it is important to revisit the concept of job satisfaction in light of these technological transformations considering its potential impact.

Given its organizational importance and sensitivity to change, numerous alternative definitions of job satisfaction have been proposed in addition to the one applied in this study. Some scholars describe it as "the extent to which people enjoy their jobs" (Lent and Brown, 2006) or as "an employee's subjective assessment of their well-being and level of fulfillment derived from their work" (Chuang et al., 2025). Where others define it as "a pleasurable or positive emotional state resulting from the appraisal of one's job or job experiences" (Chuang et al., 2025). This last definition is said to take a psychological perspective, where job satisfaction increases when it aligns with one's interest, has fair pay, promotion opportunities, honest colleagues, capable supervisors, good leadership, and reasonable benefits (Locke, 1976).

Recent studies have mostly focused on the effects of dispositional factors on job satisfaction, and most of these studies treat job satisfaction as a dependent variable (Bryman and Buchanan, 2009). For example, Spector (1985) developed the Job Satisfaction Survey based on the theoretical position that unmet expectations, unfulfilled needs, and misaligned values lead to job dissatisfaction. Similarly, Roelen et al. (2008) states that task variety, career perspectives, working conditions, workload, colleagues, and job autonomy are among the most important factors impacting job satisfaction. However, in times of organizational change induced by AI, growth opportunities are found to be more important than one's perception of their colleagues or supervisors, mainly because employees require clear career prospects and development opportunities to remain satisfied (Howard and Frink, 1996).

Taking the definitions together highlights the psychological, subjective, and multi-dimensional nature of job satisfaction: employees might perceive job satisfaction differently depending on personal values. For example, one may feel satisfied with their pay and colleagues, but dislike the organization's policies or their career perspectives. This underscores that job satisfaction is not a single dimension and that its subjective character necessitates a nuanced approach. Consequently, researching the different facets of job satisfaction can support organizations in identifying targeted improvements for the workplace to enhance job satisfaction and, in turn, organizational performance (Lepold et al., 2018) (Spector, 1985). Similarly, Hemmer et al. (2023) conceptualizes job satisfaction as task satisfaction and shows that it contributes to long-term organizational success as it strengthens employees' commitment and productivity levels, again underlining its importance.

2.2. Artificial Intelligence

Most studies do not distinguish between traditional AI and Generative AI as these technologies are not mutually exclusive (Chuang et al., 2025) (Zhang and Tong, 2025). Although technically different, this study assumes that the distinction has limited relevance from an employee's perspective. Therefore, the term ”AI” is applied throughout to refer to both Generative AI and traditional AI. However, rather than measuring AI adoption rates in organizations as the independent variable, this study focuses on employees' knowledge of AI, which has been conceptualized in several ways.

Firstly, Brougham and Haar (2018) introduces the concept of Smart Technology, Artificial Intelligence, Robotics, and Algorithms (STARA) awareness, which refers to employees' perceptions of how these technologies affect their daily work. More recently, Zhao et al. (2025) and Teng et al. (2024) adopted the same concept but labeled it ”AI awareness”, formally defined as ”... employee perceptions and insights on how AI technologies could impact their future career prospects.” Finally, Ma and Chen (2024) proposed the broader concept of AI literacy, defined as “A set of competencies that enable individuals to critically evaluate AI technologies, communicate and collaborate effectively with AI, and use AI as a tool in online, home, and workplace settings”. This study adopts AI literacy as the independent variable because it encompasses multiple facets, allowing for a more nuanced analysis (see Table 2.1). AI literacy, however, can be understood as a double-edged sword: while it enhances employees' competence and productivity, it also heightens awareness of potential risks to employees' jobs.

For example, it was found that those showing higher levels of AI usage experienced increased personal confidence in their work (self-efficacy), resulting in higher task performance and consequently increased job satisfaction (Hemmer et al., 2023). Additionally, a study conducted among pharmaceutical employees showed a positive effect of AI usage on job satisfaction through the elimination of routine and low-value tasks. This increased the employees' productivity, efficiency, and subsequently led to more patient contact (Bhargava et al., 2021). Finally, research among teachers found that technology literacy positively influences job satisfaction due to increased capability of effectively applying technologies and addressing the challenges that come with it (Lyu and Luo, 2024).

In contrast, when focus is placed on awareness of the challenges posed by AI, the dynamic changes.

Considering AI's ability to, for example, write code and perform analyses, employees with higher AI literacy may increasingly question the relevance of their skills and professional competence (Arntz et al., 2017). For example, Brougham and Haar (2018) found that if an employer starts testing technologies, these employees might feel threatened when knowing it has the potential to replace them, which triggers feelings of job insecurity, undervaluation, and reduced control over career goals, all lowering job satisfaction. These concerns are becoming more pressing, as 92% of companies plan to increase their AI investments in the coming three years (Mayer et al., 2025). In conclusion, the higher someone's knowledge about AI's human-like traits and its ability to take over tasks, the more people are aware of its possible threats and the more they compare themselves to it (Zhang and Tong, 2025) (Zhao et al., 2025). Naturally, this is assumed to decrease one's self-esteem, increase anxiety and the fear of job lay-offs, and thereby reduce job satisfaction over the years (Ai, 2024).

In conclusion, AI literacy reflects a dilemma: on the one hand, it can enhance satisfaction through efficiency gains, but on the other, it may reduce satisfaction by fueling insecurity and anxiety. This points towards a potential inverted-U relationship. However, considering the definition of job satisfaction applied in this research, the emphasis is placed on how greater someone's AI literacy, the higher someone's awareness of its disruptive potential on their careers, which reduces employees' overall satisfaction with their work. Thus, productivity or self-efficacy gains fall outside the scope of this analysis. Building on this reasoning, the following hypothesis is proposed:

Hypothesis 1 - AI literacy negatively affects job satisfaction

Table 2.1: Definitions of AI literacy's different facets, provided by Ma and Chen (2024)

Facet	Definition
AI Awareness	"The understanding of AI concepts and basic principles."
AI Evaluation	"The ability to critically assess AI tools and AI-generated content."
AI Usage	"The ability to use AI in daily life and learning."
AI Ethics	"The ethical and safe use of AI."

2.3. Technostress

As stated in paragraph 2.2, AI literacy enhances efficacy and productivity, while it simultaneously triggers insecurity and anxiety due to AI's increasing human-like capabilities. This suggests that AI literacy may positively affect job satisfaction up to a certain threshold, after which further increases in AI literacy lead to declining job satisfaction, see Hypothesis 1. This study argues that the proposed inverted-U relationship can be explained by technostress as the underlying mechanism driving this downward slope.

Technostress is the feeling of anxiety negatively impacting someone's thoughts, behavior, or body psychology as a result of directly or indirectly using IT products, information technologies, or other computer technologies (Litan, 2025) (Weil and Rosen, (1997) cited in Kumar et al., 2024). A more extreme definition is applied by Brod (1984), cited by Califf et al. (2020), referring to it as a modern disease of adaptation due to the inability to cope with technologies.

Although often associated with unfavorable outcomes, technostress does not inherently lead to negative consequences. Conceptually, technostress consists of techno-eustress and techno-distress, with the former referring to the positive effects and the latter to the negative effects of stress. High levels of eustress lead to higher job satisfaction, whereas distress results in lower job satisfaction, possibly increasing turnover rates Califf et al. (2020). For the remainder of this research, for the sake of readability, the term technostress is used to refer to techno-distress specifically. Techno-distress consists of five technostress creators: techno-overload, techno-invasion, techno-complexity, techno-insecurity, and techno-uncertainty (Ragu-Nathan et al., 2008). See Table 2.2 for the definitions of each creator. Techno-invasion is considered beyond the scope of this study, as it primarily addresses constant connectivity, which is assumed to be an unlikely effect resulting from AI use. By contrast, techno-insecurity, techno-uncertainty, techno-overload, and techno-complexity are amplified, as employees face both the uncertainty of AI's effects on their jobs and the fear of skill obsolescence.

Table 2.2: Definitions of technostress creators, provided by Ragu-Nathan et al. (2008) and their connections to AI

Technostress Creator	Definition	Connection to AI
Techno-overload	The technology imposes longer working hours and an accelerated work pace.	AI accelerates tasks, pressuring employees to keep up.
Techno-uncertainty	Technologies are constantly upgrading, requiring users to re-educate themselves.	AI evolves rapidly, creating stress from constant adaptation.
Techno-complexity	Users feel incompetent regarding the technology, which forces them to spend time understanding it.	AI systems are getting more complex, which can be perceived by people as a threat to their skills.
Techno-insecurity	the fear of losing one's job to automation or more skilled colleagues.	AI increasingly performs human tasks, threatening jobs.
Techno-uncertainty	Constant technology changes require users to continuously learn, unsettling them.	AI is introduced rapidly in workplaces, forcing employees to stay updated.

Findings by Chuang et al. (2025) support the potential of technostress as the mechanism driving the downward slope of job satisfaction due to AI literacy, as this research did not identify a direct connection between AI and job satisfaction. Instead, their findings indicate that AI works through exhaustion caused by technostress, which then shows a lowering effect on job satisfaction. Similarly, Zhang and Tong (2025) showed that AI-induced anxiety mediates user dissatisfaction. Such findings underline that AI's impact on employees' work outcomes tends to operate through mediating mechanisms rather than direct effects.

Studies are increasingly focusing on technostress as a result of AI and suggest that AI technologies can negatively affect someone's mental health through anxiety, depression, and burnout effects, subsequently affecting their life quality (Litan, 2025). Additionally, it was found that the faster IT systems evolved, the higher the experienced workload and role ambiguity, and technostress consequently (Suh and Lee, 2017) (Suh and Lee, 2017). The growing complexity of AI, combined with employees' awareness of its rapid advancements and capacity to perform human tasks, may generate doubts about future career prospects and pose a threat on existing skills. For example, when considering the professional services sector, an employee's awareness of AI's potential to rapidly generate draft reports, automate data analysis, or prepare client deliverables may overwhelm consultants. Taking together, it is argued that AI can intensify techno-overload, techno-insecurity, techno-complexity, and techno-uncertainty (Zhang and Tong, 2025). Although Zhang and Tong (2025) focused on technology satisfaction rather than job satisfaction, comparable mediating effects of technostress on employees' work outcomes are assumed. Considering that AI has the potential to transform businesses (Mayer et al., 2025), employees may experience increased insecurity regarding the impact of these changes on their jobs, which in turn heightens anxiety and lowers job satisfaction subsequently.

Building on this, several studies have specifically examined the effects of technostress on job satisfaction. For instance, research on teleworkers identified work overload, privacy invasion, and role ambiguity as the main predictors of strain leading to lower job satisfaction. It found that the faster the IT changes, the greater the experienced workload and role ambiguity. Specifically, work overload results from large amounts of information and rapid pace of IT developments, privacy invasion is caused by constant connectivity of employees also outside of their work hours, and role ambiguity arises when technology-related tasks increasingly blur the line between employees' primary responsibilities and technical duties (Suh and Lee, 2017).

Similarly, Khan et al. (2013) conducted research among Pakistani university librarians, also showing a significant negative correlation between job satisfaction and techno-overload, techno-invasion, and techno-uncertainty, all technostress distress factors. Results showed that these factors were responsible for about 27% of the variance in job satisfaction. First of all, the volume and intensity of work increase the working hours of librarians. Secondly, the boundaries between work and personal life got blurred, leading to a constant feeling of reachability, and thirdly, as technological change can be unpredictable, librarians experienced lower confidence in their work. Although this research might be perceived as outdated (2013), it does clearly highlight the potential effects of technostress on job satisfaction.

In the healthcare sector, technostress was found to be significantly positively related to burnout emotions, and negatively with job satisfaction. Doctors, who already face heavy workloads, experienced lower levels of job satisfaction when dealing with high technology complexity, slow systems, or information overload (Bail et al., 2023). Taken together, these studies highlight the crucial role of AI-induced technostress in shaping employees' job satisfaction and thus underline technostress as the mechanism driving down job satisfaction. Accordingly, this study proposes the following hypothesis:

Hypothesis 2 – AI literacy is positively related to technostress, and technostress negatively mediates the relationship between AI literacy and Job Satisfaction

2.4. Self-construal Theory

Individuals differ in their values and characteristics, which may shape how they respond to AI's increasingly human-like capabilities and skills. Consequently, the extent to which AI literacy induces technostress is likely to depend on personal values and perceptions of such developments. Self-construal theory explains how individuals use their perceptions to regulate emotions and guide behavior, and recent research shows that it influences someone's response to AI, where independents appeared to show more reflective and interdependents revealed more dependent behavior (Zhao et al., 2025).

Self-construal consists of independent and interdependent self-construal. As for Independent people, they prefer to have autonomy. Meaning, their behavior is mainly focused on their thoughts, feelings, and actions, and they are focused on developing their personal potential, distinguishing themselves from others, and promoting their own goals (Rose Markus and Kitayama, 1991). On the contrary, those identifying with interdependent self-construal perceive themselves as part of the social context, viewing their identity as interconnected with others. They value virtues such as belonging to a certain group, having relationships, and meeting social responsibilities; they would furthermore promote others' goals before their own and adapt their goals and actions to the needs of others (Downie et al., 2006). Meaning, those being more interdependent define their identity by their social surroundings and perceive other individuals as part of it (Rose Markus and Kitayama, 1991). Those having high levels of independent self-construal still take into account their social surroundings, but mainly to figure out where they stand themselves, and thus to validate their personal identity. Additionally, self-construal theory influences decision-making; independent people favored deciding and performing self-chosen tasks, whereas interdependent individuals preferred outcomes chosen for them by someone else (Pöhlmann et al., 2007). Taken together, interdependence is about fitting in and acting in favor of the group, whereas independence is about standing out and pursuing personal goals.

Although self-construal theory is often associated with cultural contexts where independent self-construal is typically linked to Western societies and interdependent self-construal to collectivist cultures often present in Asia, research shows that culture is not a rigid determinant of self-construal (Li et al., 2024). It was, for example, found that North Americans do not show higher levels of independent self-construal compared to Asians (Cross et al., 2011). Meaning, different self-construals can exist in different cultures, suggesting that individual differences may be present within one country.

In conclusion, as AI continues to evolve and develop its increasingly human-like capabilities, it is expected to become an integral part of society. Those with higher levels of interdependent self-construal may therefore view AI as a collaborative partner, while those with a stronger independent orientation may perceive it as a threat to personal autonomy and goals. Additionally, as self-construal influences emotion regulation, and technostress reflects an emotional response triggered by AI literacy, this study argues that self-construal theory influences the degree of technostress experienced due to AI literacy. Where independent self-construal amplifies technostress levels, and interdependent self-construal absorbs technostress levels, see Hypothesis 3A and 3B.

Hypothesis 3A – Independent self-construal positively moderates the effect of AI literacy on technostress.

Hypothesis 3B – Interdependent self-construal negatively moderates the effect of AI literacy on technostress.

3 Methodology

This chapter outlines the methodological approach adopted in this study. First, it describes the research design and the sampling strategy, including the rationale for selecting employees in the professional services sector. Then, it explains how the core concepts (job satisfaction, AI literacy, technostress, and self-construal) are measured, followed by a description of the methods used to explore data, ensure reliable and valid results, and calculate the weighted average of the variables. Each construct is then separately examined in greater detail, with subsections devoted to the measurement, exploration, and validation. Finally, the chapter concludes with an explanation of the moderated mediation model tested through regression analysis and bootstrapping procedures. Together, these methodological steps provide the foundation for the hypothesis testing presented in Chapter 4.

3.1. Research & Sample Strategy

The sample in this study consisted of employees from the professional services industry. Data on AI literacy, job satisfaction, self-construal, and technostress were collected through a quantitative, cross-sectional survey created in Qualtrics. To achieve a sufficient sample size, various survey distribution approaches were employed, including direct messages to consultants and accountants on LinkedIn, distributing QR codes in the Amsterdam business district (Zuid-as), and subsequently sharing a LinkedIn post. The collection period lasted from June 2nd, 2025, until July 7th, 2025. This research aimed for 100 respondents, but the study managed to collect 141 survey respondents, and LinkedIn direct messages appeared to be the most successful strategy, see Table 3.1 for the number of respondents per method.

