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AI revolution: trust and the perceived threat to job security

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Resumo

A relação entre a confiança nos serviços de IA e o receio de perda de emprego tornou-se uma questão relevante à medida que a IA transforma indústrias. Este estudo aborda duas questões: Quais fatores influenciam a confiança nos serviços de IA e existe uma correlação entre a confiança na IA e o receio de perda de emprego? Foi aplicado um questionário a 137 participantes, recolhendo dados sobre confiança na IA, receios de perda de emprego e características demográficas. A análise foi feita com modelos de regressão linear e o método Bootstrap para lidar com a não normalidade dos resíduos.

Os resultados revelaram que a confiança na IA é influenciada por fatores como a confiança nas instituições, capacidade de adaptação e atitudes face à IA. Verificou-se uma correlação negativa entre o receio de perda de emprego e a confiança na IA, sugerindo que, à medida que aumentam as preocupações com a automação, a confiança nos sistemas de IA diminui. A capacidade de adaptação pessoal foi um preditor significativo, com indivíduos mais confiantes na sua capacidade de adaptação a mudanças tecnológicas demonstrando maior confiança na IA. O método Bootstrap confirmou a robustez destes resultados.

Este estudo destaca a necessidade de empresas abordarem as dimensões técnicas e sociais da adoção da IA, promovendo confiança através da transparência e comunicação, enquanto lidam com receios de perda de emprego. As implicações para decisores políticos e líderes industriais sublinham a importância da requalificação e do envolvimento para mitigar o impacto social da IA.

Palavras-Chave: Confiança em IA, Automação, Adaptação ao mercado de trabalho, Transformação digital, Desemprego Tecnológico

Código de Classificação JEL: O33, J24

Abstract

The relationship between trust in AI services and the growing fear of job displacement is an increasingly important issue as AI continues to reshape industries. This study addresses two primary research questions: What factors influence trust in AI services, and is there a correlation between trust in AI and the fear of job displacement? Using a quantitative approach, a structured questionnaire was administered to 137 participants, collecting data on their trust in AI, fears of job loss, and demographic characteristics. The analysis was conducted using linear regression models and employing the Bootstrap method to address non-normality in the residuals.

The findings revealed that trust in AI was influenced by multiple factors, including institutional trust, personal adaptability, and attitudes toward AI. The results showed a negative correlation between fear of job displacement and trust in AI, suggesting that as concerns about automation increase, trust in AI systems decreases. Personal adaptability emerged as a significant predictor of trust, with individuals who believe in their ability to adapt to technological changes reporting higher trust in AI services. The Bootstrap method confirmed the robustness of these findings despite the small sample size and demographic limitations.

This study also highlighted the need for businesses to address both the technical and social dimensions of AI adoption by fostering trust through transparency and communication while addressing fears about job displacement. The implications for policymakers and industry leaders underscore the importance of reskilling initiatives and proactive engagement to mitigate the social impact of AI integration.

Keywords: Trust in AI, Automation, Labor market adaptation, Digital transformation, Technological Unemployment

JEL Classification Code: O33, J24

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List of Abbreviations

AI - Artificial Intelligence

HC3 - Heteroscedasticity-Consistent Covariance Matrix Estimator

IA - Inteligência Artificial

IT - Information technology

LLM - Large Language Model

OLS - Ordinary Least Squares

RESET - Ramsey Regression Equation Specification Error Test

VIF - Variance Inflation Factor

WLS - Weighted Least Squares

Chapter 1

Introduction

This dissertation is the final project for the Research Seminar course, presented in partial fulfillment of the requirements for obtaining a Master's degree in Management of Services and Technology at Iscte Business School. The research focuses on the intersection between trust in Artificial Intelligence (AI) services and the growing fear of job displacement, an issue that has become increasingly important as AI continues to reshape industries across the globe. In recent years, AI has undergone significant advancements and has become a critical component in various sectors, including healthcare, finance, transportation, and customer service. Its ability to automate complex tasks and improve decision-making processes has captured the attention of both academics and professionals, highlighting its potential to drive innovation and transform business practices. The magnitude of AI's impact is often compared to other landmark technological revolutions, such as the advent of electricity and the internet, due to its capacity to fundamentally alter how industries operate.

The integration of AI into service-related operations is particularly noteworthy, as it touches upon two critical aspects that are often overlooked in more technical discussions: trust and fear. As AI systems become increasingly integrated into daily operations, the question of whether users trust these systems is paramount. Trust is a complex and multifaceted concept, especially when applied to technology. Users need to believe that AI systems are reliable, transparent, and fair in their operations, particularly when these systems are used in sensitive or high-stakes environments. For instance, when AI is applied in healthcare for diagnostic purposes or in financial services for risk assessment, trust becomes a critical factor in determining the technology's success. However, building trust in AI systems is not always straightforward. Many users remain skeptical about how these systems work, and this skepticism is often fueled by the perceived opacity and complexity of AI algorithms, which can function as "black boxes" where decisions are made in ways that are not easily understood by humans.

Alongside the issue of trust, there is an equally pressing concern regarding the impact of AI on employment. As AI technologies become more adept at performing tasks that were once the exclusive domain of human labor, there is a growing fear that AI might displace workers, particularly in industries that rely heavily on routine tasks and services. This fear is not unfounded;

industries such as customer service, logistics, and retail are already experiencing the effects of automation, with many jobs being replaced by AI-driven systems that can handle tasks such as answering customer inquiries, managing inventory, and processing transactions. These developments have led to widespread concerns about job security, as workers in these sectors worry that their roles may soon be rendered obsolete by AI. The fear of job displacement is particularly acute in sectors that employ large numbers of low- or medium-skilled workers, as these jobs are often the first to be affected by automation. The question of whether AI will lead to widespread unemployment or whether it will create new opportunities for employment in AI-related fields remains a topic of intense debate among economists, policymakers, and business leaders.

Given the rapid pace of AI development and its far-reaching implications, this dissertation aims to address two key research questions: What factors influence trust in AI services, and is there a correlation between trust in AI and the fear of job displacement? These questions are at the heart of the current discourse on AI, as they touch on both the technological and social dimensions of AI adoption. The first research question seeks to understand how users perceive AI in the context of service industries. Trust is not a binary concept but rather a spectrum that is influenced by various factors, such as the perceived reliability, transparency, and fairness of AI systems. Users may trust an AI system if they believe it provides accurate and unbiased results, but this trust can be undermined if they feel the system lacks transparency or if they are unsure about how decisions are being made. In exploring this question, the research aims to uncover the determinants of trust in AI and provide insights into how businesses can foster greater trust in their AI systems.

The second research question addresses the potential correlation between trust in AI and the fear of job displacement. As AI technologies continue to advance, they are increasingly being integrated into roles that were traditionally performed by humans. This has sparked concerns among workers about the future of their jobs, particularly in industries where AI has the potential to automate large portions of the workforce. The fear of job displacement is not only a personal concern for individual workers but also a societal issue, as it raises questions about the broader economic implications of AI adoption. By examining the relationship between trust in AI and the fear of job displacement, this research aims to provide a deeper understanding of how these two factors interact and how they influence users' willingness to engage with AI technologies.

The objectives of this research are threefold. First, the study aims to identify the key factors that influence trust in AI services. This includes examining elements such as transparency, reliability, and user experience, and analyzing how these factors contribute to building trust in AI systems. Understanding the determinants of trust is crucial for organizations that are looking to implement AI technologies, as it will allow them to develop strategies that foster greater trust and ensure the successful adoption of AI systems. Second, the research seeks to explore the relationship between trust in AI and the fear of job displacement. Specifically, it will investigate whether individuals who fear losing their jobs to AI are less likely to trust AI systems, and whether this fear influences their perceptions of AI technologies. Finally, the dissertation

aims to provide practical recommendations for businesses and policymakers on how to build trust in AI while addressing concerns about job security. The findings of this research will help organizations understand how to navigate the complex interplay between trust and fear in the context of AI adoption, and how to manage the potential social and economic impacts of AI on employment.

To achieve these objectives, the research adopted a quantitative approach, using a structured questionnaire to collect data from individuals, including those working in industries where AI is already being implemented. The questionnaire was designed to measure participants' levels of trust in AI services, as well as their concerns about job displacement. The data collected was analyzed using statistical methods to identify trends and correlations, providing a comprehensive understanding of the factors that influence trust in AI and the relationship between trust and fear. This methodology was intended to provide robust and reliable findings that can be generalized to a broader population, offering valuable insights for both academic and practical applications.

The remaining chapters of this dissertation are structured as follows. Chapter 2 offers a detailed review of the existing literature, analyzing current research on AI, trust, and job displacement. This chapter establishes the theoretical foundation on which the research is based, critically examining how trust in AI is conceptualized and how fears surrounding AI's impact on employment have been addressed in previous studies. Chapter 3 outlines the research methodology, providing a thorough explanation of the research design, data collection methods, and analytical techniques used, focusing on the statistical methods. This chapter ensures transparency in the research process, detailing how the questionnaire was developed and the rationale for the chosen quantitative approach. Chapter 4 presents the research findings, offering a detailed analysis of the data and highlighting key trends and correlations between trust in AI and the fear of job displacement, as well as a comparison with the known literature. Finally, Chapter 5 discusses the possible implications of these findings, drawing conclusions based on the research and offering recommendations for future studies and practical applications in business and policy settings. The conclusions aim to contribute to a better understanding of how trust in AI can be cultivated while addressing concerns related to job security in an era of rapid technological change.

