Exploring Generation Z's Use of AI Advice in Business Decision-Making

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Abstract

Title: Exploring Generation Z's Use of AI Advice in Business Decision-Making

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There is an increasing number of companies employing AI in business decision-making. Companies are composed by a diverse workforce with different experiences and backgrounds thus, it becomes imperative to understand if generations rely differently on AI. This thesis aims to understand the differences between Generation Z and Generation X regarding their reliance on AI advice and explore how this relationship is affected by trust. Additionally, it assesses the moderating effect of confidence in own judgement. To collect the data, a quantitative between-subjects survey was employed, where participants from both generations were presented with two hypothetical decision-making scenarios to evaluate their reliance on AI advice. Findings reveal that Gen Z relies more on AI advice compared to Gen X. Interestingly, no significant differences were found in dispositional trust in AI between the two generations. However, a strong positive correlation was identified between dispositional and situational trust, with situational trust significantly enhancing reliance on AI advice. This indicates that higher levels of situational trust are correlated with greater reliance on AI. Surprisingly, the moderating effect of confidence in own judgment was not confirmed. Exploratory analysis suggests that familiarity with AI might mediate the relationship between generational differences and reliance on AI advice. Additionally, it was found that higher confidence in own judgement negatively impacts reliance on AI advice. These insights underscore the complexity of understanding how trust affects reliance on AI across generational cohorts and highlight the importance of considering this factor in order to foster effective AI integration strategies within companies.

Keywords: Artificial Intelligence, Generation Z, Generation X, Business Decision-Making, AI Advice, Trust

Sumário

Título: Explorar a utilização de Inteligência Artificial, pela Geração Z, no processo de tomada decisões empresariais

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À medida que mais empresas integram Inteligência Artificial (IA) nos seus processos de tomada de decisão, torna-se crucial compreender se pessoas de diferentes idades depositam diferentes níveis de confiança em IA. A presente tese visa compreender as diferenças entre a Geração Z e Geração X quanto à utilização de IA e explora como esta relação e mediada pela confiança depositada em IA. Além disso, explora o efeito moderador da confiança que os indivíduos depositam no seu próprio julgamento. Os dados foram recolhidos através de um inquérito quantitativo, onde os participantes foram apresentados com dois cenários hipotéticos de tomada de decisões. Os resultados revelam que a Geração Z confia mais em IA do que a Geração X. Curiosamente, não foram encontradas diferenças significativas na confiança disposicional em IA entre as duas gerações. No entanto, foi encontrada uma forte correlação entre a confiança disposicional e situacional, com a confiança situacional a aumentar significativamente os níveis de utilização de IA. Surpreendentemente, o efeito moderador da confiança no próprio julgamento não foi confirmado. A análise exploratória sugere que a familiaridade com a IA pode mediar a relação entre as diferenças geracionais e a utilização de IA. Verificou-se ainda que uma maior confiança no próprio julgamento afecta negativamente a utilização de IA. Estas conclusões sublinham a complexidade da compreensão da forma como a confiança afecta a adoção da IA entre grupos geracionais e realça a importância de considerar este elemento para promover estratégias eficazes de integração da IA nas empresas.

Palavras-chave: Inteligência Artificial, Geração Z, Geração X, Tomada de Decisões Empresariais, Conselhos de IA, Confiança

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List of Abbreviations & Symbols

AI	Artificial Intelligence
Gen X	Generation X
Gen Z	Generation Z
GPT	Generative Pre-trained Transformer
IoT	Internet of Things
IQR	Interquartile Range
JAS	Judge-Advisor System
LMM	Linear Mixed Model
M	Mean
ML	Machine Learning
R-square	Coefficient of Determination
SD	Standard Deviation
WOA	Weight of Advice
α	Significance Level
&	And

1 Introduction

"*While AI will radically alter how work gets done and who does it, the technology's larger impact will be in complementing and augmenting human capabilities, not replacing them.*"

Wilson and Daugherty, 2018

1.1 Relevance of the Topic

AI has been a topic of extreme relevance in the past years, not only for individuals but also for companies (Wilson & Daugherty, 2018). Due to the vast amounts of data available today, which, when correctly analysed, provides valuable insights, companies have turned to Artificial Intelligence (AI) to exploit this data and help them make more informed decisions. This accounts for a significant shift in the decision-making process that, previously, was highly dependent on traditional methods like manual data analysis, relying mainly on human expertise (Füller et al., 2022). Previous research from Provost and Fawcett (2013) and Wilson and Daugherty (2018) have emphasised the importance of using this technology for automating complex analysis, providing data-driven insights and enhancing decision-making while also reducing human bias present in most decisions.

Supported by the increase in available data, AI is able to augment judgements by analysing data and identifying patterns that go beyond the capabilities of humans (Wang et al., 2019). On the other hand, it is crucial to acknowledge the evidence that AI is also subject to errors. AI systems can manifest biases, reflecting those found in their human creators or the data they are trained on (Binz & Schulz, 2023). For companies to fully capitalise on their AI investments, they must first guarantee that their employees are willing to trust and rely on these systems. Previous literature suggested that not everyone relies on AI systems to the same degree (Logg et al., 2019). Moreover, companies employ a wide range of individuals with different characteristics and age groups. While there has been previous literature on how different generations use technology (Kian & Yusoff, 2012; Pichler et al., 2021), how this affects their reliance on AI is still unclear. This study aims to fill this gap by comparing the AI reliance between Generation Z (Gen Z) and Generation X (Gen X), providing crucial insights for organisations aiming to effectively integrate AI into their operations.

The findings will guide companies in tailoring AI implementation strategies and educational initiatives to account for generational preferences and capabilities. Furthermore, this research will bring insights to AI developers on how to build user-centric algorithms, potentially increasing AI adoption.

1.2 Research Objective

AI has been widely applied in the business context and has proven to help individuals make more accurate decisions in various fields, including healthcare, finance, Law, and others (Lai et al. 2021). By leveraging the data available and reducing potential biases, AI systems have been used to improve the quality of decisions (Wang et al., 2019). At this point, it is imperative to understand whether individuals are ready to rely on AI systems to support their decisions or if there is still some resistance to using AI systems in business. Different research has yielded different conclusions about this matter, empathising the complexity of the topic and the need for further research. On the one hand, despite the fact that algorithmic judgements may outperform human judgement in several settings (Vodrahalli et al., 2022), according to Castelo et al. (2019), individuals are still reluctant to rely on its advice. On the other hand, a more recent stream of research shows that individuals prefer to rely on algorithm advice compared to human advice (Logg et al., 2019). Having these two contradicting perspectives, it is vital to understand the factors that led individuals to rely on AI systems. According to Lee and See (2004), the reliance on automation systems is highly influenced by the level of trust individuals have in AI and other factors, such as their confidence in own judgement. This thesis aims to combine this finding and better understand the effect of trust in AI and confidence in own judgement on reliance on advice.

Furthermore, this thesis introduces a component to the research, which is the generational characteristics. Previous research conducted in generational cohorts, particularly studies conducted by Pichler, Kohli, and Granitz (2021) and Lanier (2017), substantially contributed to our knowledge of the distinct features and technological inclinations of various generations. These studies provide an in-depth perspective on the diverse degrees of technology use and familiarity across different generations. However, little research has compared how people from different generations trust AI and utilise its advice. This thesis addresses this research gap by analysing how different generations, namely Gen Z and Gen X, trust AI and consequently rely on its advice.

It is important to understand how generational differences influence individual's reliance on AI advice, considering their different career stages and levels of technical proficiency. Gen X often occupies senior positions and holds considerable influence over strategic decisions (Asoba & Mefi, 2022a). It becomes essential for them to embrace new technologies in order to sustain their competitiveness in the market. On the other hand, Gen Z, who are joining the workforce at a fast pace, will soon make up a significant portion of the labour market. Their inherent aptitude for digital technology and high expectations for its application in the workplace will determine the future patterns of technology adoption inside organisations. Recognising these generational differences is crucial because variations in AI reliance across various groups might significantly impact workforce management, training programs, and the overall success of AI integration in businesses.

In order to address the research gap previously identified, the following research question was developed:

Research Question: "How do generational differences between Gen Z and Gen X impact their trust and reliance on AI advice in the decision-making processes?"

Given the complexity of this question and to better understand the nuances of all the variables that compose the study, I aim to answer the following questions: 1) Are Gen Z individuals more likely to trust AI advice when compared to Gen X?, 2) Are Gen Z individual more likely to rely on AI advice than Gen X?, 3) Are higher levels of trust in AI-related to an increase in the reliance on AI advice?, 4) How does the confidence individuals show for their decisions influences the relationship between trust and the reliance on AI advice?.

The answer to these questions is not evident based on the existing literature. Thus, to better understand this phenomenon, an experimental survey was developed. A total of 206 participants took part in the study where they were presented with two decision-making scenarios (*house price prediction* and *song forecasting*) and had to make predictions. After being presented with the AI advice, the participants were asked to reevaluate their initial predictions, which allowed me to measure their reliance on AI advice. Additionally, the survey contained questions that aimed to measure the participants' level of trust in AI.

The research objective is to explore how trust in AI varies across generations and its impact on their reliance on AI for decision-making. Assessing generational differences in AI trust and reliance is crucial as it guides the development of customised AI implementation strategies and educational initiatives. Gaining insights into these differences enables the development of AI systems and interfaces that are inclusive and attractive to individuals of all age groups, hence fostering fair and efficient integration of AI. It will provide practical implications for businesses and organisations in optimising AI strategies for a diverse workforce. This research can also guide AI developers (that align with the distinctive characteristics and preferences of different generations, hence improving overall user engagement. Lastly, understanding these differences is crucial for addressing potential labour market disparities that may arise from unequal AI proficiency among employees. A crucial policy issue is ensuring workers have the appropriate skills to effectively use emerging technologies (Felten et al., 2021).

1.3 Structure of Thesis

This master thesis is structured in seven main Chapters. The first Chapter focuses on introducing the topic and research objective as well as stating the specific research question at hand. The second Chapter focuses on conducting an extensive literature review covering topics such as generational differences, the processes of decision-making, and the role of AI in business decision-making. Sequentially, Chapter 3 is based on the literature reviewed in the previous Chapter and derives the hypothesis to test in the experimental survey as well as provides the conceptual framework. Chapter 4 introduces the methodology used to test the hypothesis derived from the previous Chapter. Chapter 5 analyses the data and derives the most important insights and findings. Subsequently, Chapter 6 is dedicated to the discussion of the results, together with the implications, limitations and future research streams. Lastly, the conclusion is presented, summarising the results and takeaways of the research.

2 Literature Review

2.1 Generation Z vs Generation X

A Generation is defined as people born in the same historical, social, and chronological period (Twenge, 2010). The number of companies that aim to introduce AI in their decision-making process is increasing. Considering the rapidly evolving landscape of the modern workforce, understanding the dynamics between generations and their reliance on AI advice becomes highly important.

Gen Z includes individuals born between the years of 1997 and 2012, and this is the first generation to be considered "*digital natives*" (Lanier, 2017; Pichler et al., 2021). Because they were raised in a setting that was highly connected to technology, they inherently gravitate toward digital communication and employ technology-centric methods for learning and problem-solving. It is widely acknowledged that this generation is characterised by their higher familiarity with technology and a preference for pragmatic solutions (Pichler et al., 2021). Furthermore, by 2025, Gen Z workers are expected to account for 27% of the *OECD* workforce (Bloomgarden, 2022), so a better understanding of how they work and interact with technology is crucial. According to Seemiller and Grace (2015), Gen Z exhibits a significant reliance and dependency on technology, with 90% of participants expressing distress over losing internet access.

By understanding this generation's relations with technology, one can infer the importance of engaging Gen Z through digital means in various contexts, including in the business context. This study builds on the idea that Gen Z, being *digital natives*, want to integrate the latest technological developments in their professional jobs and use this technology to enhance problem-solving. Their familiarity with technology and openness to integrate it into their lives leads me to believe that this generation is more likely to trust AI and thus rely on its advice. Additionally, given that they perceive technology as an opportunity to enhance productivity and personal development, Gen Z anticipates their workplaces to be at the forefront of technological advancements (Schroth, 2019). Gen Z strongly prioritises finding work experiences reflecting their beliefs and purposes. They seek positions that not only relate to their aspirations but also provide opportunities for making a meaningful contribution and fostering innovation. Thus, if companies want to attract a motivated and tech-oriented workforce, they have to promote an environment within the organisation that not only welcomes but develops the digital proficiency of employees. When exploring the intersection between AI and business decision-making, this research focuses on how Gen Z's unique workplace preferences and background influence their trust and reliance on AI. Gen Z values dynamic, engaging environments where their ideas are actively incorporated, suggesting they may also appreciate AI tools that enhance task efficiency and decision quality. This research aims to quantify whether there is indeed a higher trust towards AI among Gen Z compared to Gen X and whether this trust translates into greater reliance on AI in their decision-making processes. Understanding this correlation is crucial for companies, as it indicates the necessity to tailor AI integration strategies to harness the distinctive characteristics of Gen Z, who are joining the workforce.

Conversely, Gen X, which consists of individuals born from 1965 to 1980 (Beresford Research, 2024), holds distinctive characteristics from Gen Z that might impact their degree of trust and reliance on AI. This generation grew up in a period when they were not surrounded by technology, which affected how they interacted with it. Nowadays, they have adapted to the digital era, although their early years were not as significantly impacted by it as the subsequent generations were. According to Kian and Yusoff (2012), this generation places a high importance on independence and self-reliance when it comes to problem-solving. Since they are not as familiar with technology as individuals from the following generations, they have developed a certain level of scepticism towards new technology, especially AI (The Economic Times, 2021).

Asoba and Mefi (2022b) state that there is a generational gap between individuals of Gen X and other generations when it comes to the use of technology. They approach AI with reservations and optimism, seeing its capacity to enhance operational effectiveness in scenarios where its applications are clear and advantageous. Research suggests that individuals value technology that increases their autonomy and productivity, and they favour AI solutions that support human judgment instead of replacing it (Kapoor & Solomon, 2011). Despite their initial hesitation about implementing new technology, they see its potential to enhance productivity. One possible approach for effectively employing AI in the workplace with Gen X could be to design systems that leverage their experience and enhance their capacity to solve problems independently (Kapoor & Solomon, 2011). This pragmatic approach to AI in the workplace underscores a preference for tools that streamline processes, facilitate decision-making, and foster productivity, aligning with their goal-oriented and results-driven focus. Moreover, when it comes to reliance on others' advice, prior literature has claimed that, compared to younger individuals, this generation is characterised for having more rigid beliefs and is less receptive to relying on advice from others (Hess & Pullen, 1994).

The different experiences and backgrounds of Gen Z and Gen X may influence their willingness to rely on AI technology in the workplace and this relation is what the current study aims to address. Since Gen Z was raised in a world where technology was valued above all else, they are more likely to naturally trust and rely on AI. Their expectations of a work environment centred around technology derive from their digital fluency and willingness to adapt (Harari et al., 2023). On the other hand, Gen X's background leads them to have a more cautious view of technology. Even though they see its potential and are willing to adopt it, they are more sceptical and need strong evidence that this technology can disrupt traditional workplace methods.
Even though both generations are capable of using AI effectively, there may be differences in how much each generation relies upon and trusts AI due to their technological experiences and backgrounds.

2.2 Understanding the Decision-Making Process

The study at hand focus on exploring the use of AI in business decision making. In the following Chapters, I will review literature on human decision-making processes to establish a foundational understanding on how individuals make decisions and what are some biases that influence the process. This background will help assess how AI can potentially streamline this process and increase the quality of decisions made (Alon-Barkat & Busuioc, 2023).

People have to make hundreds of decisions every day, both at work and in their personal lives. The persistent question is how people make decisions. (Samuelson & Zeckhauser, 1988). The decision process is defined by Mintzberg, Raisinghani, and Théorêt (1976, p. 246) as a “set of actions and dynamic factors that begins with the identification of a stimulus for action and ends with the specific commitment to action.”. To arrive at the most effective decision, this procedure requires an in-depth analysis, evaluation, and prioritization of every relevant factor influencing the decision (Johns, 1996).

2.2.1 Bounded Rationality

Despite seeking rationality in the decision-making process, individuals often encounter constraints such as uncertainty, limited time, and personal biases, which leads them to rely on heuristics (Kahneman, 2003; Camerer, 1998; Simon, 1955). This concept, known as bounded rationality, explains that humans are inherently limited by their cognitive shortcuts, leading to deviations from optimal judgment (Simon, 1955). Recognizing the impact of bounded rationality can significantly enhance the quality of decisions, thereby benefiting individuals and organizations (Milkman et al., 2009).

Additionally, it is essential to recognize the role of uncertainty in the organizational decision-making processes. Berkley and Humphreys (1982) highlighted that decisions often emerge as reactions to uncertain situations. This uncertainty is particularly prevalent in dynamic environments where high-quality decisions must be made quickly despite having limited capacity to process vast amounts of information in a short period of time. Thus, the capacity for quick decision-making becomes crucial for organizational success (Eisenhardt & Bourgeois, 1988). This underscores the importance of refining decision-making strategies to enhance agility and precision, acknowledging the constraints posed by the lack of human processing capacity (Eisenhardt, 1989).

2.2.2 Heuristics and Cognitive Bias in Business Decision-Making

Heuristics streamline the process of decision-making by allowing individuals to review fewer data points and simplify the importance of different information, thus minimizing the amount of data processed and ultimately limiting the number of alternatives considered. They provide mechanisms to facilitate decision-making. However, heuristics can also lead to sub-optimal decisions which are often mentioned as cognitive biases (Shah & Oppenheimer, 2008). Previous research indicated that the most common biases in decision-making reduce the accuracy of judgments (Samuelson et al., 1988). Bazerman and Moore (2012) have highlighted three key biases that have a significant impact on decision-making, that are availability bias, anchoring bias, and overconfidence bias. This study will focus on Overconfidence bias which refers to the inclination of individuals to overrate their knowledge, skills, and the precision of their forecasts, leading to an increased feeling of assurance that exceeds what is supported by evidence (Fischhoff et al., 1977). AI has the potential to optimize the decision-making process by making less biased decisions but at the same time it might also amplify biases (Alon-Barkat & Busuioc, 2023).

