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Leveraging AI for Enhanced Personal Branding on LinkedIn:

Implications of User Engagement and Trust

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Abstract

Title: Leveraging AI for Enhanced Personal Branding on LinkedIn: Implications of User Engagement and Trust

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Keywords: AI Exposure, Attitudes towards AI, Perception of AI Accuracy, Brand Trust, Technology Acceptance Model, AI-Powered Profile Building, LinkedIn.

Thesis Purpose: This study aims to quantitatively examine the influence of exposure to AI as an independent variable, attitudes toward AI, and perceptions of AI accuracy as a mediating variable on people's trust in brands that utilize AI in their services using AI Powered Profile Building by LinkedIn as the context.

Methodology: We employ a quantitative approach, using a survey instrument to measure exposure to AI, attitudes toward AI, perceptions of AI accuracy, and brand trust. Participants will be recruited from LinkedIn users engaging with AI-powered features, and data will be collected via an online survey platform. Linear Regression will analyze the relationships and test the mediation roles between variables.

Empirical Data: Participants will provide demographic information and respond to items assessing research variables. Measures will include Likert-type scales for variables.

Theoretical Contribution: This study has contributed to a deeper understanding of the role of AI in fostering trust in brands that utilize it by extending the previous research model. It highlights the significance of people's exposure to AI in shaping brand trust, with attitudes toward AI and perceptions of AI accuracy mediating this relationship.

Managerial Contribution: Companies should take into account factors influencing customer acceptance of AI, including exposure to AI, attitudes toward AI, and perceptions of AI accuracy. These factors play a crucial role in shaping customer trust in brands, which is essential for sustaining long-term customer relationships.

Conclusion: High exposure to AI positively influences trust in brands that utilize AI in their services. Additionally, attitudes toward AI and perceptions of AI accuracy positively mediate these relationships. Furthermore, positive attitudes toward AI are shown to have a significant influence on brand trust. However, the influence of the accuracy perception of AI on brand trust is found to be insignificant.

Acknowledgment

We would like to express our gratitude to everyone who helped us in completing this research. Firstly, we express our sincere appreciation to our supervisor, Javier Cenamor, for his unwavering support and guidance throughout the entirety of our research journey. Secondly, we are immensely grateful to our respondents, who generously dedicated their time to complete our questionnaire and share their honest opinions. Their invaluable input allowed us to gather significant data and offer fresh insights into this research. Finally, we extend our deepest thanks to our family and friends for their constant encouragement and motivation throughout this master’s program.

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1. Introduction

In the introductory chapter, we will explain the concept of Artificial Intelligence (AI) within the framework of LinkedIn as a professional networking platform. This chapter will underscore the potential impact of AI on personal branding and consumer perceptions, with a particular emphasis on the critical role of trust in AI systems. Additionally, subsequent sections will address the research problem, present research questions, articulate the research aims, and provide a comprehensive overview of the thesis structure.

1.1 Background

AI is a versatile technology that requires specialized training and customization for precise application in specific tasks (D'Arco et al., 2019). As AI rapidly evolves, numerous tools have been developed for commercial use, enhancing various business processes (Haleem et al., 2022). In marketing, AI is integrated into CRM systems, chatbots, personalization tools, predictive analytics, image recognition, and sentiment analysis, all aimed at enriching the customer experience (Peyravi, Nekrošienė & Lobanova, 2020). Additionally, companies leverage AI to analyze competition, identify trends, and formulate strategic plans for a competitive edge, as well as to monitor customer behaviour and digital footprints to better understand consumer needs and boost conversion rates (Perifanis & Kitsios, 2023). The adoption of advanced AI tools is encouraged in the literature to enhance organizational capabilities (Yigit & Kanbach, 2021).

Additionally, in the contemporary digital landscape, social media has emerged as a vital platform for the job search process, particularly as recruitment specialists increasingly leverage these platforms to identify potential candidates. Hence, job seekers are endeavouring to showcase themselves on social media to make a favourable impression on recruiters (Marin & Nilă, 2021). In this way, job hunters are trying to build their personal branding to be able to attract recruiters. According to Marin and Nilă (2021), personal branding is *'the process of establishing a unique personal identity, developing an active communication approach of one's brand identity to a specific target market and evaluating its impact on one's image and reputation, to fulfil personal and professional objectives'*. Moreover, Leo et al. (2024) indicate that effectively utilizing social media professional networks such as LinkedIn for communicating one's personal brand could give a competitive advantage that could unlock more job opportunities. Furthermore, a robust personal brand enhances an individual's competitiveness in the job market (Marin & Nilă, 2021). As a result, personal branding can contribute to achieving favourable results in the job market (Leo et al., 2024).