Overall, this dissertation addresses a critical issue at the intersection of technology, trust, and employment. As AI continues to reshape the landscape of service industries, it is essential to understand the factors that influence trust in these technologies and to explore the potential social and economic consequences of AI adoption. By examining the relationship between trust in AI services and the fear of job displacement, this research aims to contribute to the growing body of knowledge on AI and its implications for the future of work. Furthermore, it seeks to provide practical recommendations for fostering trust in AI technologies and ensuring their responsible and ethical deployment in service industries.

Chapter 2

Literature Review

2.1 Definitions and Concepts of Trust in AI

Trust is a deeply complex concept, and its meaning and application can vary considerably across various disciplines. In philosophical discussions, trust is often linked to moral and ethical considerations. Authors such as Gambetta (1988), Baier (1986), and Holton (1994) view trust as essential for maintaining social cohesion and facilitating cooperation among individuals. In these frameworks, trust is not merely an instrument for achieving practical outcomes; rather, it embodies moral virtues such as responsibility and integrity. Specifically, Baier (1986) argues that trust necessitates mutual vulnerability. This means that individuals must open themselves to potential harm, trusting that the other party will not exploit their vulnerability. In this sense, trust is deeply tied to the concept of human agency, where individuals are expected to behave ethically. These concepts, however, raise a critical question in the recent realm of AI: can we apply the same moral and ethical expectations to machines, which lack human consciousness¹ and moral reasoning? If AI systems are devoid of human qualities like empathy or moral judgment, how can users reconcile these differences when deciding whether or not to trust them?

This question becomes particularly important when the philosophical distinction between trust in humans and trust in machines is considered. In the case of human-to-human trust, there is often an implicit understanding that trust involves not only competence but also ethical behavior. Humans are expected to act with integrity and in the best interest of others. On the contrary, AI systems, as tools created and to a certain extent controlled by humans, are driven by algorithms and data rather than moral principles. Therefore, trusting AI could be seen as more of a pragmatic decision than a moral one. Users might trust an AI system because it performs well or produces accurate outcomes, but this type of trust lacks the deeper ethical underpinnings present in human trust. The absence of moral accountability in AI further complicates the trust dynamic, particularly in situations where AI systems are making decisions that have ethical implications,

¹ Although a seemingly ubiquitous term, the definition of human consciousness can be quite complex and still an open topic. Even though this discussion is out of the scope of this dissertation, see, for example, Noel et al. (2019) for a review.

such as in healthcare or criminal justice.

Sociological perspectives, particularly those of Luhmann (1979) and Deutsch (1962), approach trust from a different angle. Sociologists often emphasize trust as a functional tool for managing the complexities of social life. Luhmann (1979) argues that trust is a mechanism for reducing uncertainty and complexity in human interactions, enabling individuals to function in unpredictable environments. This functional view of trust is highly relevant to human-AI interactions, where users must navigate the uncertainty associated with complex, often opaque AI systems. AI technologies, especially those involving machine learning, operate in ways that are difficult for users, and sometimes even developers, to fully understand. Thus, trusting AI becomes a matter of managing uncertainty rather than making a moral judgment. This notion of trust as a “leap of faith”, as described by Hoff and Bashir (2015), is particularly prevalent in fields where the stakes are high, such as autonomous vehicles or financial decision-making, where users are asked to trust systems that they may not fully comprehend.

The issue of opacity in AI systems further exacerbates this uncertainty. Many AI technologies, particularly those that rely on a myriad of deep learning algorithms, are often referred to as “black boxes” because their decision-making processes are not easily interpretable or even understood by humans. In fact, in most cases those decision-making processes rely on billions or trillions of “pre-trained” (or learned) variables, which a human cannot possibly hope to analyse by themselves (Bubeck et al., 2023). As a result, users are forced to place trust in systems that they cannot fully understand, leading to a significant dilemma. On one hand, users may appreciate the efficiency and accuracy of these systems, but on the other hand, the lack of transparency can foster skepticism and distrust. This paradox is central to the contemporary discourse on trust in AI, as it highlights the tension between the benefits of AI systems and the need for transparency and accountability. While technological advancements promise greater accuracy and efficiency, they also create new challenges for building and maintaining trust.

Expanding on this, trust within organizational contexts adds another layer of complexity. Scholars like McEvily and Tortoriello (2011) and McAllister (1995) highlight that trust in institutions, particularly with respect to the adoption of new technologies, plays a critical role in shaping organizational behavior. Trust is not only a personal or emotional matter but also an institutional one. In organizations, employees may not have direct control or input over the AI systems they use, making their trust in these systems reliant on the assurances provided by their employers, industry standards, and regulatory bodies. This form of institutional trust is built on policies, protocols, and the perceived reliability of the technology itself, rather than the emotional bonds often found in personal relationships. However, trust in AI within organizations also depends on the broader organizational culture. If an organization fosters a culture of transparency, open communication, and accountability, employees are more likely to trust the AI systems introduced into their workflows. Conversely, if there is a lack of clear communication or a history of technological failures, organizational trust can quickly disappear, leading to resistance and skepticism.

In addition to institutional trust, the concept of trust as a form of social capital is important in understanding trust in AI from an economic perspective. Economists such as Dasgupta (1988) view trust as an essential component of efficient economic transactions, serving to reduce transaction costs and mitigate risks. Trust, in this context, is instrumental: it helps streamline interactions by minimizing the need for complex monitoring and enforcement mechanisms. This is particularly relevant when considering AI systems that are integrated into economic transactions, such as financial trading algorithms or customer service chatbots. When businesses trust AI to handle routine tasks, they can operate more efficiently and reduce overhead costs associated with human oversight. However, this economic view of trust also brings with it certain risks, as over-reliance on AI systems could lead to vulnerabilities, particularly if these systems fail, behave unpredictably, or are the target of planned attacks that exploit possible vulnerabilities. Therefore, economic models of trust in AI must also account for the potential risks and uncertainties involved in deploying AI technologies at scale.

The integrative model of trust developed by Rousseau et al. (1998) and Mayer et al. (1995) provides a comprehensive framework for understanding trust in various contexts, including human-AI interactions. Their model identifies three key dimensions of trust: ability, benevolence, and integrity. In the case of AI, “ability” refers to the technical competence of the system, including its accuracy, efficiency, and reliability. “Benevolence” refers to the system’s alignment with human values and goals, which is crucial in ensuring that the AI system acts in the best interest of its users. Finally, “integrity” refers to the transparency and consistency of the AI system’s actions, which is essential for building and maintaining trust over time. These dimensions are particularly important in high-stakes environments, such as healthcare or autonomous driving, where trust in AI systems can have life-or-death implications. For example, an AI system used in medical diagnostics must not only be accurate but also transparent in explaining its reasoning to doctors and patients. As noted by Doran et al. (2017), if users cannot understand or verify the system’s decisions, trust may be compromised, even if the system is technically proficient and achieve high accuracy on the tasks it performs.

Moreover, the role of anthropomorphism in fostering trust in AI systems cannot be ignored. Studies by Waytz et al. (2014) and others highlight the impact of attributing human-like qualities to AI systems on trust formation. Anthropomorphism, or the tendency to attribute human characteristics to non-human entities, can enhance emotional trust by making AI systems seem more relatable and less mechanical. This phenomenon is particularly evident in customer service applications, where chatbots that mimic human conversation are often perceived as more trustworthy than their purely mechanical counterparts. However, as Mori et al. (2012) caution, there is a risk of the “uncanny valley”, where systems that appear almost human but not quite can evoke feelings of discomfort or distrust. This highlights the complexity of designing AI systems that strike the right balance between human-like interaction and technical performance, as too much or too little anthropomorphism can negatively affect user trust.

In addition to cognitive and emotional trust, the dynamic nature of AI systems adds another

dimension to the trust discussion. Unlike traditional machines, which perform predefined tasks, AI systems are capable of learning, adapting, and evolving over time. This adaptability introduces a new level of uncertainty, as users cannot always accurately predict how the system will behave in the future. Chakraborti and Kambhampati (2020) note that this dynamic nature of AI systems requires continuous trust calibration, where users must adjust their trust levels based on the system's performance and any changes in its behavior. This is particularly important in fields like autonomous driving, where even small deviations in the system's performance can have serious consequences. Trust calibration, as discussed by Hoff and Bashir (2015), is therefore a critical component of successful human-AI interaction, ensuring that users neither over-trust nor under-trust the system, but rather trust it to the appropriate degree based on its current and known capabilities.

It is evident that the context in which AI systems are used plays a significant role in determining the level of trust required. As Weber and Crozier (2022) argue, trust in AI is highly context-dependent, with different applications necessitating different degrees of trust. For example, users may be more willing to trust AI in low-stakes environments, such as entertainment or retail, where the consequences of failure are minimal. However, in high-stakes environments like healthcare or transportation, users demand a higher level of trust due to the potentially severe consequences of AI errors. This context-dependence suggests that trust in AI cannot be treated as a one-size-fits-all concept but must be tailored to the specific application and the risks involved. Moreover, it underscores the importance of designing AI systems that are transparent, reliable, and capable of adapting to the specific needs and expectations of users in different contexts. Trust in AI is a multifaceted and evolving concept that touches on various dimensions, including emotional, cognitive, and institutional factors. By understanding the different forms of trust—whether it is based on technical competence, emotional engagement, or institutional safeguards—designers and policymakers can better create AI systems that inspire confidence and foster effective human-AI collaboration. As AI continues to evolve, so too must our understanding of the trust dynamics at play, ensuring that users feel comfortable relying on AI systems in both low-stakes and high-stakes environments.