2.2.3 Overconfidence in Business Decision-Making

In this Section, I will analyse how overconfidence impacts business decision-making. This bias holds significant importance for my thesis as I will further analyse how individual's confidence in their judgements moderates the relationship between trust and reliance on AI advice. Individuals frequently exhibit a rooted overconfidence in their opinions and beliefs, which goes beyond simply failing to grasp one's limitations (Russo & Shoemaker, 1992).

In business settings, overconfidence has proven to impact decision-making significantly. For instance, Malmendier and Tate (2015) discovered that CEOs with higher confidence levels tend to retain their company stocks longer, reflecting an altered perception of risk that could cover the actual risks inherent in strategic choices. Moreover, this trait also impacts managerial decisions, such as issuing management forecasts and financial decisions. Overconfident individuals who believe strongly in their company's future are more prone to issuing forecasts (Libby & Rennekamp, 2012). Additionally, they are more likely to overvalue projected cash flows, leading to higher than advisable debt levels (Dedu et al., 2012). Therefore, many market inefficiencies have been attributed to overconfidence. Organisations can improve their overall effectiveness and resilience by adapting decision-making approaches to mitigate the impact of biases and optimising outcomes in uncertain environments. Moreover, it is essential to recognise the irreversible consequences of decisions, as biases can result in costly errors (Milkman et al., 2009). By acknowledging and addressing these cognitive biases, both individuals and organisations can strive for more knowledgeable and efficient decision-making approaches. This emphasises the significance of critically assessing and adapting in order to achieve rationality.

To address the problems that arise from the challenges mentioned previously, companies are increasingly using technology as part of their decision-making process (Phillips-Wren et al., 2009). Technology supports decision-makers by helping them choose valuable data and by supporting them in the interpretation of results (Phillips-Wren, 2012). Additionally, it establishes a logical framework for evaluating different options, which helps reduce human cognitive biases (Doumpos & Grigoroudis, 2013). Thus, the following Section will explore the impact of the emerging technology, AI, on business decision-making.

2.3 Artificial Intelligence

2.3.1 The Continuous Evolution of AI

The emergence of AI more than six decades ago triggered a revolutionary process in the areas of computing and data analysis (Pan, 2016). Due to the complexity and continuous progress of the science, a universally accepted definition of AI remains ambiguous despite its longstanding existence. Initially, Professor J. McCarthy and his colleagues conceptualized AI as the "ability of machines to understand, think, and learn in a similar way to human beings, indicating the possibility of using computers to simulate human intelligence." (Crevier, 1993 cited on Pan, 2016, p.410). Subsequently, this concept has been broadened to include the capacity of algorithms to acquire knowledge through experience, adjust to new inputs, and enhance their performance over time (Duan et al., 2019) as a result of notable developments in data processing and storage technology (Burgess, 2018).

Nowadays, companies have shown a growing interest in this technology and are implementing it to enhance their decision-making processes (Ransbotham et al., 2017). The significant advancements leading to the development of AI have been facilitated by the exponential increase in data availability (Gentsch, 2018) and the widespread adoption of *Internet of Things (IoT)* devices, which significantly add to the amount of data generated by machines (Sides et al., 2019). However, there is a dual-edged sword when we talk about *Big Data*. On the one hand, it offers vast opportunities for gaining societal and economic knowledge, but on the other hand, it also creates substantial barriers to effectively manage and extract value from this data (Labrinidis & Jagadish, 2012). This is where advanced algorithms and computing infrastructures add value as they are instrumental in navigating these challenges, strengthening the fundamental role of AI in this emerging era (Fahad et al., 2014).

Building upon the foundational aspects and transformative impact of AI and Big Data outlined previously, it becomes essential to address the critical challenge of synthesizing vast datasets into actionable intelligence. The task at hand is not merely the accumulation of data but the strategic integration and analysis of this data to uncover patterns and trends vital for decision-making (Cheng & Hackett, 2021). For organizations aiming to secure a competitive edge in this dynamic landscape, the deployment of AI extends beyond the implementation of advanced technologies. An extensive redesign of decision-making processes is necessary to fully harness the range of AI's capabilities, guaranteeing that investments in AI translate into significant operational and strategic benefits (BCG, 2024). It is essential to understand how AI works but even more important to understand how individuals perceive and rely on this technology.

2.3.2 AI in Business Decision-Making

AI has the capability to outperform individuals in regard to information processing, analytical ability, and learning capacity. Consequently, it has been increasingly implemented in many organisational processes (Jarrahi, 2018). Its adoption is not captive to one domain, as many fields, ranging from Law to Business and Medicine, have seen the potential and started implementing AI (Lai et al., 2021). As this research focuses on business decisions, the subsequent Section will explore in more detail the specific types of decision-making tasks in which AI has been implemented. Numerous studies have demonstrated that AI has been consistently used to assist or augment human decision-making processes in areas such as Financial Analysis and Forecasting, Real Estate, Marketing and Customer engagement, Human Resources, and Economic and Environmental Analysis (Chua et al., 2023; Lai et al., 2021; Logg, 2017; Logg et al., 2019; Stone et al., 2020).

When it comes to improving the accuracy of financial predictions and forecasting, AI plays a significant role. In the field of sales forecasting, for example, AI is capable of determining future sales of items or services, which is essential for both planning and inventory management (Lai et al., 2021). Moreover, AI models estimate stock prices based on historical data and market patterns, which supports investors in making informed trading decisions (Chua et al., 2023). Furthermore, in the Real Estate sector, AI has shown high capabilities in making property price predictions. Algorithms are capable of making estimations of real estate properties based on indicators such as location and size, thus contributing to market analysis, investment decisions, and transactions (Lai et al., 2021). In addition, AI effectively augments the decision-making process in Marketing and Customer Engagement by transforming how marketing strategies are developed and enhancing customer interactions. It forecasts the effectiveness of marketing emails, allowing companies to personalise their strategies and achieve maximum engagement (Lai et al., 2021). Additionally, AI technologies can use the data collected to learn about customer preferences and identify patterns unclear to human sight, enabling targeted and efficient customer approaches (Stone et al., 2020). Moreover, within the Human Resources field, AI's predictive algorithms are revolutionising recruiting and job performance evaluations. These algorithms use data from the internet to analyse and anticipate employees' job performance. For example, they evaluate an individual's communication abilities and problem-solving skills, ultimately finding the most promising candidates for recruitment (Logg, 2017). Lastly, AI has shown efficiency in Economic and Environmental Analysis. It can examine patterns and forecast future changes in economic and environmental circumstances. This is crucial for informing policy-makers and providing valuable insights that aid in developing sustainable and economically feasible plans (Logg, 2017).

This highlights an increasing tendency to employ AI advice in business decision-making processes. Previous studies primarily examines the efficacy of AI-assisted decisions, focusing less on the user's readiness to use AI advice (Chua et al., 2023; Lai et al., 2021; Logg, 2017; Logg et al., 2019; Stone et al., 2020), which may also be affected by age-related factors. To bridge this research gap, the present study delves into understanding the correlation between generational differences and an individual's reliance on AI advice.

2.3.3 Criticism and Limitations of Artificial Intelligence

As previously highlighted, AI can transform how decisions are made in the business context by enabling rapid and data-driven decisions and reducing cognitive biases, thereby improving accuracy and efficiency across various domains. This research focuses on understanding how different generations utilise AI for business decision-making. Thus, to better understand why different generations might rely differently on AI, it is crucial to address its main limitations. Assessing AI limitations is imperative as these might play a role in how individuals and organisations rely on this type of technology.

AI is ultimately constrained by its substantial dependence on data, which includes the volume of data needed to feed the algorithms and the data quality. If one of these components is not met, this can promise the accuracy of the AI output. In order to extract valuable insights and to fully understand how useful and generalisable the dataset is, there is the need to know exactly how it was gathered, labelled, and handled and in most cases, this information is not accessible (Daneshjou et al., 2021). Moreover, according to Halevy et al. (2009), the lack of sufficient data may compromise the capacity of AI algorithms to identify patterns and trends, limiting its power to provide precise forecasts and fully understand complex settings. In case companies are using outdated or non-representative data it may hinder the precise evaluation of a situation, perhaps leading to undesirable and costly implications for the company.

Furthermore, the high dependency of algorithms on data makes them extremely vulnerable to the biases present in that data. It is important to recognise the growing evidence that AI systems might exhibit biases, which may mirror those present in their human developers or the data they are taught (Binz & Schulz, 2023). As an example, the study of Binz and Schulz (2023) reveals that while GPT-3 exhibits impressive performance on many tasks, it is still susceptible to different biases that might impact its decision-making and reasoning skills. This reinforces that the underlying data, structure, and techniques the model uses to generate answers are extremely vulnerable to bias, thus perpetuating preconceived ideas. This problem becomes more complex as previous research has identified that individuals tend to over-rely on AI algorithms, even when the system produces biased results (Schemmer et al., 2022). Knowing this, both individuals and corporations should make an effort to wisely use this technology and critically question its outcome.

Another crucial factor to take into account is the concept of the "*black box*". This term refers to any system, particularly in technology and AI, where the processes between input (data) and output (decisions) are not visible or understandable to those outside of the system's development (Pasquale, 2015). This characteristic makes it hard to uncover, analyse, and prevent any biases that may be embedded in the systems (Dewandre, 2015). This raises another issue, which is the accountability of the AI systems (Diakopoulos, 2016; Glikson & Woolley, 2020). Diakopoulos (2016) calls for the attention to understand who should be held accountable when mistakes and discrimination occur. He strongly advocated for the importance of transparency and accountability, suggesting that algorithms should be carefully designed and implemented to take into account their effects on both individuals and society. Glikson and Woolley (2020) further build on this topic, arguing that this is not just a matter of individuals relying on AI, but the system's transparency and reliability highly influence cognitive trust.

Lastly, data privacy and security are two important issues that have gained importance alongside the rapid growth and implementation of AI systems. Since these systems depend on large amounts of data, the way they are collected, stored, and analysed can lead to privacy violations and illegal access to private data. Kuner et al. (2018) argues that attempting to balance the requirements of AI technology with existing data protection laws might seriously compromise data protection regulations or hinder the progress and advantages of AI.

Failing to recognise these limitations of AI can cause unpredictable and extremely costly consequences for individuals and companies. Thus, it is necessary to use AI in a responsible and educated manner. This includes recognising and actively working towards solving AI constraints. Ignoring these limitations decreases AI application's ability to solve complex issues and poses ethical, legal, and social concerns that might damage user trust and AI adoption. Several researchers have expanded upon the concept of using AI as a complementary tool rather than a substitute for human decision-making. This approach enhances human capacities, leading to more educated and accurate judgments while cautiously mitigating its limitations (Claudé & Combe, 2018). This method aligns with the notion of *Hybrid Intelligence*, which will be further explained in the next Section.

2.3.4 The interaction between Humans and AI: Hybrid Intelligence

Exploring the synergy between human intelligence and AI becomes vital, building upon the debates on the emergence of AI, its applicability in business decision-making, and its inherent limitations. This synergy, known as *hybrid intelligence*, captures the cooperation of AI's computing efficiency and human cognitive capacities (Bouschery et al., 2023). The goal of hybrid intelligence is to improve decision-making across a range of domains by establishing a complementary relationship between the two and compensating for each other's deficiencies (Ferràs-Hernández, 2018; Parasuraman & Riley, 1997; van der Aalst, 2021). Hybrid intelligence combines AI's speed of processing and analysis with the unique advantages of human intuition, creativity, and ethical judgment (van der Aalst, 2021). This collaborative effort is crucial in situations where AI may not be sufficient on its own, such as when making decisions that call for ethical considerations, creative thinking, and in-depth contextual knowledge (Shrestha et al., 2019). Shrestha et al. (2019) research suggests different models for structuring human-AI collaboration, including full human-to-AI delegation, hybrid sequential decision-making (either AI to human or human to AI) and aggregated human–AI decision-making.

The first category, full human-to-AI delegation, represents a situation where all decision-making tasks are given to an AI system. This model works most effectively when the decision field is well-defined and decisions can be made using precise, quantitative indicators. AI's capacity to handle vast volumes of data quickly makes decisions in these situations both accurate and efficient. Digital advertising, online fraud detection, and dynamic pricing are common examples of this situation (Shrestha et al., 2019).

The second category, hybrid sequential decision-making, is defined as a process with two structures involving AI and human decision-makers. This category of sequential decision-making is further segmented into AI to human and human to AI, based on which entity starts the decision-making process. In AI to human sequential decision-making, after gathering data, the AI system makes a preliminary judgment, which a human decision-maker subsequently considers, changes, or approves. This method ensures that ethical issues and contextual information are taken into account in the decision-making process by utilising AI's analytical capabilities while maintaining human oversight for the ultimate decision-making stage. An example is idea evaluation and the hiring process. On the other hand, in sequential decision-making involving humans to AI, human input is initially gathered and subsequently enhanced or expanded upon by AI algorithms. Under this concept, human creativity and intuition may be used from the beginning, while AI's computational capability can be used to improve the conclusion. A typical example of this case is health monitoring.

The third category, aggregated human-AI decision-making, is a cooperative method in which decisions are reached by combining human and AI knowledge. This paradigm is based on the idea that combined humans and AI can be more intelligent than either one operating alone. It is especially useful when complex decisions need to be made at the top management teams or board level.

The present research will focus on a scenario where there is an interaction between AI and humans in the sense that AI acts as a decision aid, but humans are responsible for making the final decision. Nevertheless, hybrid intelligence adoption comes with multiple challenges, such as building human-AI trust and maintaining the interpretability of AI-driven choices. This calls for organisational efforts in addition to technical solutions in order to give decision-makers the necessary tools to efficiently work with AI (Lee & See, 2004).

2.3.5 Algorithm Aversion

There is a noticeable conflict in the field of automation between the potential efficiency that algorithms offer and individual's reliance on them. Individuals continue to favour human judgment over AI advice, even in the presence of evidence indicating the better efficiency of automated aids in activities like visual detection (Dzindolet et al., 2002). This phenomenon, known as *algorithm aversion*, occurs as individuals are prone to mistakenly avoid relying on algorithms after witnessing them err, even when these algorithms statistically outperform human decision-making over time (Dietvorst et al., 2015).

Factors including task complexity, the subjective nature of some decisions (Castelo et al., 2019), confidence in own judgement (Lee & Moray, 2004), and lack of understanding of the algorithm (Yeomans et al., 2019) enhance the resistance to trust and adopt these algorithms. For example, individuals show algorithm aversion for tasks traditionally performed by humans, especially if they are considered subjective. They mistakenly think algorithms cannot handle these tasks (Castelo et al., 2019). The present study addresses the effect of confidence in own judgement. Moreover, trust, which guides reliance in complex and unpredictable situations, is compromised by a lack of understanding of the algorithm system workings and an overestimation of one's reasoning capabilities (Lee & Moray, 2004).

Two crucial actions need to be taken to close the gap between users' acceptance of algorithms and their efficacy: fostering transparency and building trust. Encouraging people to fully understand the algorithmic decision-making process can significantly increase their readiness to trust AI advice (Yeomans et al., 2019).

2.3.6 Algorithm Appreciation

On the other hand, a recent stream of research by Logg et al. (2019) suggests a counter-narrative to *algorithm aversion*, *algorithm appreciation*, where people express a clear preference for AI-driven advice over human advice. This shift is evident in several domains, suggesting widespread trust in the consistency and objectivity of algorithms.

There are multiple reasons explaining this phenomenon. First, the decision-making domain strongly affects the level of algorithm appreciation since, in more objective tasks, a constant preference for algorithmic advice is observed (Dijkstra et al., 1998; Logg, 2017; Logg et al., 2019). Nevertheless, when people have to choose between the advice of an algorithm and their own judgment, this appreciation decreases, emphasising the role that self-confidence plays in moderating algorithm reliance. Decision-makers' tendency to trust AI is also influenced by their level of experience thus, more experienced individuals tend to rely less on algorithms (Logg et al., 2019).

This indicates an increasing trust in the objectivity and rationality of algorithms, especially for tasks involving exact logic. This shift raises doubt on earlier theories of *algorithmic aversion* and creates new opportunities for incorporating AI into decision-making processes, highlighting the significance of understanding why people might choose to rely on AI advice.

3 Hypothesis Formulation and Conceptual Framework

Chapter two provided a literature review of pertinent studies on the distinctive characteristics of Gen Z and Gen X, the process of decision-making as well as the biases hindering rational decision making. Additionally, I explored the role of AI in business decision-making, its limitations and concluded by exploring the concept of hybrid intelligence and how individuals might over or under-rely on AI advice. This Chapter focuses on the precise research question stated in Section 1.1. The hypotheses are formulated based on previous research, and a conceptual model is introduced to offer a systematic framework for the dissertation.

3.1 Reliance on AI Advice for Decision Making

In the context of organisational decision-making, asking for advice is an instinctive human behaviour meant to improve judgment and decision results (Bonaccio & Dalal, 2006). Additionally, according to Sniezek & Buckley (1995), people seek advice to confirm their judgments and enhance the quality of their decisions. This approach underlines the inherent benefit of collaborative knowledge over individual decision-making procedures and is especially common in challenging or uncertain circumstances where the stakes are high.

The *Judge-Advisor System* (JAS) paradigm offers a methodical framework for evaluating the complex nature of interactions between those who are giving and receiving advice (Sniezek & Buckley, 1995; Tauchert & Mesbah, 2019). Within this paradigm, there are the judge (decision-maker) and the advisor (who provides the advice). Sniezek and Buckley (1995) argue that the judge is the ultimate decision-maker and has complete power, while the advisor only contributes by providing insights to take into account for the final decision. In the context of this research, the judge represents the individual making the final decision, while the advisor is the AI system. The advisor's experience and the quality of the advice are among the variables considered when assessing the advisor’s recommendations. This paradigm makes it possible to understand advice utilisation methodically and understand the role that factors, such as perceived expertise, power, experience, trust, and confidence in own judgement, play in the efficacy of advice utilisation (Bonaccio & Dalal, 2006; Logg et al., 2018; See et al., 2011; Van Swol & Sniezek, 2005).