Table 3.1: Number of respondents recruited per survey distribution method

Distribution Method	Number of Respondents
LinkedIn Post	27
LinkedIn Direct Messages	95
QR code distribution	19
Total	141

The survey started by asking respondents to state their gender (male, female, non-binary, prefer not to say), their age (20-30, 31-40, 41-50, 51+), their computer confidence, and their profession and work sector. The professions were carefully analyzed to ensure all respondents were employed within the professional services sector; those who did not were eliminated from the sample. As it was expected that not all respondents would complete the survey, the data was checked for missing values. Surveys completed > 50% were included in the analysis, and the empty survey items were predicted using the MissForest() function from the CRAN package in R. This function imputes missing values when dealing with mixed-type data and applies random forest on the values to predict the missing ones. MissForest does not require any assumptions about the data distribution, such as normal distribution. It was furthermore shown to outperform similar imputation methods such as k-nearest neighbors, regardless of the variable types, number of missing values, and the dataset's dimensionality. Additionally, MissForest() works well with high-dimensional datasets, e.g., the number of variables is much higher than the number of observations, making it highly suitable for this research. Finally, it does not require any tuning parameters, nor does it necessitate foreknowledge about the dataset (Stekhoven and Bühlmann, 2012). There are two options for imputation: a numerical and a factorial imputation, and as this research applies a 7-point likert scale, data can be treated as both ordinal and categorical (Saqr and López-Pernas, 2024). First, only the control variables were transformed to factors, and the others were kept numeric; followed by transforming all variables to factors. For both types of datasets, the imputation was run, and the imputation generating the lowest out-of-bag (OOB) error (PFC for categorical/factors and NRMSE for numeric/continuous data) was selected to continue the data analysis with (Stekhoven and Bühlmann, 2012). Factor imputation resulted in the lowest OOB error and was therefore preferred, see Table 3.2 for the OOB errors. The final dataset consisted of 106 useful responses, and of those, 74.5% were male, and 25.5% were female respondents. None of the respondents identified as non-binary or selected the ”prefer not to say” option. Furthermore, the sample consisted of relatively young employees, about 75.5% identified as 20-30 years old, and only 24.5% were 31+ years old, indicating a young sample. Using these items as control variables required dummy creation. See Table 3.3 for the sample specifications and dummy clarification.

Finally, this study was approved by the Human Research and Ethics Committee (HREC) of TU Delft. The data collected during this research was stored solely on TU Delft's OneDrive and automatically gets deleted after this research has been finished. All respondents were informed about the data storage methods, about the fact that contributing to this research is entirely voluntary, and about their option to withdraw at any time. Respondents needed to comply to the consent form, see Appendix A, before being able to take the survey. Non-compliance sent the respondent to the end of the survey. In addition, potential respondents were motivated by the possibility of winning a 25-euro gift card, which one could apply for by leaving their e-mail address. However, e-mail addresses were not used for research purposes as all respondents were kept anonymous.

Table 3.2: The out-of-bag imputation error for categorical and numerical data imputation

Proportion of Falsely Classified entries (PFC)	0.1948687
Normalized Root Mean Squared Error (NRMSE)	0.3634912

Table 3.3: Sample details: gender, age and the dummy values

Sample Specification	Dummy Value	Number of Respondents
Male	0	79
Female	1	27
20-30 years old	0	80
31+ years old	1	26
Total		106

3.2. Measurement of Concepts & Data Exploration

The hypotheses given in Chapter 2 are tested using four concepts: Job Satisfaction, AI literacy, Technostress, and self-construal, measured using survey items created by Spector (1985), Wang et al. (2023), Ragu-Nathan et al. (2008), and Singelis (1994). As the concepts, called latent variables, in this research are not directly measurable, they require different sub-constructs measured by items (e.g., the statements in the survey). In other words, each latent variable was subdivided into constructs (e.g., job satisfaction consists of constructs such as promotion and contingent rewards), and these constructs were measured using the survey items. Considering that this study employed predefined statements to measure the latent variables, these items had previously been validated by earlier research, and it was therefore assumed that they possess sufficient content validity and face validity.

3.2.1. Measurement of Concepts

The data was transformed from Qualtrics to a CSV file, which was subsequently loaded into RStudio for data analysis. The questionnaire applies a 7-point likert scale, where 1 = strongly disagree, and 7 = strongly agree. The fourth option represents a neutral ”Neither agree nor disagree” option. Doing so avoids respondents feeling forced to take an opinion on the statement even though they might not have one. Some variables include negatively formulated statements which require reversed scoring. For instance, a response of ‘strongly agree’ (7) to the item ‘I can distinguish between AI systems and non-AI systems’ indicates high AI literacy. Conversely, for a negatively worded item such as ‘I do not know how AI technology can help me’, a response of ‘strongly agree’ would instead reflect low AI literacy. To correct for this, responses to negatively worded items were reverse-coded, so that agreement corresponds to lower scores (e.g., ‘strongly agree’ recoded to 1), thereby aligning all items within the construct. However, technostress items do not require reversed scaling. For example, the item: ”I need a long time to understand and use AI” reflects higher levels of technostress when answered with ”strongly agree” (7). Similarly, a negatively worded technostress item, such as ”I do not know enough about AI to handle my job satisfactorily” also represents high technostress when answered with ”strongly agree”. Concluding, the scale of the technostress items does not need to be reversed. The list of all survey items can be found in Appendix D, and all items marked with (R) indicate negatively worded statements that require reverse-coding before analysis.

3.2.2. Data exploration

To better understand the data characteristics, such as correlations among variables, standard deviations, ranges, and means, a correlation matrix was generated for each construct. were examined for correlations and multicollinearity by identifying correlations above .80 and calculating the determinant of the correlation matrix. A determinant $> .00001$ disproves multicollinearity. Items lacking correlations $> .30$ with items measuring the same latent variable may indicate that the item does not measure the latent variable adequately and would potentially harm construct validity (Field et al., 2012). It is, however, important to be cautious when eliminating items solely based on their correlations as this may lead to a bad theoretically motivated model, especially as this research adopted its questions from existing literature (O'Brien, 2007). For each latent variable, the items were examined by considering their correlations as well as their range, minimum and maximum values, standard deviations, and means. This provides an overview of the data distribution and relationships among variables before any data transformations.

3.2.3. Common Method Bias, Construct Validity, & Weighted Average

Common Method Bias (CMB) is one of the main sources of measurement error in behavioral science and requires control measures to minimize its negative effects. According to Podsakoff et al. (2003), one method is to allow the respondents to answer anonymously. This will avoid socially desirable answers and stimulate honest responses. Additionally, an Exploratory Factor Analysis (EFA) was conducted to examine whether the items load on the constructs they are supposed to measure. To check for CMB, Harman's one-factor test was conducted (Podsakoff et al., 2003 cited by Stam, 2009). If one factor accounts for most of the covariance among the items, this may indicate the presence of CMB. Performing an EFA also checks for construct validity. Although this research used existing scales, it excluded certain items within a dimension or rephrased items, making a construct validity check necessary.

An EFA, however, can only be performed on continuous data. As stated before, this research applied a seven-point likert-scale and uses mutliple items to measure a concepts. Hence, this study's data can be treated as continuous (Saqr and López-Pernas, 2024). Before this EFA was conducted, a Kaiser-Meyer-Olkin (KMO) statistic and the Barlett's test of sphericity were derived to assess the item-suitability to conduct an EFA. Generally, a KMO value above $MSA \geq .5$ is considered acceptable, and a Barlett's test is used to indicate if the correlation matrix differs from the identity matrix. If this test yields significant ($p < .05$) outcomes, sufficient correlation among variables is confirmed, making an EFA appropriate (Field et al., 2012). All KMO values exceeded the $MSA \geq .5$ threshold, and all latent variables, sub-variables yielded significant results for the Barlett's test. Thus, an EFA is considered a suitable method, see Appendix E for all KMO and Barlett's test of sphericity outcomes.

Considering that this thesis used the same scale of measurement for every item, applying the weighted average method was therefore found suitable (Field et al., 2012). The weighted average method was selected as it includes the loading of each item on a variable. Meaning, items having a high loading have a larger effect on the variable than those having a low loading (DiStefano et al., 2009). This method is a non-refined method, and although refined methods are statistically superior to non-refined methods, they require a large dataset to generate reliable outcomes (Feißt et al., 2019), whereas non-refined factor scores depend less on the specific sample that is used in the research (DiStefano et al., 2009). Hence, given this study's relatively small sample size, non-refined methods were deemed suitable.

The factor loadings obtained from the EFA were subsequently used to compute weighted averages for the latent variables. For this purpose, all items belonging to each latent variable (AI Literacy, Technostress, and Self-Construal) were loaded onto a single factor. The factor scores were subsequently calculated by multiplying each respondent's item response by the corresponding factor loading, see Equation 3.1. Finally, the weighted average for each latent variable was computed by averaging these scores across all items for each respondent, see Equation 3.2.

$$Y_i = b_1 X_{1i} + b_2 X_{2i} + \cdots + b_n X_{ni} + \varepsilon_i \tag{3.1}$$

$$Z = \sum_{i=1}^{n} Y_i = \sum_{i=1}^{n} (b_1 X_{1i} + b_2 X_{2i} + \cdots + b_k X_{ki} + \varepsilon_i) \tag{3.2}$$

3.2.4. Reliability

To review the reliability of the variables and their items, the Cronbach's α values were generated. A value $\geq .70$ indicates good reliability (Field et al., 2012). If variables exceed this threshold, it is assumed to yield reliable research outcomes.

3.3. Measurement of Job Satisfaction

Job satisfaction can be measured through various methods. One approach considers job satisfaction as a global construct and is applied to achieve a general evaluation of whether an individual likes or dislikes the job, without differentiating the concept into underlying dimensions. Another approach is to parse the concept over different facets. This approach enables the identification of which dimensions of job satisfaction are causing the liking or disliking of the profession. This study argues the latter method to be most suitable, considering the subjective nature and multi-dimensionality of job satisfaction.

Considering that job satisfaction is a widely studied topic and has a multi-dimensional nature, it is not surprising that many scales exist trying to measure it. van Saane et al. (2003) measured the psychometric quality, internal consistency, the test-retest validity, and construct validity of 29 instruments measuring job satisfaction and found that only seven met adequate content validity: the Job in General Scale, Andrew and Withey Job Satisfaction Questionnaire, Job Satisfaction Survey, Emergency Physician Job Satisfaction Scale, McCloskey/Mueller Satisfaction Scale, Measure of Job Satisfaction, and The Nurse Satisfaction Scale, see Appendix B for an overview of all job satisfaction scales.

The Job Satisfaction Survey/Scale (JSS) by Spector (1985) was considered the best option for this research. The JSS uses a 6-point likert-scale and consists of 36 items divided over nine subscales: Pay, Promotion, Supervision, Benefits, Contingent Rewards, Operating Procedures, Co-workers, Nature of Work, and Communication. The factor analysis performed showed the sub-scales were not strongly overlapping and each subscale showed a coefficient alpha $> .70$, indicating that the sub-scales measured a different job satisfaction aspect and can thus be used separately (Spector, 1985). As this study solely focuses on career perspectives as a consequence of AI literacy, not all sub-scales were deemed relevant to this study. This research limits itself to the following dimensions: Promotion, Contingent Rewards, and Nature of Work. An example of a promotion item is: "There is really too little chance for promotion in my job." Contingent rewards were measured with items such as: "When I do a good job, I receive the recognition for it that I should receive." An example of a nature of work item is: "I sometimes feel my job is meaningless." See Appendix D Table D.1 for a full overview of the dimensions, the items, and scoring method. The wording of all items remained unchanged from the literature.

Job satisfaction's other dimensions: pay, supervision, benefits, operating procedures, co-workers, and communication were considered unaffected by AI literacy Spector (1985), see Appendix C Table C.1 for the eliminated dimensions and items.

3.3.1. Exploration of Job Satisfaction items

Most means are > 4 and < 6, indicating a relatively high score of job satisfaction. However, almost all items used the full response range ($1 - 7$),with the exception of the contingent rewards items($1 - 6$), and promotion 2 having a range of ($1 - 5$). This suggests sufficient variability among respondents: although most reported high scores, some provided lower ratings. As all items showed a standard deviation between 1 and 2, the variability can be considered moderate. Thus, there appears to be agreement among respondents concerning job satisfaction, but still meaningful personal differences are present. Promotion 2, contingent rewards 3, and contingent rewards 4 show a mean > 3 but < 4, and thereby indicate a slightly lower average job satisfaction score. Interestingly, Promotion 2 touches on the fairness of promotion; the lower score might suggest that doing well in your job does not necessarily reflect in better promotion possibilities. Additionally, the lower mean score of contingent rewards items 3 and 4 may reflect that employees feel like they deserve more rewards and appreciation for their work.

Furthermore, all variables demonstrated significant correlations within their respective sub-groups, indicating overall sufficient internal consistency. However, Nature of Work item 4 correlated $> .80$ with Nature of Work item 2, which could suggest multicollinearity. However, since both items belong to the same sub-dimension and the determinant of the correlation matrix was $.0026709591$, multicollinearity is not considered a concern. Finally, every variable consists of at least one correlation $> .30$ within its sub-group, indicating sufficient internal consistency. The control variables, Gender, Age, and Computer Confidence showed no strong correlations. Although Gender correlated significantly with contingent rewards 3, and age with nature of work 3, suggesting that gender may be associated with perceived reward satisfaction, while age may be linked to how much employees enjoy their job. See Table 3.4 for the descriptive statistics and correlations.

Table 3.4: Descriptive statistics and correlations of job satisfaction items

	Item	M	SD	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Promotion 1	5.25	1.49	1.00	7.00	–														
2	Promotion 2	3.59	1.03	1.00	5.00	.42**	–													
3	Promotion 3	4.85	1.46	1.00	7.00	.24*	.17	–												
4	Promotion 4	5.17	1.21	1.00	7.00	.59**	.50**	.36**	–											
5	Contingent rewards 1	4.36	1.12	1.00	6.00	.20*	.40*	.25*	.41**	–										
6	Contingent rewards 2	4.25	1.20	1.00	6.00	.22*	.47**	.25**	.32**	.47**	–									
7	Contingent rewards 3	3.81	1.54	1.00	6.00	.35**	.30**	.49**	.46**	.21*	.35**	–								
8	Contingent rewards 4	3.70	1.44	1.00	6.00	.18	.37**	.18	.37**	.46**	.41**	.31**	–							
9	Nature of work 1	4.47	1.69	1.00	7.00	.37**	.30**	.27**	.22*	.21*	.43**	.22*	.27**	–						
10	Nature of work 2	5.43	1.37	1.00	7.00	.22*	.23**	.31**	.35**	.15	.35**	.25*	.21*	.63**	–					
11	Nature of work 3	5.21	1.41	1.00	7.00	.28**	.26**	.18	.34**	.13	.32**	.16	.23*	.47**	.67**	–				
12	Nature of work 4	5.49	1.21	1.00	7.00	.28**	.09	.31**	.36**	.16	.38**	.28**	.19	.57**	.81**	.64**	–			
13	Age	0.25	0.43	0.00	1.00	.22*	-.07	-.02	.01	.01	-.08	-.07	-.00	-.00	.17	.20**	.08	–		
14	Gender	0.25	0.44	0.00	1.00	-.03	-.00	-.03	-.10	-.09	-.05	.24**	-.18	.03	.00	.02	-.08	-.18	–	
15	Computer confidence	6.25	1.12	1.00	7.00	-.06	-.02	.06	.02	-.01	.02	.07	.01	.01	.08	-.00	.02	.18	-.15	–
	Determinant	.002670959																		

Note. $n = 106$. *$p < .05$, **$p < .01$.

3.3.2. CMB, Construct Validity, & Weighted Average of Job Satisfaction

The Job Satisfaction measures are theoretically divided into different constructs, and this research selected Promotion, Contingent Rewards, and Nature of Work as the relevant ones. The model showed a poor to moderate fit, having a $\chi^2(33) = 63.82$, $p < .001$, and a Tucker-Lewis Index (TLI) of 0.869, just below the $.90$ threshold. The Promotion items, except for Promotion 2, showed the highest loadings on $ML1$. The Contingent Reward items all loaded on $ML3$, and the Nature of Work items on $ML2$. Furthermore, Promotion 3 and Contingent Rewards 3 showed very low h^2 values and high u^2 values. It is therefore likely that these items are insufficiently explained by the factors, whereas Promotion 4 and Nature of Work 2 show very high communalities and low uniqueness scores. Finally, Harman's one-factor test confirmed that no single factor accounted for the majority of the variance ($ML1 = 28\%$, $ML2 = 42\%$, $ML3 = 30\%$), and CMB is therefore considered unlikely. See Table 3.5 for all factor loadings, communalities, and uniqueness scores. Table 3.6 represents the factor loadings when the items load onto one factor. These loadings are applied to calculate the weighted average of Job Satisfaction.

Table 3.5: Exploratory Factor Analysis: Job satisfaction

Item	ML1	ML2	ML3	h2	u2
Promotion 1	.52	.08	.10	.365	.635
Promotion 2	.28	-.10	.56	.474	.526
Promotion 3	.22	.20	.15	.271	.729
Promotion 4	.97	.05	.02	.995	.005
Contingent rewards 1	.17	-.11	.59	.413	.587
Contingent rewards 2	-.09	.15	.73	.584	.416
Contingent rewards 3	.28	.07	.29	.195	.805
Contingent rewards 4	.11	-.02	.55	.363	.637
Nature of work 1	-.15	.60	.33	.534	.466
Nature of work 2	.02	.15	-.01	.835	.165
Nature of work 3	.08	.69	.02	.530	.470
Nature of work 4	.11	.89	-.06	.797	.203

Table 3.6: Factor loadings of job satisfaction's items for weighted average computation

Item	ML1
Promotion 1	.41
Promotion 2	.37
Promotion 3	.40
Promotion 4	.51
Contingent rewards 1	.31
Contingent rewards 2	.51
Contingent rewards 3	.39
Contingent rewards 4	.35
Nature of work 1	.70
Nature of work 2	.86
Nature of work 3	.72
Nature of work 4	.84

3.3.3. Reliability of Job Satisfaction

Table 3.7 contains the values of Cronbach's α for each item to Job Satisfaction. All values exceed the threshold of $\alpha > .70$. Meaning, these variables suggest that the items measuring these concepts are consistent enough to be considered a reliable scale. Table 3.8 represents Cronbach's α for all items on their sub-variable. Each sub-variable showed a reliability of $\alpha > .69$, which nearly exceeds the threshold. Nature of work showed a very high reliability of $\alpha = .862$. Overall, the reliability of the latent variables, the sub-variables, and the items appeared to be consistent and non-problematic.