2.2 Historical Perspectives on Technological Displacement

The lack of trust in technology and the fear of technological displacement is not unique to the rise of AI; rather, it has been a recurring concern throughout various waves of technological innovation. Historically, periods of rapid technological advancement have often sparked fears about the replacement of human labor by machines. One of the most significant examples of this was the Industrial Revolution in the late 18th and early 19th centuries, which introduced mechanized production processes that drastically altered the nature of work. This period is often cited as the beginning of widespread anxiety about job displacement, as machines began to perform tasks that were previously done by skilled artisans. However, while the Industrial

Revolution did lead to the displacement of certain jobs, it also created new industries and roles, forcing societies to adapt to a changing labor market.

During the Industrial Revolution, the mechanization of industries such as textiles, agriculture, and manufacturing led to significant increases in productivity but also generated concerns about the future of human labor. The famous “Luddite” movement, which involved workers destroying machinery that they believed threatened their livelihoods, exemplifies the anxiety that accompanied these early technological changes (Brynjolfsson and McAfee, 2012). While the fears of job displacement were justified to an extent, new types of work eventually emerged, requiring different skills and allowing for an increase in overall employment levels. This historical example highlights the cyclical nature of technological disruption and adaptation, offering important lessons for today’s AI-driven economy.

Another critical period of technological disruption occurred in the early 20th century with the advent of mass production and automation. Fordism, characterized by the assembly line and standardization of work processes, drastically increased productivity and reduced the need for certain types of labor, particularly in manufacturing (Autor et al., 2003). However, as with the Industrial Revolution, new jobs were created in areas such as engineering, logistics, and management, illustrating once again that technological advancement can be both a threat and an opportunity. The societal response to these shifts was shaped by an increasing focus on education and skills development, which enabled workers to transition into new roles created by the evolving economy.

Additionally, the rise of computing in the mid-20th century marked another significant moment in the history of technological displacement. With the development of early computers and automated systems, tasks that required significant human labor, such as data processing and record-keeping, could now be performed by machines. This raised concerns about the potential for widespread unemployment, particularly in industries such as banking and accounting. However, the rise of computing also created entirely new sectors of employment, including software development, IT support, and cybersecurity (Brynjolfsson et al., 2014). While certain jobs were undoubtedly lost to automation, the overall impact of computing was a net gain in employment, particularly for workers with the skills to adapt to the new technological landscape.

In the latter half of the 20th century, robotics and automation continued to reshape industries such as manufacturing, leading to further concerns about job displacement. Robots began to take over tasks that were repetitive, dangerous, or required high levels of precision, such as assembling cars or welding metal components (Frey and Osborne, 2017b). While this reduced the need for manual labor, it also led to an increase in demand for workers with technical skills in robotics maintenance and programming. As with previous technological shifts, the impact of automation was not only negative. Although some jobs were eliminated, others were created in areas that required higher levels of education and training. This pattern of displacement followed by adaptation has become a hallmark of technological progress.

However, the rise of AI and machine learning in the 21st century represents a new phase

of technological disruption that has sparked renewed concerns about job displacement. Unlike previous waves of innovation, which primarily impacted manual and routine tasks, AI has the potential to automate cognitive tasks that were once considered the exclusive domain of humans (Brynjolfsson and McAfee, 2018). Jobs in fields such as finance, law, and healthcare, which were previously protected from automation, are now being transformed by AI systems capable of performing complex data analysis, pattern recognition, and decision-making at a super-human level. This raises the question of whether the lessons of past technological disruptions—such as the creation of new industries and jobs — will apply in an AI-driven economy where machines can perform both physical and cognitive tasks.

One key lesson from historical perspectives on technological displacement is the importance of adaptability. As seen in the Industrial Revolution and subsequent waves of automation, societies that invested in education and skills development were better equipped to transition workers into new roles created by technological advancements. In today's AI-driven economy, the need for reskilling and upskilling has become more urgent than ever. Governments and businesses must prioritize workforce development to ensure that workers can adapt to the rapidly changing demands of the labor market. Failure to do so could exacerbate economic inequalities and lead to greater societal unrest, much like the Luddite movement during the Industrial Revolution. Additionally, one can learn from history by looking at the role of policy in managing technological disruption. During the 20th century, policies that promoted workers' rights, education, and social safety nets helped mitigate the negative impacts of automation. These policies ensured that workers had the support they needed to transition into new roles and adapt to changing technological landscapes. In the context of AI, similar policies will likely be essential to managing the displacement of jobs. For instance, policies that promote lifelong learning, provide unemployment benefits, and incentivize businesses to invest in worker training will be critical in ensuring that the benefits of AI are distributed equitably (World Economic Forum, 2018).

The societal response to AI-driven technological displacement will, likely, also account for the ethical dimensions of trust in AI, as described in the previous section. As machines take on increasingly complex and decision-making roles, the question of whether AI can be trusted to act in the best interests of society becomes more pressing. Historical examples of technological disruption show that trust in machines is often built through transparency, accountability, and regulation. As AI systems become more integrated into daily life, building trust through ethical AI design and governance will be essential to ensuring societal acceptance and minimizing resistance (Taddeo, 2009).

Thus, the historical perspectives on technological displacement provide valuable insights into how societies can navigate the challenges posed by AI. While the fear of job displacement is real, history shows that technological advancements have also created new opportunities and industries.

2.3 Job Displacement Concept in Today's World

The fear of job displacement due to AI is one of the most pressing concerns in today's world, both within academic circles and in public discourse. As described in the previous section, fears of machines replacing human labor have emerged during significant technological shifts. While these fears were somewhat mitigated over time as economies adjusted, the rise of AI has brought these concerns back to the forefront, but in a different context. Unlike previous technological advancements, AI has the potential to automate not only manual labor but also cognitive tasks, some of which were previously considered irreplaceable by machines. This has led to a renewed debate about the role of AI in job displacement and whether it could ultimately lead to mass unemployment or transform the nature of work in more positive ways.

A notable historical moment that often symbolizes the potential of AI to surpass human capabilities is the chess match between Garry Kasparov and IBM's Deep Blue in 1997². Kasparov, the reigning world chess champion, was defeated by the machine, which many viewed as a demonstration of AI's capacity to outperform humans in specific domains. This event fueled the public imagination, with some seeing it as evidence that AI could replace human intelligence across a broad range of activities. However, as Kasparov and Greengard (2017) points out, the reality has been far more nuanced. Instead of replacing human chess players, AI has been used as a tool to enhance human performance, assisting players in refining their strategies. This trend of AI augmenting rather than replacing human abilities is not limited to chess but can be seen in a variety of fields such as medicine, law, and finance. In these sectors, AI helps professionals perform tasks more efficiently and with greater accuracy, allowing them to focus on more complex and higher-level decision-making. This symbiotic relationship between humans and AI illustrates that, in many cases, AI may serve as a complement to human labor rather than a direct substitute.

Regarding technological advances' effects on the job market, the concept of "technological unemployment" was coined by John Maynard Keynes in the 1930s to describe the displacement of workers by machines (Keynes, 1933). Keynes believed that technological advancements would eventually lead to machines taking over many tasks previously performed by humans, resulting in widespread unemployment. Decades later, Herbert Simon echoed these concerns, predicting that machines could eventually perform nearly every task that humans can do (Simon, 1965). While these predictions have not fully materialized, recent advances in AI have brought us closer to a reality where machines can perform a wide variety of tasks, raising renewed concerns about the future of work itself. While some jobs have certainly been displaced by automation, the degree to which AI will continue to replace human labor, particularly in cognitive fields, remains an open question, as every day new algorithms are developed that can outperform humans in various complex cognitive tasks. The most recent examples include Large Language

² In fact, Deep Blue has been beaten by countless other algorithms since then. AlphaZero, one of the most advanced AI chess players, has learned to play chess "alone" by playing millions of games with itself, in only a few days of human time (Silver et al., 2018).

Models (LLMs), which have exhibited advanced capabilities in reasoning and problem-solving, leading some to argue they have approached or even surpassed certain benchmarks of human-like reasoning, though they do not truly ‘think’ like humans. These models have even been said to pass versions of the Turing test in specific contexts.(Bubeck et al., 2023). Nonetheless, these historical perspectives highlight the long-standing tension between technological progress and its impact on employment.

In particular, one of the areas most vulnerable to AI-driven job displacement has been proposed to be middle-skill jobs that involve routine, repetitive tasks. Frey and Osborne (2017b) argue that these jobs, which are prevalent in sectors such as manufacturing, transportation, and retail, are particularly susceptible to automation as AI systems become more capable of handling tasks that require little human judgment or creativity. In manufacturing, for example, AI-driven robots now perform tasks that were once the exclusive domain of human workers, such as assembling products or conducting quality control checks. This has led to significant reductions in the demand for human labor, particularly among workers with lower or medium levels of education and skills. However, while this automation may increase efficiency and reduce costs for businesses, it also raises critical questions about the social and economic impacts of displacing large numbers of workers in these industries.