Empirical evidence suggests that individuals in positions of power, who often are more experienced, tend to disregard advice, potentially due to higher confidence in their own judgment (See et al., 2011). This is particularly true for Gen X, who commonly hold senior roles in organisations and exhibit stronger self-confidence and established beliefs (Hess, 1994). Consequently, they may show less propensity to seek or rely on advice. In contrast, Gen Z, being newer to the workforce, may not exhibit the same level of self-confidence and could be more open to embracing AI-driven advice.

According to Asoba and Mefi (2022b), Millennials, compared to Gen X, are more inclined towards using technological systems and platforms. Considering that Gen Z is notably more familiarized with technology than Millennials, it is logical to assume that this connection may extend further, resulting in Gen Z displaying a greater dependence on AI in comparison to Generation X.

Based on those empirical findings, I argue that Gen Z is more likely to rely on AI advice. Thus, my first hypothesis goes as follows:

H1: Generation Z shows, on average, more reliance on AI advice compared to Generation X.

The main focus of the JAS research has been on human-to-human interactions (Bonaccio & Dalal, 2006). However, as previously covered in Section 3.2, integrating AI in business decision-making processes adds an innovative dimension to the traditional JAS paradigm, suggesting the emergence of hybrid intelligence systems that combine human and AI capabilities (Tauchert & Mesbah, 2019).

The evolving dynamics of advice, propelled by this integration, underscores the importance of reevaluating trust in AI systems. According to Parasuraman and Riley (1997), human judges tend to either under-rely or over-rely on AI advice. These two streams of research are *algorithm aversion* and *algorithm appreciation*, which were presented previously in Sections 3.5 and 3.6. Cummings (2017) has expressed concerns about individuals over relying on AI, leading to potential biases such as *automation bias*. This bias is reflected when individuals excessively trust AI and employ it without a critical judgement. Thus, understanding the influence of trust on AI advice reliance is critical, especially understanding if this relationship changes based on generational differences.

3.2 The Impact of Trust in AI on Advice Reliance

Trust is part of many aspects of human interaction, as people believe in a variety of entities, from scientific organisations to personal intuitions, that are suited to specific goals and circumstances. For instance, while one might rely on a friend's expertise in finance, trusting them with a simple task such as personal advice could be considered unwise (Ferrario et al., 2019). In numerous academic fields, including psychology, sociology, political science, and economics, trust is a fundamental concept because it influences social interactions and group dynamics. Experts have researched trust in detail, but they have not been able to agree on a single definition, highlighting how context-dependent and complex trust is. This divergence emphasises how difficult it is to describe how trust affects interactions in various contexts (Mayer et al., 1995; Rotter, 1967).

This research will rely on Lee and See's (2004, p.51) definition of trust as "the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability.". This definition, which focuses on the judge's belief in the advisor's ability and willingness to act in the best interest, highlights the role that trust plays in promoting cooperative behaviour in the face of ambiguity. Despite the lack of consensus, this definition is a valuable starting point for discussing trust, capturing its essence as a crucial component in handling the complexity of reliance on others' advice (Hoff & Bashir, 2014). This factor has been identified as highly important for influencing advice utilisation behaviour (Jungermann, 1999; Tauchert & Mesbah, 2019; Van Swol, 2011).

Moreover, this relationship continues to hold when AI is introduced (Vodrahalli et al., 2022). In human-automation interaction, people's willingness to rely on automated systems is heavily influenced by their level of trust (Hoff & Bashir, 2014). Lee and Moray (1994) argue that trust in automation is grounded in the system's perceived reliability, the transparency of its operational processes, and the alignment of its functions with the user's goals. In order to achieve the best possible human-automation collaboration, trust is essential. Insufficient or excessive trust might result in operational failures or inefficiencies (Lee & Moray, 1994). Therefore, understanding and designing for trust in automation involves an in-depth knowledge of these underlying factors to foster appropriate levels of user reliance.

Hoff and Bashir (2015) developed a comprehensive three-layered framework for conceptualising the variability of trust in automation, which divides trust into dispositional, situational, and learned trust. The present research will focus on dispositional trust and how this is affected by generational differences, as well as how situational trust mediates the relationship between generational differences and AI advice reliance.

Dispositional trust refers to an individual's tendency to trust automation, shaped by stable characteristics such as culture (Naef et al., 2008), age (Czaja & Sharit, 1998), gender (Nomura et al., 2008) and personality traits (Rempel et al., 1985). This layer of trust highlights how personal predispositions can affect one's level of trust in automated systems, regardless of the specific context. Drawing from the previous findings, when considering the generational differences concerning technology, specifically AI, it is essential to understand if there is any correlation between generational characteristics and trust in AI systems. In fact, there are contradicting findings on this matter.

On one hand, according to some researchers, older adults may initially trust automated systems more than younger adults (Ho et al., 2005). However, findings also show that age-related differences in trust adjustment may vary according to the specific context of automation use (Sanchez et al., 2004; Pak et al., 2012). It is important to emphasise that the previous research mentioned focuses on the reliance on medication management systems, which is not exactly the focus of my research.

On the other hand, Morris and Venkatesh (2000) advocate for a negative influence of age on the attitude towards using new technology. Supporting this, the research from Berkowsky et al. (2017) notes that older adults consistently have lower technology adoption rates than younger cohorts, emphasising barriers such as familiarity with algorithms. Logg et al. (2019) further underscore older individuals' hesitance towards algorithmic advice, suggesting a discomfort rooted in unfamiliarity. Furthermore, Chan and Lee (2023) empathize with Gen Z's optimism about generative AI (GenAI), contrasting with Gen X's cautious stance on its implications for education, suggesting generational differences in adopting AI technologies.

Given the contrasting perspectives, I suggest that Gen Z, who have been raised in a technologically advanced world, generally exhibit a greater level of trust in AI technology compared to Gen X. This hypothesis recognises the complex environment of technology adoption among different generations. The hypothesis presented is derived from the research conducted by Logg et al. (2019), Morris and Venkatesh (2000), Berkowsky et al. (2017) and Chan and Lee (2023) and goes as follows:

H2: Generation Z shows, on average, higher dispositional trust in AI compared to Generation X.

Situational trust is influenced by the context of the interaction. In this context, an individual is influenced by both the external environment and internal, context-dependent characteristics. External factors include the type and complexity of the system, task difficulty, perceived risks and benefits, and organisational setting. Internal factors that can impact situational trust include self-confidence and subject matter expertise (Hoff & Bashir, 2015). In contrast with dispositional trust, which is mostly constant over time, in situational trust the level of trust in a given situation might vary significantly based on the specific and changing circumstances (Hoff & Bashir, 2015). This layer captures the fluctuating nature of trust as it responds to immediate circumstances and the environment in which the automated system is deployed.

The third hypothesis lies in the relationship between dispositional and situational trust in AI. Based on the literature presented above, I suggest that there is a positive correlation between dispositional trust in AI and situational trust, meaning that individuals who show greater dispositional trust in AI will also show greater situational trust. The following hypothesis reads as follows:

H3: Dispositional trust in AI shows a positive association with Situational trust, such that more dispositional trust is associated with higher Situational trust.

Taddeo further elaborates on the importance of trust explaining the reliance on AI advice by introducing the concept of E-trust, defined as “trust specifically developed in digital contexts and/or involving artificial agents” (Taddeo & Floridi, 2011, p. 1). This notion of trust specifically tailored to digital interactions provides a relevant framework for analysing interactions with AI systems.

Building upon the foundational work of Chua et al. (2023), Muir and Moray (1996), and Schaffer et al. (2019), it is hypothesised that a direct correlation exists where higher trust in AI advice leads to a greater likelihood of using the advice. This hypothesis is central to understanding the dynamics of AI advice reliance. The relevance of trust as a mediator in the utilization of AI advice is further underscored by the work of Mosier and Skitka (2018), who suggest that the choice to rely on AI hinges on the perceived trust in the AI system. Thus, in the context of AI advice reliance, it is hypothesized that:

H4: Situational trust in AI shows a positive association with reliance on AI advice, such that more trust in AI is associated with higher reliance on AI advice.

This elucidates that trust mediates the individual's reliance on AI advice however, this is not the only factor determining this relationship. Prior studies have identified factors such as the perceived competence of AI systems (Vodrahalli et al., 2022), algorithmic errors (Dietvorst et al., 2015), and self-confidence (Dzindolet et al., 2002). Therefore, it is crucial to take into account factors other than trust. This study will address how an individual's confidence in their own judgment affects this relationship.

3.3 The Impact of Confidence in own Judgement on Advice Reliance

As previously mentioned confidence in the accuracy of the judgment has been identified as another factor influencing the reliance on advice (Bonaccio & Dalal, 2006). Sniezek and Van Swol (2001, p.290) defined confidence as "the strength with which a person believes that a specific statement, opinion, or decision is the best possible". Empirical studies have provided compelling evidence of a widespread tendency among people to discount the advice of others and place more importance on their own judgment (Gino & Moore, 2007; Logg et al., 2018; Moore & Healy, 2008; Moore et al., 2015). This can be due to various reasons, such as power (See et al., 2011), overconfidence (Harvey, 1997) and egocentrism discounting (Soll & Mannes, 2011; Yaniv & Kleinberger, 2000).

Egocentric discounting is described as the tendency for people to value their own judgments more highly than those of others, typically adjusting their initial estimates towards any advised direction by only 20% to 30% (Yaniv & Kleinberger, 2000). Such behaviour can limit the accuracy of decisions, in contrast to the potential benefits of incorporating diverse viewpoints. Research by Soll and Larrick (2009) suggests that improving accuracy frequently results from combining one's own judgment with external advice, ideally by averaging the two.

However, individuals vary in their approach to integrating advice, from completely disregarding it to fully embracing it, indicating a nuanced pattern of decision-making.

Chong et al. (2022) emphasizes that while trust in AI depends on how capable we think it is, our self-confidence affects our readiness to rely on the advice. Often, people trust their own judgment more than others, as shown by Logg (2017). Overconfidence, as more deeply explored in Section 2.3, can lead to underusing helpful AI advice (Lee & See, 2004). Thus, this leads me to conclude that individuals with high confidence in their own judgments tend to rely less on advice from others especially if they do not trust the advisor.

Drawing from these findings, the last hypothesis argues that the confidence individuals show in their own judgment can moderate the relationship between trust in AI and their reliance on AI, potentially reducing the strength of this relationship at higher levels of confidence. Thus, my last hypothesis reads as follows:

H4.1: Confidence moderates the association of trust in AI and reliance on AI advice, such that high levels of confidence in own judgement decrease the positive effect of trust on reliance on advice.

3.4 Conceptual Framework

The conceptual model (Fig. 1) incorporates all five hypotheses. The model aims to reveal insights into the effects of generational differences (Gen Z and Gen X) on the reliance on AI advice and whether this relationship is mediated through trust in AI. Additionally, it explores how this relationship is moderated by the confidence individuals show in their own judgment.

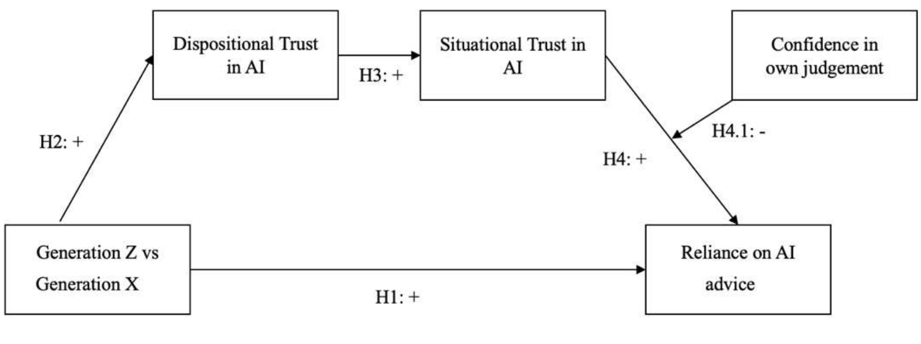

Figure 1: Conceptual Model

4 Methodology

Chapter 3 hypothesises the relationships between Gen Z and Gen X, reliance on AI advice, dispositional and situational AI trust, and confidence in own judgement. This chapter outlines the methodology employed to empirically test the theoretical hypotheses that were derived. Section 3.1 introduces the empirical setup, while Section 3.2 provides a detailed description of the sample and the procedure used to collect the data. In addition, Section 3.3 provides a comprehensive explanation of how the study was developed employing recognised research designs. Finally, section 3.4 provides a detailed description of the variables that are utilised in the study.

4.1 Empirical Setting

The study utilised a quantitative research method to understand the relationship between generational differences and their reliance on AI advice. After analysing the existing literature, a quantitative research design was used to better understand how different generations rely on AI advice and how trust levels might affect this relation. Expanding on past research based on the JAS paradigm, a *between-subjects* design was applied (Charness et al., 2012), enabling a generational comparison to be performed, where the participant's behaviours was analysed through an online survey developed in Qualtrics. In order to test the correlational relationships, the participants were presented with two hypothetical scenarios, which will be further explained in Section 3.3. In the circumstances where participants interact with hypothetical scenarios, there is the risk of not fully relating to the task being presented, which can create bias in the study. Thus, this thesis employed realistic decision making scenarios and performed two manipulation checks during the course of the survey (McDermott, 2011).

4.2 Sample & Data Collection Procedure

This study's *experimental survey* places a strong emphasis on business decision-making across two different generations, Gen Z and Gen X. Thus, it is important to ensure that participants have experience as being part of an organisation or, especially for Gen Z, that they are at least high school or university students since these groups will soon be joining the workforce and will be affected by the increased use of AI systems. The fulfilment of these criteria was assessed at the beginning of the survey where participants were asked questions regarding their present employment status and educational background. All participants who did not meet these criteria were considered not eligible for the study and were not considered for the analysis of the survey results. Additionally, the target participants were people who were part of Gen Z (1997 – 2012) and Gen X (1965 – 1980) (Beresford Research, 2024). In order to determine the required sample size in advance, a power analysis in G Power was conducted resulting in a needed sample size of 156 responses, 78 from Gen Z and 78 from Gen X.

To reach this target group, the survey was distributed through a variety of methods, with a focus on social media platforms such as WhatsApp groups, LinkedIn and university communities. By sharing the survey through multiple platforms, I ensured to gather a more representative sample of the population, which I was then used to test my hypothesis and capture the diverse perspectives of different generations towards AI advice-taking.

4.3 Research Design

The following Section describes in detail the design of the survey to test the hypothesis and find correlational relations between the two different generational groups (Gen Z vs Gen X) and their reliance on AI advice (see Appendix 1 for the complete survey). The initial section of the survey seeks participants' informed consent. The section emphasises the hypothetical nature of the scenarios presented and underscores the significance of providing accurate responses without seeking external information (Logg et al., 2019). Sequentially, participants were requested to provide demographic data, including *age*, *gender*, *employment status*, *education level, nationality*, and *familiarity with AI* systems, using a 7-point Likert scale. These questions, designed as covariates, aimed to capture a comprehensive demographic profile to analyse the survey responses in the context of various background factors.

Before presenting the participants with the decision-making scenarios and to first understand how different generations trust AI (*dispositional trust*), participants were asked to provide their level of agreement with four sentences[1] aiming to assess their propensity to trust AI systems (Scholz et al., 2024). Subsequently, all participants were provided with two decision-making scenarios: *Apartment Price Prediction* and *Song Forecasting*. Each scenario required participants to make predictions based on the provided information, followed by an AI-generated recommendation providing the participants the opportunity to reassess their

[1] Details on all sentences are provided in Appendix 1

estimates, illustrating a scenario where decisions are made in a specific order (Friedel et al., 2014). At this stage, the participants could either accept the advice and adjust their initial prediction or discard the advice, which allowed me to measure the reliance on the AI advice (Schemmer et al., 2022). To provide a more comprehensive understanding of the correlational relationship between the independent and dependent variable, *dispositional* and *situational trust* in AI advice were added as mediators and *confidence in own judgement* was included as a moderator (MacKinnon, 2011).

To test the hypothesis, two decision-making scenarios where AI has been previously employed were replicated in the areas of House Price Prediction (McGrath et al., 2023) and Song Forecasting (Logg et al., 2019). In both decision tasks, the utilisation of AI has proven to enhance the decision-making process (Lai et al., 2021).

For the first decision-making scenario, participants were asked to assume the role of a Real Estate Agent tasked with predicting the monthly rental price of an apartment in Cambridge based on certain attributes. This experiment is based on the study of McGrath et al. (2023) and adapted to study the effect at hand. Participants are provided with information about an apartment, including the number of bedrooms, square footage (in square meters[2]), and relative size compared to average apartments with the same number of bedrooms. Based on this information, participants had to use the provided data to estimate a rental price for the apartment. This task aimed to replicate a real-world scenario where individuals have to make decisions based on limited information. After making their initial prediction, participants were introduced to "*Chrono*", an AI algorithm created especially for the purpose of my experiment. *Chrono* is described as a sophisticated tool that leverages past and current data to offer unbiased advice on rental price predictions. Participants were shown a specific price predicted by *Chrono* for the apartment in question. A linear regression model was employed to predict the house price, ensuring the reliability of the AI advice. The model was built using data from a sample of 75 Cambridge apartments listed on Zillow.com in November 2019. It considered the square footage and number of bedrooms as factors (McGrath et al., 2023).

[2] For the purpose of my study and as most participants are Europeans the square feet scale has been adapted to square metres so that participants are familiar with the measurement scale.