Table 3.7: Cronbach's α for job satisfaction and its items

	Item	alpha
1	Promotion 1	.848
2	Promotion 2	.842
3	Promotion 3	.847
4	Promotion 4	.834
5	Contingent rewards 1	.846
6	Contingent rewards 2	.837
7	Contingent rewards 3	.843
8	Contingent rewards 4	.845
9	Nature of Work 1	.836
10	Nature of Work 2	.833
11	Nature of Work 3	.839
12	Nature of Work 4	.834
	Job Satisfaction	**.851**

Table 3.8: Cronbach's α for sob satisfaction's sub-variables and their items

	Item	alpha
1	Promotion 1	.594
2	Promotion 2	.651
3	Promotion 3	.746
4	Promotion 4	.516
	Job Satisfaction: Promotion	**.697**
1	Contingent Rewards 1	.624
2	Contingent Rewards 2	.590
3	Contingent Rewards 3	.702
4	Contingent Rewards 4	.592
	Job Satisfaction: Contingent Rewards	**.691**
1	Nature of Work 1	.876
2	Nature of Work 2	.777
3	Nature of Work 3	.842
4	Nature of Work 4	.803
	Job Satisfaction: Nature of Work	**.862**

3.4. Measurement of AI Literacy

Brougham and Haar (2018) developed a STARA awareness scale; consisting of four negatively formulated items, such as "I am personally worried that what I do now in my job will be able to be replaced by STARA", and although these measures have been proven reliable and used to define AI awareness in studies conducted by Teng et al. (2024) and Zhao et al. (2025), they appear to focus on an employee's perceived anxiety about job replacement rather than taking a more neutral point of view and measuring someone's experience with AI. This study argues that the STARA awareness scale focuses more on the fear of job replacement rather than on measuring the awareness of smart technologies.

Another relatively recent study by Ma and Chen (2024) developed the AILS-CCS scale (Artificial Intelligence Literacy Scale for Chinese College Students). However, this scale was developed to measure AI literacy of Chinese college students, and it is recommended to only apply it to such samples. Therefore, this study uses the Artificial Intelligence Literacy Scale (AILS) defined by Wang et al. (2023) instead. The scale was developed using a more diverse sample: multiple age groups, genders, and education levels. This study, therefore, considered this scale as more reliable.

AILS thoroughly measures a person's AI competence using a 12-item questionnaire consisting of four different constructs: AI awareness, usage, evaluation, and ethics. Ethics was considered out of scope, and these items were excluded from the survey; see Appendix C, Table C.2 for excluded items. The AILS constructs all indicated acceptable discriminant validity (< 0.85). Indicating that each construct measures distinct dimensions of AI literacy. The separate use of the dimensions, and thus excluding ethics, is therefore justified. However, the reliability ($Cronbachs\ \alpha$) of the aggregate dimensions appears to be higher than when using the dimensions separately. The study applied a used a 7-point likert-scale ranging from 1 to 7, where 1 indicates low AI literacy, and an average of 7 indicates high literacy. The same scale was applied in this study, where the statements were 1 = strongly disagree, and 7 = strongly agree, with a neutral midpoint of “neither agree nor disagree. An example of a question measuring AI Awareness is ”I can distinguish AI-systems from non-AI systems.” AI Usage is measured with items such as: ”I can skillfully use AI applications or products to help me with my daily work.” And finally, an example of an AI Evaluation item is ”I can choose a proper solution from various solutions provided by AI”. Only one item was reworded for the sake of applicability, see Table 3.9. Table D.2 in Appendix D provides an overview of the dimensions, items, and scoring method of AI literacy’s items.

Table 3.9: An original and an adapted AI awareness survey item

AI Awareness item original	AI Awareness item adapted
• I can distinguish between smart devices and non-smart devices.	• I can distinguish AI-systems from non-AI systems.

3.4.1. Exploration of AI Literacy items

AI awareness 1 and 2, AI usage 1 and 2, and AI evaluation 2 showed a rather high mean (≥ 4.00), indicating high literacy. The minimum and maximum values showed that these items were answered using almost the entire scale, resulting in a large range. Additionally, the standard deviation for these items was higher than for the items showing a lower mean (≤ 4.00). Meaning, there appears to be variability in the dataset for these items, and they thus cluster less tightly around the mean. In conclusion, the items showing a rather high mean still indicate differences among respondents, indicating differences in perceived literacy. However, considering the high mean, most respondents scored high on these items. Interestingly, AI awareness 3 shows a rather low mean compared to the other two awareness items. When looking at these items, awareness 3 appears to touch upon a respondent’s more technical knowledge about AI rather than general awareness. Meaning, respondents are likely to have less deeper technical than general awareness. The same pattern is visible for AI usage: item 3 shows a lower mean than the other items. This might be because of item 1 and 2 address skill and learning ability, while item 3 focuses on the added value AI contributes to work outcomes. Furthermore, most variables showed significant correlations within their sub-group. For example, AI awareness 3 correlates significantly with AI awareness 1 and AI awareness 2, as do the AI evaluation variables. AI usage items 1 and 2 were also significantly correlated. In addition, the AI usage variables correlated significantly with both AI awareness and AI evaluation items. Taken together, these patterns suggest satisfactory internal consistency at face value. The control variables did not show any strong and/or significant correlations with the other items. Furthermore, all correlations are $< .80$, and the determinant was $.06856281$, suggesting no multicollinearity. However, the variables AI awareness 2 and AI usage 2 do not show any correlations $> .30$, which might indicate low internal consistency. Possible reasoning for the correlations between awareness and evaluation items with usage items is that awareness of AI and the ability to evaluate it are naturally connected to actual usage of AI. See Table 3.10 for the descriptive statistics and correlations.

Table 3.10: Descriptive statistics and correlations of AI literacy items

	Item	M	SD	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12
1	AI awareness 1	4.57	1.09	1.00	6.00	–											
2	AI awareness 2	5.75	1.30	2.00	7.00	.14	–										
3	AI awareness 3	3.51	1.04	1.00	5.00	.57**	.26**	–									
4	AI usage 1	4.91	0.98	1.00	6.00	.31**	.14	.51**	–								
5	AI usage 2	5.51	1.27	1.00	7.00	.07*	.12	.19*	.24*	–							
6	AI usage 3	3.24	0.76	1.00	4.00	.25**	.14	.28**	.44	.16	–						
7	AI evaluation 1	3.79	0.78	1.00	5.00	.40**	.17	.29**	.54**	.10	.42**	–					
8	AI evaluation 2	4.51	1.08	1.00	6.00	.31**	.09	.17	.22*	.18	.33**	.31**	–				
9	AI evaluation 3	3.98	1.29	1.00	6.00	.33**	.10	.34**	.28**	.28**	.18	.33**	.62**	–			
10	Age	0.25	0.44	0.00	1.00	-.08	-.05	-.03	-.12	-.00	.01	-.14	-.09	.04	–		
11	Gender	0.25	0.44	0.00	1.00	-.03	.05	.01	.06	.12	.08	-.03	.07	-.03	-.18	–	
12	Computer Confidence	6.25	1.12	1.00	7.00	.07	-.05	.08	.13	.09	.11	.04	.02	.06	.18	-.15	–
	Determinant	.06856281															

Note. $n = 106$. *$p < .05$, **$p < .01$.

3.4.2. CMB, Construct Validity, & Weighted Average of AI Literacy

AI literacy consists of three dimensions, which were confirmed by the EFA: the model showed an acceptable fit with a $\chi^2(12) = 18.48$, $p < .10$, and a TLI of 0.907. The factor loadings showed that the AI Awareness items loaded highest on $ML2$. AI Usage, besides AI Usage 2, loaded mainly on $ML3$, and AI Evaluation, besides AI Evaluation 1, had the highest loadings on group 1. The communalities (h^2) were very low for AI Usage 2 and AI Awareness 2, and it is therefore unlikely that the variability of these items is explained by the three variables. The uniqueness values (u^2) confirmed this; AI Usage 2 is, for example, 93.7%, meaning that almost all of its variance is item-specific rather than shared with the latent construct. Finally, Harman's one-factor test confirmed that no single factor accounted for the majority of the variance ($ML1 = 33\%$, $ML2 = 33\%$, $ML3 = 34\%$), and CMB is therefore unlikely. See Table 3.11 for all factor loadings, communalities, and uniqueness scores. 3.12 represents the factor loadings when the items load onto one factor. These loadings are applied to calculate the weighted average of AI Literacy.

Table 3.11: Exploratory Factor Analysis: AI literacy

Item	ML1	ML2	ML3	h2	u2
AI awareness 1	.16	.46	.19	.405	.595
AI awareness 2	.01	.22	.10	.079	.921
AI awareness 3	-.01	1.01	-.02	.995	.005
AI usage 1	-.04	.28	.56	.513	.487
AI usage 2	.13	.14	.08	.063	.937
AI usage 3	.15	.06	.45	.308	.692
AI evaluation 1	.01	-.07	.86	.699	.301
AI evaluation 2	1.01	-.03	-.01	.995	.005
AI evaluation 3	.55	.20	.08	.447	.553

Table 3.12: Factor Loadings of AI literacy's items for weighted average computation

Item	ML1
AI awareness 1	.61
AI awareness 2	.26
AI awareness 3	.64
AI usage 1	.68
AI usage 2	.29
AI usage 3	.53
AI evaluation 1	.64
AI evaluation 2	.50
AI evaluation 3	.56

3.4.3. Reliability of AI Literacy

Almost all items of AI literacy exceed the threshold of $\alpha > .70$ 3.13. Meaning, the items measure AI Literacy reliably. In contrast, the sub-dimensions demonstrate weaker internal consistency. Specifically, AI Evaluation shows moderate reliability ($\alpha = .686$) whereas AI Usage ($\alpha = .498$) and AI Awareness ($\alpha = .536$) 3.14 do not exceed the required thresold. This suggests that AI literacy can be measured reliably as a single latent construct, while analyses based on its sub-dimensions are likely to produce less reliable results.

Table 3.13: Cronbach's α for AI Literacy as the latent variable and its items

	Item	alpha
1	AI awareness 1	.707
2	AI awareness 2	.767
3	AI awareness 3	.696
4	AI usage 1	.701
5	AI usage 2	.745
6	AI usage 3	.720
7	AI evaluation 1	.710
8	AI evaluation 2	.711
9	AI evaluation 3	.698
	AI literacy	**.741**

Table 3.14: Cronbach's α for all AI Literacy sub-variables and their items

	Item	alpha
1	AI awareness 1	.415
2	AI awareness 2	.726
3	AI awareness 3	.231
	AI Awareness	**.536**
1	AI usage 1	.246
2	AI usage 2	.595
3	AI usage 3	.382
	AI Usage	**.498**
1	AI evaluation 1	.756
2	AI evaluation 2	.451
3	AI evaluation 3	.453
	AI Evaluation	**.686**

3.5. Measurement of Technostress

Ragu-Nathan et al. (2008) provides items that measure technostress, including creators and inhibitors. The Cronbach's alpha for all constructs varied from 0.71 to 0.91 and is therefore considered reliable. Moreover, technostress creators and technostress inhibitors are two distinct constructs, which was confirmed by comparing three models on their chi-square ratios, and discriminant validity: model 1, assumed overlap between the constructs, and models 2 and 3, assumed the constructs are separable. It is therefore possible for this research to solely use technostress creator measures, rather than using both the inhibitors and creators. The technostress creators consist of five dimensions: techno-overload, techno-complexity, techno-insecurity, techno-uncertainty, and techno-invasion (Ragu-Nathan et al., 2008). Califf et al. (2020) identified the same five concepts capturing the negative effects of technostress, referring to them as technostressors. This research aimed to keep the survey as short as possible and was therefore selective about what dimensions to include. As a result, this study excludes techno-invasion and selected techno-uncertainty items, as this study assumed that it is unlikely for artificial intelligence literacy to, for example, force people to be connected to work, even on the weekends. The separation of the technostress creators, meaning excluding techno-invasion, is validated as the values of $Cronbachs\ \alpha > 0.70$ for all dimensions, which indicates good independent reliability. Hereby, only those dimensions directly relevant to AI literacy are retained. See Appendix C, Table C.3 for the excluded technostress items.

An example of an item measuring Techno-complexity is "I often find it too complex for me to understand and use new AI technologies." See Appendix D, Table D.3 provides an overview of the dimensions, items, and scoring method. Subsequently, some items were reformulated for the sake of readability and applicability to AI literacy: all items referring to general technology were replaced with "AI". Moreover, techno-overload items were reformulated, see Table 3.15 for the adapted items.

Originally, each item within the concept is measured using a five-point likert-scale: 1 representing “strongly disagree” and 5 being “strongly agree”. A sixth option representing the possibility “I do not know” was also provided by Ragu-Nathan et al. (2008). However, as stated before, this research applies a 7-point likert scale.

Table 3.15: Original and adapted techno-overload survey items

Techno-overload original	Techno-overload adapted
• I am forced by this technology to do more work than I can handle.	• I take up more work than I can handle because of AI.
• I am forced by this technology to work with very tight time schedules.	• I have to work with very tight schedules because of AI.
• I am forced to change my work habits to adapt to new technologies.	• I am forced to change my work habits to adapt to AI.
• I have a higher workload because of increased technology complexity.	• I have a higher workload because of increased AI complexity.

3.5.1. Exploration of Technostress items

Most items showed significant correlations within their sub-group, and each item, besides Techno-overload 2, Techno-overload 4, Techno-complexity 1, and Techno-complexity 2, reflected the complete range of $1-7$. Additionally, all items revealed a mean value between 2 and 4, indicating low to medium technostress scores. However, the items techno-uncertainty 1 and 2 showed a higher average score, indicating medium to higher scores of technostress. Since these items capture perceptions of constant technological change within organizations, this finding appears consistent with the rapid developments currently taking place in AI. Techno-overload, complexity, and insecurity showed a lower mean, indicating low stress. Together with the high computer confidence mean value, this perhaps suggests that those working in the professional services industry already have high digital competence and score therefore low on these items. Moreover, no variable showed a standard deviation > 2, and it is therefore considered for the items to have moderated variability. When looking at the correlations, the variables showed significant correlations within their sub-group and also outside of their sub-group, indicating sufficient internal consistency. No correlations exceeded $.80$, and the determinant of the correlation matrix was $.005643295$, thereby disproving potential multicollinearity. Though, the Techno-uncertainty variables did not indicate correlations $> .30$, possibly suggesting lower internal consistency within this sub-group. Finally, computer confidence did not show strong correlations to the other items. Only Techno-complexity 5 and Techno-insecurity 1 suggested significant correlations with computer confidence. See Table 3.16 for the descriptive statistics and correlations.

Table 3.16: Descriptive statistics and correlations of technostress variables

	Item	M	SD	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	Techno-overload 1	3.33	1.72	1.00	7.00	–																	
2	Techno-overload 2	2.30	1.05	1.00	6.00	.49**	–																
3	Techno-overload 3	3.93	1.77	1.00	7.00	.10	.29**	–															
4	Techno-overload 4	2.69	1.38	1.00	6.00	.31**	.46**	.23*	–														
5	Techno-complexity 1	2.33	1.27	1.00	6.00	-.12*	.25*	.21*	.21*	–													
6	Techno-complexity 2	2.38	1.25	1.00	6.00	-.24*	.12	.10	.05	.56**	–												
7	Techno-complexity 3	3.84	1.77	1.00	7.00	-.14	.08	.35**	.24*	.36**	.30**	–											
8	Techno-complexity 4	3.13	1.63	1.00	7.00	-.02	.13	.18	.09	.38**	.53**	.27**	–										
9	Techno-complexity 5	2.20	1.11	1.00	7.00	-.04	.20*	.26**	.19	.51**	.63**	.42**	.42**	–									
10	Techno-insecurity 1	2.30	1.42	1.00	7.00	.18	.31**	.25**	.36**	.31**	.30**	.21*	.28**	.36**	–								
11	Techno-insecurity 2	2.99	1.67	1.00	7.00	.08	.15	.32**	.28**	.20*	.12	.13	.23*	.22*	.49**	–							
12	Techno-insecurity 3	2.42	1.32	1.00	7.00	.26**	.34**	.25**	.38**	.28**	.15	.29**	.23**	.18	.42**	.31**	–						
13	Techno-insecurity 4	2.29	1.52	1.00	7.00	.06	.18	-.07	.23*	.33**	.28**	.09	.19*	.36**	.40**	.36**	.35**	–					
14	Techno-uncertainty 1	5.22	1.52	1.00	7.00	.18	.10	.19*	.05	-.10	-.11	-.17	.07	-.12	.04	.15	.07	.01	–				
15	Techno-uncertainty 2	4.12	1.78	1.00	7.00	.08	.08	.29**	.04	.10	.11	.09	.07	.09	.14	.24*	.23*	.19*	.27**	–			
16	Age	0.25	0.43	0.00	1.00	-.02	.05	-.10	-.01	-.08	.00	-.06	.14	-.02	-.04	.07	.05	.11	-.02	.19**	–		
17	Gender	0.25	0.44	0.00	1.00	.05	.02	.07	-.01	.00	-.06	.10	.03	-.03	.03	-.07	.08	-.03	-.06	.10	-.18	–	
18	Computer Confidence	6.25	1.12	1.00	7.00	.07	-.04	-.07	-.08	-.11	-.19	.00	-.14	-.25*	-.22*	-.10	-.10	-.16	.16	.03	.18	-.15	–
	Determinant	.005643295																					

Note. $n = 106$. *$p < .05$, **$p < .01$.