The fear of job displacement due to AI is not, however, limited to low-skill and middle-skill jobs. High-skill jobs, particularly those that require complex problem-solving, creativity, and cognitive flexibility, are also at an increasing risk of being transformed by AI technologies. Ferràs-Hernández (2018) argue that while AI may not entirely replace high-skill workers, it is likely to significantly alter their roles. For example, in the legal profession, AI systems are already being used to analyze vast quantities of legal documents, identify relevant precedents, and even assist in predicting legal outcomes. These systems allow lawyers to focus on higher-order tasks, such as crafting legal strategies and advising clients. However, the growing sophistication of AI systems raises concerns that even these high-level tasks could eventually be automated. If AI becomes capable of making nuanced decisions, it could potentially displace even high-skill professionals, raising questions about the long-term viability of certain high-paying, cognitively demanding jobs.

Healthcare offers another example of how AI is augmenting, rather than replacing, human labor. AI systems are increasingly used to assist doctors in diagnosing diseases, recommending treatments, and even predicting patient outcomes based on large data sets. Topol (2019) suggests that AI’s ability to process vast amounts of medical data far surpasses that of human doctors, allowing for more informed and precise decision-making. However, as AI systems become more advanced, there are growing concerns that certain aspects of medical decision-making could be automated, potentially reducing the need for human doctors in specific contexts. This raises important ethical questions about the role of AI in healthcare: to what extent should machines be entrusted with human health? And how comfortable are patients with the idea of being treated by an algorithm rather than a human doctor? These questions highlight the broader societal

implications of AI-driven automation in fields that have traditionally relied heavily on human expertise.

Naturally, however, the fear of job displacement is especially pronounced among low-wage, low-skill workers, who are often employed in sectors where routine tasks are most easily automated. Webb (2020) argue that these workers are particularly vulnerable to AI-driven displacement, as their jobs are more likely to involve tasks that require minimal human judgment or creativity. In the retail industry, for example, AI systems are increasingly being used to manage inventory, track customer preferences, and recommend products, thereby reducing the demand for human workers in positions such as cashiers and stock clerks. This trend has significant implications for social inequality, as lower-wage workers are often the least equipped to transition into new roles that require higher levels of education and training. Thus, AI-driven job displacement could exacerbate existing inequalities in the labor market, particularly if policies are not put in place to support these workers in reskilling or finding new employment opportunities.

Despite these concerns, there is growing recognition that AI has the potential to create new jobs even as it displaces others. Autor et al. (2003) point out that technological advancements have historically led to the creation of new industries and job opportunities, even as they have displaced workers in older industries. The rise of AI is no exception. The growing demand for AI-driven technologies has created a need for new roles in fields such as data science, machine learning engineering, and AI ethics. These roles require a different set of skills than the jobs they are replacing, which means that workers will need to reskill and upskill in order to remain competitive in the labor market. However, this also presents a challenge: how can governments and organizations ensure that workers are equipped with the skills they need to succeed in a rapidly changing job market?

Thus, one of the most significant challenges in managing the impact of AI on the labor market is ensuring that displaced workers are able to transition into new roles. This requires not only technical skills but also social and emotional competencies such as communication, teamwork, and adaptability. World Economic Forum (2018) predict that AI will create millions of new jobs in the coming decade, offsetting the losses caused by automation. However, the jobs created by AI are likely to require different skills than the jobs they replace, meaning that workers will need to continuously update their skillsets³. This highlights the importance of lifelong learning and reskilling programs that help workers adapt to the evolving demands of the labor market. Without such programs, there is a risk that many workers, particularly those in low-skill and middle-skill positions, will be left behind.

Finally, the fear of job displacement due to AI is a legitimate concern and is widely described in the literature. This fear is particularly present for workers in industries that are most susceptible to automation, a number that continuously grows. However, literature on past technological innovations suggests that AI has the potential not only to displace jobs but also to create new

³ A clear example here is the recent job of *prompt engineering*, i.e., a job that specializes in writing better prompts to get better and more precise results from LLMs.

opportunities for workers, provided that the right policies and programs are in place. To fully realize the benefits of AI while addressing the challenges it presents, it might be essential to promote a culture of lifelong learning and adaptability, as well as to implement policies that support workers in transitioning to new roles. Such policies, however, might only be effective if they are implemented in a society that trusts and does not fear AI.

Chapter 3

Methodology

This chapter provides a comprehensive overview of the data collection and analytical methods utilized to explore the relationship between trust in AI and the fear of job displacement. A quantitative approach was selected as the most suitable method for this investigation, given its ability to control variables and produce statistically significant results. Unlike qualitative or mixed methods, which provide rich narrative insights but can be less generalizable, the quantitative method allows for rigorous testing of hypotheses through statistical analysis of relationships between variables. By employing structured surveys, this approach facilitates the collection of measurable data that supports statistical techniques, which are critical to understanding the dynamics at play (Wienclaw, 2021). Moreover, a quantitative model ensures replicability and objectivity, aligning with the hypothesis-driven framework of the research and allowing for a clearer interpretation of the impact of AI-related fears on trust in AI.

3.1 Data Collection: Online Questionnaire

The data for this study was collected using an online questionnaire administered via Google Forms - each person was allowed to submit only one complete answer. The survey design relied exclusively on closed-ended questions to streamline the statistical analysis process, with a particular emphasis on the 5-point Likert scale (Likert, 1932). The questionnaire received responses from 10.04.2024 to 17.06.2024 and was aimed at individuals who are either current or potential users of AI technologies. The survey featured five demographic questions, followed by 36 questions based on and adapted from prior research by Choung et al. (2023a, 2023b)¹. The total 40 questions (or variables) were divided into main categories taking into consideration the following topics:

- **Demographics:** Demographic factors such as age, education level and income, providing context for understanding how societal and economic variables may influence trust in AI

¹ Importantly, their studies targeted U.S. populations and emphasized Acceptance and Ethics. This research, however, aimed to explore the relationship between fear of job displacement and trust in AI.

services. For example, younger individuals, being more familiar with technology, might be hypotesised to demonstrate higher trust levels.

- **Trust Propensity:** This variable measured the natural inclination to trust, helping to assess individuals' general predisposition toward trust.
- **Familiarity with AI Technologies:** Knowledge about AI shaped perceptions and trust, as those more familiar with AI might possess a more informed and nuanced understanding.
- **Perceived Ease of Use & Perceived Usefulness:** These variables assess the perceived usability and utility of AI services, which can significantly impact trust. If users find AI easy to use and perceive it as beneficial, their trust may increase.
- **Human-like Trust in AI Servicea & Functionality Trust in AI Services:** These variables differentiated between trust based on human-like attributes and trust based on functionality, offering insights into the nuanced aspects of trust.
- **Attitude toward AI Services:** This variable captured the general sentiment toward AI services, providing an overall perspective that could influence trust.
- **Attitude toward AI Replacing Jobs & Fear of Job Displacement:** These variables captured individuals' sentiments about AI's impact on employment. Given the novelty of this study, there was an extensive focus on understanding whether fear of job displacement could be correlated with trust levels, with multiple statements addressing these variables.

The source and numbering of each question (variables) can be found at Table 3.1 and the range of available answers displayed in the questionnaire (5-point Likert scale and others) can be found at Table 3.2. Questions without a source have been asked specifically for this questionnaire, considering the objectives of this work.

Question	Variable	Source
Please select your age group.	1.1	-
What is the highest level of education you have completed?	1.2	-
Which of the following best describes your current employment status?	1.3	-
What is your approximate annual income before taxes (€)?	1.4	-
Which industry do you work in? (Select the one that best represents your current occupation)	1.5	-

Question	Variable	Source
My typical approach is to trust new acquaintances until they prove I should not trust them	2.1	(Choung et al., 2023a)
In general, how willing are you to trust new technologies that you encounter?	2.2	(Choung et al., 2023a)
To what extent do you trust governmental institutions?	3.1	Choung et al., 2023a
To what extent do you trust large corporations (e.g., Siemens, Nestlé)?	3.2	(Choung et al., 2023a)
To what extent do you trust technology corporations/institutions (e.g., Facebook, Google, Apple)?	3.3	(Choung et al., 2023a)
How often do you use these technologies? Smart devices (e.g., Google Nest, Ring, Blink) or/and Large Language Models (LLMs) (e.g., GPT, Bert)	4.1	(Choung et al., 2023a)
How often do you use these technologies? Smart speakers (e.g., Amazon Echo, Google Home, Apple Homepod, Sonos)	4.2	(Choung et al., 2023a)
How often do you use these technologies? Virtual assistants (e.g., Siri, Alexa, Google Assistant)	4.3	(Choung et al., 2023a)
How often do you use these technologies? Wearable devices (e.g., Fitbit, Apple Watch)	4.4	(Choung et al., 2023a)
I know which types of products and services use artificial intelligence.	4.5	(Ipsos, 2022)
I feel positive toward AI virtual assistants/AI technologies.	5.1	(Choung et al., 2023b)
Using AI virtual assistants/AI technologies is a smart way to get things done.	5.2	(Choung et al., 2023b)
To what extent do you believe current AI technology can perform human tasks at or above the level of a typical human?	5.3	(Gruetzemacher et al., 2020)
How much do you anticipate AI technology will be able to perform human tasks at or above the level of a typical human in 10 years?	5.4	(Gruetzemacher et al., 2020)
AI technologies/solutions care about our well-being.	6.1	(Choung et al., 2023b)
AI technologies/solutions are sincerely concerned about addressing the problems of human users.	6.2	(Choung et al., 2023b)
AI technologies/solutions keep their commitments and deliver on their promises.	6.3	(Choung et al., 2023b)