For the second decision-making scenario, participants are placed in the scenario of working for *Billboard Magazine*. They are required to predict a song's ranking on the "*Hot 100*" list for the upcoming week. This task involved predicting the future ranking of a song on Billboard Magazine's "*Hot 100*" list, which reflects a combination of record sales and streaming frequency. Participants made their predictions using a scale from 1 (*most popular*) to 100 (*least popular*) after examining the song's ranking trends from previous weeks (Logg et al., 2019). Similar to the first task, after participants submited their initial prediction, they are introduced to "*TrackRank*", an AI algorithm designed to estimate song rankings accurately and, once again, an AI algorithm created especially for the purpose of my experiment. *TrackRank's* prediction for the same song is shared and described as being derived from unbiased analysis of past and current data trends. Since this is a time-sensitive task, the song presented to participants was updated from the one used in previous studies. This adjustment ensured that the task remained pertinent and engaging at the time the survey was conducted. The selected song was "*Texas Hold 'Em*" by Beyonce. To ensure the reliability of the advice provided, the value shared with the participant was the actual value that the song was ranked in the following week presented on the graph. Additionally, to ensure that participants only used the information presented in the survey, they were asked in the beginning of the survey not to search for any information on the internet, and at the end, there was an additional question asking if participants had searched for any information on the internet. If participants answered "*Yes*" or "*Rather not Say*", they were excluded from the analysis.

For both tasks and to ensure the integrity of my study while avoiding any potential biases associated with the AI systems brand, the participants were presented with two AI systems specifically designed for my research, "*Chrono*" and "*TrackRank*". This approach was designed to evaluate the advice based on its output rather than the AI's brand reputation (MacKenzie et al., 1986). Moreover, providing unbiased advice in both tasks enhances the credibility of this study.

In both scenarios, participants' confidence in own judgement is measured, alongside their willingness to adjust their estimate after reviewing the AI's advice. A series of statements were presented to assess their trust in the AI advice (Scholz et al., 2024). After disclosing the AI advice, participants were invited to either revise their initial prediction based on the AI's input or choose to stick with their original prediction. Finally, to measure if the AI advice has increased the participant's confidence level in performing the task, they were asked to reevaluate their level of confidence in their performance using a Five point Likert scale (See et al., 2011). Both tasks are structured to explore the dynamics of human-AI interaction in decision-making, specifically focusing on how the two generations trust and rely on AI advice. To follow research best practices throughout the survey there were two attention checks. One is presented at the beginning to make sure that participants have read the instructions carefully, while the second is positioned towards the end of the survey. Additionally, the order in which the two decision-making tasks were presented was randomised, ensuring that this did not impact the studied effect.

4.4 Variables

In this Section, I will explain in detail the variables that compose my study. I will explain the value that each variable brings to the conceptual framework and how they will be measured based on previously validated scales. I will start by conceptualising my independent and dependent variables and following that, I will introduce the mediators, moderator and covariables.

4.4.1 Independent Variable: Age

In the conceptual framework, *age* is defined as the categorical independent variable that distinguishes between two generational cohorts: Gen Z, born from 1997 to 2012, and Gen X, born from 1965 to 1980 (Beresford Research, 2024). *Age* will be assessed through an open-ended question, which will enable participants to provide their precise age. Afterwards, the responses will be divided into the two specified generational categories. This categorisation allows for the analysis of variations between the two different generations.

4.4.2 Dependent Variable: Reliance on AI Advice (WOA)

The dependent variable of the study is the *reliance on AI advice,* which quantifies the degree to which participants modify their initial prediction in response to the AI advice that was provided. Following the research of Sniezek and Buckley (1995), Tauchert and Mesbah (2019) and Logg et al. (2019), the JAS paradigm was utilised. Participants are asked to provide an initial estimate in a situation where there is uncertainty. After receiving the AI advice, they are allowed to change their prediction (Tauchert & Mesbah, 2019).

The *Weight of Advice* (WOA) was used to measure the participants' reliance on advice. It is calculated by dividing the difference between the final and initial prediction by the difference between the AI advice and the initial prediction (Logg et al., 2019). WOA quantifies the extent to which a participant's initial estimate changes based on their exposure to AI advice. The range of variation for this can be anywhere from 0% to 100%. A value of zero represents that there was no change in the initial prediction, reflecting a complete disregard for the AI advice. Conversely, a value of 100% indicates a full acceptance of the AI advice. Values within this range indicate different degrees of influence the AI advice exerted on the participant's final decision. Scenarios in which the participant's initial prediction matches the AI advice were omitted from the analysis as they do not provide valuable insights on the reliance on advice. A WOA below zero suggests a counterintuitive shift away from the AI's advice, while those exceeding 100% imply an excessive dependency on the AI (Tauchert & Mesbah, 2019). In order to maintain the statistical reliability and significance of the study, a normalisation technique called "*winsorisation*" was applied (Logg et al., 2019). This technique normalises any extreme data by capping negative values at 0% and values above 100% at 100%, thus establishing a consistent range for analysis and guaranteeing the integrity and interpretability of the findings.

4.4.3 Mediator: Dispositional Trust in AI Advice

As mentioned before, the variable trust highly influences the reliance on AI advice. The study distinguishes between dispositional trust and situational trust. Dispositional trust refers to an individual's general inclination to trust automation, regardless of the situation or a particular technology (Hoff & Bashir, 2014). Given that this can be significantly influenced by age (Mayer et al., 1995; Rotter, 1967), dispositional trust was included in the analysis to examine potential differences in how Gen Z and Gen X trust AI systems. To measure this variable, a modification of the Scholz et al. (2024) scale was used. Slight modifications were implemented to tailor the questions to my hypothetical scenario. Participants were asked to state their level of agreement with the following questions: 1) "*Even though I may sometimes suffer the consequences of trusting AI recommendation systems, I still prefer to trust than not to trust them*"; 2) "*I feel good about trusting AI recommendation systems*"; 3) "*I believe that I am generally better off when I do not trust AI recommendation systems than when I trust them.*"; 4) "*I rarely trust AI recommendation systems because I can't handle the uncertainty.*". A Five-point Likert scale was used ranging from 1 "*Strongly disagree*" to 5 "*Strongly Agree*". The average of these four items measures *dispositional trust* in AI.

4.4.4 Mediator: Situational Trust in AI Advice

The second mediator is *situational trust* in AI, which is argued to vary significantly depending on the context (Hoff & Bashir, 2014). In order to measure this variable, the Trust Scale for the AI Context (TAI) by Scharowski et al. (2024) was applied. This scale is composed of eight items using a Five-point Likert scale ranging from 1("*Strongly Disagree*") to 5 ("*Strongly Agree*"). The question "*I am wary of the AI*" was adapted to ensure that the survey had a vocabulary that all participants would understand since it was expected that most of the answers would come from individuals whose English is not their native language. The average of these eight items measures Situational Trust in AI advice.

4.4.5 Moderator: Confidence in own Judgement

Drawing from previous research, confidence in own judgement has been shown to have a moderating effect between trust in AI advice and reliance on the advice (Bonaccio & Dalal, 2006). Thus, to measure the potential moderation effect of this variable I employed the items from the experiment of See et al. (2011). Minor changes were made to the questions and they go as follows: 1) "*I feel confident with my performance in this task*" and 2) "*I believe my prediction is accurate*". To ensure consistency throughout the survey, the measurement of all items is based on self-reports using a Five-point Likert scale, with responses ranging from 1 ("*Strongly Disagree*") to 5 ("*Strongly Agree*"). The mean of these two items quantifies confidence in own judgement. Drawing from the findings of See et al. (2011), following the submission of their final answers, participants were once again asked to provide their level of confidence in their final (post-advice) answers by responding to the same two confidence items. By asking these questions again, I aim to understand if the AI advice provided increased the confidence level of the participants regarding their final estimate.

According to Hinshaw (2007), the moderator was measured before providing any interaction with AI advice. This ensures that I am capturing the participants' preexisting levels of self-confidence, which can then be examined for its moderating effects on the relationship between trust and reliance on AI advice. This is essential for appropriately interpreting the moderating effect of self-confidence on participants' reliance on AI while making decisions.

4.4.6 Covariates

Covariates are incorporated to mitigate the influence of confounding variables that may impact the primary outcomes. By considering these additional variables, I aim to clarify the specific effects of the independent variable on the dependent variable, thereby enhancing the precision and validity of the study's results. Covariates play a crucial role in isolating the relationship between important variables by minimising bias and providing a more detailed understanding of the data.

4.4.6.1 Demographics

Participant's demographics are important as they allow for a better understanding of the sample, supporting the analysis of possible connections between the dependent variable and demographic characteristics. Within particular population segments, demographic characteristics help with the generalizability and interpretation of the study findings. Building on existing studies, the *gender*, *nationality*, *educational background*, and *employment status* of the participants were also considered as controlling factors (Vodrahalli et al., 2022; See et al., 2011).

4.4.6.2 Difficulty of the task

Moreover, *task difficulty* has been identified in past studies as a factor influencing the reliance on advice. Thus, this variable was added to the study as a control variable (Gino & Moore, 2007). Therefore, participants were asked, after performing the tasks, the following question: "*How difficult was it to perform these tasks?*" and answered using a seven-point Likert scale (1= "*Not difficult at all*"; 7= "*Extremely Difficult*") (Logg et al., 2019).

4.4.6.3 Familiarity with AI

Lastly, *familiarity with AI* has been recognised as a significant element that affects the reliance on AI advice and for this reason, this was included as a controlled variable (Logg et al., 2019; Belanche et al., 2019). The participant's familiarity with AI was assessed using a modified version of the Logg (2019) scale. Participants were asked to state their level of agreement with the following statement: "*I am familiar with AI and AI contents*". The Likert scale used was a Seven-point Likert scale (1= "*Strongly Disagree*"; 7= "*Strongly Agree*"). Additionally, before the question was asked and to ensure that participants were aware of the term AI, a concise explanation of AI was provided based on McKinsey & Company (2023).

5 Data Analysis and Results

In this Chapter, the data analysis and results will be presented. This Chapter is divided into five main sections. In the first Section, I will present an overview of the sample of my study, characterising the participants that compose the sample of analysis. Afterwards, I will provide a comprehensive understanding of the data preparation procedures undergone to be able to proceed to the analysis of the results. The descriptive statistics are then presented in Section 5.3 and the hypothesis are tested in Section 5.4. Lastly, an exploratory analysis is presented in Section 5.5.

5.1 Sample Description

The survey responses were collected via Qualtrics from April 16th to May 4th, 2024. During this period, I was able to collect a total of 282 finished responses. However, only 249 passed all attention checks and were suitable for the analysis. Additionally, as the study focuses on Gen Z and Gen X, only participants within this age range were considered. This resulted in a total of 206 responses that were analysed, including 104 from Gen X and 102 from Gen Z.

With an observed range of min = 18 to max = 59 years, the variable Age (in years) has a mean (*M*) of 27.4 and a standard deviation (*SD*) of 14.08. The age distribution histogram (Appendix 2) indicates a bimodal pattern aligning with Gen Z and X. Gen Z's distribution is more concentrated, particularly around the 20-25 age range, while Gen X displays a more even spread across the 44-59 age range. This difference highlights varying representational densities within each generational cohort.

The following table contains detailed information on the demographic characteristics of participants.

Demographic characteristics of participants

	Counts and Percentages	
	n	%
Gender		
Male	110	53.39%
Female	95	46.11%
Prefer not to say	1	0.48%
Employment Status[3]		
Employed	117	56.79%
Students	50	24.27%
Students & Workers	31	15.04%
Unemployed	4	4.19%
Other	4	1.94%
Highest educational level[4]		
Bachelor's degree	94	45.65%
Master's degree	64	31.07%
High School degree	35	16.99%
Doctoral degree	8	3.88%
Other	4	1.94%
Nationality		
Portugal	148	71.84%
Austria	24	11.65%
German	8	3.88%
Other[5]	26	12.63%

Table 1: Demographic Characteristics of Participants

[3] For the purpose of this analysis and for the interpretability of the results participants from Gen X who were *retired* were excluded.

[4] For the Gen Z cohort, individuals with less than a High School education were excluded from the analysis.

[5] The Other category include nationalizes such as French, Spanish, Swiss, Danish, Brazilian, British, American, Canadian, and Australian participants, each comprising less than 1% to just under 1% (see Appendix 3 for more details)

5.2 Data Preparation

5.2.1 Scale Reliability

Prior to the analysis, I performed all required tests to validate the analysis, which can be accessed in more detail in the appendix chapter (4-7).

First, it is important to test for the reliability of the multi-item scales used to assess the main variables of my analysis (*dispositional trust*, *situational trust*, and *confidence in own judgement*). Even though the scales used in this survey have been shown to be reliable in previous studies (Scholz et al., 2024; Scharowski et al., 2024; See et al., 2011), *Cronbach's alpha* (Vaske et al., 2017) was tested using a reliability analysis. *Alpha* measures the internal consistency of a scale, representing the extent to which the scale items measure the same underlying concept across various participants. This is particularly crucial for self-reported measures, as testing scale reliability helps reduce potential measurement biases (Tavakol & Dennick, 2011). The scale used by Scholz et al. (2024) to measure *dispositional trust* in AI yields a Cronbach's alpha of 0.8 (Appendix 4). This indicates a good level of reliability, according to Streiner (2003). The scale used to measure the *dispositional trust* had two items that showed a negative correlation with the other two items, and to proceed with the analysis, these items were recoded. The Cronbach's alpha was also computed for the reliability of the *confidence in own judgement* scale and it exhibited a value of 0.88 (Appendix 5), which is a very good value of reliability. Lastly, the *situational trust* scale led to Cronbach's alpha of 0.8 (Appendix 6), showing a good level of internal consistency. Once again, the 6th item of this scale had to be recoded as it presented a negative correlation with the other items on the scale.

5.2.2 Task Randomisation

The tasks were presented in a randomized order to guarantee that there was no influence between the order of the task and the effect being measured. Descriptively, there was an even distribution of the tasks, with 100 participants being shown the *house price prediction* task first and 106 participants being shown the *song forecasting task* first (see Appendix 7). Thus, I assume that the randomisation function of Qualtrics was applied effectively, neutralising any ordering effects.

5.3 Descriptive Statistics

In this Section, descriptive statistics will be presented to provide a fundamental understanding of the data before conducting the hypothesis testing. Along with providing insights into the distribution of the most critical variables and their central tendencies, this first analysis helps to gain insights into the hypothesis testing section. These steps are crucial for contextualising the findings within the broader study framework.

5.3.1 Dispositional Trust

The first variable analysed was *dispositional trust*. This aims to measure participants' initial trust in AI without being influenced by any particular task. Gen X has a mean dispositional trust score of 3.36 and a median of 3.5, with a standard deviation (*SD*) of 0.986. Gen Z shows a slightly higher mean score of 3.38, with the same median of 3.5, but a lower *SD* of 0.846. This descriptive analysis shows that both generations show a central tendency of *dispositional trust* towards AI at 3.5, the mean is slightly higher for Gen Z and this generation also shows a smaller variability in their responses, suggesting a more consistent and positive perception of AI. When assessing the distribution of Gen Z dispositional trust, one can infer that this is slightly skewed towards higher trust levels, which aligns with the literature previously analysed (Schroth, 2019) (Figure 2). Even though Gen X shares a similar median dispositional trust level, this descriptively shows greater variability in their trust towards AI. The boxplot presented in Appendix 8 further emphasises the previous findings, showing that both generations have similar mean values. However, Gen Z has a smaller interquartile range (IQ*R*) than Gen X, which suggests that the trust levels are more concentrated around the median.

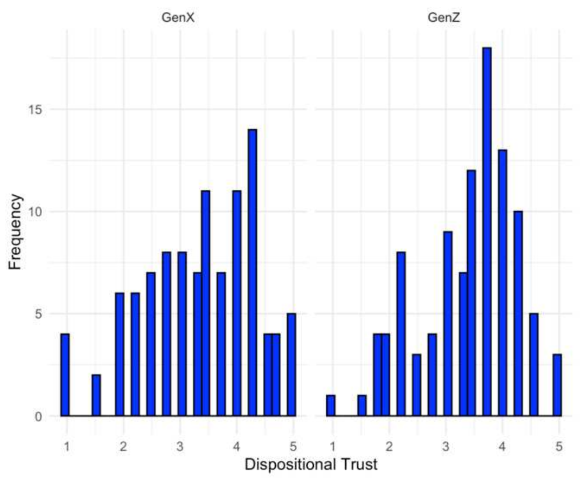

Figure 2: Histogram of Dispositional Trust in AI across Generations

5.3.2 Situational Trust by Generation and by Task Type

Concerning the descriptive statistics of situational trust, no substantial differences were found when comparing the two tasks and generations (see Appendix 9 for further details). Overall, in both tasks, there seems to be a relatively symmetrical distribution of answers for each generation, taking into account the close alignment of means and medians. Additionally, the level of variability in situational trust scores is similar across generations and tasks.

5.3.3 Confidence in own Judgement Before and After AI Advice

Before and *after* participants were presented with the AI advice, their confidence level was assessed to understand both the impact of this variable on the reliance on the AI advice (WOA) and if the level of confidence changed by disclosing the AI advice. Analysing the variation in participants' confidence levels *before* and *after* receiving AI advice could bring insights into how AI affects individuals' trust in their own decision-making.

When assessing the results from the *house price prediction* task, the confidence scores participants reported *before* the AI advice was provided were much smaller than the confidence score *after* the AI advice was disclosed, 2.55 compared to 3.50, respectively. Descriptively, this represents a substantive increase in the confidence scores of participants, suggesting that the disclosure of the AI advice was perceived as beneficial. Considering the *song forecasting* task, the results are not as substantial as in the previous task (see Appendix 10). Nevertheless, the confidence scores of participants slightly increased, which points to a moderate positive impact of AI advice on confidence.

Descriptively, there is a difference in the effect of confidence before and after the disclosure of the AI advice for the two types of tasks. Detailed descriptive values and boxplots can be found in Appendix 10. The statistical effect of confidence in own judgement on reliance on AI advice is further analysed in section 5.4.5.

5.3.4 Reliance on AI Advice (WOA)

I will now focus on the actual reliance on AI advice (WOA) shown by participants by considering the actual change of the initial assessment in response to AI advice.

Firstly, the variable WOA is computed by dividing the difference between the final estimate and the initial estimate by the difference between the AI advice and the initial estimate. As mentioned in Section 3.4.2, the cases in which the initial estimate is equal to the AI advice were excluded from the analysis. Additionally, the values that are less than 0 and more than 1 were *winsorised* in accordance with the methods used by Logg et al. (2019).