3.5.2. CMB, Construct Validity & Weighted Average of Technostress

Literature showed that technostress can be divided over different factors and this research selected the four most relevant ones. This theoretical structure was confirmed by the EFA: the model showed an acceptable fit with a $\chi^2(51) = 51.13$, $p < .47$ and a TLI of 0.999. The factor loadings revealed that the Techno-overload items had the highest loadings on $ML3$, however, Techno-overload 3 appeared to have the highest loading on $ML1$. The techno-complexity items loaded strongest on $ML2$, and the Techno-insecurity items on $ML4$. However, Techno-usage 1 loaded highest on $ML1$ and Techno-usage 2 on $ML4$, both items having very low h^2 values and high u^2 values. Indicating that the variance of these items are most likely unique and not explained by the factors of the model. The same applies to Techno-complexity 3, 4, Techno-overload 4, and Techno-insecurity 3. Finally, Harman's one-factor test confirmed that no single factor accounted for the majority of the variance ($ML1 = 19\%$, $ML2 = 35\%$, $ML3 = 22\%$, $ML4 = 24\%$), and CMB is therefore unlikely. See Table 3.17 for all factor loadings, communalities, and uniqueness scores. Table 3.18 represents the factor loadings when the items load onto one factor. These loadings are applied to calculate the weighted average of technostress.

Table 3.17: Exploratory Factor Analysis: Technostress

Item	ML1	ML2	ML3	ML4	h2	u2
Techno-overload 1	-.03	-.29	.66	.07	.499	.501
Techno-overload 2	.07	.13	.81	-.06	.678	.322
Techno-overload 3	.98	.02	.03	.02	.995	.005
Techno-overload 4	.04	.03	.46	.24	.363	.637
Techno-complexity 1	.05	.64	.09	.08	.485	.515
Techno-complexity 2	-.05	.88	-.05	-.04	.738	.262
Techno-complexity 3	.28	.39	-.05	.04	.276	.724
Techno-complexity 4	.06	.52	.00	.10	.338	.661
Techno-complexity 5	.09	.70	.05	.07	.578	.422
Techno-insecurity 1	.03	.17	.16	.55	.498	.502
Techno-insecurity 2	.16	-.07	-.09	.71	.515	.485
Techno-insecurity 3	.05	.07	.27	.41	.371	.629
Techno-insecurity 4	-.28	.21	.07	.57	.459	.541
Techno-usage 1	.18	-.25	.06	.17	.105	.895
Techno-usage 2	.24	-.03	-.06	.29	.153	.847

Table 3.18: Factor Loadings of technostress items for weighted average computation

Item	ML1
Techno-overload 1	.06
Techno-overload 2	.39
Techno-overload 3	.38
Techno-overload 4	.40
Techno-complexity 1	.66
Techno-complexity 2	.64
Techno-complexity 3	.48
Techno-complexity 4	.55
Techno-complexity 5	.70
Techno-insecurity 1	.60
Techno-insecurity 2	.45
Techno-insecurity 3	.49
Techno-insecurity 4	.49
Techno-uncertainty 1	-.01
Techno-uncertainty 2	.24

3.5.3. Reliability of Technostress Items

All Technostress items exceeded the threshold of $\alpha > .70$. Meaning, the items reliably measure Technostress, see Table 3.19. However, splitting technostress into the sub-variables resulted in mixed reliability of the items and the sub-dimensions: Techno-complexity and Techno-insecurity appeared to be reliable ($\alpha = .769\ and\ \alpha = .714$ respectively), whereas Techno-overload and techno-uncertainty suggested low reliability ($\alpha = .598\ and\ \alpha = .417$ respectively), see Table 3.20. Meaning, technostress as a latent variable is considered a reliable measure, whereas using its sub-dimensions separately might result in less reliable outcomes.

Table 3.19: Cronbach's α of technostress and its items

	Item	alpha
1	Techno-overload 1	.788
2	Techno-overload 2	.763
3	Techno-overload 3	.762
4	Techno-overload 4	.762
5	Techno-complexity 1	.760
6	Techno-complexity 2	.766
7	Techno-complexity 3	.771
8	Techno-complexity 4	.763
9	Techno-complexity 5	.759
10	Techno-insecurity 1	.750
11	Techno-insecurity 2	.758
12	Techno-insecurity 3	.754
13	Techno-insecurity 4	.764
14	Techno-usage 1	.789
15	Techno-usage 2	.775
	Technostress	**.778**

Table 3.20: Cronbach's α for technostress' sub-variables and their items

	Item	alpha
1	Techno-overload 1	.545
2	Techno-overload 2	.430
3	Techno-overload 3	.654
4	Techno-overload 4	.488
	Technostress: Overload	**.598**
1	Techno-complexity 1	.715
2	Techno-complexity 2	.692
3	Techno-complexity 3	.787
4	Techno-complexity 4	.745
5	Techno-complexity 5	.703
	Technostress: Complexity	**.769**
1	Techno-insecurity 1	.603
2	Techno-insecurity 2	.655
3	Techno-insecurity 3	.677
4	Techno-insecurity 4	.669
	Technostress: Insecurity	**.714**
1	Techno-uncertainty 1	.227
2	Techno-uncertainty 2	.314
	Technostress: Uncertainty	**.417**

3.6. Measurement of Self-Construal

Singelis (1994) developed a 24-item scale to measure the level of independent or interdependent self-construal within an individual. It is argued that these two levels can be measured using a scale consisting of 24 items, 12 measuring independent self-construal and 12 measuring interdependent self-construal (Singelis, 1994). For every item, the respondents were requested to fill in their level of agreement on a seven-point likert scale. Moreover, it was found for some items to overlap with others, which suggests the coexistence of the two construals within one person (Singelis, 1994). Originally, the items within this survey were developed for students, and this scale has been used in different research, such as in **Villibharathan2022PDFSelf-construals<empty citation>**, who used this scale to research the adjustment ability of international students in India based on self-construal theory.

D'Amico and Scrima (2016) reviewed this 24-item scale and reduced the number of items to 10, with five items measuring independent self-construal, and five items measuring interdependent self-construal. They even argue that a shorter scale might capture independence and interdependence even better than the longer Singelis' self-construal scale. It is thought that the elimination of sub-dimensions possibly reduces the misunderstanding of items among respondents. This study argues that a misunderstanding of items might lead to the two construals overlapping within one respondent, blurring the line between the two different personalities. Additionally, as a shorter survey is preferred, this study applied the 10-item scale to measure self-construal. Example of an item measuring independent self-construal is: ”I’d rather say ”No” directly than risk being misunderstood.” Interdependent self-construal consists of items such as: ”My happiness depends on the happiness of those around me.” See Appendix D, Table D.4 for all the items per dimension. Again, a seven-point likert scale is applied, and one of the questions within this scale has been adapted, see Table 3.21.

Table 3.21: An original and an adapted interdepdendent self-construal survey item

Interdependent self-construal item original	Interdependent self-construal item adapted
• If my brother or sister fails, I feel responsible.	• If one of my family members fails, I feel responsible.

3.6.1. Exploration of Interdependent & Interdependent Self-Construal items

The correlations show that both independent items generally correlate positively with each other, indicating good internal consistency within the construct. Similarly, interdependent items also show internal consistency. Notably, some interdependent items showed (significant) negative correlations with Independent items (e.g., Independent 2 with Interdependent 2: $r = .21$, $p < .05$). This suggests that participants who define themselves more with independent self-construal score lower on interdependent items, supporting the theoretical distinction between the two latent variables. Furthermore, all variables, besides Independent 3, had a range of $1-7$ and no variable showed a standard deviation > 2.0. The items are therefore considered to have moderated variability. Meaning, there is overall consistency among respondents, but also sufficient differences. Interestingly, Age was the only control variable representing significant correlations with other items, namely Independent 2 and Interdependent 3. Independent 2 reflects the tendency to behave consistently regardless of the social context, while Interdependent 3 captures the extent to which individuals value their relationships with others above their own accomplishments. These correlations suggest that older individuals may exhibit more stable relationship behaviors, possibly due to a more established sense of identity, and may place greater value on their personal relationships. Age might therefore play a role in shaping someone’s self-construal. Finally, no variable demonstrated a correlation $> .80$ with any other variable, and the determinant was $.1559273$, thus disproving multicollinearity. While every variable exhibited at least one statistically significant correlation, some variables showed weak correlations $< .30$, potentially harming internal consistency. In conclusion, the correlations show an overall sufficient internal consistency. See Table 3.22 for the descriptive statistics and correlations.

Table 3.22: Descriptive Statistics and Correlations Among Independent & Interdependent Self-Construal Variables

	Item	M	SD	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13
1	Independent 1	4.75	1.55	1.00	7.00	–												
2	Independent 2	3.90	1.65	1.00	7.00	.38**	–											
3	Independent 3	3.63	1.49	1.00	6.00	-.05	.29**	–										
4	Independent 4	4.70	1.62	1.00	7.00	.13	.17	.27**	–									
5	Independent 5	4.64	1.60	1.00	7.00	.13	.30**	.24*	.37**	–								
6	Interdependent 1	4.48	1.20	1.00	7.00	.07	-.03	-.15	-.20*	-.13	–							
7	Interdependent 2	4.59	1.32	1.00	7.00	-.20*	-.21*	-.12	-.17	-.19	.15	–						
8	Interdependent 3	3.93	1.33	1.00	7.00	.11	.12	-.19	-.02	.12	.19	.34**	–					
9	Interdependent 4	3.67	1.53	1.00	7.00	-.18	.13	.02	-.04	-.14	.01	.30**	.18	–				
10	Interdependent 5	3.74	1.65	1.00	7.00	-.07	.17	.10	-.06	.15	.07	.05	.03	.26**	–			
11	Age	0.25	0.43	0.00	1.00	.19	.25**	.10	.17	.17	-.12	-.09	-.22*	.07	.16	–		
12	Gender	0.25	0.44	0.00	1.00	-.15	-.04	-.10	-.05	-.14	.00	.07	.11	.10	.04	-.18	–	
13	Computer confidence	6.25	1.12	1.00	7.00	.12	.03	-.01	.17	.10	-.02	-.06	-.08	-.05	-.01	.18	-.15	–
	Determinant	.1559273																

Note. $n = 106$. $^{*}p < .05$, $^{**}p < .01$.

3.6.2. CMB, Construct Validity & Weighted Average of Self-Construal

Self-Construal theory consists of independent self-construal and interdependent self-construal, and it is therefore assumed that this variable consists of two different factors. These factors should be dinstinct from each other to confirm the different construal types in people. However, the EFA deos not underline this structure: $\chi^2(26) = 56.31, p < .00051$ and a $TLI = .471$. The poor fit is also underlined by the high u^2 values and the very low, except for Independent 2, h^2 values. It is therefore unlikely that these items are explained by their factors. Finally, Harman's one-factor test confirmed that no single factor accounted for the majority of the variance ($ML1 = 54\%$, $ML2 = 46\%$), and CMB is therefore unlikely. See Table 3.23 for all factor loadings, communalities, and uniqueness scores. To compute the weighted average for each latent variable, independent and interdependent self-construal were separated, and each was loaded onto one factor, these factor loadings were used to calculate the weighted average of independent and interdependent self-construal, see Table 3.24 and Table 3.25.

Table 3.23: Exploratory Factor Analysis: Self-Construal

Item	ML1	ML2	h2	u2
Independent 1	.37	-.15	.173	.827
Independent 2	.99	.00	.970	.030
Independent 3	.27	-.18	.120	.880
Independent 4	.14	-.27	.103	.897
Independent 5	.27	-.22	.140	.860
Interdependent 1	.00	.25	.064	.936
Interdependent 2	-.12	.67	.487	.513
Interdependent 3	.19	.45	.212	.788
Interdependent 4	.20	.49	.251	.749
Interdependent 5	.20	.19	.063	.937

Table 3.24: Factor Loadings of independent self-construal for weighted average computation

Item	ML1
Independent 1	.31
Independent 2	.56
Independent 3	.43
Independent 4	.50
Independent 5	.58

Table 3.25: Factor Loadings of interdependent self-construal for weighted average computation

Item	ML1
Interdependent 1	.23
Interdependent 2	.66
Interdependent 3	.49
Interdependent 4	.44
Interdependent 5	.17

3.6.3. Reliability of Self-Construal

The latent variables Independent and Interdependent self-construal show very low reliability (Independent: $\alpha = .590$; Interdependent: $\alpha = .478$), and therefore may produce unreliable outcomes in further analysis, which should be considered, see Table 3.26. These variables do not have distinct sub-dimensions and can therefore not be separated accordingly.

Table 3.26: Cronbach's α for independent and interdependent self-construal and their items

	Item	alpha
1	Independent 1	.597
2	Independent 2	.469
3	Independent 3	.565
4	Independent 4	.524
5	Independent 5	.502
	Independent Self-Construal	**.590**
1	Interdependent 1	.479
2	Interdependent 2	.364
3	Interdependent 3	.403
4	Interdependent 4	.364
5	Interdependent 5	.489
	Interdependent Self-Construal	**.478**

3.7. Control Variables

According to Ragu-Nathan et al. (2008), individual differences among people influence the level of technostress. They tested sex, age, education, and computer confidence as influences and found that females are less prone to technostress, and the stress appeared to go down with age, education, and increasing computer confidence (Ragu-Nathan et al., 2008). Moreover, according to Brougham and Haar (2018), STARA awareness was higher for people below 30 years old compared to the other groups (31-50 years and over 50 years old). They found that older employees barely show a difference in job satisfaction with increasing levels of STARA awareness. Possibly, older employees are not knowledgeable enough to feel the threat of such technologies, but a more likely explanation might be the fact that older employees are approaching the end of their career cycle and are therefore not worried about possible job changes. Finally, Rose Markus and Kitayama (1991) states that gender might influence whether someone identifies with an interdependent self-construal. This research, therefore, also applied gender (female/male/non-binary, prefer not to say) and age (20-30 and 30+) as control variables. Education level was not considered in this research as the sample only consisted of theoretically schooled employees (e.g., working in the professional service sector).

3.8. Moderated Mediation

This research investigates a moderated mediation model, where independent self-construal is expected to moderate the level of technostress, which in turn mediates the relationship between AI literacy and job satisfaction. According to Preacher et al. (2007), a moderated mediation "occurs when the strength of an indirect effect depends on the level of some variable or, in other words, when mediation relations are contingent on the level of a moderator." One approach to testing such models involves running three linear regression analyses to assess mediation, followed by two additional models to examine moderation and mediated moderation. This method was developed by Baron and Kenny (1986), but was criticized by Preacher and Hayes (2004) who found that this method has low statistical power, especially in smaller samples. Additionally, the method is sensitive to Type 1 errors, as a very small effect of the mediator between the independent and dependent variables may change the outcome from significant to non-significant. This might lead to false mediation conclusions. Contrary to this, a very large effect might have no impact on the significance and therefore could overlook a real mediation effect (Type 2 error) (Preacher and Hayes, 2004). As this research dealt with a relatively small sample, SEM and CFA were not suitable either (Saqr and López-Pernas, 2024). Hence, this research applied the PROCESS() Model 7 (moderated mediation). Using this model required the bruceR::PROCESS() package, which was installed from GitHub using the devtools package (Han-Wu-Shuang Bao, 2025). This research runs this model two times to test the hypotheses. The first model (Model 1A) tests the mediated moderation of independent self-construal. The second model (Model 1B) tests the mediated moderation of interdependent self-construal.

Equation 3.3 represents the formula of the mediator, and tests whether AI literacy predicts technostress, and whether this effect depends on the level of independent or interdependent self-construal. If the interaction term is significant, the moderation of the "a" path (AI literacy - technostress) is confirmed. Furthermore, Equation 3.4 tests how much technostress explains the link between AI literacy and job satisfaction, after including the moderators and controls. If the indirect effect through technostress is significant, and if technostress significantly predicts job satisfaction, then moderated mediation is confirmed. To give the model more statistical power, bootstrapping ($covs = 1000$) was applied. Bootstrapping is a "nonparametric approach to effect-size estimation and hypothesis testing that makes no assumptions about the shape of the distributions of the variables or the sampling distribution of the statistic" (Preacher and Hayes, 2004). That is, this solves the potential power problem induced by the potential asymmetries and non-normality of the data, and it does not require large samples (Preacher and Hayes, 2004).

$$\text{Technostress} \sim \text{Gender} + \text{Age} + \text{Computer Confidence} + \text{AI Literacy} \times \text{self-construal} \tag{3.3}$$

$$\text{Job Satisfaction} \sim \text{Gender} + \text{Age} + \text{Computer Confidence} + \text{AI Literacy} + \text{self-construal} + \text{Technostress} \tag{3.4}$$

4

Results

4.1. Exploration of Weighted Variables

As a result of applying weighted averages, comparisons of absolute ranges became less meaningful. Nonetheless, a relative comparison is still insightful. For example, job satisfaction displays the widest range among the variables, suggesting that respondents evaluated the items within this construct more heterogeneously than those of other variables. This highlights that individuals differ in terms of job satisfaction, which underlines its subjective nature.