Question	Variable	Source
AI technologies/solutions are honest and do not abuse the information and advantage they have over their users.	6.4	(Choung et al., 2023b)
AI technologies/solutions work well.	7.1	(Choung et al., 2023b)
AI technologies/solutions have the features necessary to complete key tasks.	7.2	(Choung et al., 2023b)
AI technologies/solutions are competent in their area of expertise.	7.3	(Choung et al., 2023b)
AI technologies/solutions are reliable.	7.4	(Choung et al., 2023b)
AI technologies/solutions are dependable.	7.5	(Choung et al., 2023b)
Learning to use AI services / technologies would be easy for me.	8.1	(Choung et al., 2023b)
I would find it easy to get AI services / technologies to do what I want it to do.	8.2	(Choung et al., 2023b)
I would find AI services / technologies to be easy to use.	8.3	(Choung et al., 2023b)
Using AI services / technologies would enable me to accomplish tasks more quickly.	9.1	(Choung et al., 2023b)
Using AI services / technologies for accomplishing tasks would increase my productivity and effectiveness.	9.2	(Choung et al., 2023b)
I find AI services / technologies useful for me to accomplish tasks.	9.3	(Choung et al., 2023b)
How concerned are you that AI advancements will lead to widespread unemployment?	10.1	-
Do you believe that AI will significantly reduce the number of available jobs in your industry?	10.2	-
How confident are you in your ability to adapt to changes in the job market caused by AI?	10.3	-
How fearful are you of losing your job due to advancements in AI technology?	10.4	-
Do you want to participate in this survey?	11.1	-

Table 3.1: Questions presented in the Online Questionnaire.

Variables	Possible Answers
1.1	1. Under 18; 2. 18-24; 3. 25-34; 4. 35-44; 5. 45-54; 6. 55-64; 7. 65 or older

Variables	Possible Answers
1.2	1. Less than high school; 2. High school diploma or equivalent; 3. Some college or associate degree; 4. Bachelor's degree; 5. Master's degree; 6. Doctoral degree or higher
1.3	1. Employed full-time; 2. Employed part-time; 3. Self-employed; 4. Unemployed; 5. Student; 6. Retired; 7. Other (please specify)
1.4	1. Less than 10,000; 2. 10,000 - 19,999; 3. 20,000 - 34,999; 4. 35,000 - 59,999; 5. 60,000 - 99,999; 6. 100,000 or more; 7. Prefer not to say
1.5	1. Technology/IT; 2. Healthcare; 3. Finance/Banking; 4. Education; 5. Manufacturing; 6. Retail; 7. Government; 8. Entertainment/Media; 9. Services; 10. Other (please specify); 11. Not Applicable
2.1; 4.5; 5.1; 5.2; 6.1; 6.2; 6.3; 6.4; 7.1; 7.2; 7.3; 7.4; 7.5; 8.1; 8.2; 8.3; 9.1; 9.2; 9.3; 10.2; 10.3; 10.4	1. Strongly disagree; 2. Disagree; 3. Neutral; 4. Agree; 5. Strongly agree
2.2; 3.1; 3.2; 3.3; 10.1	1. Not at all; 2. Slightly; 3. Moderately; 4. Very much; 5. Completely
4.1; 4.2; 4.3; 4.4	1. Never; 2. Rarely; 3. Occasionally; 4. Frequently; 5. Always
5.3; 5.4	1. 0% feasible; 2. 25% feasible; 3. 50% feasible; 4. 75% feasible; 5. 100% feasible
11.1	1. Yes

Table 3.2: Possible answers for each variable.

3.2 Statistical Analysis and Model

3.2.1 Cronbach's alpha

Cronbach's alpha is a statistical measure used to assess the internal consistency of a set of survey items intended to measure a latent variable. It quantifies the extent to which all the items in a survey work together to measure the same underlying concept. In other words, it provides a metric of how consistently the items are capturing what they are meant to measure. The formula for calculating Cronbach's alpha is shown in Equation 3.1:

$$\alpha = \frac{k}{k-1} \left(1 - \frac{\sum_{i=1}^k \sigma_i^2}{\sigma_T^2} \right) \quad (3.1)$$

where k is the number of items in the scale, σ_i^2 is the variance of the scores on the i th item, and σ_T^2 is the variance of the total scores across all k items. Cronbach's alpha values range between 0 and 1, with values above 0.7 generally considered to indicate acceptable internal consistency, as shown in Table 3.3.

Cronbach's Alpha	Internal consistency
$\alpha \geq 0.9$	Excellent
$0.8 \leq \alpha < 0.9$	Good
$0.7 \leq \alpha < 0.8$	Acceptable
$0.6 \leq \alpha < 0.7$	Questionable
$0.5 \leq \alpha < 0.6$	Poor
$\alpha < 0.5$	Unacceptable

Table 3.3: Internal consistency in Cronbach's Alpha

This study adopted an iterative process in which Cronbach's alpha values were calculated and variables were removed to achieve optimal internal validity. This approach allowed for the refinement of categories, ensuring that each category had Cronbach's alpha values above the 0.7 threshold. Some variables were excluded from each category to enhance internal consistency, as shown in Table 3.4.

Category	Cronbach's Alpha	Variable
Trust in institutions	0.8162	3.2; 3.3
Attitude towards AI	0.7488	5.1; 5.2; 5.3; 5.4
Human-like trust in AI	0.7762	5.1; 5.2
Functionality	0.8251	6.1; 6.2
Perceived ease of use	0.8004	8.1; 8.2; 8.3
Perceived usefulness	0.8939	9.1; 9.2; 9.3

Table 3.4: Cronbach's alpha results and selected variables.

3.2.2 Model

To provide convincing evidence of the impact of fear of job displacement on trust in AI solutions, an econometric model was constructed using an Ordinary Least Squares (OLS) standard equation, as shown in Equation 3.2. This model includes job displacement variables, control variables, and demographic variables.

$$\gamma = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p + \epsilon \quad (3.2)$$

where γ is the dependent variable, β_0 is the intercept, β_i are the coefficients of the independent variables, X_i are the independent variables, and ϵ represents the error terms. However, it was suspected that the data may suffer from heteroskedasticity, which would make the OLS model an unbiased fit. Therefore, a Weighted Least Squares (WLS) model was adopted to account for the non-constant variance across all observations in the error terms. WLS is a technique that addresses this issue by allowing each observation to contribute unequally to the estimation of the regression parameters, based on the inverse of the variance of the residuals (i.e., the weights selected for this study). The standard equation for the WLS model follows the standard OLS equation, but the error terms are weighted as shown in Equation 3.3, using the variance of the residuals obtained from the preliminary OLS model.

$$\text{weights} = \frac{1}{\text{var}(\text{residuals})} \quad (3.3)$$

Furthermore, robust standard errors were used while estimating the model, as they are designed to provide valid standard errors of coefficient estimates in the presence of heteroskedasticity. Specifically, the Heteroscedasticity-Consistent Covariance Matrix Estimator (HC3) was employed, which involves calculating the covariance matrix of the coefficient estimates using Equation 3.4.

$$\text{Var}_{\text{HC3}}(\hat{\beta}) = (X'X)^{-1} X' \Omega X (X'X)^{-1} \quad (3.4)$$

where X' is the transpose of matrix X , $(X'X)^{-1}$ is the inverse of matrix $X'X$, and Ω is a matrix incorporating the residuals adjusted for leverage and the number of observations.

Chapter 4

Results

This chapter presents the results of the quantitative analysis based on the responses gathered from the online questionnaire outlined in the previous chapter. By applying statistical methods, this study aimed to explore how different variables - such as demographic factors, trust propensity, and familiarity with AI - relate to participants' attitudes towards AI technologies and their concerns about job displacement.

4.1 Descriptive Statistics

4.1.1 Demographics

The online questionnaire gathered a total of 137 independent responses. Each participant answered all questions, providing values for every variable. All responses were willingly provided, as each participant answered "Yes" to question 11.1 - *Do you want to participate in this survey?*. Regarding gender distribution, approximately 54% of respondents identified as male, 45% as female, and 1% as other. Further details on the demographic variables are shown in Figure 4.1.

In terms of age distribution, the majority of participants fall within the 25-34 age range, making up 45.7% of the total. Smaller but still significant portions are in the 35-44 range (23.9%) and 18 - 24 (10.9%). This suggests that the survey predominantly reached individuals in early to mid-career stages, who potentially have had more exposure to technology than the average person. Regarding education, a considerable proportion of respondents hold a bachelor's degree (36.2%), followed by those with a master's degree (34.8%). This points to a well-educated sample group, with only a small percentage having less than a high school diploma. In terms of employment, a significant 72.5% of respondents are employed full-time, indicating that the majority of the participants are actively engaged in the workforce, which aligns well with their reported education levels. The survey also captures a range of industries, with technology/IT (14.5%) and services (14.5%) being the most represented sectors. In terms of income, responses are spread relatively evenly, though a significant portion of respondents (25.7%) earn between 20,000 and 39,999 euros annually.