On average, Gen X participants revised their estimate by 55.9% (*SD* = 0.391) towards AI advice in the *house price prediction* task and 26.3% (*SD* = 0.35) in the *song forecasting* task. Considering Gen Z, on average, participants revised their estimate by 61.9% (*SD* = 0.37) in the *house price prediction* tasks and 39.3% (*SD* = 0.36) in the *song forecasting* task (Appendix 11). That is, for the *house price prediction* task, the mean values of the variable WOA are higher than those of the *song forecasting* task. Additionally, the means suggest that both generations rely on AI advice, with Gen Z showing slightly higher reliance. The boxplot presented below (Figure 3) indicates a moderately high level of reliance for both generations. In section 5.4.1, the statistical significance of these differences is tested.

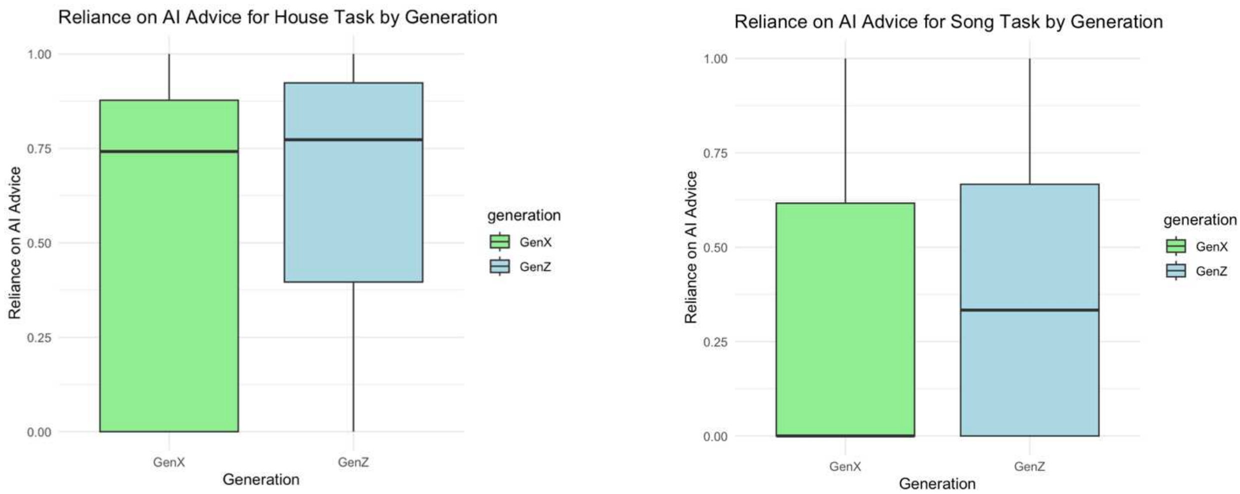

Figure 3: Boxplot of Reliance on AI Advice by Task Type and Generation

5.3.5 Familiarity with AI

It is not possible to determine the scale reliability of the variable *familiarity with AI* since the familiarity scale is a single-item scale (Tavakol & Dennick, 2011). Figure 4 exhibits a slightly right-skewed distribution[6], with $M = 5.50$ and $SD = 1.42$ (Appendix 12). Descriptively, the data supports the notion Gen Z is more familiar with AI than Gen X. Gen Z shows a mean familiarity with AI of $M = 5.77$ compared to $M = 5.24$ for Gen X (see Appendix 12)

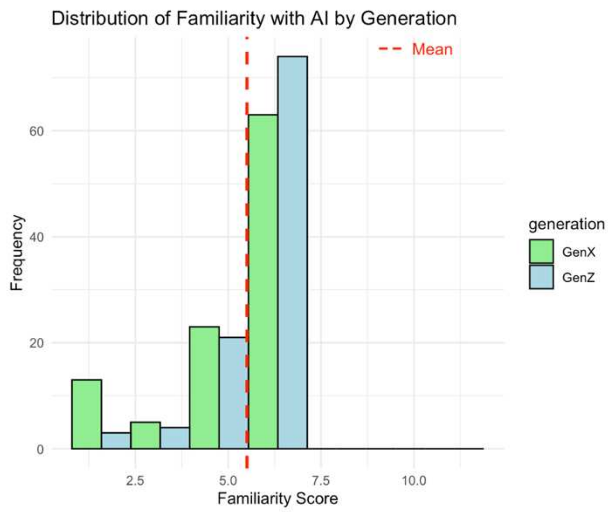

Figure 4: Histogram of Familiarity level of participants

5.4 Hypothesis Testing

To test hypotheses 1,3,4 and 4.1, a statistical analysis was conducted using *linear mixed models* (LMM). This approach was employed due to its robustness in handling data complexities that arise from repeated measures and hierarchical data structures. LMMs are suitable for analysing the dataset as the participants have several observations nested inside them. The dataset contains the same participant answering two different tasks, which violates the independence assumption required by traditional regression analyses. LMMs can handle these limitations by accounting for fixed and random effects (Response ID and task-related variability). The random intercept for each Response ID specifies setting control for the subjects, meaning that the subject can explain some variance of the WOA. In the case of the task, the random intercept is

[6] As mentioned in Section 3.4.6 the scale used to measure familiarity with AI modified version of the Logg (2019) scale and the Likert scale used was seven points

controlling for the variance between the WOA that is explained by the nature of the task. This leads to more accurate estimates of the effect of the independent variable on the dependent variable. LMMs help to accurately estimate the influence of predictors while accounting for the correlation within individual responses across different conditions (Cnaan et al., 1997).

All the analysis was conducted with R (v. 4.4.0) (R Core Team, 2024) using R Studio (v. 2023.12.1.402) (RStudio Team, 2024). The R package "lme4" and “lmerTest" were used to fit all *linear mixed models* and provide all p-values, respectively (Bates et al., 2015; Kuznetsova et al., 2015). The hypothesis developed in Chapter 3 will now be tested. The rejection of null hypotheses occurs at a significance level of $\alpha = 5\%$.

5.4.1 Hypothesis 1

The first hypothesis states that Gen Z shows, on average, more reliance on AI advice compared to Gen X. Descriptive statistics indicated that Gen Z shows a consistently higher reliance on AI across both tasks. The following Section will test these differences for their statistical significance. Model 1 employs *linear mixed models* as a statistical method to determine the significance of differences in the mean WOA values among Gen Z and Gen X. In Model 1, the dependent variable is WOA, the independent variable is the generational differences and the random effects integrated are Response ID and task.

The results of the LLM (Appendix 13) show that the effect of Gen Z on WOA is 0.09, with a p-value of $p = 0.024$. When adjusted for one-sided testing (as the hypothesis is directional) (Ludbrook, 2013), the p-value would be even smaller, $p = 0.012$ (0.024/2), which is considered statistically significant for $\alpha = 5\%$. One-sided tests have more statistical power to detect an effect in one direction and this test is supported by previous research on generational differences towards technology (Asoba & Mefi, 2022b).

The variance components for the random effects (Response ID and task) indicate that differences across Response ID and tasks account for some variability in WOA. This model has a *marginal R-square* of 0.013, indicating that the fixed effect explains a small portion of the variance of the outcome, whereas a substantially larger amount of the variation in the result is explained by the complete model incorporating random factors, as shown by the *conditional R-square* of 0.471. Given the significant positive coefficient for Gen Z, I can confirm hypothesis 1, that Gen Z, on average, relies more on AI advice compared to Gen X. However, the effect size is relatively small, suggesting that while the difference is statistically significant, the difference in reliance on AI advice between the generations is not very large.

To further test the robustness of the previous findings by mitigating the risk of confounding factors, the covariates were introduced in the statistical model. This enables their possible impact on the dependent variable to be considered and adjusted. Model 1C (Appendix 14) shows a coefficient for Gen Z of 0.07 with a p-value of p = 0.183, p = 0.092 (for a one-sided test), indicating that, while there is a positive effect of being from Gen Z on reliance on AI advice, this effect is not statistically significant for an *alpha* of 0.05 once other covariates are controlled. Additionally, there is a decrease in the Gen Z coefficient (from 0.09 to 0.07), suggesting that generational differences are not as significant in predicting the reliance on AI advice as initially hypothesised.

Two additional variables show a statistically significant impact on Model 1.1, namely *education* and *familiarity with AI*. *Education* presents a coefficient of 0.05 with a p-value of p = 0.026, suggesting that higher *education* is associated with a greater reliance on AI advice, and this effect is statistically significant for a significance level of 5%. Similarly, familiarity has a significant positive effect of 0.04 with a p-value of p = 0.010. This means that familiarity explains part of the variance of the WOA that is also explained by the generation and this is why the effect on Gen Z becomes smaller. This points at something one can further analyse in a mediation analysis (further analysed in Section 5.5) that familiarity may be a mediator of the model.

5.4.2 Hypothesis 2

Hypothesis 2 states that Gen Z shows, on average, higher dispositional trust in AI compared to Gen X. Model 2 employs a simple *linear regression* that aims to measure the direct generational effect of generation on dispositional trust (Appendix 15).

The coefficient for Gen Z is 0.03, with a *SD* = 0.13 and a p-value of p = 0.821. This indicates that the *generational effect* on *dispositional trust* in AI is not statistically significant at a 5% *alpha* level. Even for the one-sided testing, the p-value would still be above the 5% confidence level (0.441). The multiple R-squared value is 0.0003, indicating that approximately 0.03% of the variance in *dispositional trust* in AI is explained by the model. The *adjusted R-squared* is negative, suggesting a very poor fit, meaning that the generational effect does not effectively explain the variation in dispositional trust. The model is not statistically significant ($F = 0.05$; $p = 0.821$), meaning it does not statistically significantly predict *dispositional trust* when all predictors are considered. Given that the p-values for the generational effect and the overall model are not significant at $\alpha = 5\%$, Hypothesis 2 cannot be confirmed, thus challenging the underlying assumptions of the proposed mediation model.

Taking into account the poor model fit of Model 2 and recognising the potential influence of the covariates in the model, a more comprehensive model was performed, which controls for *gender*, *employment*, *education*, *country* and *familiarity with AI* (Appendix 16). Model 2C showed an increased predictive power (*adjusted R-squared* = 0.09711), empathising the role of these covariates in understanding dispositional trust in AI. *Familiarity with AI* was the only variable that showed a statistically significant positive association with dispositional trust (Coefficient = 0.20, $p = 0.012$), suggesting, once again, that *familiarity with AI* might play an important role in shaping trust levels, potentially mediating the relationship more significantly than generational differences.

5.4.3 Hypothesis 3

The third hypothesis states that *dispositional trust* in AI positively correlates with *situational trust*, such that higher dispositional trust is associated with higher situational trust. Similar to hypothesis 1, model 3 employs a *linear mixed model* to predict situational trust as a function of dispositional trust, incorporating random intercepts for Response ID and task to handle within-subject and task-related variance, respectively. The results are detailed in Appendix 17 and additional analysis, including the covariates, can be found in Appendix 18.

Model 3 shows a significant positive association between dispositional and situational trust, with a coefficient of 0.28 and a p-value of $p < 0.001$. Since the significance level was set at $\alpha = 0.05$, the null hypothesis of no association can be rejected. This suggests an increase in dispositional trust is associated with an increase in situational trust.

According to the model fit, 15.8% of the variance in situational trust is explained by dispositional trust alone. Additionally, the *conditional R-squared* value of 0.662 suggests that the model accounts for 66.2% of the variance in situational trust when considering both fixed effects and random effects are taken into account (Appendix 17). Figure 5 further illustrates the statistical results, visually representing the relationship between dispositional and situational trust, clearly showing a positive relationship between these two variables.

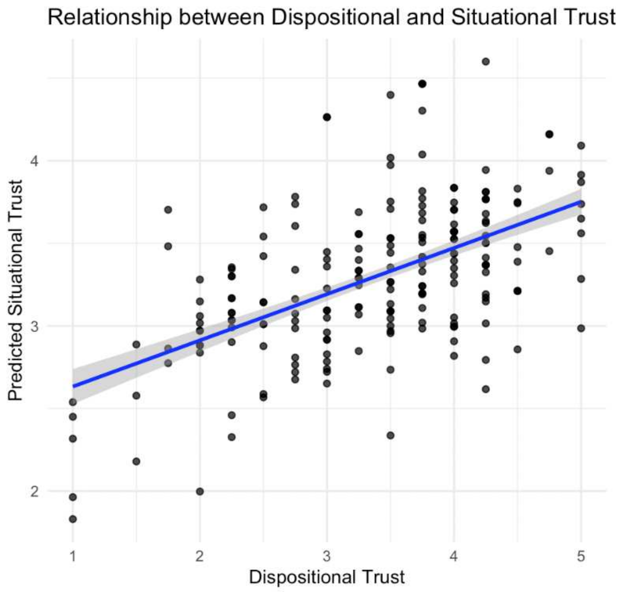

Figure 5: Scatter Plot of the relationship between Dispositional trust and predicted Situational trust

This finding emphasises the interdependence of the different dimensions of trust in AI, as outlined by (Hoff and Bashir, 2015).

5.4.4 Hypothesis 4

Given the non-significant results of hypothesis 2, the scope of analysis focused instead on assessing the direct effect of situational trust on the WOA, foregoing the broader mediation model initially proposed. The fourth hypothesis states that situational trust in AI shows a positive association with reliance on AI advice, such that more situational trust in AI is associated with higher reliance on AI advice. Once again, Model 4 utilises a *linear mixed model* to predict WOA as a function of situational trust, incorporating random intercepts for Response ID and task. An extensive summary of the findings can be found in Appendix 19.

The coefficient for situational trust is 0.26 with a p-value of $p < 0.001$, statistically significant for a significance level of 5%. This test confirms hypothesis 4, indicating that as *situational trust* increases, the WOA also increases significantly. The model fit points for a *marginal R-*

squared value of 0.159, meaning that 15.9% of the variance in WOA is solely explained by situational trust. According to the *conditional R-squared*, 51.4% of the variation in the WOA is explained when both fixed and random effects are considered (Appendix 19). The scatter plot with the regression line provided below shows a growing trend in the reliance on AI advice as situational trust grows (Figure 6), supporting the previous analysis.

Figure 6: Scatter Plot of the relationship between Situational trust and predicted WOA

The confirmation of Hypothesis 4 continues to hold when adding the covariates to Model 4 (Appendix 20). Even after controlling for factors such as *gender*, *employment*, *education*, *country*, *familiarity with AI* and *difficulty* of the tasks, the coefficient for situational trust remained similar (0.25) and significant, with a p-value of $p < 0.001$. Therefore, it is reasonable to state that the covariates do not weaken the relationship between situational trust and reliance on AI advice. Although situational trust remains a strong predictor, adding these variables showed that education is statistically significant when explaining the WOA and this enhances the explanatory power of the model (*Marginal* $R^2 = 0.188$, *Conditional* $R^2 = 0.520$), suggesting that other factors contribute to the overall variation of the reliance on AI advice.

5.4.5 Hypothesis 4.1

Lastly, hypothesis 4.1 states that *confidence in own judgement* moderates the association between *situational trust* in AI and *WOA*, such that high levels of confidence in own judgement decrease the positive effect of situational trust on WOA. Model 4.1 employs a *linear mixed model* to measure the moderation effect through an interaction term between situational trust in

AI and confidence in own judgment. This model accounts for the random effects by incorporating random intercepts for Response ID and task. (Appendix 21).

Model 4.1 interaction term is -0.02 with a p-value of p = 0.421, showing no statistical significance for α = 5% or even higher levels of 10%. This indicates that the relation between situational trust and WOA is independent of the level of confidence participants show in their own judgement. Thus, higher confidence scores in own judgment do not significantly decrease the positive effect of situational trust on WOA. When incorporating the covariates in the statistical model, the coefficient of the interaction term continues to hold and the moderation effect is still not statistically significant (see Appendix 22 for more detailed statistics). Therefore, hypothesis 4.1 cannot be confirmed however, a direct effect of confidence in own judgement on WOA was found and is further explored in the exploratory analysis (Section 5.5.2)

5.5 Exploratory Analysis

In this Section, the exploratory analysis will be presented, aiming to uncover relations and patterns that were not initially predicted by the conceptual framework but instead emerged from the survey data. This analysis helps to broaden the understanding of the dataset and contributes to the validity of the research.

5.5.1 The Impact of Familiarity with AI on WOA

The potential mediating effect of *familiarity with AI* in the relationship between generational differences and reliance on AI advice will be explored. As previously mentioned in Section 5.4.1, when including familiarity in Model 1, the impact on WOA for Gen Z decreases, indicating that familiarity may explain a part of the variance of WOA that is also explained by the generation (Appendix 23). This elucidates a new area of research in my study, where familiarity takes the role of a mediator.

Model E2 explores the relation between generation and familiarity (Appendix 24), employing a *simple linear model*. The model indicates that Gen Z has a significantly higher familiarity with AI than Gen X, with a positive coefficient of 0.53 and a p-value of p = 0.007. Additionally, there is a significant positive correlation between familiarity and dispositional trust in AI, with a coefficient of 0.21 and a p-value of $p < 0.001$ (Appendix 25). This means individuals who are more familiar with AI show a higher dispositional trust in AI. Similar to dispositional trust, familiarity has a statistically significant positive effect on situational trust, with a coefficient of 0.14 and a p-value of $p < 0.001$ (Appendix 26), further emphasising that familiarity enhances trust in specific AI contexts. When building a more comprehensive model including *generations*, *familiarity with AI* and s*ituational trust* as predictors of *WOA*, both situational trust (Estimate = 0.26, $p < 0.001$) and generation (Estimate = 0.10, $p = 0.005$) are statistically significant. However, the effect of familiarity becomes non-significant (Estimate = 0.01, $p = 0.450$) (Appendix 27).

The exploratory analysis shows that individuals in Gen Z are more familiar with AI, which is also associated with higher dispositional trust. Furthermore, this is associated with higher situational trust and higher situational trust is further associated with a higher WOA. There seems to be a gap in the conceptual model presented in Section 4.4 regarding the relationship between generations, familiarity and dispositional trust. This partially explains why the expected effect in hypothesis 2 was not observed.