The correlations among the latent variables revealed a significant negative correlation between technostress and job satisfaction ($r = -.24$, $p < .05$), and between AI literacy and technostress ($r = -.28$, $p < .01$). This may indicate that AI literacy may be mitigating technostress rather than inducing it. Additionally, interdependent self-construal positively correlated with technostress ($r = .20$, $p < 0.05$). However, independent self-construal showed no significant correlations with any other latent variable, and no significant correlations between AI literacy and Job Satisfaction were found, potentially disproving a direct effect. Additionally, the determinant disproved multicollinearity.

Each latent variable was also tested against the control (dummy) variables, Age, Gender, and Computer confidence. The mean value of computer confidence (6.25) suggests high overall confidence among respondents. However, the standard deviation is 1.12, indicating some variability among respondents. Age and Gender both show a mean value of 0.25 and considering that ”0” represented ”male” or ”20-30 years old”, and ”1” symbolizes ”female” or ”31+ years old”, it proves that most respondents were males between 20 and 30 years old, see also Table 3.3.

Table 4.1: Correlations and Descriptive statistics among latent variables after applying the weighted average

	Variable	M	SD	Min	Max	1	2	3	4	5	6	7	8
1	Job-satisfaction	2.55	0.47	0.8465	3.4681	–							
2	Technostress	1.19	0.35	0.5113	2.3467	-.24*	–						
3	AI literacy	1.89	0.42	1.024	2.931	-.00	-.28**	–					
4	Independent self-construal	1.70	0.46	0.672	2.666	.18	-.03	.10	–				
5	Interdependent self-construal	1.70	0.35	0.828	2.470	-.09	.20*	.05	-.08	–			
6	Age	0.25	0.43	0.00	1.00	.04	.03	.00	.28**	-.08	–		
7	Gender	0.25	0.44	0.00	1.00	-.07	.03	-.04	-.11	.12	-.18	–	
8	Computer Confidence	6.25	1.12	1.00	7.00	.03	.21*	-.04	.08	-.08	.18	-.15	–
	Determinant	.6006422											

Note. $n = 106$. *$p < .05$, **$p < .01$.

Table 4.2 shows the correlations for the sub-variables. These results are insightful as they provide more insight into which categories were evaluated more heterogeneously. For example, the Nature of Work exhibited a relatively wide range compared to the other sub-variables. This suggests variation in how respondents evaluated their contentment with their work tasks and the level of meaningfulness they derived from them. However, the mean score of Nature of Work appears to be closer to the maximum value with a relatively small standard deviation, indicating that most respondents scored overall rather high on this sub-variable. Additionally, the means of independent and interdependent self-construal are near the midpoint of their respective range, with relatively small standard deviations. Meaning, respondents generally positioned themselves moderately on both dimensions instead of identifying strongly with either independent or interdependent self-construal.

Furthermore, the correlations suggested a negative and significant correlation between Techno-overload and Contingent Rewards ($r = -.23$, $p < .01$), the same applied for Techno-complexity and Contingent Rewards ($r = -.32$, $p < .05$), and also for Techno-insecurity and Contingent Rewards ($r = -.26$, $p < .01$). Furthermore, AI Awareness, AI Usage, and AI Evaluation all negatively correlate with Techno-complexity ($r = -.40$, $p < .01$), ($r = -.40$, $p < 0.01$), ($r = -.31$, $p < 0.01$), and AI awareness also correlates negatively and significantly with Techno-insecurity ($r = -.24$, $p < .05$). This suggests that AI literacy might mitigate certain dimensions of technostress. Independent Self-Construal showed no significant correlations with any other latent variable, and Interdependent Self-Construal showed only one significant positive correlation with Techno-complexity ($r = .22$, $p < .05$). The lack of significant correlations for independent self-construal implies that it may not be a meaningful influence on technostress in this sample. Finally, the determinant disproves multicollinearity, see Table 4.2 for all the descriptive statistics of each sub-variable.

Table 4.2: Correlations and Descriptive statistics among subvariables after applying the weighted average

	Variable	M	SD	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Promotion	2.47	0.52	0.750	3.360	–														
2	Contingen Rewards	2.17	0.51	1.095	3.180	.53**	–													
3	Nature of Work	4.03	0.92	0.7725	5.4075	.42**	.40**	–												
4	Techno-overload	1.35	0.52	0.4875	2.7600	-.17	-.23**	-.06	–											
5	Techno-complexity	1.64	0.65	0.626	3.696	-.09	-.32*	-.06	.12	–										
6	Techno-insecurity	1.43	0.63	0.5625	3.7950	-.08	-.26**	-.11	-.35**	.44**	–									
7	Techno-uncertainty	0.97	0.28	0.2100	1.4700	.06	-.01	.07	.15	.04	.26**	–								
8	AI awareness	2.30	0.50	0.930	3.117	-.12	-.06	.04	-.01	-.40**	-.24*	.01	–							
9	AI usage	1.55	0.27	0.6467	1.9067	-.01	.12	.04	.10	.-40**	-.03	.05	.49**	–						
10	AI evaluation	2.26	0.54	0.5233	3.1367	.04	.04	.06	-.01	-.31**	-.09	-.14	-.32**	-.35**	–					
11	Independent self-construal	1.70	0.46	0.672	2.666	.08	.12	.18	.06	-.04	-.08	.14	.06	-.09	.16	–				
12	Interdependent self-construal	1.70	0.35	0.828	2.470	-.14	-.04	-.06	-.02	.22*	.10	-.01	.01	-.04	.02	-.08	–			
13	Age	0.25	0.43	0.00	1.00	-.09	-.05	.13	.00	-.03	.07	.13	-.05	-.09	-.04	.28**	-.08	–		
14	Gender	0.25	0.44	0.00	1.00	-.07	-.14	-.01	.03	.02	-.02	.05	.01	.09	.03	-.11	.12	-.18	–	
15	Computer Confidence	6.25	1.12	1.00	7.00	-.00	.03	.03	-.00	-.16	-.19	.10	.06	.14	.04	.08	-.08	-.18	-.15	–
	Determinant	.05727899																		

Note. $n = 106$. $^*p < .05$, $^{**}p < .01$.

4.2. Moderated mediation

This section provides the results of the moderated mediation models (bruceR::PROCESS, model 7). First, the latent variables are tested, aiming to answer the three hypotheses established in the theoretical framework. These models are called model 1A and model 1B, where the former uses independent self-construal, and the latter uses interdependent self-construal as the moderator. The results of these models are visualized in Figure 4.1, and a thorough explanation is given in paragraphs 4.2.1 and 4.2.2.

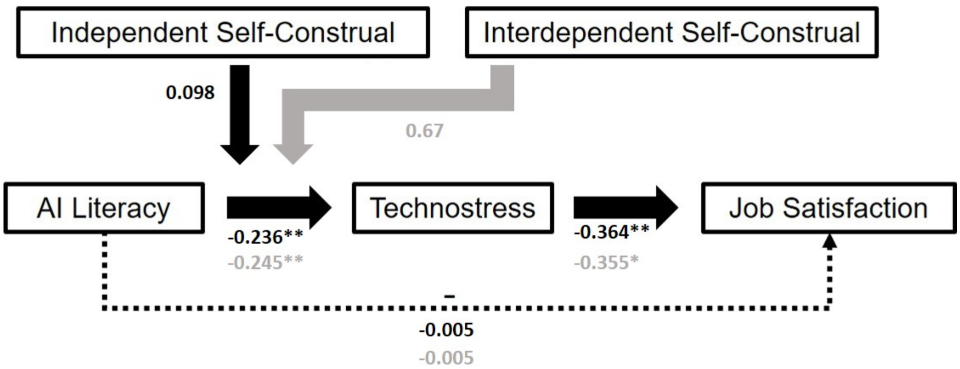

Figure 4.1: Results of Moderated Mediation Analysis: AI Literacy, Technostress, Job Satisfaction, and Self-Construal. Note: $n = 106$. $^*p < .05$, $^{**}p < .01$

4.2.1. Model 1A: Independent Self-Construal Moderation

Model 1A examines the effect of AI use on job satisfaction, mediated by technostress, and moderated by independent self-construal. Table 4.3 provides a summary of the model outcomes and reveals no significant direct effect of AI literacy on job satisfaction. In other words, there is no evidence that AI literacy directly reduces or increases job satisfaction. Hence, Hypothesis 1 is rejected. However, the model suggests a direct reducing effect of AI Literacy on technostress ($b = -0.236$, $p < .01$), and technostress also appeared to negatively influence job satisfaction($b = -0.364$, $p < .01$), which suggests an indirect effect of AI literacy on job satisfaction through technostress. Since AI does not directly influence job satisfaction, and job satisfaction is only affected through technostress, an indirect-only mediation is suggested (Zhao et al., 2010). This effect remained significant when independent self-construal was included as the moderator, but only among individuals with low to moderate levels of independent self-construal. See Appendix F Table F.2 for an overview of the effects of AI literacy on technostress for different levels of independent self-construal.

Furthermore, the indirect effect of AI literacy on job satisfaction through technostress is marginally significant at the mean level of independent self-construal, with the 95% confidence interval excluding 0 at low and medium levels but not at high levels. However, the interaction term between AI literacy and independent self-construal on technostress is not significant ($b = -0.010$, $p > .05$), indicating that the moderating effect of independent self-construal was not supported, thereby leading to the rejection of Hypothesis 3, see Table 4.3 for the summary and Appendix F, Table F.1, and Table F.3 for further details.

Table 4.3: Regression results for moderated mediation model (PROCESS Model 7)

	(1) Job Satisfaction	(2) Technostress	(3) Job Satisfaction
Intercept	2.556***	1.173***	2.561***
	(0.063)	(0.045)	(0.061)
Gender_1	-0.064	-0.003	-0.054
	(0.110)	(0.078)	(0.105)
Age_1	0.027	0.053	-0.007
	(0.111)	(0.082)	(0.111)
Computer Confidence	0.009	-0.073*	-0.020
	(0.043)	(0.030)	(0.042)
AI Literacy	-0.005	-0.236**	-0.112
	(0.111)	(0.079)	(0.112)
Independent self-construal		-0.010	0.189
		(0.077)	(0.103)
AI Literacy × Ind. sc.		0.098	
		(0.185)	
Technostress			-0.364**
			(0.136)
R^2	0.006	0.132	0.101
Adj. R^2	-0.034	0.079	0.047
N	106	106	106

*Note.** $p < .05$, ** $p < .01$,*** $p < .001$.

4.2.2. Model 1B: Interdependent Self-Construal Moderation

Model 1B examines the effect of AI use on job satisfaction, mediated by technostress, and moderated by interdependent self-construal. See Table 4.4 for the model summary. Again, there appears to be no significant effect of AI literacy on job satisfaction ($b = -0.005$, $p > .05$). Therefore, Hypothesis 1 is not supported. Meaning, there is no evidence that AI literacy reduces or increases job satisfaction.

However, the model suggests a direct reducing effect of AI Literacy on technostress ($b = -0.245$, $p < .01$), and technostress also appeared to negatively influence job satisfaction ($b = -0.355$, $p < 0.05$), which suggests an indirect effect of AI literacy on job satisfaction through technostress. Since AI does not directly influence job satisfaction, and job satisfaction is only affected through technostress, an indirect-only mediation is suggested (Zhao et al., 2010). This effect remained significant when interdependent self-construal was included as the moderator, but only among individuals with low to moderate levels of interdependent self-construal. See Appendix F Table F.5 for an overview of the effects of AI literacy on technostress for different levels of interdependent self-construal.

Additionally, the indirect effect of AI literacy on job satisfaction through technostress is marginally significant ($p = .058$ and $p = .068$) at low and mean values of interdependent self-construal. Although the p-values do not show a significant effect, the boot 95% confidence interval excludes 0 for both levels, supporting the presence of an indirect effect. However, at high levels of interdependent self-construal, the effect is not significant and the 90% confidence interval includes 0. However, the interaction term between AI and interdependent self-construal does not reach significance ($b = 0.67$, $p > 0.05$), disproving the moderating effect of Interdependent self-construal on the effects of AI literacy on technostress. See Appendix F, Table F.6, and Table F.4 for further details.

Table 4.4: Regression results for moderated mediation model (PROCESS Model 7)

	(1) Job Satisfaction	(2) Technostress	(3) Job Satisfaction
Intercept	2.556***	1.178***	2.551***
	(0.063)	(0.043)	(0.061)
$Gender_1$	-0.064	-0.025	-0.062
	(0.110)	(0.076)	(0.108)
Age_1	0.027	0.057	0.045
	(0.111)	(0.078)	(0.109)
Computer Confidence	0.009	-0.067*	-0.018
	(0.043)	(0.030)	(0.043)
AI Literacy	-0.005	-0.245**	-0.088
	(0.111)	(0.077)	(0.114)
Interdependent self-construal		0.203*	-0.040
		(0.092)	(0.134)
AI $\times$ Int. sc.		0.67	
		(0.221)	
Technostress			-0.355*
			(0.142)
R^2	0.006	0.176	0.071
Adj. R^2	-0.034	0.126	0.015
N	106	106	106

Note. * $p < .05$, ** $p < .01$, *** $p < .001$.

4.3. Evaluation of Hypotheses

Based on models 1A and 1B, the main hypotheses of this research can be evaluated . An answer and justification for rejection or acceptance is given per hypothesis.

Hypothesis 1 - AI literacy has a negative effect on job satisfaction

This hypothesis is not supported; both model 1A and model 1B show no significant impact of AI literacy on job satisfaction ($b = -0.005, p > .05$; $b = -0.005,\ p > .05$), see Table 4.3 and Table 4.4. In other words, the level of AI literacy does not independently predict increases or decreases in Job Satisfaction.

Hypothesis 2 – AI literacy is positively related to technostress, and technostress negatively mediates the relationship between AI Literacy and Job Satisfaction

This hypothesis was partially supported, but in the opposite direction of what was expected. Both models, 1A and 1B, show that AI Literacy is negatively and significantly related to Technostress (Model 1A: $b = -0.236, p < 0.1$; Model 1B: $b = -0.245, p < .01$). This means that AI Literacy reduces rather than increases Technostress. At the same time, Technostress significantly and negatively affects Job Satisfaction in both models (Model 1A: $b = -.364, p < 0.01$; Model 1B: $b = -.355, p < .05$). Meaning, an indirect-only mediation is identified (Zhao et al., 2010): AI Literacy is negatively related to Technostress, and Technostress negatively mediates the relationship between AI Literacy and Job Satisfaction. See Table 4.3 and Table 4.4 for all the details.

Hypothesis 3A – Independent self-construal positively moderates the effect of AI literacy on technostress

Hypothesis 3B – Interdependent self-construal negatively moderates the effect of AI literacy on technostress.

The findings did not support either hypothesis, contrary to what was expected in this study. Neither independent nor interdependent self-construal showed a significant moderated path between AI Literacy and Technostress. However, conditional indirect effects indicated that the effect of AI on Technostress reached significance at lower levels of Independent self-construal ($b = -0.281, p < 0.05; b = -0.236, p < 0.01$) . However, this effect turned insignificant for the indirect path of AI Literacy to Job Satisfaction through Technostress for all levels of independent self-construal. Interdependent self-construal suggested similar outcomes, but the indirect path also reached significance for low and medium levels of Interdependent self-construal ($b = -0.304, p < 0.01; b = -0.245, p < 0.01$). Additionally, Interdependent self-construal appeared to have a positive and significant direct effect on Technostress ($b = 0.203, p < 0.05$), whereas independent self-construal showed an insignificant negative effect ($b = -0.012, p > 0.05$). This suggests that Interdependents generally experience more stress, while Independents show no effect. See Table 4.3 and Table 4.4 for all the details.

4.4. Robustness Checks

The sample size of this research was relatively low, and Models 1A and 1B resulted in low R^2 values, indicating low explanatory power. Meaning, the model did not explain much of the variance found in the dependent variable. To test the robustness of the outcomes generated in model 1A and 1B, two different methods are applied. Firstly, the classic method of Baron and Kenny (1986) was reviewed, as this provides step-by-step insights by running five different linear regression models on how the inclusion of a mediation or moderating variable affects the model rather than providing the statistics all at once. The models were initially estimated without control variables, after which the control variables were added to identify the effects of the control variables on the model's explanatory power.

The second robustness check performs a model-based causal mediation analysis, based on Tingley et al. (2014). Using two statistical models, one mediator model and one outcome model, the average causal mediation effects are computed. Considering that this study aims to identify the existence of a moderated mediation, both statistical models must contain the moderator and its interaction terms with respect to the treatment (AI literacy) and the mediating variable (technostress). Thereafter, two different levels of the moderating variables are specified to identify the moderating effects for either low or high in(ter)dependent self-construal.