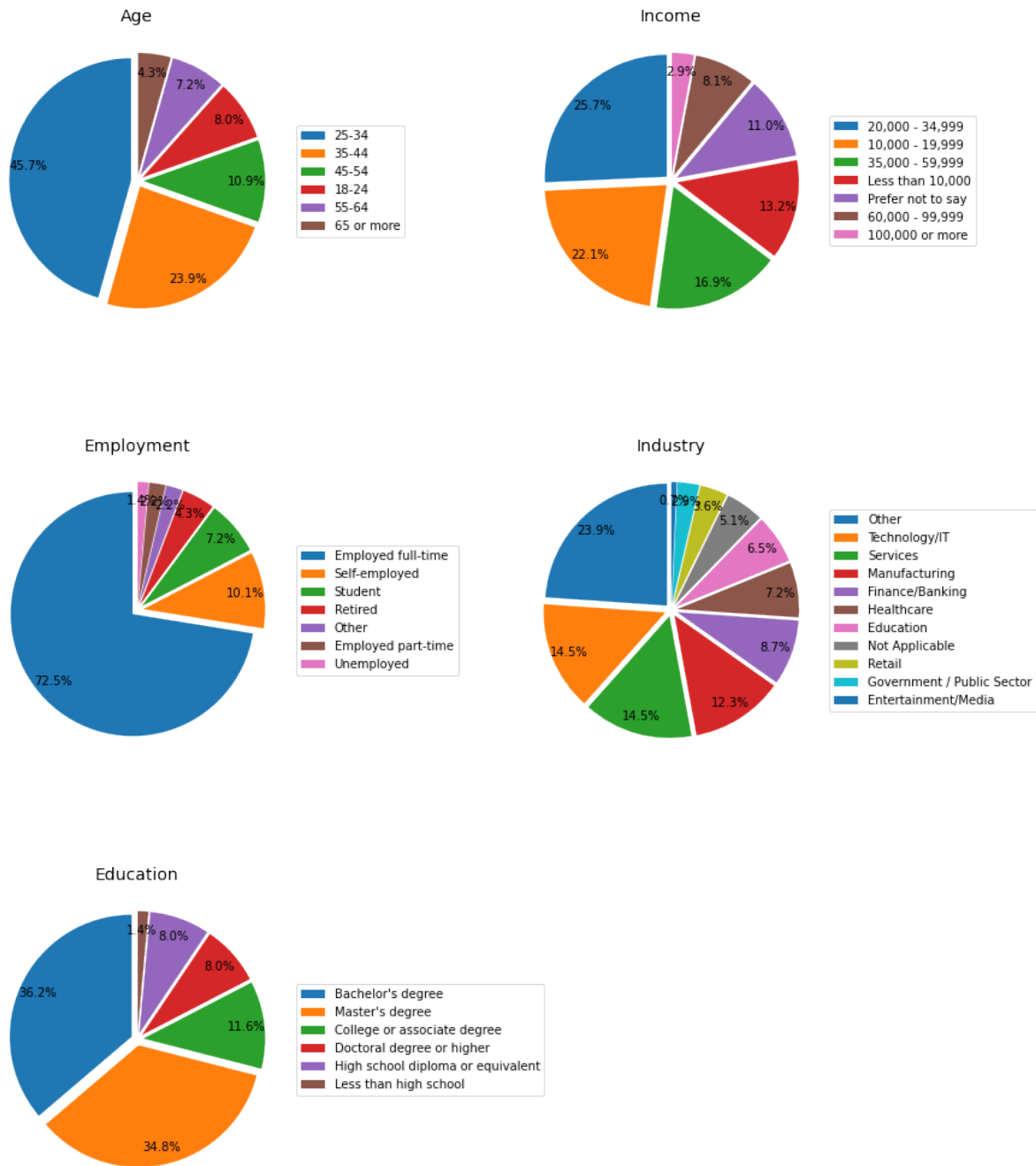


Figure 4.1: Descriptive demographics for the Online Questionnaire answers.

This basic overview offered a basic descriptive of the demographic characteristics of the survey participants. While it provides valuable insight into their background, a deeper analysis of how these specific demographics may influence the survey results is beyond the scope of this study. The demographics highlighted, including the predominant age groups, education levels, and employment sectors, suggest that the sample might not be necessarily representative of the broader population. It is important to note that the sample reflected a particular subset of individuals, likely with more education and career experience than the general population. This could naturally affect the perspectives and responses gathered in the survey. Therefore, any conclusions drawn from these results should be interpreted with caution, especially regarding their applicability to a more general population. The demographic skew observed, particularly in age, education, and industry, may have introduced biases that could influence the overall findings. For example, higher levels of education and full-time employment may affect respondents' opinions, behaviors, and trust in technology in ways that differ from those with less education or different employment statuses. Thus, while the results offer useful insights into the surveyed group, generalizing them to broader contexts requires future careful consideration of these demographic factors.

4.1.2 Combined Variables

To enhance the accuracy and clarity of the analysis, several variables collected through the questionnaire were combined to allow for a more meaningful interpretation of the data. Specifically, interaction terms were created by multiplying predetermined variables that represented key aspects of trust and familiarity with AI. This approach helped in examining how the interplay of factors such as trust in institutions, attitudes toward AI, and perceived ease of use influences trust in AI solutions. For the purposes of the regression analysis, the final categories included the combined variables: *trust in institutions*, *attitude toward AI*, *human-like trust*, *functionality trust*, *perceived ease of use*, and *perceived usefulness*, each of which contributes to understanding the broader framework of AI trustworthiness. These variables were selected as control variables according to the Cronbach's alpha statistical measure described in the previous chapter (i.e., variables that had a Cronbach's alpha classified as acceptable or above).

To improve the interpretability of the dependent variable *trust propensity* - representing the respondents' overall likelihood to trust AI technologies - a logarithmic transformation was applied. This transformation was necessary to normalize the distribution of the trust propensity scores, ensuring that the assumptions of the regression model were met. The use of such transformations is common in statistical analyses when variables are skewed, and it allows for more robust and reliable results. Descriptive statistics for each of the key variables are detailed in Table 4.1, providing a comprehensive overview of the data's central tendencies, variability, and relationships. This setup established a solid foundation for the subsequent regression analysis, facilitating a deeper understanding of the drivers behind trust in AI.

Variable	Count	Mean	Std. Deviation	Min	Max
Trust					
Log. trust propensity	137	1.1769	0.3067	0	1.6094
Job Displacement					
AI replacing jobs	137	3.1532	1.1173	1	5
Personal ability to adapt	137	3.4963	0.8755	1	5
Control variables					
Trust in institutions	137	7.9635	5.0035	1	25
Attitude towards AI	137	153.8832	109.4488	1	625
Human-like trust in AI	137	7.3284	4.27773	1	25
Functionality	137	140.8978	102.3359	1	625
Perceived ease of use	137	51.8321	29.1972	1	125
Perceived usefulness	137	59.5693	31.8890	1	125
Demographics					
Age	137	2.7737	1.2366	1	6
Education	137	4.1897	1.1016	1	6
Industry Technology	137	0.1459	0.3543	0	1
Employment full-time	137	0.7226	0.4493	0	1

Table 4.1: Descriptive Statistics

4.2 Model diagnostics

To evaluate how well the model fits the data and to check whether the assumptions of OLS regression were met, several diagnostic tests were conducted (Table 4.2). These tests helped identify potential issues such as omitted variable bias, autocorrelation, heteroskedasticity, and normality of residuals, which are important for ensuring the validity of the model's results.

The first test performed was the Ramsey Regression Equation Specification Error Test (RESET), which checks whether the model suffers from omitted variable bias and whether the relationship between the independent and dependent variables is truly linear (Ramsey, 1969). This test was done by adding squared and cubed terms of the fitted values into the regression equation. The p-values for both the squared and cubed terms were non-significant, with values of 0.672 and 0.903, respectively. These results suggest that there was no evidence of omitted variable bias or non-linearity in the model, giving confidence in the model's specification.

Next, the Durbin-Watson test was performed to check for autocorrelation in the residuals (Durbin and Watson, 1950). Autocorrelation occurs when the residuals from one observation are correlated with those from another, which would violate the assumption of independence. The Durbin-Watson statistic was 2.0259, which is close to 2, indicating no significant autocorrelation. This means the residuals were independent, a key assumption in OLS models.

The Breusch-Pagan test was used to check for heteroskedasticity, which refers to unequal variance in the residuals (Breusch and Pagan, 1979). Heteroskedasticity can lead to inefficient estimates and underestimated standard errors. The test produced a non-significant p-value of 0.073, indicating no strong evidence of heteroskedasticity. This result aligns with the application

of the WLS model, reinforcing the reliability of the model's estimates.

However, the Shapiro-Wilk test for normality of the residuals showed a significant p-value of 0.000, suggesting that the residuals deviate from a normal distribution (Shapiro and Wilk, 1965). While this could be a concern, it is important to note that OLS models are generally robust to small deviations from normality, especially with large samples. Additionally, the mean and standard deviation of the residuals were -0.006 and 0.259, respectively, which are close to 0. This helps reassure that the residuals do not have extreme skewness or kurtosis, and the model's predictions remain reliable.