5.5.2 The impact of Confidence in own Judgement on WOA

In an additional exploratory analysis, the direct effect of confidence in own judgement on WOA was analysed. To test for this effect, LLM was employed with the variable before confidence as the independent variable and WOA as the dependent variable. The random effects included in the model were the Response ID and task-related variability. Model E4.1 uncovers a negative direct effect of confidence in own judgement on WOA with a coefficient of -0.04 and a p-value of $p = 0.036$ (Appendix 28). The effect is statistically significant for a significance level of 5%, implying that individuals with higher confidence in their initial judgement are less likely to rely on AI advice.

Additionally, as part of the exploratory analysis, the differences in confidence scores *before* and *after* the AI advice was provided were analysed to assess if the disclosure of the AI advice significantly increased the confidence score of participants. The LMM revealed that the confidence scores *after* introducing the AI advice were significantly higher compared to the confidence scores *before* the introduction of AI advice ($p < 0.001$) (see Appendix 29).

6 Discussion

6.1 Research Findings

This section will highlight the main findings of the research at hand as well as discuss them in line with current existing literature. Additionally, both the theoretical and managerial implications of the research will be addressed. Lastly, the limitations and future research will be explored.

6.1.1 Hypothesis 1

This thesis addresses the role generational differences play in an individual's inclination to rely on AI advice for business decision-making, exploring how individuals from Gen Z and Gen X adjust their initial estimations in response to AI advice in two different tasks: house price prediction and song popularity forecasting.

The findings reveal there is evidence that Gen Z relies more on AI advice than Gen X however, this effect is considerably small. This aligns with current literature suggesting that younger generations, typically more prompt to use digital technology, may integrate AI tools more seamlessly into their decision-making processes (Asoba & Mefi, 2022). However, when adjusting for covariates such as *education*, *employment* and *familiarity* with AI, the variable age no longer shows significance in explaining the reliance on AI advice. This is consistent with the findings of Logg et al. (2019), suggesting that other factors play a role in explaining why individuals rely on AI advice that is not explained by the generation. Notably, it was found that higher levels of education and familiarity with AI significantly increased the reliance on AI advice (also found by Belanche et al., 2019), indicating that these factors may overshadow generational effects.

According to the findings, both generations exhibit significant reliance on AI advice, however, the degree also depends on the nature of the tasks being performed (see Figure 3). Participants show more reliance on AI advice for objective tasks (*house price forecasting*) than for subjective tasks (*song popularity forecasting*), this aligns with the existing literature of Logg (2017). Additionally, it was found that participants from Gen X show a higher variability towards WOA, suggesting some degree of scepticism toward AI within this generation, which is consistent with previous research conducted by Kapoor and Solomon (2011). Moreover, consistent with Parasuraman and Riley (1997) research, which states that individuals either underutilize or overutilize automated advice, a substantial number of participants either fully relied on AI advice or fully disregarded it, as shown by the histograms in Appendix 15.

These findings add to the growing research on the use of AI in business decision-making, emphasising the importance of contextual and demographic factors in the adoption of AI systems.

6.1.2 Hypothesis 2

The results from hypothesis 2 reveal that there is no significant difference in dispositional trust in AI between Gen Z and Gen X. This contrasts with previous findings of Chan and Lee (2023), suggesting that younger generations are more prompt to trust AI than older generations. Thus, generational differences are not significant in explaining dispositional trust in AI. Previously, in Section 4.3, the contradicting research streams on how generational differences affect individuals' trust in AI were discussed. Not being able to confirm hypothesis 2 highlights the complexity of this relationship, suggesting that trust in AI does not solely depend on generational differences but rather on other factors, such as the individual's familiarity with the technology.

The exploratory analysis has provided insights into a possible new mediation effect present in the conceptual model that influences the dynamics between generational differences and dispositional trust. Familiarity with AI has been shown to influence the dynamics of trust and reliance on AI advice across generations. The results suggest that Gen Z is more familiar with AI which leads them to have a higher dispositional trust in AI. Consequently, this leads to a higher situational trust in AI that is finally associated with an increased reliance on AI advice. This finding aligns with previous literature by Morris & Venkatesh (2000) and Berkowsky et al. (2017), who highlighted that the variation in technology adoption rates may be attributed to familiarity rather than generational differences alone. Even though the analysis points to the possibility that familiarity is a mediator, I did not conduct a statistical mediation analysis that would be required to test for the statistical validity of this statement.

6.1.3 Hypothesis 3

Results from hypothesis 3 reveal a significantly positive correlation between dispositional and situational trust in AI. This posits that individuals who inherently trust AI in the first place are also more prompt to trust AI in context-specific situations, aligning with the research of Hoff and Bashir (2015). Trust is a crucial factor for effective reliance on automated technologies, as discussed by Lee and Moray (1994) and Muir and Moray (1996). Thus, this finding suggests that individuals who show higher dispositional trust in AI will consequently show higher levels of situational trust, which will then lead to higher reliance on AI advice. This illustrates a multi-level approach for building trust in AI that aligns with the multi-layered trust model developed by Hoff and Bashir (2015).

6.1.4 Hypothesis 4

Hypothesis 4 has revealed a significant direct effect of situational trust on reliance on AI advice. The aim was to understand if higher levels of trust would lead to higher reliance on AI advice and in accordance with the findings of Lee and Moray (1994) and Muir and Moray (1996), trust is a strong predictor of how much an individual is willing to rely on advice. The results indicate that individuals who show higher levels of situational trust in AI lead to a stronger reliance on AI advice. This could be explained by the fact that when individuals trust AI, they tend to perceive it as more competent and reliable, enhancing their willingness to utilise its advice for business decision-making. When controlling for confounding effects, situational trust remained statistically significant for explaining participants' reliance on AI advice. Thus, it can be concluded that even though other facts might influence how likely an individual is to rely on AI advice, situational trust plays a crucial role in fostering an effective adoption and integration of AI advice.

6.1.5 Hypothesis 4.1

Results from hypothesis 4.1 reveal that the effect between situational trust and WOA is not moderated by the confidence individuals show in their own judgement. The hypothesis argued that higher levels of confidence in own judgement would decrease the positive effect of situational trust on WOA. However, the *linear mixed model* used to evaluate this relation found no significant moderation effect, revealing that high levels of confidence in own judgement do not affect the relation between trust and reliance on advice. This contrasts with the findings of Lee and Moray (1994) and requires further investigation to assess the reason why I was not able to find this relation and address potential factors that may be causing this contrast between the present study and previous literature, such as the sample used to test the hypothesis and the decision-making scenarios.

Additionally, even though the moderation effect was not confirmed, through the exploratory analysis, a direct relationship was identified between confidence in own judgement and reliance on advice, meaning that higher levels of confidence were associated with a decreased reliance on AI advice. This aligns with previous findings of Bonaccio and Dalal (2006), Chong et al. (2022) and Logg et al. (2019), who suggest that confidence affects how individuals are willing to rely on external advice, where higher levels of confidence lead to a decreased reliance on advice which reinforces the validity of my study.

Lastly, as part of the exploratory analysis, a significant difference between the levels of confidence *before* and *after* the disclosure of the advice was found. The disclosure of the AI advice significantly increased the participants' level of confidence. This comes as additional insightful information, meaning that the advice provided by the AI system was seen by participants as a trustworthy source that made them more confident in their final decision. Additionally, the results indicate that the nature of the task influences the extent to which the confidence scores of individuals changed before and after the advice (see Appendix 13). This leads me to conclude that the house price prediction task, often seen as more objective, leads people to see AI advice as a credible and reliable source, thus increasing their level of confidence. On the other hand, the song forecasting task is often perceived as more subjective and, therefore, sees a smaller change in confidence.

6.2 Implications

6.2.1 Theoretical Implications

The results suggest a subtle difference between Gen Z and Gen X's reliance on AI advice, revealing that more than only generational differences play a role in how individuals trust and rely on AI advice. Contextual factors such as familiarity with AI and education level influence the extent to which individuals rely on AI advice. This broadens our understanding of how different backgrounds and interactions with technologies can help shaping individual’s willingness to utilise AI advice. Additionally, these results challenge existing literature (Asoba & Mefi, 2022) that suggests a direct link between generational differences and their trust and reliance on AI advice. This relation seems to be more complex, meaning that there are not only the broad generational characteristics that affect how likely are individuals to trust and rely on

AI but rather factors such as familiarity and education, which is consistent with prior research by Belanche et al. (2019).

Additionally, results suggest that one way to enhance reliance on advice in the context of business decision-making is to increase familiarity with AI systems. Gen Z has shown to be more familiar with AI systems which reflects on them being more prompt to trust AI and thus utilize its advice. Gen X, on the other hand, show less familiarity with AI which leads to lower levels of trust and consequently, lower rates of reliance on AI advice. This study further contributes to prove the interdependency between dispositional and situational trust, uncovered in the research of Hoff and Blair (2015). This builds on understanding the dynamics between trust and reliance on AI advice proving that to successfully promote the adoption of AI advice, individuals should first trust the AI systems in general, which will then lead them to trust it in context-specific scenarios.

Furthermore, the study contradicts the general body of research which argues that confidence acts as a moderation factor for the effect of trust on the reliance on AI. This calls for future research that investigates the complex relationship between generational differences, trust, confidence and reliance on AI advice. Moreover, factors such as the nature of the decision-making task (whether it is objective or subjective) as well as the empirical setting in which the experiment is being developed should be taken into account.

6.2.2 Managerial Implications

Over the years, companies have shown an increasing interest in adopting AI technologies in their daily operation. This comes from the vast potential uncovered by using Big Data, which has proven to bring benefits in increased speed and accuracy when processing vast amounts of data. This leads to time and cost savings, as well as reducing bias in decision-making (Doumpos & Grigoroudis, 2013; Wamba-Taguimdje et al., 2020). As companies exploit the possibility of incorporating AI in their operations, it is important that they first assess the level of familiarity their employees have with this technology. Additionally, they must build a robust implementation plan to ensure a successful integration of AI within the company.

The research at hand focuses on two generations that play a crucial role and that are currently essential to companies. On one hand, Gen X hold longstanding positions within companies and typically holds more hierarchical roles (Asoba & Mefi, 2022a). On the other hand, Gen Z, which has recently started to join the workforce, brings a fresh and new perspective to the organisation (Aggarwal et al., 2020). With their distinct characteristics, companies have to adapt in order to leverage the strengths and weaknesses of both generations to maximise added value.

Indeed, findings suggest that Gen Z is more familiar with AI. Therefore, when implementing AI in the workplace, employers must balance the levels of familiarity displayed by individuals. Given the importance of familiarity with AI for consequent adoption and trust, organisations should invest in developing targeted training programs that enhance the understanding and skills related to AI technologies. This becomes particularly important as Gen X have shown to have lower levels of familiarity with AI. As AI technologies continue to evolve, companies should provide continuous learning and development programs that focus on educating employees and building digital literacy across all age groups, from new joiners to longstanding talent retained by the company. To ensure that the AI advice is understandable and successfully integrated into the decision-making process, companies must develop targeted and personalised strategies that take into consideration the different degrees of familiarity shown by employees. The personalisation of AI strategies to address different levels of familiarity, education and trust can more effectively address different levels of digital proficiency and potentially increase the successful utilisation of AI advice. Through the implementation of educational programs companies should further empathise a collaborative environment where human emotional intelligence and AI's computational capabilities combined lead to optimal decision-making outcomes. This builds on the concept of Hybrid intelligence, presented by van der Aalst (2021).

Additionally, this research uncovered the importance of building trust in AI systems for their successful implementation. To foster trust, companies should promote transparency in how these systems operate and make decisions (Ehsan et al., 2021), which involves a clear communication about AI's capabilities and limitations. This leads to the next point, which concerns the implications this study has for AI developers. AI developers should create transparent AI systems that explain decision-making processes and outcomes to users, thereby enhancing trust. Lastly, given that people tend to rely more on AI advice for objective tasks, it is advisable that companies initially implement AI technologies in more objective domains and afterwards start to incorporate them in more subjective domains. This way, companies can ensure to build a strong foundational base of familiarity with AI, which is then reflected in higher levels of trust and consequently, higher levels of advice utilisation.

6.3 Limitations

The research at hand has provided important findings, however, it is crucial to consider its main limitations. The first limitation is the sample representativeness. Given the time and budget constraints, I primarily relied on my personal network to gather responses, which may affect the generalizability of the results. The majority of the participants are Portuguese, limiting the generalizability of the results as this sample is not likely to capture the full spectrum of generational attitudes towards AI. Additionally, the research design was based on hypothetical scenarios where participants were asked to imagine themselves in certain situations. Even though this is a highly used method to test for correlation analysis, it might not capture the true behaviours of participants (Queirós et al., 2017). Since they know they are participating in a study, participants are likely to change their behaviour to act according to the research objectives. Moreover, the study only considers two decision-making scenarios, which is a very narrow sample of all the scenarios in which AI can be applied for business decision-making, compromising the generalizability of the findings to other domains. As mentioned by Lai et al. (2021), AI has been implemented in multiple fields and this should also be an object of analysis. Furthermore, the present study employed self-reported scales to measure the main variables. While this has proved to be efficient in previous research to measure subjective perception (Scholz et al., 2024; Scharowski et al., 2024; See et al., 201), participants are likely to incur in social desirability bias by providing answers that they believe to be socially acceptable rather than their true opinion (Nederhof, 1985).

Moreover, while the study controlled for several confounding effects, other factors, such as previous experience with AI, could be taken into account to assess if they play a role in explaining why generations rely differently on AI advice.

Additionally, the conceptual model presented in Section 4.4 introduced a multiple-mediated moderation model with two mediators (dispositional and situational trust) and a moderator (confidence in own judgement). However, the analysis conducted in Chapter 5 focused only on assessing the direct effect of the variables without thoroughly testing the proposed complex model. The initial analysis of the direct effect of generational differences on dispositional trust did not yield significant results ($p > 0.05$), thus compromising the validity of the full multi-level mediation moderation model. Consequently, without a significant direct effect, proceeding with a complex Bayesian multi-level mediation analysis was deemed inappropriate. This underscores the need to reassess the conceptual framework, particularly considering the role of familiarity in mediating the relationship between generational differences and dispositional trust, before testing the multi-level mediation model using a Bayesian analysis (Berger et al., 1994).

Lastly, while the findings from the exploratory analysis are not the primary focus of the research, they also provide some valuable insights. However, these may not apply to the wider population as they are often specific to the dataset under analysis. This limitation is empathised by the previous concern on the sample representativeness. To validate these findings, it is required to perform in-depth statistical testing together with triangulating the findings with previous research.

6.4 Future Research

Taking into account the limitations acknowledged in the previous Section, I would like to propose some avenues for future research that might expand the analysis at hand and find more relevant relations on why people rely differently on AI advice. For instance, the degree of familiarity as well as the educational level should be introduced in the conceptual model to assess its mediating effect between generational differences and dispositional trust. The findings should be triangulated with previous literature on this topic to increase the validity of the study. Additionally, a statistical mediation analysis testing for the validity of the comprehensive multi-mediation model should be conducted.

Furthermore, it would be important to control for the confounding effects of previous experience with AI as this might influence the degree to which individuals trust AI (Bedué & Fritzsche, 2022). Additionally, this analysis could be expanded to include other generational cohorts such as Millennials to provide a more comprehensive perspective on how different generations trust and rely on AI advice across different domains.

The findings of my research underscore the importance of conducting an in-depth analysis of the subjective perspective of trust in AI systems. By gathering qualitative data, future researchers could better understand the factors that explain why individuals trust or distrust AI and what leads them to utilize its advice.

While this study focuses on understanding the relationship between generational differences, trust, confidence in own judgement, and reliance on advice future studies could explore how different levels of power within an organization utilize AI advice and how the reliance on advice varies based on the nature of the task (See et al., 2011; Logg et al., 2019). As an example, future research could examine in a certain industry, such as consulting, how different positions within the organization utilize AI, from the entry-level positions to managers and even partners. Additionally, this should take into account the fact that junior positions are linked to more analytical roles whereas more hierarchical positions are often linked with strategic ones. This links with the difference between the objectivity and subjectivity of the task domains which have been shown to influence how individuals rely on AI (Castelo et al., 2019).

Lastly, linked to the business, setting there is a tendency that can be observed in the market where companies are now developing their own source of AI tools to be used by its employees (BCG Global, 2024). It would be interesting to analyse how having an internal or external source of AI providers influences how individuals rely on AI advice. This could also uncover additional information on what are the main concerns companies face when incorporating AI into their daily operations.

7 Conclusion

Artificial Intelligence is increasingly integrated into decision-making in the business context, enhancing the accuracy and quality of decisions (Jarrahi, 2018). To fully harness the potential of AI, organisations must prepare their workforce to work collaboratively with, rather than in opposition to, this technology. This will ensure that human critical thinking is maximised alongside the processing capacity of AI.

The findings reveal that Gen Z exhibits a slightly higher tendency to rely on AI advice compared to Gen X. Additionally, it uncovered the importance of factors such as education level and familiarity with AI significantly affecting trust and reliance on AI advice. This indicates that the individual's tendency to trust automation is not only routed in demographical factors but also contextual factors. Additionally, the present thesis revealed a gradual process for building trust in AI. Individuals who are more familiar with AI show a higher dispositional trust in this technology and thus, they are more likely to rely on AI for context-specific situations. Finally, higher situational trust leads individuals to rely more on AI advice. It was also found that higher levels of confidence in own judgement decrease the degree to which individuals rely on AI advice.

These findings highlight that it is imperative for companies to develop strategies that enhance trust and understanding of AI technologies. Additionally, the strategies should be targeted to accommodate the different levels of employees' familiarity with AI, aiming to standardise this familiarity across the workforce.

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Appendix

Appendix 1: Survey

Start of Block: Informed consent

Thank you for your participation in this research project for my Master's Thesis at the Universidade Católica Portuguesa and WU University of Economics and Business. This study involves two decision-making scenarios and several related questions, estimated to take about 7 minutes of your time.

You will be presented with two hypothetical scenarios so please make an effort to imagine yourself in those scenarios and answer as truthful as possible. Also, I ask you not to search the internet for information as that would compromise the results of the survey.

This survey protects against the potential of identifying participants through their responses by guaranteeing anonymity and confidentiality. The information acquired for this survey will only be used for my academic research.