4.4.1. Robustness check 1

Using the Baron & Kenny approach confirmed that AI literacy has no direct effect on job satisfaction. Additionally, it indicates that AI Literacy does not affect Technostress. Instead, the results indicate that AI literacy significantly reduces technostress, which in turn negatively predicts job satisfaction. This supports a mediation pathway: AI literacy indirectly contributes to higher job satisfaction by lowering technostress. However, moderation by either independent or interdependent self-construal was not supported. While adding self-construal variables slightly improved model fit, neither type of self-construal significantly moderated the relationship between AI literacy and technostress. Overall, this model strengthens the evidence for an indirect-only mediated relationship between AI literacy and job satisfaction through technostress, but rejects the idea of moderated mediation. See Appendix G for the detailed results.

4.4.2. Robustness check 2

Four different models were run: first, moderated-mediation by low levels of independent self-construal was tested, the second model included high levels of independent self-construal, and the last two models applied the same method, but for interdependent self-construal. Remarkably, a significant mediation effect emerged only at high levels of independent self-construal. However, the total moderated mediation did not reach significance. Low levels of independent self-construal did not yield any significant outcomes and thus disproved moderated mediation. The same applied to interdependent self-construal, although low and high levels of interdependent self-construal indicated a marginally significant mediation effect. See Appendix G for the detailed results.

4.4.3. Conclusion of Robustness Checks

Both checks returned comparable results to models 1A and 1B. Check 1 supported the indirect-only mediation, which was also found in models 1A and 1B. However, check 2 indicated a significant effect of AI literacy on job satisfaction through technostress for high levels of independent self-construal. This finding was not supported in Model 1A, which indicated no significant effects of AI literacy on job satisfaction through technostress for any level of independent self-construal. Overall, as none of the models indicated significant moderated mediation, it can be safely assumed that study's results are stable. See Appendix G for the detailed results.

4.5. Exploratory Checks

This subsection focuses on the sub-variables that significantly correlated according to Table 4.2. Different sub-variables, such as AI Awareness or contingent rewards, are viewed in isolation from the other sub-variables; doing so might provide nuance to the outcomes, and give more detailed insight into the conceptual framework. Additionally, since both Model 1A and 1B suggest that technostress directly affects Job Satisfaction, it is relevant to examine whether this relationship is moderated by self-construal. Therefore, a robustness check was conducted using BruceR::PROCESS Model 14, which specifies moderation on the path between technostress and Job Satisfaction. This examines whether individuals with different self-construals vary in how stress influences job satisfaction, depending on their level of AI literacy.

4.5.1. Exploratory check 1

Check 1 excluded Techno-uncertainty from the technostress variable, as it did not show significant correlations with techno-complexity and techno-overload, or with any AI literacy variables, and this variable showed a deviating mean compared to the other technostress variables. Additionally, job satisfaction is represented by contingent rewards. Results indicate that although AI literacy does not directly predict contingent rewards, it does significantly reduce technostress, which in turn decreases contingent rewards. The model partially supports moderated mediation for medium levels of independent self-construal. Replacing independent by interdependent self-construal suggests similar outcomes and suggests partial moderated mediation at low and medium levels of interdependent self-construal. Concluding, AI literacy is indirectly linked to contingent rewards through technostress. The strength of this indirect pathway depends on the level of self-construal, supporting a conditional moderated mediation pattern rather than a direct effect of AI literacy on contingent rewards. See Appendix H, H.1 for the detailed results.

4.5.2. Exploratory check 2

Given that techno-complexity significantly correlated with all three AI Literacy variables, this check examines the effects when isolating techno-complexity. AI Literacy did not directly predict Techno-complexity. However, Techno-complexity significantly lowered Contingent Rewards, and AI literacy reduced Techno-complexity only at low levels of independent self-construal. However, no evidence of indirect moderated mediation was found. Replacing Independent by Interdependent self-construal resulted in a direct effect of AI Literacy on Techno-Complexity, and suggested a reducing effect of AI Literacy on techno-complexity at medium levels of Interdependent self-construal, but again, no support was found for indirect moderated mediation. However, a direct effect of Interdependent self-construal on techno-complexity was observed. See Appendix H, H.2 for the detailed results.

4.5.3. Exploratory check 3

Remarkably, techno-insecurity only significantly correlated with AI awareness, and this check only includes AI awareness as the AI literacy indicator, techno-insecurity as the technostress indicator, and, again, contingent rewards as the job satisfaction indicator. AI awareness did not directly predict Techno-insecurity or Contingent Rewards. techno-insecurity significantly reduced contingent rewards, and AI awareness lowered techno-insecurity only at low and medium levels of independent self-construal. Yet, no evidence for indirect moderated mediation was found. The same results were found for Interdependent self-construal. See Appendix H, H.3 for the detailed results.

4.5.4. Conclusion Exploratory checks

In sum, the exploratory checks provide additional nuance to the main findings by isolating sub-variables of technostress and job satisfaction based on their correlations. While indirect moderated mediation lacked support, the results indicate that AI literacy can reduce certain dimensions of technostress and that self-construal occasionally influences these effects. Overall, it is suggested that the relationships between AI literacy, technostress, and job satisfaction are more complex at the sub-variable level, supporting the need to treat job satisfaction and technostress as a multidimensional construct.

5

Discussion

This study aimed to investigate a moderated mediation model of the relationship between AI literacy and job satisfaction, mediated by technostress, and having self-construal theory as the moderator. The data was collected by surveying 141 employees in the professional services industry, whereof a final 106 responses appeared to be relevant. The theoretical framework argued that AI literacy would influence an employee's career perspectives and thereby lower their job satisfaction in terms of promotion, contingent rewards, and the nature of work. However, results showed no significant direct effect of AI literacy on job satisfaction.

Additionally, this study predicted that AI literacy would increase technostress, with technostress negatively mediating the relationship between AI literacy and job satisfaction. The data revealed an opposite effect: AI literacy appeared to decrease technostress. That is, higher levels of AI awareness, AI usage, and AI evaluation (literacy) resulted in lower negative psychological effects compared to those with low AI literacy. However, Technostress itself appeared to decrease job satisfaction, and therefore, an indirect-only mediation effect was supported: AI literacy indirectly contributes to higher job satisfaction by decreasing technostress.

Finally, self-construal theory was expected to either amplify or buffer AI-literacy-induced technostress; however, no significant moderating effects were found for either independent or interdependent self-construal. See Table 5.1 for an overview of this research's hypotheses and outcomes.

Table 5.1: List of this research's hypotheses and outcomes

Number	Hypothesis	Outcome
H1	AI literacy negatively affects job satisfaction.	Rejected
H2	AI literacy is positively related to technostress, and technostress negatively mediates the relationship between AI literacy and job satisfaction.	Partially supported: indirect-only mediation via technostress, positively influencing job satisfaction
H3A	Independent self-construal positively moderates the effect of AI literacy on technostress.	Rejected
H3B	Interdependent self-construal negatively moderates the effect of AI literacy on technostress.	Rejected

5.1. Theoretical Contribution

This study contributes to the debate on AI's effects on work outcomes by clarifying the inconsistent findings on the relation between AI literacy and job satisfaction: where Bhargava et al. (2021) and Hemmer et al. (2023) suggested a positive effect on job satisfaction through productivity gains, whereas Ai (2024) and Brougham and Haar (2018) found that one's awareness about AI's potential threats to, for example, skill relevance negatively impacts job satisfaction. This contradiction in the literature might point towards an inverted-U relationship between AI literacy and Job satisfaction. This thesis proposed technostress as the mechanism driving the downward slope and therefore focused specifically on the linear decreasing effect of AI literacy on job satisfaction through technostress.

The results indicated that AI literacy did not directly affect job satisfaction but was associated with reduced technostress. This potentially suggests that the effects of AI awareness, evaluation, and usage on productivity and self-efficacy potentially outweigh its negative effects and thus reduce technostress. This disproves the suggested downward slope of job satisfaction induced by AI literacy through the mechanism of technostress. Meaning, AI literacy can be seen as a protective resource lowering technostress rather than a liability, challenging the conclusions by Arntz et al. (2017), Spagnoli et al. (2012), and Ai (2024), who argued that AI would negatively affect job satisfaction by driving organizational transformations and intensifying perceived career instability due to its expanding capabilities. Instead, the results of this study confirm findings by Bhargava et al. (2021), who highlighted that an upgrade in employees' skill sets, such as AI literacy, will build work confidence and increase job satisfaction accordingly.

Several mechanisms may account for this effect. First, a thorough understanding of AI may increase employees' productivity and efficiency levels, which in turn reduces stress by lowering workload pressure and simplifying tasks. Consequently, this strengthens self-esteem, rather than lowering it through fear of skill obsolescence. At the same time, Bhargava et al. (2021) suggested that AI lacks human soft-skills, such as decision-making, building relationships, reading emotions, and creativity. As a result, employees perceived RAIA more as an assistant than a competitor, reinforcing a sense of human superiority and thereby potentially reducing technostress (Bhargava et al., 2021). However, these increasingly human-like capabilities of AI may challenge these perceptions in the future. According to Zhang and Tong (2025) and Zhao et al. (2025), such developments could increase anxiety and the fear of job displacement, ultimately reducing job satisfaction over time. However, the absence of such effects in this study may suggest that employees either continue to feel superior in their soft skills or that their reported level of AI literacy is overestimated. The former scenario may cause organizations and employees to underestimate AI's disruptive potential once it begins replicating soft skills, leaving employees unprepared and potentially more vulnerable to heightened stress levels. Conversely, if employees' AI literacy is in fact overestimated, this could prevent employees from educating themselves while AI continues to develop. This may lead to AI becoming more skillful than workers, leaving employees poorly prepared for the future. Concluding, the findings of this study align with Bhargava et al. (2021), but should be interpreted with caution: AI is developing fast, and humans might overestimate their superiority and underestimate AI's soft skills.

Additionally, self-construal theory was incorporated as AI is increasingly getting more human-like features, which may affect whether someone perceives AI as a team member (interdependent self-construal) or as a competitor (independent self-construal). Where the former was thought to absorb, and the latter to amplify technostress. Earlier research has confirmed a connection between self-construal and Artificial Intelligence (Zhao et al., 2025), and this research aimed to control for individual characteristics to provide more nuanced outcomes. However, support for self-construal theory as the moderator between AI literacy and technostress was not found, as both self-construal types yielded similar outcomes when tested as moderators. Yet, interdependent self-construal showed a direct increasing effect on technostress levels, whereas independent self-construal did not (Califf et al., 2020). This direct link between interdependent self-construal and technostress suggests that individual differences matter although no moderating effects were found. These findings also suggest that varying levels of self-construal exist within the same country and even within the same industry, supporting the assumption that self-construal theory is less rigid than often is assumed (Califf et al., 2020). The findings align with Bhargava et al. (2021), who conclude their study with ”Due to individual differences, participants perceived technological changes in a similar but not in the same manner.”

5.2. Practical Contributions

Given that AI literacy indirectly influences job satisfaction through technostress, employees’ satisfaction is suggested to be sustained by mitigating uncertainty and perceived threats by increasing AI literacy.

Rogers (2003), cited in Sahin (2006), studied the adoption and diffusion of innovations. Within his study, he found that innovations often lead to some degree of uncertainty caused by the possible changes a technology has on the social system or on an individual. This same effect is expected for AI adoption within professional services organizations. It was found for AI to continuously update and improve itself, and even develop human-like features. These effects naturally induce a level of uncertainty in employees about the relevance of their skills and career prospects. Considering that this study found that AI literacy indirectly improves job satisfaction by reducing technostress, Rogers’ framework provides valuable guidance on how to strengthen AI literacy by concrete measures. These measures will accelerate AI adoption while reducing potential uncertainty and stress among employees and thereby maintaining job satisfaction (Sahin, 2006). Based on Rogers’ theory, effective AI literacy training should emphasize five key characteristics of AI that influence its adoption:

- Relative advantage: technologies that are perceived as an improvement of the status quo are adopted more quickly. It is therefore recommended to emphasize why collaborating with AI offers greater benefits than not adopting it. This could be achieved by highlighting AI’s potential to be employed as an assistant, and focusing on its ability to take over low-value tasks.
- Compatibility: highlight how AI aligns with and enhances existing values and needs, rather than undermining them. Demonstrate how AI directly addresses employees’ existing needs, workflows, or bottlenecks instead of introducing unfamiliar processes.
- Complexity: the higher the perceived difficulty of a technology, the slower the adoption. It is therefore recommended to focus on the training of employees’ hard skills and make the AI applications as easy as possible.
- Trialability: Offer employees the opportunity to experiment with AI before it is implemented. It was found that the more a technology is tested, the faster the adoption rate. Feedback from employees on how to simplify AI applications should also be taken into serious consideration. Potentially, work groups could be formed to test AI applications collaboratively and provide structured feedback and support adjustments before permanent implementation within the organization.
- Observability: Peer observation and role models are found to be of great influence on technology adoption. It is therefore recommended to find employees already possessing high AI literacy and high levels of AI enthusiasm to promote AI use within the organization.

Rogers furthermore underlines the key role of communication during the technology diffusion process.

He highlights the importance of interpersonal relationships, as it was found that people find information provided by trusted friends more reliable than when provided by experts (Sahin, 2006). This finding is particularly relevant to this research, considering that interdependents, those who prioritize group goals and social belonging, were found to be more sensitive to technostress than individuals with a more independent orientation. Practically, this means that organizations should recognize interdependent employees as a group facing a higher risk of technostress and thus lower job satisfaction, regardless of their level of AI literacy. Given the sensitivity to trusted relationships of collective-oriented employees, it is recommended that AI literacy training, including all five aspects, should be facilitated by a respected and trusted member of the organization to stimulate the adoption of AI (Sahin, 2006). Additionally, organizations are advised to closely monitor AI developments and ensure that employees maintain sufficient AI literacy as the technology advances and acquires more human-like capabilities. For instance, by offering AI literacy training sessions on a regular basis. This is important, as employees may be unaware of or underestimate AI's rapid advancements, and sudden organizational transformations can otherwise trigger high levels of stress.

Finally, Tarafdar et al. (2019) suggests several information design recommendations to reduce technostress. This study found a direct effect of technostress on job satisfaction, and therefore, decreased technostress will likely directly increase job satisfaction. One of their suggestions that might apply to AI is to increase the enjoyment of using AI through gamification and allowing users to modify and control their applications. Another suggestion made within this study concerns clear information and guidance, which this thesis argues aligns with increasing AI literacy.

5.3. Limitations & Future Research

Several limitations should be acknowledged, beginning with the reliance on a cross-sectional survey design, which may affect this research's internal validity. Meaning, no statements about the causality of the four effects can be made, limiting the applicability of this study. Another limitation often present in behavioral science is the existence of common method bias. Since this research used the same survey for all respondents, and this data was collected at a single point in time, a CMB could be affecting the study's results. To reduce the risk of CMB, the research applied existing scales, and all survey responses were anonymous. Subsequently, the research checked for CMB by conducting an EFA and Harman's one-factor test. The outcomes suggested that CMB was likely not an issue within this study. However, CMB cannot be fully ruled out and should therefore be acknowledged. Additionally, by conducting Harman's one-factor test, the CMB is not actually reduced; rather, it is a diagnostic technique to identify if CMB is a problem (Podsakoff et al., 2003). Therefore, it is recommended for future research to conduct a longitudinal study or apply experimental designs to overcome the issues with internal validity and common method bias. Especially considering AI's rapid developments, a longitudinal study is recommended.

Additionally, the explanatory checks revealed the possibility of more complex relationships when focusing on the latent variable's dimensions rather than solely on the overarching latent variable. It is therefore suggested for future research to apply the facets separately instead of using them as a global measure. Moreover, in retrospect, measuring job security would potentially have been a more suitable measure to capture an employee's concern about their career prospects. Future research is therefore recommended to replace the job satisfaction scale with a measure of job insecurity, as this would more directly capture the primary concern associated with AI literacy and technostress. In line with this, scale development is advancing rapidly: a new AI awareness scale published in July 2025 explicitly captures employees' awareness of AI-related job insecurity (Gui et al., 2025). Considering AI's quick developments, applying the most recent AI awareness/literacy scales is recommended. Above this, focus was exclusively on the negative aspects of technostress, techno-distress, while overlooking potential techno-eustress effects. No downward slope was introduced by techno-distress. Instead, it reduced these stress factors. Future research could therefore examine techno-eustress as a mediator to assess whether it leads to direct mediation that increases job satisfaction, rather than indirect-only mediation introduced by the techno-distress factors.

The sample of this study consisted predominantly of males aged 20 to 30, with female respondents underrepresented and no non-binary respondents included. To enhance the generalizability of the results, future research should aim for greater diversity in both gender and age. Additionally, the relatively small sample size of this study (106 respondents) limited the statistical power of the tested models. This might have affected certain correlations among variables, or left existing correlations unidentified. Furthermore, the sample was limited to employees in the professional services sector in the Netherlands, which may restrict the generalizability of the findings to other sectors or countries. Although the professional services sector is expected to be among the most affected by AI, restricting the sample to this group may have resulted in limited differentiation in AI literacy levels among respondents, as respondents within this sector are likely to share similar education backgrounds and are presumably exposed to comparable technologies and tasks in their daily work. This could have skewed results and further constrained the generalizability of the results; hence, a bigger sample size is recommended. This could be achieved by collaborating with large corporations in the professional services industry. Preferably, one that has multiple offices in different countries. To ensure different levels of AI literacy, it is recommended to include different professions, preferably having different educational backgrounds too.