To establish a personal brand on online platforms, LinkedIn offers sections for users to showcase their expertise, skills, experience, or interests through headlines and descriptions. This section holds great significance because when recruiters seek out candidates for available positions, the first information they encounter is the candidate's name and headline, followed by the description section, making it a crucial aspect of one's profile (Marin & Nilă, 2021). Recognizing its importance, LinkedIn has introduced AI-Powered Profile Building which aims at enhancing user experience by identifying user skills and experiences, providing personalized headlines and descriptions, thus reducing the writing effort required for users to represent themselves on the platform (T., 2023). Moreover, if job seekers perceive this service as useful and user-friendly (Davis, 1989) for profile creation and personal branding, they are likely to adopt it.

However, even though Yuan et al., (2022) suggest that brands should utilize AI to assist the company in managing problems and adapting to novel challenges, there remains a "mystery" regarding how people accept AI as a new technology. AI is defined as a system's ability to interpret external data, learn from it, and use that knowledge to achieve goals in flexible ways (Zhang et al., 2022). According to Kim, Giroux & Lee (2021), AI systems' algorithmic judgments frequently surpass human assessments in accuracy and precision. However, individuals still want to ensure that the forecasts and suggestions generated by AI are accurate and reliable; otherwise, they might perceive them as a risk (Zhang et al., 2021) since AI is a new technology that is unfamiliar to many people.

On the other hand, individuals with high exposure towards AI are more inclined to possess high self-efficacy, facilitating their ability to adopt and proficiently utilize AI which fosters positive attitudes towards it (Kim et al., 2024). Additionally, Wei et al., (2024) argue that those with substantial exposure to AI are more prone to recognize its utility, thus nurturing a favourable perception of the technology. However, given that AI represents novel technology, trust in a specific brand plays a significant role in shaping perceptions about the potential risks associated with new technology (Planing et al., 2011). Hence, the brand trust holds considerable importance for companies aiming to introduce AI features to customers.

1.2 Research Problem

Numerous research has been conducted to understand the impact of AI on people's daily lives. One of the studies conducted by Cristobal Rodolfo Guerra-Tamez et al., (2024), aimed to examine AI's influence, encompassing people's exposure to AI, their attitudes and perceptions towards it, and how it affects consumer trust in brands that utilize AI and their purchasing behavior, particularly among Generation Z. While this study yielded remarkable findings, we identified a gap in the model that warrants further investigation. The model in the study by Cristobal Rodolfo Guerra-Tamez et al., (2024) employs AI Exposure, Attitude Towards AI, and Accuracy Perception Towards AI as independent variables, which are presumed to influence people's trust towards brands utilizing AI in their services. However, we believe that individuals' perceptions of AI accuracy and their attitudes towards AI are likely influenced by their level of exposure to AI. Those who are less familiar with AI may struggle to accurately judge its accuracy and may develop negative attitudes towards it. Therefore, we aim to improve the model to more accurately capture this dynamic.

1.3 Research Question

Based on the previous explanation, this thesis aims to address the following question:

1. What is the relationship between individuals' exposure towards AI technology to their trust in brands utilizing AI, and is this relationship directly influenced or mediated by their perceptions and attitudes towards AI?
2. Which factor (individuals' perceptions towards AI or their attitudes towards AI) demonstrates a stronger influence on their trust towards brands employing AI services?

1.4 Aim and Purpose

Therefore, our research objective is to address this gap by proposing an updated model, focusing on a specific AI application: AI-Powered Profile Building. We aim to explore how this technology enhances individuals' personal branding on their LinkedIn, thereby increasing their chances of being hired by companies. Through this study, we aspire to contribute to enriching the study of AI especially in the branding field, and offer valuable insights to companies who consider integrating AI into their services.

1.5 Delimitations

In this study, we specifically focus on LinkedIn's AI-Powered Profile Building. We aim to understand how AI influences individuals in their professional network by enhancing their personal branding using AI-Powered Profile Building. This choice stems from the broad range of AI tools and applications, which are difficult to measure comprehensively. Consequently, our respondents are limited to LinkedIn user. However, we will not delve deeper into generational perspectives due to limited time and resources. Furthermore, since LinkedIn is widely used globally, we do not impose any geographical limitations on our study.

Additionally, this research investigates the relationship between AI exposure, AI attitudes, and AI accuracy perception in relation to brand trust. We exclude the purchase intention variable found in previous literature, as our focus is solely on people's acceptance of AI concerning trust. The study also utilizes the Technology Acceptance Model (TAM) theory and incorporates one variable from TAM 2 which is experience, to capture participants' exposure to AI generated by their direct experience. Hence, other variables from TAM 2 are not included. Lastly, the research employs a quantitative approach, focusing on survey data and does not include in-depth interviews.