Test	Result
RESET	$p_{\text{val}}^2 = 0.672$ $p_{\text{val}}^3 = 0.903$
Durbin-Watson	2.0259
Breusch-Pagan	$p_{\text{val}} = 0.073$
Shapiro-Wilk	$p_{\text{val}} = 0.000$
Mean of residuals	-0.006
Std. of residuals	0.259

Table 4.2: Summary of statistical tests performed

To assess the presence of multicollinearity between the independent variables, the Variance Inflation Factor (VIF) was calculated for each variable. Multicollinearity occurs when two or more independent variables in a regression model are highly correlated, which can inflate the variance of the estimated regression coefficients, making the model unstable and difficult to interpret. VIF is a commonly used diagnostic tool to detect multicollinearity, with higher VIF values indicating a greater level of multicollinearity (Kutner et al., 2005).

A VIF value below 10 is generally considered acceptable, with values above this threshold indicating a potential problem of multicollinearity that may need to be addressed (Montgomery et al., 2012). As shown in Table 4.3, all of the variables in the model had VIF values well below the threshold of 10, suggesting no significant multicollinearity was present. The highest VIF value was 2.1692 for the variable "Perceived ease of use," which is still comfortably within acceptable limits.

The variable "AI replacing jobs" had the lowest VIF value at 1.1106, indicating a very low correlation with other independent variables in the model. Other key variables, such as "Trust in institutions" and "Attitude towards AI" had moderate VIF values of 1.5563 and 2.0907, respectively, which suggested a reasonable level of independence from the other predictors in the model. Similarly, demographic variables such as "Age" and "Education" also had low VIF values (1.2491 and 1.1501, respectively), reinforcing the idea that the independent variables were not highly correlated.

Overall, the VIF results provided reassurance that multicollinearity was not an issue in this model, allowing for reliable estimation of the regression coefficients. This meant the relationships between the independent variables and the dependent variable can be interpreted with

confidence, as the model was not affected by inflated standard errors or unstable estimates.

Variable	VIF
AI replacing jobs	1.1106
Personal ability to adapt	1.5563
Trust in institutions	1.5563
Attitude towards AI	2.0907
Human-like trust in AI	1.3423
Functionality	1.5933
Perceived ease of use	2.1692
Perceived usefulness	2.0039
Age	1.2491
Education	1.1501
Industry Technology	1.2760
Employment full-time	1.1857

Table 4.3: Summary of VIF results

4.2.1 Bootstrap

Since signs of non-normality were found in the residuals, an additional robustness test was conducted using the Bootstrap method. This method involves repeatedly sampling observations (with replacement) from the original dataset to create multiple bootstrap samples, each of the same size as the original dataset (Efron and Tibshirani, 1994). A total of 10,000 bootstrap samples were generated, and the average coefficients, standard errors, and p-values were calculated. The Bootstrap method is particularly useful in cases where assumptions like normality may not hold, as it does not rely on such assumptions (Davison and Hinkley, 1997). This provided a more robust estimate of the model parameters.

For the p-values, two-tailed values were calculated based on the proportion of bootstrap samples where the coefficients were either greater than or less than zero. The calculation for the p-values is shown in Equation 4.1:

$$p_{\text{value}} = 2 \times \min(\hat{p}_+, \hat{p}_-) \quad (4.1)$$

here, $\hat{p}_+$ is the proportion of bootstrap samples where the estimated coefficient is greater than or equal to 0, and $\hat{p}_-$ is the proportion of bootstrap samples where the coefficient is less than or equal to 0. The min function ensures that the p-value accounts for both positive and negative deviations from zero, making the test two-tailed. This approach provides a more accurate measure of statistical significance when there are concerns about the distribution of the residuals.

The results of the Bootstrap analysis were compared to those of the standard OLS regression. While the coefficient estimates were generally similar, the Bootstrap standard errors tended to be slightly larger, reflecting the added uncertainty due to the non-normality of the residuals.

This indicated that the original OLS estimates were reliable, but the Bootstrap results provided additional confidence in the robustness of the findings.

4.2.2 Models results

The results of the regression analysis can be found in Table 4.4. Four different model specifications (henceforward called models) were tested to examine how the fear of job displacement impacts trust in AI. The dependent variable in all models is “Trust in AI” while the key independent variable is “Fear of job displacement”. The models aim to assess the relationship between these two variables, progressively incorporating additional controls and demographic factors, and addressing issues of non-normality in the residuals.

In the first model, only the two main variables of interest were included: “Fear of job displacement” and “Personal ability to adapt”. The results indicated a significant negative association between fear of job displacement and trust in AI, suggesting that individuals who are more afraid of losing their jobs to AI tend to have lower levels of trust in AI. Meanwhile, the ability to adapt has a significant positive effect, implying that those who feel capable of adapting to technological changes are more likely to trust AI.

Model (2) introduced several control variables, including “Trust in institutions”, “Attitude toward AI”, “Human-like trust in AI”, and others. With these controls, the negative relationship between fear of job displacement and trust in AI remained significant, while the ability to adapt continued to have a positive and significant effect. The control variables, particularly “Trust in institutions” and “Attitude toward AI”, also played an important role, as shown by their significant coefficients.

In model (3), demographic variables were added, including “Age”, “Education”, “Industry Tech”, and “Employment full-time”. The inclusion of these demographics did not substantially alter the relationship between the fear of job displacement and trust in AI, as the coefficients remained consistent with earlier models. However, age and education showed significant effects on trust in AI, indicating that older and more educated individuals may trust AI more.

Finally, model (4) applied the Bootstrap method to account for the non-normality in the residuals, as identified in preliminary diagnostics. While the main relationships between the key independent and dependent variables remained, the standard errors became larger, resulting in some coefficients becoming marginally significant. This suggested that the non-normality in the data might have introduced some uncertainty, though the overall relationships were relatively stable across models.

In all models, the WLS method and robust standard errors were applied to ensure consistency in the presence of potential heteroskedasticity. The fourth model, in particular, demonstrated the robustness of the findings by addressing distributional issues in the residuals.

	(1)		(2)		(3)		(4)	
	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
Job displacement								
AI replacing jobs	-0.0178 (0.005)***	0.006	-0.0299 (0.000)***	0.005	-0.0366 (0.000)***	0.007	-0.0397 (0.061)*	0.022
Personal ability to adapt	0.1111 (0.000)***	0.009	0.0472 (0.000)***	0.009	0.0590 (0.000)***	0.013	0.0643 (0.082)*	0.037
Control variables								
Trust in institutions			0.0128 (0.000)***	0.001	0.0146 (0.000)***	0.002	0.0158 (0.002)***	0.005
Attitude toward AI			0.0005 (0.000)***	0.000	0.0004 (0.000)***	0.000	0.0005 (0.149)	0.000
Human-like trust in AI			0.0028 (0.059)*	0.001	0.0024 (0.232)	0.002	0.0050 (0.466)	0.007
Functionality			-0.0001 (0.111)	0.000	-0.0001 (0.069)*	0.000	-0.0001 (0.780)	0.000
Perceived ease of use			0.0005 (0.023)*	0.000	0.0006 (0.050)*	0.000	0.0009 (0.346)	0.001
Perceived usefulness			0.0014 (0.000)***	0.000	0.0013 (0.000)***	0.000	0.0011 (0.277)	0.001
Demographics								
Age					0.0166 (0.027)**	0.007	0.0192 (0.310)	0.019
Education					0.0240 (0.001)**	0.007	0.0234 (0.374)	0.027
Industry Tech					0.0006 (0.972)	0.017	0.0137 (0.807)	0.052
Employment full-time					-0.0440 (0.007)***	0.016	-0.0376 (0.499)	0.056
WLS	X		X		X		X	
Robust SEs	X		X		X		X	
Bootstrap							X	

Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.4: Regression results for different model specifications

4.3 Discussion

The results from the four models, as presented in Table 4.4, consistently highlighted the significant relationship between “Fear of job displacement” and “Trust in AI”. Across the first three models, “Fear of job displacement” had a negative and highly significant impact on trust in AI, with coefficients ranging from -0.0178 to -0.0366. These findings aligned with prior studies that emphasized the negative perception of AI in the workplace and its potential to displace jobs (Brynjolfsson et al., 2014). In model (4), where the Bootstrap method was applied to address the issue of non-normality, the coefficient for “Fear of job displacement” remained negative but became marginally significant ($p = 0.061$), suggesting that the relationship was sensitive to the method of estimation. Comparable studies have reported similar magnitudes and significance when examining perceptions of job displacement and automation (Frey and Osborne, 2017a).

It is also important to note that the dependent variable, “Trust in AI”, was transformed using a logarithmic scale. As such, the coefficients in all models represented the percentage change in the dependent variable for a one-unit change in the independent variable (Wooldridge, 2015). Specifically, in model (4), a coefficient of -0.0397 for “Fear of job displacement” indicated that a one-unit increase in fear corresponded to a 3.97% decrease in trust in AI. This highlighted the detrimental effect that fear of automation can have on individuals’ trust in AI technologies.