Moreover, to avoid demotivating respondents and thereby stimulating the response rate, this study employed a shortened version of the self-construal scale. However, reliability checks showed low values for Cronbach's alpha, which might have affected the research's results and might be a possible explanation for the lack of moderating effects. While the robustness checks generally produced consistent results, one exploratory test (check 2) yielded a contradictory outcome: whereas the main model (Model 1A) showed no significant indirect effects of AI literacy on job satisfaction at any level of independent self-construal, the exploratory check indicated a significant effect at high levels of independent self-construal. This inconsistency suggests that the inclusion of self-construal produced unstable results. It is therefore suggested to apply the longer version of the self-construal scale in future research, as it is expected to provide more reliable and robust results.

Although this research suggested that AI literacy is a more sophisticated measure than AI adoption rates, AI literacy was measured through self-reports, which may have biased the results. Some individuals may overestimate their literacy due to limited knowledge about recent AI developments, while others may have underestimated their literacy. Although it is not assumed that AI adoption rates are a better alternative, it is suggested for future studies to use a more objective measure, such as conducting experimental or performance-based assessments to objectively, rather than subjectively, measure a respondent's AI literacy.

6 Conclusion

This thesis examined the relationship between AI literacy and job satisfaction in the professional services sector, focusing on the mediating role of technostress and the moderating role of self-construal theory, thereby addressing the following research question:

To what extent does AI literacy in the professional services sector affect job satisfaction, to what degree is this effect mediated by technostress, and how much is technostress moderated by self-construal theory?

To answer this research question, three hypotheses were formulated and examined, see Table 5.1. Hypothesis 1 was rejected, as no evidence was found that AI literacy directly influenced job satisfaction. Hypothesis 2, however, was partially supported: although no direct effect between AI literacy and job satisfaction was found, AI literacy revealed a negative and significant effect on technostress, and technostress revealed a significant reducing effect on job satisfaction. This indicates an indirect-only mediation. AI literacy thus exerts a buffering effect on technostress and, in turn, contributes to higher levels of job satisfaction. This outcome contrasts with the initial expectation of a reducing effect, whereby greater AI literacy would heighten technostress and ultimately reduce job satisfaction. Yet, this indirect-only mediation was not observed at any level of independent or interdependent self-construal, and moderated mediation through self-construal did not hold; hence, hypothesis 3 was rejected. Interdependent self-construal suggested, however, an increasing direct effect on technostress, indicating that those having higher associations with interdependent self-construal are more sensitive to technostress overall. When isolating the pathway from AI literacy to technostress, a significant technostress-reducing effect was observed at both low and medium levels of independent and interdependent self-construal. However, this effect disappeared at higher levels. Meaning, AI literacy lowers technostress for individuals with lower levels of either self-construal. Finally, neither the exploratory nor the robustness checks revealed any major deviating outcomes, underlining the robustness of the results.

Theoretically, this research contributes to the literature exploring the effects of Artificial Intelligence on employees' job satisfaction. Since job satisfaction affects employee well-being and organizational performance, and given its sensitivity to business transformations alongside AI's potential to reshape work processes, it becomes increasingly important to study job satisfaction in the light of Artificial Intelligence to sustain content workers. Earlier research produced contradictory findings, leading this thesis to propose an inverted-U relationship between AI literacy and job satisfaction, with the downward slope expected to result from increased levels of technostress. The results did not support this downward slope, and instead indicated that AI literacy was associated with reduced technostress.

Additionally, the study also introduced self-construal theory as an important variable when researching the effects of AI literacy on technostress. Given AI's increasingly human-like features, individuals with interdependent orientations might perceive it as a collaborative team member, whereas those with independent orientations may experience it as a competitor, thereby buffering or amplifying technostress. However, this research found no support for such moderating effects.

Practically, this thesis reveals that AI literacy functions as a buffer against technostress rather than a factor that increases it. Its indirect effect on job satisfaction suggests that organizations should focus on AI literacy training in times of change induced by Artificial Intelligence. These measures should focus on the five factors provided by Rogers (2003) and are recommended to especially fit the values of those having higher levels of interdependent self-construal, given their general sensitivity to technostress. Hence, this research provides organizations with more insights into how to manage AI-induced change in a way that retains their workers' job satisfaction.

However, this study is subject to some limitations. First of all, its cross-sectional design prevents causal claims, and the sample is restricted to the Dutch professional services industry. This sample consisted mostly of male respondents between 20 and 30 years old. Meaning, females, non-binary, and older employees were underrepresented, potentially affecting the generalizability of this research. Hence, future research is encouraged to aim for a more diverse sample. Additionally, the sample was relatively small, affecting the statistical power of the models run; consequently, larger samples are recommended. Moreover, the level of AI literacy relied on someone's personal judgment, which induced subjectivity. Future studies should include an experimental setting to measure this more objectively, and given the rapid developments of AI, it is recommended for future research to perform a longitudinal study rather than a cross-sectional study. Finally, the self-construal items appeared to be unreliable in this study's sample; a more thorough measure is therefore suggested.

In conclusion, this thesis shows that while AI literacy does not directly affect job satisfaction, it indirectly enhances it by reducing technostress, thereby supporting an indirect-only mediation and contradicting the proposed inverted-U relationship where the downward slope was expected to be induced by technostress. Since AI literacy lowers technostress, and reduced technostress improves job satisfaction, the value of AI literacy training is underlined. Enhancing employees' AI literacy can thus indirectly strengthen job satisfaction, which is a key to sustaining well-being and organizational performance during AI-driven change. Additionally, although AI is increasing its human-like features, no moderating effects of self-construal were found. However, its influence cannot be fully ruled out, and further research is recommended.

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A

Informed consent

Survey completion time: 15 minutes

You are being invited to participate in a research study titled **”AI at Work: Examining the Impact of AI Usage on Job Satisfaction Through Technostress and the Moderating Role of Self-Construal”**. This study is performed by **Lotte van Veldhuizen from the TU Delft**.

This research aims to understand your experiences with AI usage in your profession and the effects it has on your job satisfaction. The data will be used for a Master’s thesis research. We will be asking you to rate questions about your personality, AI use, your experience with AI, and how you feel about your job from strongly disagree to strongly agree.

Leaving your e-mail to win a 25 euros gift card is optional. You can leave the input blank if you are not interested in participating. **Your e-mail will not be used for any research purposes**. As with any online activity, the risk of a breach is always possible. To the best of our ability, your answers in this study will remain confidential. **We minimize any risks by storing the collected data (e.g. the survey answers) on the TUD Institutional storage which is only accessible by the Team TU Delft**. Only anonymous results and data analysis will be made public, and all **personal data will be deleted end of October 2025**.

If you have any concerns, please feel free to e-mail us. **Your participation in this study is entirely voluntary, and you can withdraw at any time**. You are free to omit any questions. Results of this study can be shared upon request.

Thank you!

Our contacts are:

Lotte van Veldhuizen (G.L.vanveldhuizen@student.tudelft.nl) Dr. Sander Smit (A.C.Smit@tudelft.nl)

- I have read and understood the study information provided and I consent to participate in the study and to the data processing described.
    - Yes

  - No
- I consent voluntarily to be a participant in this study and understand that I can refuse to answer questions and I can withdraw from the study at any time, without having to give a reason.
  - Yes
  - No

B

Job Satisfaction Scales

Table B.1: Characteristics of job satisfaction scales van Saane et al. (2003)

Measure	Scale type	Industry	No. of items
Job in General Scale	Global scale	Unspecified	18
Andrew and Withey Job Satisfaction Questionnaire	Global/Unidimensional scale	Unspecified	5
Job Satisfaction Survey	Composite/Multidimensional scale	Multiple sectors	36
Emergency Physician Job Satisfaction Scale	Multidimensional scale	Emergency department physicians	79
McCloskey/Mueller Satisfaction Scale	Multidimensional scale	Hospital staff nurses	31
Measure of Job Satisfaction	Multidimensional scale	Community nurse sector	38
The Nurse Satisfaction	Multidimensional scale	Nursing sector	24

C

Excluded survey items

Table C.1: Excluded Job Satisfaction Items

Dimension	Items
Pay	• I feel I am being paid a fair amount for the work I do. • Raises are too few and far between. • I feel unappreciated by the organization when I think about what they pay me. • I feel satisfied with my chances for salary increases.
Supervision	• My supervisor is quite competent in doing his/her job. • My supervisor is unfair to me. • My supervisor shows too little interest in the feelings of subordinates. • I like my supervisor
Benefits	• I am not satisfied with the benefits I receive. • The benefits we receive are as good as most other organizations offer. • The benefit package we have is equitable. • There are benefits we do not have which we should have.
Operating Procedures	• Many of our rules and procedures make doing a good job difficult. • My efforts to do a good job are seldom blocked by red tape. • I have too much to do at work. • I have too much paperwork.
Co-workers	• I like the people I work with. • I find I have to work harder at my job than I should because of the incompetence of people I work with. • I enjoy my co-workers. • There is too much bickering and fighting at work.
Communication	• Communications seem good within this organization. • The goals of this organization are not clear to me. • I often feel that I do not know what is going on with the organization. • Work assignments are often not fully explained.

Table C.2: Excluded AI literacy items

Dimension	Items
Ethics	• I always comply with ethical principles when using AI applications or products. • I am never alert to privacy and information security issues when using AI applications or products • I am always alert to the abuse of AI technology.

Table C.3: Excluded Technostress items

Dimension	Items
Techno-invasion	• I have to be in touch with my work even during my vacation due to this technology. • I have to sacrifice my vacation and weekend time to keep current on new technologies. • I feel my personal life is being invaded by this technology.
Techno-uncertainty	• There are constant changes in computer hardware in our organization. • There are frequent upgrades in computer networks in our organization.

D

Survey items per latent variable

Job Satisfaction items

Table D.1: Survey items job satisfaction & calculation of score

Job Satisfaction	**Items**	**Calculation of score**
Promotion	• There is really too little chance for promotion in my job (R) • Those who do well on the job stand a fair chance of being promoted • People get ahead as fast here as they do in other organizations • I am satisfied with my chances for promotion	Each question is measured on a 7-point Likert scale: • 1 = strongly disagree • 2 = disagree • 3 = somewhat disagree • 4 = neither disagree nor agree • 5 = somewhat agree • 6 = agree • 7 = strongly agree Items marked (R) are reverse-coded. The average score per dimension is then computed using the factor loadings extracted from the EFA.
Contingent Rewards	• When I do a good job, I receive the recognition for it that I should receive • I do not feel that the work I do is appreciated (R) • There are few rewards for those who work here (R) • I don't feel my efforts are rewarded the way they should be (R)	
Nature of Work	• I sometimes feel my job is meaningless (R) • I like doing the things I do at work • I feel a sense of pride in doing my job • My job is enjoyable	

AI literacy items

Table D.2: Survey items AI literacy & calculation of score

AI Literacy	Items	Calculation of score
AI Awareness	• I can distinguish AI-systems from non-AI systems. • I do not know how AI technology can help me (R). • I can identify the AI technology employed in the applications and products I use.	Each question is measured on a 7-point Likert scale: • 1 = strongly disagree • 2 = disagree • 3 = somewhat disagree • 4 = neither disagree nor agree • 5 = somewhat agree • 6 = agree • 7 = strongly agree Items marked (R) are reverse-coded. The average score per dimension is then computed using the factor loadings extracted from the EFA.
AI Usage	• I can skillfully use AI applications or products to help me with my daily work. • It is usually hard for me to learn to use a new AI application or product (R). • I can use AI applications or products to improve my work efficiency.	
AI Evaluation	• I can evaluate the capabilities and limitations of an AI application or product after using it for a while. • I can choose a proper solution from various solutions provided by AI. • I can choose the most appropriate AI application or product from a variety for a particular task.	

Technostress items

Table D.3: Survey items Technostress & calculation of score

Technostress	Items	Calculation of score
Techno-overload	• I take up more work than I can handle because of AI. • I have to work with very tight schedules because of AI. • I am forced to change my work habits to adapt to AI. • I have a higher workload because of increased AI complexity.	Each question is measured on a 7-point Likert scale: • 1 = strongly disagree • 2 = disagree • 3 = somewhat disagree • 4 = neither disagree nor agree • 5 = somewhat agree • 6 = agree • 7 = strongly agree Items marked (R) are reverse-coded. The average score per dimension is then computed using the factor loadings extracted from the EFA.
Techno-complexity	• I do not know enough about AI to handle my job satisfactorily. • I need a long time to understand and use AI. • I do not find enough time to study and upgrade my AI skills. • I find new recruits to this organization know more about AI technology than I do. • I often find it too complex for me to understand and use new AI technologies.	
Techno-insecurity	• I feel a constant threat to my job security due to AI. • I have to constantly update my skills to avoid being replaced. • I am threatened by coworkers with newer AI skills. • I feel there is less sharing of knowledge among coworkers for fear of being replaced.	
Techno-uncertainty	• There are always new developments in the AI technologies we use in our organization. • There are constant changes in computer software in our organization.	

Self-construal items

Table D.4: Survey items self-construal theory & calculation of score

Self-construal	Items	Calculation of score
Independent Self-Construal	• I am the same person at home or at work • I act the same way no matter who I am with • I prefer to be direct and forthright when dealing with people I've just met. • I'd rather say "No" directly than risk being misunderstood. • I do my own thing, regardless of what others think.	Each question is measured on a 7-point Likert scale: • 1 = strongly disagree • 2 = disagree • 3 = somewhat disagree • 4 = neither disagree nor agree • 5 = somewhat agree • 6 = agree • 7 = strongly agree Items marked (R) are reverse-coded. The average score per dimension is computed using the factor loadings extracted from the EFA.
Inter-dependent Self-Construal	• My happiness depends on the happiness of those around me. • I will sacrifice my self-interest for the benefit of the group I am in. • I often have the feeling that my relationships with others are more important than my own accomplishments. • I will stay in a group if they need me, even when I am not happy with the group. • If one of my family members fails, I feel responsible.	

E

Results of the Bartlett's test & the KMO statistics

Bartlett's test of Sphericity Results

Table E.1: Bartlett's test outcomes for each latent variable

Latent Variable	χ^2	P-value	Degrees of Freedom
AI Literacy	250.5724	5.819592e-34	36
Technostress	460.5445	5.141965e-46	105
Job Satisfaction	548.9078	2.955584e-77	66
Independent Self-Construal	61.73084	1.702374e-09	10
Interdependent Self-Construal	35.76214	9.247663e-05	10

Note. $n = 106$.

Table E.2: Bartlett's test outcomes per sub-variable

Sub-Variable	χ^2	P-value	Degrees of Freedom
AI Literacy: AI Awareness	48.03748	2.090732e-10	3
AI Literacy: AI Usage	28.623	2.68744e-06	3
AI Literacy: AI Evaluation	63.30563	1.155377e-13	3
Technostress: Techno-Overload	64.84847	4.632501e-12	6
Technostress: Techno-Complexity	156.1143	2.052073e-28	10
Technostress: Techno-Insecurity	76.37374	2.00072e-14	6
Technostress: Techno-Uncertainty	7.661909	0.005639879	1
Job Satisfaction: Promotion	92.73063	8.201319e-18	6
Job Satisfaction: Contingent Rewards	75.75948	2.67757e-14	6
Job Satisfaction: Nature of Work	231.9511	2.935291e-47	6
Independent Self-Construal	61.73084	1.702374e-08	10
Interdependent Self-Construal	35.76214	9.247663e-05	10

Note. $n = 106$.

Kaiser-Meyer-Olkin-test results

Table E.3: KMO values of latent variables and their items

Item	raw_alpha
AI Literacy (MSA = .69)	MSA
AI awareness 1	.69
AI awareness 2	.71
AI awareness 3	.63
AI usage 1	.71
AI usage 2	.75
AI usage 3	.78
AI evaluation 1	.72
AI evaluation 2	.63
AI evaluation 3	.66
Technostress (MSA = .77)	MSA
Techno-overload 1	.60
Techno-overload 2	.73
Techno-overload 3	.65
Techno-overload 4	.83
Techno-complexity 1	.88
Techno-complexity 2	.72
Techno-complexity 3	.75
Techno-complexity 4	.81
Techno-complexity 5	.80
Techno-insecurity 1	.87
Techno-insecurity 2	.77
Techno-insecurity 3	.84
Techno-insecurity 4	.72
Techno-uncertainty 1	.62
Techno-uncertainty 2	.65
Job Satisfaction (JS) (MSA = .79)	MSA
Promotion 1	.71
Promotion 2	.74
Promotion 3	.82
Promotion 4	.77
Contingent rewards 1	.79
Contingent rewards 2	.82
Contingent rewards 3	.81
Contingent rewards 4	.84
Nature of work 1	.81
Nature of work 2	.76
Nature of work 3	.89
Nature of work 4	.75
Independent Self-Construal (MSA = .57)	MSA
Independent self-construal 1	.46
Independent self-construal 2	.55
Independent self-construal 3	.55
Independent self-construal 4	.62
Independent self-construal 5	.67
Interdependent Self-Construal (MSA = .57)	MSA
Interdependent self-construal 1	.57
Interdependent self-construal 2	.59
Interdependent self-construal 3	.62
Interdependent self-construal 4	.56
Interdependent self-construal 5	.50

Note. $n = 106$.