In case you have questions about this survey, please contact me: Inês Correia

s-inmocorreia@ucp.pt

By continuing you agree to participate. Thank you!

End of Block: Informed consent

Start of Block: Attention check

Q34 To make sure you read the instructions carefully, please select if the following sentence is true or false: Throughout the survey, I should not look for information online.

○ True (1)

○ False (2)

End of Block: Attention check

Start of Block: Demographic Questions

Q3 Please indicate your Age (in years)

____

Q4 What is your gender?

- ○ Male (1)
- ○ Female (2)
- ○ Non-binary (3)
- ○ Others (4)
- ○ Prefer not to say (5)

Q5 What is your present employment status?

- ○ Employed (1)
- ○ Unemployed (2)
- ○ Student (3)
- ○ Student and worker (4)
- ○ Retired (5)
- ○ Other (Please specify) (6) ____

Q6 What is the highest level of education you have completed or are currently attending?

- Less than high school degree (1)
- High school degree (2)
- Bachelor's degree (3)
- Master's degree (4)
- Doctoral degree (5)
- Other (Please specify) (6) ____

Q7 What is your Nationality?

▼ Portuguese (1) ... Other (18)

Page Break

Q9 The following question is related to your familiarity with Artificial Intelligence* (AI).

**Artificial Intelligence (AI) is a machine's ability to perform some cognitive functions we usually associate with human minds.*

Please state your agreement with the following statement your familiarity with AI.
I am familiar with AI and AI contents (produced texts, etc.)

- Strongly disagree (1)
- Disagree (2)
- Somewhat disagree (3)
- Neither agree nor disagree (4)
- Somewhat agree (5)
- Agree (6)
- Strongly agree (7)

End of Block: Demographic Questions

Start of Block: Dispositional Trust and introduction to scenarios

Q11 Please state your agreement with the following statements regarding AI.

	Strongly disagree (1)	Somewhat Disagree (2)	Neither agree or disagree (3)	Somewhat agree (4)	Strongly agree (5)
Even though I may sometimes suffer the consequences of trusting AI, I still prefer to trust than not to trust them. (1)	○	○	○	○	○
I feel good about trusting AI. (2)	○	○	○	○	○
I believe that I am generally better off when I do not trust AI than when I trust them. (3)	○	○	○	○	○
I rarely trust AI because I can't handle the uncertainty. (4)	○	○	○	○	○

Page Break

Q10 Two scenarios will now be provided to you. Please try to imagine yourself in the described situations and answer as accurately as you can.

End of Block: Dispositional Trust and introduction to scenarios

Start of Block: Task 1: Apartment Price Prediction

Q12 Suppose you are a Real Estate Agent and you are asked to predict the monthly rental price of an apartment in Cambridge.

You will be provided with some information about the apartment, such as the number of square meters, the number of bedrooms, and the relative size of the apartment (i.e., whether the apartment size is smaller than average, average, or larger than average for its number of bedrooms).

Below you can find information on the number of square meters, number of bedrooms, and relative size of the apartment.

This apartment has **3 bedrooms** and **74 square meters**.
This apartment is **smaller than average** for 3 bedrooms.

Q13 Based on the information provided above, What is your estimate for the **monthly rental price** of this apartment in Cambridge?

____

Q14 State your level of agreement with the two following statements.

	Strongly disagree (1)	Somewhat Disagree (2)	Neither agree or disagree (3)	Somewhat agree (4)	Strongly agree (5)
I feel confident with my performance in this task. (1)	○	○	○	○	○
I believe my prediction is accurate. (2)	○	○	○	○	○

Page Break

Q15 Here is some advice that may help you make your final estimate.

Chrono is an AI algorithm that learns from past and current data to provide unbiased advice. Previously, Chrono has shown a high level of effectiveness in forecasting the monthly rental prices of apartments in Cambridge.
Chrono predicted that this apartment should cost: **$3258 per month**

Q16 Please state your agreement with the following statements regarding Chrono's recommendation.

	Strongly disagree (1)	Somewhat Disagree (2)	Neither agree or disagree (3)	Somewhat agree (4)	Strongly Agree (5)
I am confident in Chrono's recommendation. I feel that it works well. (1)	○	○	○	○	○
The output of Chrono is very predictable. (2)	○	○	○	○	○
Chrono is very reliable. I can count on it to be correct all the time. (3)	○	○	○	○	○
I feel safe that when I rely on Chrono I will get the right answers. (4)	○	○	○	○	○
Chrono is efficient and it works very quickly. (5)	○	○	○	○	○
I am cautious when using Chrono. (6)	○	○	○	○	○
Chrono can perform the task better than a novice human user. (7)	○	○	○	○	○
I like using Chrono for decision-making. (8)	○	○	○	○	○

Q17 Based on the information provided by Chrono's, would you like to reconsider your previous estimate?

If so, specify your final estimate below, otherwise leave it empty.

____

Q19 Based on your final estimation, state your level of agreement with the following statements.

	Strongly disagree (1)	Somewhat Disagree (2)	Neither agree or disagree (3)	Somewhat agree (4)	Strongly agree (5)
I feel confident with my performance in this task (1)	○	○	○	○	○
I believe my prediction is accurate (2)	○	○	○	○	○

Q21 Thank you for completing this task. Please click to continue.

End of Block: Task 1: Apartment Price Prediction

Start of Block: Task 2 – Song Forecasting

Q32 In this task, imagine you are working in Billboard Magazine's. You will predict the rank of a song on the Billboard Magazine's "Hot 100" song list. This ranking is based on a combination of record sales and how frequently people stream songs online.

The "Hot 100" list ranks songs from 1 to 100 where a **rank of 1 means it is the most popular song** and a rank of 100 means it is ranked last.

You will be shown the ranks of the same song from prior weeks so you can get a sense of how song ranks change over time.

Q23 Based on the information provided, **What rank will "Texas Hold 'Em" by Beyonce place on the Billboard Magazine "Hot 100"** the following week, meaning **week 5?**
Enter only a number between 1 and 100 (1 means ranked first and 100 means ranked last).

____

Q24 State your level of agreement with the following statements.

	Strongly disagree (1)	Somewhat Disagree (2)	Neither agree or disagree (3)	Somewhat agree (4)	Strongly agree (5)
I feel confident with my performance in this task. (1)	○	○	○	○	○
I believe my prediction is accurate. (2)	○	○	○	○	○

Page Break

Q25 Here is some advice that may help you make your final estimate.

TrackRank is an AI algorithm that learns from past and current data to provide unbiased advice. Previously, TrackRank has shown a high level of effectiveness in estimating the ranking of songs in the Billboard Magazine's.

The ranking that TrackRank predicted was: **11**

Q26 Please state your agreement with the following statements regarding TrackRank's recommendation.

	Strongly disagree (1)	Somewhat Disagree (2)	Neither agree or disagree (3)	Somewhat agree (4)	Strongly agree (5)
I am confident in this recommendation. I feel that it works well. (1)	○	○	○	○	○
The output of TrackRank is very predictable. (2)	○	○	○	○	○
TrackRank is very reliable. I can count on it to be correct all the time. (3)	○	○	○	○	○
I feel safe that when I rely on TrackRank I will get the right answers. (4)	○	○	○	○	○
TrackRank is efficient and it works very quickly. (5)	○	○	○	○	○
I am cautious when using TrackRank. (6)	○	○	○	○	○
TrackRank can perform the task better than a novice human user. (7)	○	○	○	○	○
I like using TrackRank for decision-making. (8)	○	○	○	○	○

Q27 Based on the information provided by TrackRank's, would you like to reconsider your previous estimate?

If so, specify your final estimate below, otherwise leave it empty

Q28 Based on your final estimation, state your level of agreement with the following statements.

	Strongly disagree (1)	Somewhat Disagree (2)	Neither agree or disagree (3)	Somewhat agree (4)	Strongly agree (5)
I feel confident with my performance in this task. (1)	○	○	○	○	○
I believe my prediction is accurate. (2)	○	○	○	○	○

Q30 To make sure you read this question carefully, please select “Somewhat disagree”

○ Strongly disagree (1)

○ Somewhat disagree (2)

○ Neither agree or disagree (3)

○ Somewhat agree (4)

○ Strongly Agree (5)

Q29 Thank you for completing this task. Please click to continue.

End of Block: Task 2 – Song Forecasting

Start of Block: End Questions

Q31 Performing the decision making tasks of this study was

- Extremely difficult (1)
- Moderately difficult (2)
- Slightly difficult (3)
- Neither easy nor difficult (4)
- Slightly easy (5)
- Moderately easy (6)
- Extremely easy (7)

Q32 Did you search the internet (or use other sources) for information to answer any questions in this survey?

- Yes (1)
- No (2)
- Rather not say (3)

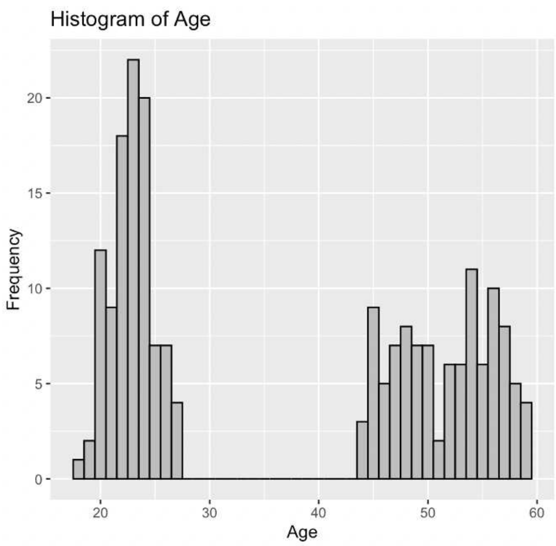
Q33 If you have any feedback or thoughts for the researcher, please feel free to share them in the space provided below. If not, you can leave the space empty.

____

End of Block: End Questions

Appendix 2: Histogram and Descriptive Statistics: Age

Histogram



Descriptive Staistics

```
> print(descriptive_stats)
# A tibble: 1 × 5
  Count   Min   Max  Mean    SD
  <int> <dbl> <dbl> <dbl> <dbl>
1   206    18    59  37.4  14.8
```

Appendix 3: Descriptive Statistics: Country

Country	Frequency	Percent	CumulativePercent
Portuguese	148	71.844660	71.84466
Austrian	24	11.650485	83.49514
French	1	0.485437	83.98058
Spanish	1	0.485437	84.46602
German	8	3.883495	88.34951
Swiss	1	0.485437	88.83495
Danish	1	0.485437	89.32039
Brazilian	1	0.485437	89.80582
British	2	0.970874	90.77670
American	2	0.970874	91.74757
Canadian	2	0.970874	92.71845
Australian	1	0.485437	93.20388
Other	14	6.796117	100.00000

Appendix 4: Calculation Cronbach´s Alpha: Dispositional Trust

```
> print(Ndispositional_trust_alpha$total)
 raw_alpha std.alpha   G6(smc) average_r      S/N        ase     mean        sd  median_r
 0.7987348  0.798388 0.7906987 0.4974888 3.960021 0.02344738 3.370146 0.9175495 0.4390802
```

Appendix 5: Calculation Cronbach´s Alpha: Confidence in own Judgement

```
> print(confidence_alpha$total)
 raw_alpha std.alpha   G6(smc) average_r      S/N        ase     mean     sd  median_r
 0.8834997  0.884588 0.7930595 0.7930595 7.664614 0.01613803 2.546117 1.1039 0.7930595
```

Appendix 6: Calculation Cronbach´s Alpha: Situational Trust

```
> print(system_trust_alpha$total)
 raw_alpha std.alpha   G6(smc) average_r      S/N        ase     mean        sd  median_r
 0.8034209 0.8001012 0.8199421  0.333474 4.002532 0.01985163 3.273058 0.6302215 0.3744401
```

Appendix 7: Randomizer check

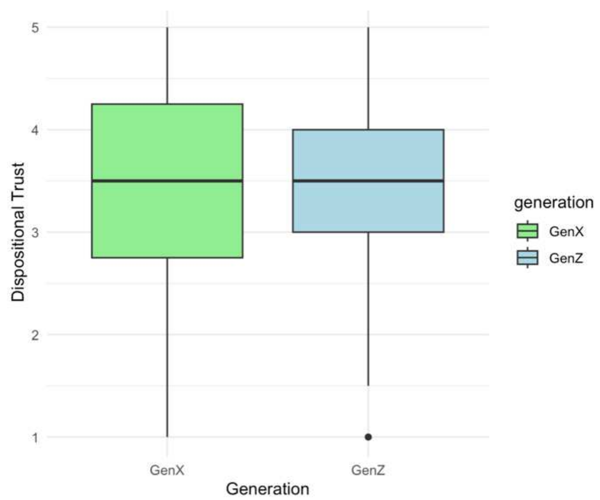
```
> table(Gen_data$TaskOrder)

Task1First Task2First
       100        106
```

Appendix 8: Descriptive Statistics & Box Plot: Dispositional Trust

```
> print(summary_stats_Dtrust)
# A tibble: 2 × 5
  generation  Mean Median    SD   IQR
  <chr>      <dbl>  <dbl> <dbl> <dbl>
1 GenX        3.36    3.5 0.986   1.5
2 GenZ        3.38    3.5 0.846   1
```

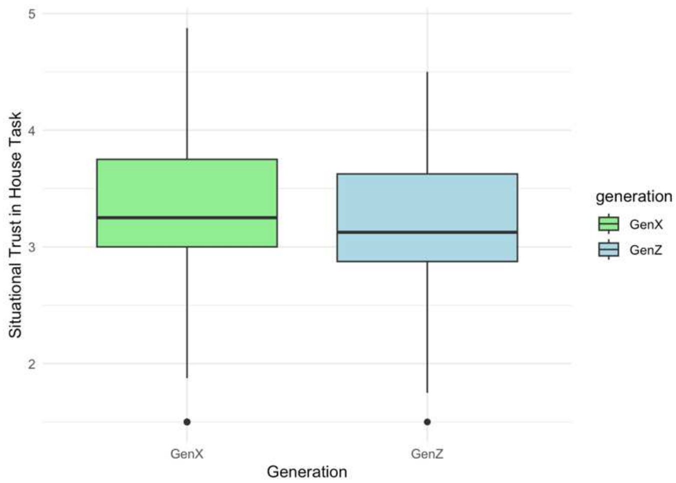
Box Plot of Dispositional Trust in AI across Generations



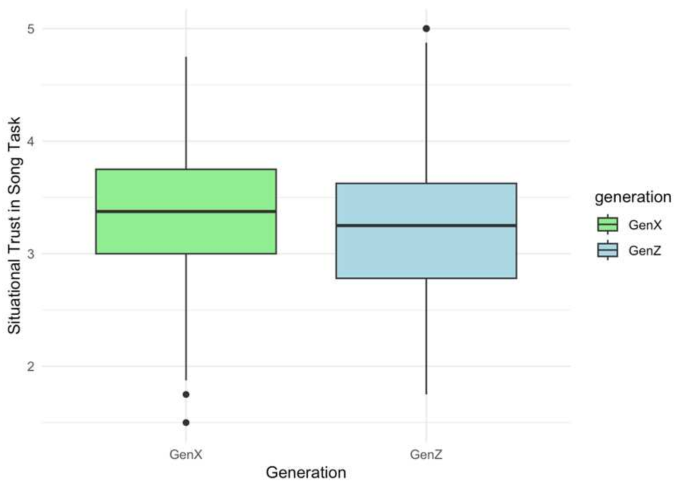
Appendix 9: Descriptive Statistics & Box Plot: Situational Trust

```
> print(summary_stats_house)
# A tibble: 2 × 5
  generation MeanH MedianH   SDH  IQRH
  <chr>      <dbl>   <dbl> <dbl> <dbl>
1 GenX        3.32    3.25 0.659  0.75
2 GenZ        3.23    3.12 0.599  0.75
> print(summary_stats_song)
# A tibble: 2 × 5
  generation MeanG MedianG   SDG  IQRG
  <chr>      <dbl>   <dbl> <dbl> <dbl>
1 GenX        3.32    3.38 0.639 0.75
2 GenZ        3.31    3.25 0.675 0.844
```

Box Plot of Situational Trust in House Tasks Across Generation



Box Plot of Situational Trust in Song Tasks Across Generations



Appendix 10: Descriptive Statistics: Confidence in own Judgement Before and After AI advice

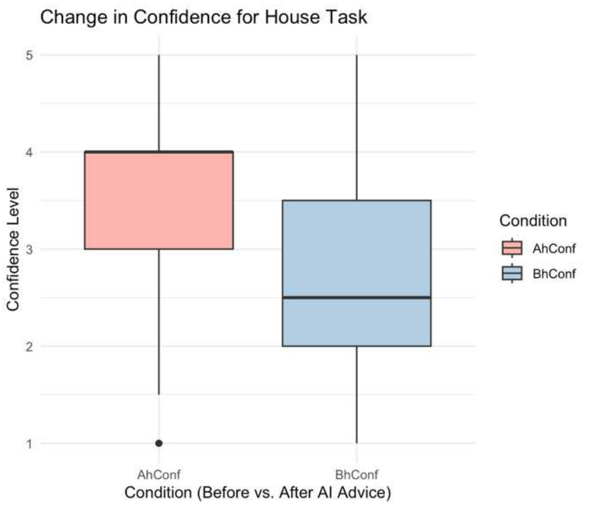
Descriptive Statistics on House Price Prediction Task

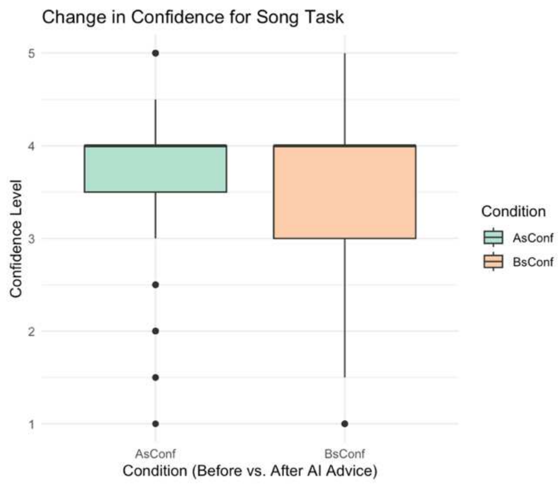
```
> print(summary_conf_house)
# A tibble: 1 × 8
  Mean_BhConf Median_BhConf SD_BhConf IQR_BhConf Mean_AhConf Median_AhConf SD_AhConf IQR_AhConf
        <dbl>         <dbl>     <dbl>      <dbl>       <dbl>         <dbl>     <dbl>      <dbl>
1        2.55           2.5      1.10        1.5        3.50             4      1.01          1
```