“Personal ability to adapt” was positively associated with trust in AI in all models, with coefficients ranging from 0.0472 to 0.0643, all of which were significant at least at the 10% level. This consistent positive relationship suggested that individuals who believe in their capacity to adapt to technological changes were more likely to trust AI. These findings were consistent with previous research on individual adaptability and resilience in the face of workplace technological changes (World Economic Forum, 2018). The significance of this factor underscored the critical role of personal resilience in maintaining trust in AI, even when individuals are faced with fears of job displacement.

The control variables, such as “Trust in institutions” and “Attitude toward AI”, were also highly significant across different models. “Trust in institutions” consistently had a positive effect on trust in AI, with coefficients ranging from 0.0128 to 0.0158, confirming the buffering role of institutional trust against technological anxiety (Choi et al., 2020). “Attitude toward AI” was significant in models (2) and (3), with coefficients around 0.0005, indicating that individuals who hold more favorable attitudes toward AI are more likely to trust it, consistent with earlier findings (Lankton et al., 2015).

Meanwhile, variables such as “Human-like trust in AI” and “Functionality” showed varying levels of significance. For example, “Human-like trust in AI” was significant at the 10% level in model (2) but lost significance in later models, indicating that its impact might be less stable across specifications. This variability is common in studies exploring human-AI interactions, where anthropomorphic features can have context-sensitive effects on trust (Glikson and Woolley, 2020). Similarly, “Perceived ease of use” and “Perceived usefulness” were significant

in early models but lost significance in model (4), likely due to the introduction of Bootstrap robustness adjustments, which typically increase standard errors. This trend is consistent with studies on the adoption of new technologies, where these factors are significant only under certain modeling assumptions (Davis, 2019).

Among the demographic variables, “Age” and “Education” were significant in model (3), with coefficients of 0.0166 and 0.0240, respectively, suggesting that older and more educated individuals are more likely to trust AI. This finding is in line with previous research showing that older, more educated individuals are more open to technological advancements (Center, 2017). However, in model (4), these variables lost their significance due to the application of the Bootstrap method, which increased the standard errors. “Industry Tech” and “Employment full-time” did not show significant effects in most models, implying that these factors may not play a substantial role in determining trust in AI within this sample.

The models utilized both WLS and Robust Standard Errors in models (1) through (3) to address potential heteroskedasticity. In model (4), the Bootstrap method was applied to account for the non-normality observed in the residuals (Efron and Tibshirani, 1994). The application of the Bootstrap method resulted in larger standard errors, which in turn reduced the significance of some variables. Nevertheless, the coefficients remained relatively stable, suggesting that the key relationships were robust even when addressing issues of non-normality. This method aligned with best practices in statistical modeling when normality assumptions are violated.

Overall, the results suggested that fear of job displacement and personal adaptability are key predictors of trust in AI. Control variables such as trust in institutions and attitudes toward AI also played crucial roles in shaping individuals’ trust in these technologies. The use of the Bootstrap method in model (4) provided additional robustness, though it highlighted the importance of addressing non-normality in the data. These findings were consistent with previous research on AI, trust, and job displacement (Brynjolfsson et al., 2014; Frey and Osborne, 2017a).

Chapter 5

Conclusion

This dissertation set out to explore the intersection between trust in AI services and the growing fear of job displacement, an issue that is becoming more pertinent as AI technologies increasingly dominate various industries. The research was driven by two central questions: What factors influence trust in AI services, and is there a correlation between trust in AI and the fear of job displacement? By addressing these questions, this study sought to provide a deeper understanding of how users perceive AI in service industries and how concerns over job security might influence their trust in these technologies. The quantitative analysis conducted in this study has revealed several important findings that contribute to both the academic discourse on AI and practical strategies for businesses looking to implement AI systems in a way that fosters trust while addressing concerns about job security.

The first key finding from this research is the confirmation that trust in AI services is a multifaceted concept, influenced by a range of factors including transparency, reliability, and fairness. These findings aligned with previous literature on the topic, which has long recognized that trust in technology is not a binary outcome but rather exists on a spectrum shaped by users' perceptions of how a system operates. In this study, control variables such as "Trust in institutions" and "Attitude toward AI" emerged as determinants of trust in AI, with consistent significance across all models. These results suggested that individuals who have higher levels of trust in institutions were more likely to extend that trust to AI systems, particularly in service-related industries. Moreover, a positive attitude toward AI further enhanced trust, underscoring the importance of both individual predispositions and societal trust in shaping users' willingness to engage with AI technologies.

The second significant finding relates to the fear of job displacement. As hypothesized, the fear of losing jobs to AI had a strong and negative impact on trust in AI systems. This relationship was consistently observed across all models, with the fear of job displacement acting as a significant predictor of reduced trust in AI. The results suggested that individuals who were concerned about the impact of AI on employment were less likely to trust these systems, even when controlling for other factors such as personal ability to adapt and general attitudes toward technology. This finding supported previous studies that have highlighted the negative psycho-

logical and social effects of automation anxiety, where fears about job security diminish users' confidence in emerging technologies. As industries increasingly adopt AI-driven automation, this research highlighted the need for organizations to address these fears directly to mitigate the erosion of trust in AI systems.

Importantly, the role of personal adaptability was also explored in this study. The results indicated that individuals who believe in their personal ability to adapt to technological changes were more likely to trust AI services. This finding is particularly relevant in light of the ongoing debates about the future of work and the skills required to thrive in an AI-driven economy. Individuals with a greater sense of adaptability may feel more empowered and less threatened by the advent of AI, thereby fostering a more positive outlook on AI's role in service industries. The significance of personal adaptability in determining trust in AI aligns with broader discussions in the literature on resilience and technological change, where the ability to upskill and adjust was seen as a buffer against the negative effects of automation. These insights suggest that enhancing workers' adaptability through education and training may not only improve their employability but also increase their trust in AI systems.

In addressing the second research question, this study found a clear correlation between trust in AI and the fear of job displacement. The negative relationship between these two factors suggested that as fears about job displacement increase, trust in AI services decreases. This dynamic is important for both academic understanding and practical applications because it indicates that the social and emotional aspects of AI adoption are just as critical as the technical ones. Businesses seeking to implement AI technologies must recognize that fostering trust involves addressing not only how the technology functions but also how it is perceived in terms of its broader societal impacts, particularly on employment. By understanding the relationship between fear and trust, organizations can better navigate the complexities of AI adoption and develop strategies that reassure workers about their future roles in a changing technological landscape.

Another notable aspect of this research was the application of the Bootstrap method in model (4) to account for the non-normality of the residuals. This methodological step provided an additional layer of robustness to the findings, ensuring that the results are reliable even in the presence of distributional issues. The use of Bootstrap highlighted that while the general trends remained stable across the models, the statistical significance of some variables was affected by the increased standard errors in the final model. This finding emphasized the importance of using appropriate statistical techniques when dealing with non-normal data and adds credibility to the conclusions drawn from this analysis. It also reinforced the notion that trust in AI is a complex issue that cannot be fully captured through traditional linear models, given the potential for underlying distributional challenges.

The implications of these findings can be wide-reaching, particularly for policymakers and business leaders who are grappling with the dual challenge of integrating AI into service industries while maintaining public confidence in these technologies. The research suggests that

building trust in AI requires a multifaceted approach that not only addresses the technical performance of AI systems but also engages with the social and psychological concerns of users. Businesses must invest in transparency and communication strategies that demystify AI processes and make them more accessible to the public. At the same time, policies aimed at reskilling workers and promoting adaptability will be essential for alleviating fears of job displacement and fostering a more positive attitude toward AI.

Finally, despite the valuable insights gained from this research, it is important to acknowledge its limitations. One key limitation is the relatively small sample size of 137 responses, which restricts the generalizability of the findings. Although the sample of questionnaire answers provided a useful overview of participants' views on AI and job displacement, the limited number of respondents may not fully capture the diversity of opinions that exist within the broader population. In particular, the demographic distribution of the participants suggested a skew toward individuals in their early to mid-career stages. This group, potentially more exposed to technology due to their career stage, may have different perceptions of AI compared to younger or older individuals, which could impact the study's findings on trust in AI and fear of job displacement. Consequently, the results may not be fully reflective of the attitudes of individuals from different age groups, educational backgrounds, or career stages. Moreover, the sample also reflects a relatively educated and professionally active demographic, with a significant portion of respondents holding a bachelor's or master's degree and being employed full-time. This highly educated and career-focused sample may have more favorable attitudes toward AI and greater adaptability compared to other groups, such as those with lower educational levels or part-time employment. Additionally, the industries represented, particularly the higher concentration of participants from the technology/IT and service sectors, may have further biased the results, as individuals working in these industries were likely to have more direct exposure to AI technologies. Therefore, while the findings offer valuable insights into the perspectives of a specific subset of individuals, caution should be exercised when attempting to generalize the conclusions to a wider population, as the sample may not fully represent the diversity of views that exist in society regarding AI, trust, and job displacement, and future research should address those biases in a more systematic manner.

In conclusion, this dissertation has provided valuable insights into the relationship between trust in AI services and the fear of job displacement. The findings underscore the importance of addressing both the technical and social dimensions of AI adoption. By examining the factors that influence trust and understanding the role of fear in shaping attitudes toward AI, this research offers a comprehensive framework for approaching AI integration in service industries. As AI continues to evolve and reshape the labor market, future research should continue to explore how trust and fear interact in different contexts and industries, providing further guidance for responsible and ethical AI implementation.

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