Table E.4: KMO values of sub-variables and belonging items

Item	raw_alpha
AI Literacy: AI Awareness (MSA = .53)	MSA
AI awareness 1	.52
AI awareness 2	.64
AI awareness 3	.52
AI Literacy: AI Usage (MSA = .56)	MSA
AI usage 1	.54
AI usage 2	.67
AI usage 3	.55
AI Literacy: AI Evaluation (MSA = .60)	MSA
AI evaluation 1	.79
AI evaluation	.58
AI evaluation	.57
Technostress: Techno-Overload (MSA = .66)	MSA
Techno-overload 1	.65
Techno-overload 2	.62
Techno-overload 3	.69
Techno-overload 4	.72
Technostress: Techno-Complexity (MSA = .80)	MSA
Techno-complexity 1	.84
Techno-complexity 2	.74
Techno-complexity 3	.82
Techno-complexity 4	.84
Techno-complexity 5	.79
Technostress: Techno-Insecurity (MSA = .74)	MSA
Techno-insecurity 1	.70
Techno-insecurity 2	.73
Techno-insecurity 3	.76
Techno-insecurity 4	.78
Technostress: Techno-Uncertainty (MSA = .50)	MSA
Techno-usage 1	.50
Techno-usage 2	.50
Job Satisfaction: Promotion (MSA = .70)	MSA
Promotion 1	.71
Promotion 2	.76
Promotion 3	.74
Promotion 4	.65
Job Satisfaction: Contingent Rewards (MSA = .71)	MSA
Contingent rewards 1	.68
Contingent rewards 2	.71
Contingent rewards 3	.73
Contingent rewards 4	.72
Job Satisfaction: Nature of Work (MSA = .80)	MSA
Nature of work 1	.90
Nature of work 2	.74
Nature of work 3	.88
Nature of work 4	.77
Independent Self-Construal (MSA = .57)	MSA
Independent 1	.46
Independent 2	.55
Independent 3	.55
Independent 4	.62
Independent 5	.67
Interdependent Self-Construal (MSA = .57)	MSA
Interdependent 1	.57
Interdependent 2	.59
Interdependent 3	.62
Interdependent 4	.56
Interdependent 5	.50

Note. $n = 106$.

F

Detailed outcomes of the Moderated Mediation

Interaction Effects, Simple Slopes, and the Indirect Effects of Model 1A

Table F.1: Interaction Effect on Technostress

Interaction effect	F	df1	df2	p
AI Literacy * Independent self-construal	0.28	1	99	.596

Table F.2: Simple Slopes: AI Literacy ==> Technostress

Independent self-construal	Effect	S.E.	t	p	[95% CI]
1.242 (-SD)	-0.281	(0.113)	-2.489	0.014*	[-0.506, -0.057]
1.700 (Mean)	-0.236	(0.079)	-3.002	0.003**	[-0.393, -0.080]
2.157 (+SD)	-0.191	(0.118)	-1.620	.108	[-0.426, 0.043]

*Note.** $p < .05$, ** $p < .01$,*** $p < .001$.

Table F.3: Indirect Path AI Literacy ==> Technostress ==> Job Satisfaction

Independent self-construal	Effect	S.E.	z	p	[Boot 95% CI]
1.242 (-SD)	0.102	(0.067)	1.520	.128	[0.005, 0.264]
1.695 (Mean)	0.086	(0.047)	1.821	.069	[0.018, 0.204]
2.050 (+SD)	0.070	(0.053)	1.325	.185	[-0.007, 0.191]

*Note.** $p < .05$, ** $p < .01$,*** $p < .001$.

Interaction Effects, Simple Slopes, and the Indirect Effects of Model 1B

Table F.4: Interaction Effect on Technostress

Interaction effect	F	df1	df2	p
AI Literacy * Interdependent self-construal	0.57	1	99	.451

Table F.5: Simple Slopes: AI Literacy ==> Technostress

Interdependent self-construal	Effect	S.E.	t	p	[95% CI]
1.341 (-SD)	-0.304	(0.106)	-2.868	0.005**	[-0.498, -0.083]
1.695 (Mean)	-0.245	(0.077)	-3.203	0.002**	[-0.384, -0.086]
2.050 (+SD)	-0.186	(0.113)	-1.653	.102	[-0.409, 0.037]

*Note.** $p < .05$, ** $p < .01$,*** $p < .001$.

Table F.6: Indirect Path AI Literacy ==> Technostress ==> Job Satisfaction

Interdependent self-construal	Effect	S.E.	z	p	[Boot 95% CI]
1.341 (-SD)	0.108	(0.057)	1.896	.058	[0.017, 0.228]
1.695 (Mean)	0.087	(0.048)	1.823	.068	[0.013, 0.191]
2.050 (+SD)	0.066	(0.057)	1.156	.248	[-0.024, 0.204]

*Note.** $p < .05$, ** $p < .01$,*** $p < .001$.

G

Results of the Robustness Checks

Table G.1: Results of Robustness check 1: Baron& Kenny method, Model 1 to 3

Check	Main findings
1	Model 1 without control variables: Job Satisfaction $\sim$ AI Literacy • No significant effect found between AI Literacy and Job Satisfaction ($b = -0.002974, p > .05$) • $R^2 = 7.115e - 06$ • $Adjusted\ R^2 = -0.009608$ • AI literacy does not predict the variance in Job Satisfaction. Model 1 with control variables: Job Satisfaction $\sim$ AI Literacy + Gender + Computer Confidence + Age • No significant effect found between AI Literacy and Job Satisfaction ($b = -0.006227, p > .05$) • $R^2 = 0.006546$ • $Adjusted\ R^2 = -0.0328$ • AI literacy does not predict the variance in Job Satisfaction, but the model performs better when including control variables. Therefore, analysis is continued, including the control variables. Model 2: Technostress $\sim$ AI Literacy + Gender + Computer Confidence + Age • Significant effect found between AI Literacy and Technostress ($b = -0.2277711, p < .005$) • $R^2 = 0.1561$ • $Adjusted\ R^2 = 0.1227$ • AI Literacy predicts 15% of the variance in Technostress, and the lowering effect of AI Literacy on Technostress is found to be significant Model 3: Job Satisfaction $\sim$ AI Literacy + Technostress + Gender + Computer Confidence + Age • Significant effect found of Technostress on Job Satisfaction ($b = -0.36719, p < .05$ • Non-significant effect of AI Literacy on Job satisfaction ($b = -0.08986, p > .05$) • $R^2 = 0.07024$ • $Adjusted\ R^2 = 0.02376$ • The model suggests that the effect of AI Literacy on Job Satisfaction does not decrease. However, AI Literacy appears only to matter when Technostress is included, indicating mediation by Technostress • Sobel test: $z - value = 1.967p = .049$, this confirming mediation

Table G.2: Results of Robustness check 1: Baron& Kenny method, Model 4

Check	Main findings
1	Model 4A: Technostress $\sim$ AI Literacy * Independent Self-Construal + Gender + Age + Computer Confidence • Non-significant effect found of AI Literacy on Technostress when moderated by Independent self-construal ($b = -0.3951978, p > .05$) • $R^2 = 0.1587$ • $Adjusted\ R^2 = 0.1078$ • No moderation: The model suggests that AI literacy does not affect Technostress when including the effects of Independent self-construal on AI literacy. This nuances the findings in Model 2, which found an effect when self-construal was excluded. Additionally, the model shows no increased R^2 compared to Model 2 Model 4B: Technostress $\sim$ AI Literacy * Interdependent Self-Construal + Gender + Age + Computer Confidence • Non-significant effect found of AI Literacy on Technostress when moderated by Interdependent self-construal ($b = -0.50049, p > .05$) • $R^2 = 0.2024$ • $Adjusted\ R^2 = 0.154$ • No moderation: The model suggests that AI literacy does not affect Technostress when including the effects of Interdependent self-construal on AI literacy. This nuances the findings in Model 2, which found an effect when self-construal was excluded. However, the model shows an increased R^2 when including the effects of interdependent self-construal on AI literacy compared to Model 2 and Model 4A.

Table G.3: Results of Robustness check 1: Baron& Kenny method, Model 5

Check	Main findings
1	Model 5A: Job Satisfaction $\sim$ AI Literacy * Independent Self-Construal + Technostress + Gender + Age + Computer Confidence • Significant effect found of Technostress on Job Satisfaction ($b = -0.37258, p < .005$) • $R^2 = 0.1085$ • $Adjusted\ R^2 = 0.04482$ • The model suggests that Technostress negatively affects Job satisfaction when including the effects of Independent self-construal on AI literacy. Additionally, the model shows an increased R^2 compared to Model 3, meaning the model predicts the variance in Job Satisfaction due to Technstress better when including Independent self-construal. Model 5B: Job Satisfaction $\sim$ AI Literacy * Interdependent Self-Construal + Technostress + Gender + Age + Computer Confidence • Significant effect found of Technostress on Job Satisfaction ($b = -0.34261, p < 0.05$) • $R^2 = 0.09079$ • $Adjusted\ R^2 = 0.02585$ • The model suggests that Technostress negatively affects Job satisfaction when including the effects of Interdependent self-construal on AI literacy. Additionally, the model shows an increased R^2 compared to Model 3, meaning the model predicts the variance in Job Satisfaction due to Technstress better when including Interdependent self-construal.

Table G.4: Results of Robustness check 2: model-based causal mediation analysis; independent self-construal

Check	Main findings
2	Independent self-construal (-SD) • Indirect effect (ACME) was positive but insignificant ($b = 0.072$, $95\%CI[-0.011, 0.199]$,$p = .106$). • No significant direct effect (ADE) of AI Literacy on job satisfaction ($b = -0.173$, $p = .234$) • Total effect was not significant ($b = -0.101$, $p = .4684$) • The proportion mediated was negative and not significant ($b = -0.271$, $p = .532$)
2	Independent self-construal (+SD) • Indirect effect (ACME) was positive and significant ($b = 0.098$, $95\%CI[0.007, 0.228]$, $p = .028$) • No significant direct effect (ADE) of AI Literacy on job satisfaction ($b = -0.058$, $p = .668$) • Total effect was not significant ($b = 0.039$, $p = .790$). • The proportion mediated was negative and not significant ($b = -0.415$, $p = .779$)

Table G.5: Results of Robustness check 2: model-based causal mediation analysis; interdependent self construal

Check	Main findings
2	Interdependent self-construal (-SD) • Indirect effect (ACME) was positive but marginally significant ($b = 0.106$, $95\%CI[-0.008, 0.272]$, $p = .072$). • No significant direct effect (ADE) of AI Literacy on job satisfaction • Total effect was not significant ($b = 0.105$, $p = .441$). • The proportion mediated was positive and not significant ($b = 0.493$, $p = .496$)
2	Interdependent self-construal (+SD) • Indirect effect (ACME) was positive but marginally significant ($b = 0.065$, $95\%CI[-0.004, 0.173]$,$p = .069$). • No significant direct effect (ADE) of AI Literacy on job satisfaction • Total effect was not significant ($b = -0.137$, $p = .330$) • The proportion mediated was negative and not significant ($b = -0.257$,$p = .379$)

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Results of the Exploratory Checks

Exploratory Check 1

Table H.1: Results of exploratory checks 1A & 1B

CheckModel details		Main findings
1A	• IV: AI Literacy • Mediator: Techno-overload + techno-complexity + techno-insecurity • Moderator: Independent self-construal • DV: Contingent rewards	• No significant direct effect of AI Literacy on Contingent Rewards ($b = 0.034, p > .05$) • Significant direct effect of AI Literacy on Technostress ($b = -0.237, p < .05$) • Significant and negative direct effect of Technostress on Contingent Rewards($b = 0.435, p < .001$) • Non-significant interaction effect between AI Literacy and Independent self-construal • Simple Slopes show that: – Low Independent self-construal: AI Literacy lowers Technostress($b = 0.344, p < .05$) – Medium Independent self-construal: AI Literacy lowers Technostress ($b = 0.249, p < .05$) • Indirect moderated mediation: exists for medium levels of independent self-construal ($b = 0.108, p < .05$) • Computer Confidence has a significant negative direct effect on Technostress ($b = -0.126, p < .05$), other control variables show no significant impact.
1B	• IV: AI Literacy • Mediator: Techno-overload + techno-complexity + techno-insecurity • Moderator: Interdependent self-construal • DV: Contingent rewards	• No significant direct effect of AI Literacy on Contingent Rewards ($b = 0.022, p > .05$) • Significant direct effect of AI Literacy on Technostress ($b = -0.246, p < .05$) • Significant and negative direct effect of Technostress on Contingent Rewards($b = 0.445, p < .001$) • Non-significant interaction effect between AI Literacy and Independent self-construal • Simple Slopes show that: – Low Interdependent self-construal: AI Literacy lowers Technostress($b = -0.368, p < .005$) – Medium Interdependent self-construal: AI Literacy lowers Technostress ($b = 0.246, p < .05$) • Indirect moderated mediation: exists for low and medium levels of Interdependent self-construal ($b = 0.108, p < 0.05$; $b = 0.110, p < .05$) • Computer Confidence has a significant negative direct effect on Technostress ($b = -0.115, p < .05$), other control variables show no significant impact.

Exploratory Check 2

Table H.2: Results of exploratory checks 2A & 2B

CheckModel details		Main findings
2A	• IV: AI Literacy • Mediator: Techno-complexity • Moderator: Independent self-construal • DV: Contingent rewards	• No significant direct effect of AI Literacy on Contingent Rewards ($b = 0.006, p > .05$) • No Significant direct effect of AI Literacy on Techno-complexity ($b = -0.261, p > .05$) • Significant and negative direct effect of Techno-complexity on Contingent Rewards($b = 0.252, p < .005$) • Non-significant interaction effect between AI Literacy and Independent self-construal • Simple Slopes show that at low levels of Independent self-construal AI Literacy lowers Techno-complexity ($b = -0.431, p < .05$) • Indirect moderated mediation does not exist • Computer Confidence has a significant negative direct effect on Techno-complexity ($b = -0.187, p < .05$), other control variables show no significant impact.
2B	• IV: AI Literacy • Mediator: Techno-complexity • Moderator: Interdependent self-construal • DV: Contingent rewards	• No significant direct effect of AI Literacy on Contingent Rewards ($b = 0.015, p > .05$) • Significant direct effect of AI Literacy on Techno-complexity ($b = -0.292, p < .05$) • Significant and negative direct effect of Techno-complexity on Contingent Rewards ($b = -0.262, p < .005$) • Direct positive effect of Interdependent self-construal on Techno-complexity ($b = -0.262, p < .005$) • Non-significant interaction effect between AI Literacy and Interdependent self-construal • Simple Slopes show that at medium levels of Interdependent self-construal AI Literacy lowers Techno-complexity ($b = -0.292, p < .05$) • Indirect moderated mediation does not exist • Computer Confidence has a significant negative direct effect on Techno-complexity ($b = -0.178, p < .05$), other control variables show no significant impact.

Exploratory Check 3

Table H.3: Results of exploratory checks 3A & 3B

CheckModel details	Main findings
3A • IV: AI Awareness • Mediator: Techno-insecurity • Moderator: Independent self-construal • DV: Contingent Rewards	• No significant direct effect of AI Awareness on Contingent Rewards ($b = -0.141, p > .05$) • No Significant direct effect of AI Awareness on Techno-insecurity ($b = -0.266, p > .05$) • Significant and negative direct effect of Techno-insecurity on Contingent Rewards($b = 0.223, p < .005$) • Non-significant interaction effect between AI Awareness and Independent self-construal • Simple Slopes show that: – Low Independent self-construal: AI literacy lowers Technostress($b = -0.458, p < .05$) – Medium Independent self-construal: AI literacy lowers Technostress ($b = -0.266, p < .05$) • Indirect moderated mediation does not exist • Computer Confidence has a significant negative direct effect on Techno-insecurity ($b = -0.156, p < .05$), other control variables show no significant impact.
3B • IV: AI Awareness • Mediator: Techno-insecurity • Moderator: Interdependent self-construal • DV: Contingent Rewards	• No significant direct effect of AI Awareness on Contingent Rewards ($b = -0.135, p > .05$) • No Significant direct effect of AI Awareness on Techno-insecurity ($b = -0.270, p > .05$) • Significant and negative direct effect of Techno-insecurity on Contingent Rewards($b = -0.232, p < .005$) • Non-significant interaction effect between AI Awareness and Independent self-construal • Simple Slopes show that at medium levels of Interdependent self-construal AI Awareness lowers Techno-insecurity ($b = -0.270, p < .05$) • Indirect moderated mediation does not exist • Computer Confidence has a significant negative direct effect on Techno-insecurity ($b = -0.152, p < .05$), other control variables show no significant impact.