Descriptive Statistics on Song Prediction Task

```
> print(summary_conf_song)
# A tibble: 1 × 8
  Mean_BsConf Median_BsConf SD_BsConf IQR_BsConf Mean_AsConf Median_AsConf SD_AsConf IQR_AsConf
        <dbl>         <dbl>     <dbl>      <dbl>       <dbl>         <dbl>     <dbl>      <dbl>
1        3.54             4      1.02          1        3.79             4     0.844        0.5
```

Box Plot of Confidence in own Judgement by task type and across Generations

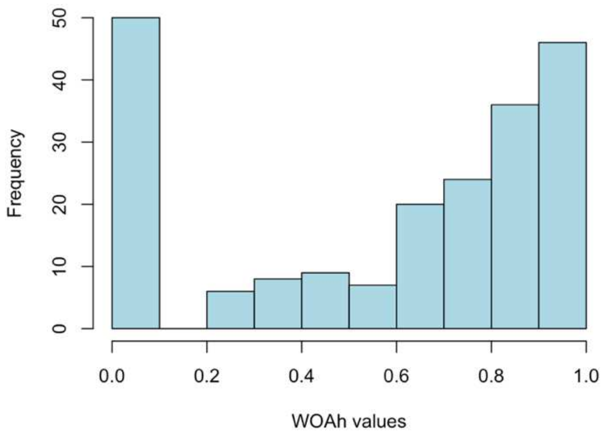




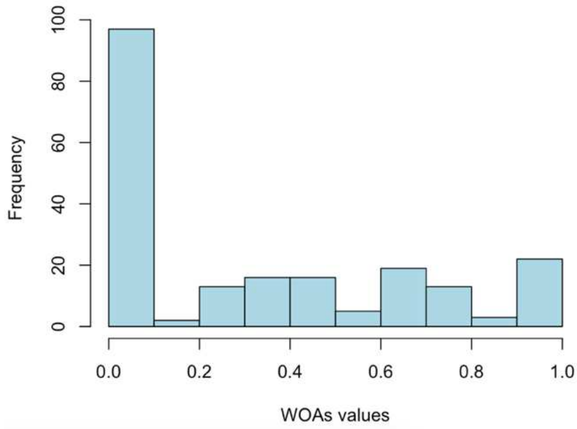
Appendix 11: Descriptive Statistics & Histogram: Reliance on AI Advice (WOA)

```
> print(summary_woa_house)
# A tibble: 2 × 5
  generation MeanWOAh MedianWOAh SDWOAh IQRWOAh
  <chr>         <dbl>      <dbl>  <dbl>   <dbl>
1 GenX          0.559      0.742  0.391   0.877
2 GenZ          0.619      0.773  0.367   0.527
> print(summary_woa_song)
# A tibble: 2 × 5
  generation MeanWOAs MedianWOAs SDWOAs IQRWOAs
  <chr>         <dbl>      <dbl>  <dbl>   <dbl>
1 GenX          0.263      0      0.353   0.617
2 GenZ          0.393      0.333  0.360   0.667
```

Histogram of WOA for House Price Prediction task



Histogram of WOA for House Price Prediction task



Appendix 12: Descriptive Statistics: Familiarity with AI

Gen Z

```
> print(summary_stats_genZ)
# A tibble: 1 × 4
   Mean    SD   Min   Max
  <dbl> <dbl> <dbl> <dbl>
1  5.77  1.12     2     7
```

Gen X

```
> print(summary_stats_genX)
# A tibble: 1 × 4
   Mean    SD   Min   Max
  <dbl> <dbl> <dbl> <dbl>
1  5.24  1.63     1     7
```

Total Sample

```
> print(summary_stats)
# A tibble: 1 × 4
   Mean    SD   Min   Max
  <dbl> <dbl> <dbl> <dbl>
1  5.50  1.42     1     7
```

Hyphothesis Testing

Appendix 13: Linear Mixed Model fit for hypothesis 1 – Model 1 – Effect of Generation on WOA accounting for Random Effects of Response ID and Task

	WOA		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	0.41	0.15 – 0.67	**0.002**
generation: Gen Z	0.09	0.01 – 0.18	**0.024**
Random Effects			
σ^2	0.09		
$\tau_{00\ ResponseId}$	0.04		
$\tau_{00\ task}$	0.03		
ICC	0.46		
N $_{ResponseId}$	206		
N $_{task}$	2		
Observations	412		
Marginal R^2 / Conditional R^2	0.013 / 0.471		

Appendix 14: Linear Mixed Model fit for hypothesis 1 – Model 1C – Effect of Generation on WOA accounting for Random Effects of Response ID and Task (including covariates)

	WOA		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	0.05	-0.32 – 0.43	0.776
generation: Gen Z	0.07	-0.04 – 0.18	0.183
Gender	-0.05	-0.12 – 0.03	0.206
Employ	-0.00	-0.04 – 0.04	0.970
Educ	0.05	0.01 – 0.10	**0.026**
Country	0.01	-0.00 – 0.02	0.076
Familiarity	0.04	0.01 – 0.07	**0.010**
Diffic	0.01	-0.02 – 0.04	0.642
Random Effects			
σ^2	0.09		
$\tau_{00\ ResponseId}$	0.04		
$\tau_{00\ task}$	0.03		
ICC	0.44		
$N_{ResponseId}$	206		
N_{task}	2		
Observations	412		
Marginal R^2 / Conditional R^2	0.065 / 0.479		

Appendix 15: Linear Regression for hypothesis 2 - Model 2 – Effect of Generation on Dispositional trust accounting for Random Effects of Response ID and Task

```
> model2 <- lm(D.Trust ~ generation, data = Gen_data)
> summary(model2)

Call:
lm(formula = D.Trust ~ generation, data = Gen_data)

Residuals:
    Min      1Q  Median      3Q     Max 
-2.3848 -0.6058  0.1442  0.6442  1.6442 

Coefficients:
               Estimate Std. Error t value Pr(>|t|)    
(Intercept)     3.35577    0.09018  37.211   <2e-16 ***
generationGenZ  0.02903    0.12816   0.227    0.821    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.9197 on 204 degrees of freedom
Multiple R-squared:  0.0002515, Adjusted R-squared:  -0.004649 
F-statistic: 0.05132 on 1 and 204 DF,  p-value: 0.821
```

Appendix 16: Linear Regression for hypothesis 2 - Model 2C – Effect of Generation on Dispositional trust accounting for Random Effects of Response ID and Task (including covariates[7])

```
Call:
lm(formula = D.Trust ~ generation + Gender + Employ + Educ + 
    Country + Familiarity, data = Gen_data)

Residuals:
    Min      1Q  Median      3Q     Max 
-2.7485 -0.4933  0.1216  0.5548  1.9440 

Coefficients:
               Estimate Std. Error t value Pr(>|t|)    
(Intercept)     2.36054    0.38459   6.138 4.45e-09 ***
generationGenZ  0.07800    0.16588   0.470    0.639    
Gender         -0.08155    0.11538  -0.707    0.481    
Employ         -0.03700    0.06235  -0.593    0.554    
Educ            0.03515    0.07206   0.488    0.626    
Country        -0.02109    0.01340  -1.574    0.117    
Familiarity     0.20317    0.04508   4.507 1.12e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.8719 on 199 degrees of freedom
Multiple R-squared:  0.1235,	Adjusted R-squared:  0.09711 
F-statistic: 4.675 on 6 and 199 DF,  p-value: 0.0001797
```

[7] The covariate difficulty of the task was not included as the independent variable under analysis was not affected by the tasks presented on the survey

Appendix 17: Linear Mixed Model fit for hypothesis 3 – Model 3 – Direct effect of Dispositional trust on Situational trust accounting for Random Effects of Response ID and Task

	Strust		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	2.35	2.08 – 2.63	**<0.001**
Dtrust	0.28	0.20 – 0.36	**<0.001**
Random Effects			
σ^2	0.14		
$\tau_{00\ \mathrm{ResponseId}}$	0.21		
$\tau_{00\ \mathrm{task}}$	0.00		
ICC	0.60		
$N_{\mathrm{ResponseId}}$	206		
N_{task}	2		
Observations	412		
Marginal R^2 / Conditional R^2	0.158 / 0.662		

Appendix 18: Linear Mixed Model fit for hypothesis 3 – Model 3C - Direct effect of Dispositional trust on Situational trust accounting for Random Effects of Response ID and Task (including covariates)

	Strust		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	2.27	1.75 – 2.78	**<0.001**
Dtrust	0.23	0.15 – 0.31	**<0.001**
Gender	-0.16	-0.29 – -0.04	**0.012**
Employ	-0.05	-0.11 – 0.01	0.075
Educ	0.02	-0.06 – 0.10	0.627
Country	0.01	-0.00 – 0.03	0.084
Familiarity	0.08	0.03 – 0.14	**0.002**
Diffic	0.01	-0.04 – 0.06	0.732
Random Effects			
σ^2	0.14		
$\tau_{00\ ResponseId}$	0.18		
$\tau_{00\ task}$	0.00		
ICC	0.57		
$N_{ResponseId}$	206		
N_{task}	2		
Observations	412		
Marginal R^2 / Conditional R^2	0.233 / 0.667		

Appendix 19: Linear Mixed Model fit for hypothesis 4 – Model 4 - Direct effect[8] of Situational trust on WOA accounting for Random Effects of Response ID and Task

	WOA		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	-0.39	-0.71 – -0.07	**0.016**
Strust	0.26	0.21 – 0.31	**<0.001**
Random Effects			
σ^2	0.08		
$\tau_{00\ \mathrm{ResponseId}}$	0.02		
$\tau_{00\ \mathrm{task}}$	0.04		
ICC	0.42		
$N_{\mathrm{ResponseId}}$	206		
N_{task}	2		
Observations	412		
Marginal R^2 / Conditional R^2	0.159 / 0.514		

[8] This analysis is limited to testing the direct effect of situational trust on WOA rather than the overall mediation model. This adjustment is due to the lack of significant findings in Hypothesis 2, which challenged the viability of the proposed mediation model.

Appendix 20: Linear Mixed Model fit for hypothesis 4 – Model 4C – Direct effect of Situational trust on WOA accounting for Random Effects of Response ID and Task (including covariates)

	WOA		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	-0.66	-1.05 – -0.27	**0.001**
Strust	0.25	0.20 – 0.31	**<0.001**
Gender	0.01	-0.06 – 0.07	0.820
Employ	0.03	-0.00 – 0.06	0.055
Educ	0.04	0.00 – 0.09	**0.034**
Country	0.01	-0.00 – 0.01	0.080
Familiarity	0.01	-0.02 – 0.04	0.472
Diffic	0.00	-0.02 – 0.02	0.998
Random Effects			
σ^2	0.08		
$\tau_{00\ ResponseId}$	0.02		
$\tau_{00\ task}$	0.04		
ICC	0.41		
$N_{ResponseId}$	206		
N_{task}	2		
Observations	412		
Marginal R^2 / Conditional R^2	0.188 / 0.520		

Appendix 21: Linear Mixed Model fit for hypothesis 4.1 – Model 4.1 – Moderation Analysis

	WOA		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	-0.48	-1.02 – 0.06	0.082
Strust	0.31	0.17 – 0.45	**<0.001**
B Conf	0.03	-0.11 – 0.16	0.708
Strust:BConf	-0.02	-0.06 – 0.02	0.421
Random Effects			
σ^2	0.08		
$\tau_{00\ ResponseId}$	0.02		
$\tau_{00\ task}$	0.03		
ICC	0.38		
$N_{ResponseId}$	206		
N_{task}	2		
Observations	412		
Marginal R^2 / Conditional R^2	0.172 / 0.490		

Appendix 22: Linear Mixed Model fit for hypothesis 4.1 (including covariates) – Model 4.1C – Moderation Analysis

	WOA		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	-0.84	-1.42 – -0.25	**0.005**
Strust	0.33	0.18 – 0.47	**<0.001**
B Conf	0.06	-0.08 – 0.20	0.419
Gender	0.00	-0.06 – 0.07	0.941
Employ	0.03	-0.00 – 0.06	0.078
Educ	0.04	0.00 – 0.08	**0.036**
Country	0.01	-0.00 – 0.01	0.077
Familiarity	0.01	-0.01 – 0.04	0.395
Diffic	0.00	-0.02 – 0.03	0.976
Strust:BConf	-0.02	-0.07 – 0.02	0.252
Random Effects			
σ^2	0.08		
$\tau_{00\ \text{ResponseId}}$	0.02		
$\tau_{00\ \text{task}}$	0.03		
ICC	0.38		
$N_{\text{ResponseId}}$	206		
N_{task}	2		
Observations	412		
Marginal R^2 / Conditional R^2	0.199 / 0.501		

Exploratory Analysis

Appendix 23: Linear Mixed Model – Model E1 – Effect of Generation and Familiarity on WOA accounting for Random Effects of Response ID and Task

	WOA		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	0.16	-0.14 – 0.46	0.300
generation: Gen Z	0.07	-0.01 – 0.15	0.097
Familiarity	0.05	0.02 – 0.08	**0.001**
Random Effects			
σ^2	0.09		
$\tau_{00\ \text{ResponseId}}$	0.04		
$\tau_{00\ \text{task}}$	0.03		
ICC	0.45		
$N_{\text{ResponseId}}$	206		
N_{task}	2		
Observations	412		
Marginal R^2 / Conditional R^2	0.039 / 0.473		

Appendix 24: Simple Linear Regression – Model E2 – Effect of Generation on Familiarity

```
> e2 <- lm(Familiarity ~ generation, data = Gen_data)
> summary(e2)

Call:
lm(formula = Familiarity ~ generation, data = Gen_data)

Residuals:
    Min      1Q  Median      3Q     Max 
-4.2404 -0.2404  0.2255  0.7596  1.7596 

Coefficients:
               Estimate Std. Error t value Pr(>|t|)    
(Intercept)      5.2404     0.1374  38.127   <2e-16 ***
generationGenZ   0.5341     0.1953   2.734   0.0068 ** 
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.402 on 204 degrees of freedom
Multiple R-squared:  0.03536,	Adjusted R-squared:  0.03063 
F-statistic: 7.477 on 1 and 204 DF,  p-value: 0.006798
```

Appendix 25: Simple Linear Regression – Model E3 - Effect of Familiarity on Dispositional Trust

```
> e3 <- lm(D.Trust ~ Familiarity, data = Gen_data)
> summary(e3)

Call:
lm(formula = D.Trust ~ Familiarity, data = Gen_data)

Residuals:
     Min       1Q   Median       3Q      Max 
-2.68143 -0.51504  0.06857  0.56857  1.85955 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)   2.2241     0.2428   9.161  < 2e-16 ***
Familiarity   0.2082     0.0427   4.875 2.18e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.8705 on 204 degrees of freedom
Multiple R-squared:  0.1044,	Adjusted R-squared:  0.09996 
F-statistic: 23.77 on 1 and 204 DF,  p-value: 2.182e-06
```

Appendix 26: Linear Mixed Model of Situational Trust on Familiarity – Model E4 - Effect of Familiarity on Situational Trust accounting for Random Effects of Response ID and Task

	Strust		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	2.52	2.22 – 2.83	**<0.001**
Familiarity	0.14	0.09 – 0.19	**<0.001**
Random Effects			
σ^2	0.14		
$\tau_{00\ \mathrm{ResponseId}}$	0.23		
$\tau_{00\ \mathrm{task}}$	0.00		
ICC	0.63		
$N_{\mathrm{ResponseId}}$	206		
N_{task}	2		
Observations	412		
Marginal R^2 / Conditional R^2	0.096 / 0.662		

Appendix 27: Linear Mixed Model – Model E5 - Effect of Situational trust, Familiarity and Generation on WOA accounting for Random Effects of Response ID and Task

	WOA		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	-0.49	-0.82 – -0.16	**0.004**
Strust	0.26	0.20 – 0.31	**<0.001**
Familiarity	0.01	-0.02 – 0.04	0.450
generation: Gen Z	0.10	0.03 – 0.17	**0.005**
Random Effects			
σ^2	0.08		
$\tau_{00\ \mathrm{ResponseId}}$	0.02		
$\tau_{00\ \mathrm{task}}$	0.04		
ICC	0.41		
$N_{\mathrm{ResponseId}}$	206		
N_{task}	2		
Observations	412		
Marginal R^2 / Conditional R^2	0.177 / 0.516		

Appendix 28: Linear Mixed Model – Model E4.1 - Effect of before confidence levels on WOA accounting for Random Effects of Response ID and Task

	WOA		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	0.57	0.32 – 0.81	**<0.001**
B Conf	-0.04	-0.07 – -0.00	**0.036**
Random Effects			
σ^2	0.09		
$\tau_{00\ \mathrm{ResponseId}}$	0.05		
$\tau_{00\ \mathrm{task}}$	0.03		
ICC	0.44		
$N_{\mathrm{ResponseId}}$	206		

N task	2
Observations	412
Marginal R^2 / Conditional R^2	0.011 / 0.445

Appendix 29: Linear Mixed Model -– Model E6 - Changes in Participant Confidence Before and After AI Advice accounting for Random Effects of Response ID and Task

	A Conf		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	2.35	2.08 – 2.61	**<0.001**
B Conf	0.43	0.36 – 0.50	**<0.001**
Random Effects			
σ^2	0.46		
$\tau_{00\ ResponseId}$	0.16		
$\tau_{00\ task}$	0.01		
ICC	0.27		
N ResponseId	206		
N task	2		
Observations	412		
Marginal R^2 / Conditional R^2	0.283 / 0.478		