1.6 Outline of the Thesis

This study comprises six chapters, each with a distinct purpose. It starts with an introduction providing background information, the research problem and questions, and the aim of the study. The second chapter reviews relevant literature, covering AI Recommendation Agents, Brand Trust, AI Exposure, Attitude Towards AI, and Perception of AI. In the third chapter, the theoretical framework is presented, alongside hypothesis development, proposed hypotheses and the conceptual model. The fourth chapter outlines the research methodology, detailing the research approach, philosophy, design, data collection, questionnaire design, validity and reliability of the study. Chapter five presents data analysis, offering insights from gathered data and discusses results within the established framework and previous research. Finally, chapter six summarizes key findings, discusses theoretical and managerial implications, addresses study limitations, and suggests directions for future research.

2. Literature Review

This chapter aims to provide a broad overview of the variables under study. It began with an explanation of AI Recommendation Agents to establish a foundational understanding of the AI system type employed in this research. Subsequently, the focus shifts to the variables under examination in this study: People's Exposure Towards AI, Brand Trust, People's Attitudes and Perceptions of AI.

2.1 AI Recommendation Agents (RAs)

AI-based algorithms, particularly through recommender systems such as recommendation agents (RAs), play a critical role in how users interact with digital platforms. These systems are designed to personalize the user experience by tailoring suggestions based on individual user characteristics, preferences, and profiles, as explained by Cabiddu et al., (2022). This personalization extends beyond mere functionality—it enhances the decision-making process online by offering users more efficient ways to locate the products or services they seek.

The customization provided by RAs goes a step further by influencing how users perceive their interactions with these systems. Not only do these tailored searches make the process simpler and more direct, but they also enhance the trustworthiness and reliability of the information provided. This results in a more satisfying emotional and cognitive experience for users, making them feel more secure in the accuracy of the results they receive (Cabiddu et al., 2022).

The impact of these recommender systems on user behavior is profound. According to Pedeliento et al., (2017), their effectiveness largely hinges on their perceived utility and their ability to reduce information asymmetry—that is, ensuring that all parties have access to the same knowledge. When RAs successfully achieve this, they are seen as more valuable by users.

Moreover, when recommendation agents offer a personalized, useful, and seemingly human-like interactive experience, they significantly boost user trust. This heightened trust, as Cabiddu et al., (2022) suggest, directly affects users' willingness to depend on these systems for making decisions.

Essentially, if users feel that the AI-driven recommendations are insightful and considerate of their individual needs, they are more likely to rely on these systems, integrating them into their decision-making processes in meaningful ways. This reliance not only enhances user engagement with the platform but can also drive user loyalty and satisfaction, as they come to view the AI system as a trusted advisor in their online activities.

In the context of professional networking, LinkedIn utilizes AI-driven recommendation features to enhance user engagement and personal branding. By analyzing user activity, skills, and network interactions, LinkedIn's AI features suggest ways to improve profile visibility and effectiveness. These recommendations can include specific skills to add, groups to join, or connections to make, thus aiding users in building a stronger professional presence and advancing their personal branding efforts.

2.2 Exposure Towards AI

In addition, Artificial Intelligence (AI) exposure, which encompasses the frequency and depth of interactions individuals have with AI technologies in their daily routines, plays a critical role in shaping consumer behavior (Cristobal Rodolfo Guerra-Tamez et al., 2024). As AI becomes more integrated into daily interactions and routines, it significantly influences how consumers engage with brands and make purchasing decisions. Additionally, positive initial experiences with AI are crucial as they foster ongoing trust in these technologies. According to Siau and Wang (2018), consumers who have a satisfactory first encounter with a new technology are more likely to continue using it and maintain their trust in it. This foundational trust is essential for developing long-term relationships between brands and consumers.

Furthermore, trust in AI is also shaped by intrinsic attitudes, knowledge, and expectations, which can predispose users to either trust or distrust the technology (Cabiddu et al., 2022). Trust dynamics are also influenced by personal attributes and life experiences, which can dictate how quickly and strongly users trust AI (Yang & Wibowo, 2022). Positive past interactions with technology tend to ease the process of trusting new AI applications, while negative experiences can complicate it.

Therefore, considering AI's omnipresence in various aspects of life, from work to personal care, understanding the psychological underpinnings and individual differences that influence AI adoption is crucial (Puntoni et al., 2020; Castillo et al., 2020). Generally, consumers are more inclined to trust AI with tasks perceived as objective, such as financial advice, due to beliefs in AI's capability to handle complex tasks impartially (Minton, Kaplan & Cabano, 2022). This nuanced understanding of how AI exposure impacts brand trust is vital for companies looking to harness AI technologies to deepen consumer engagement and trust in an increasingly digital marketplace.

2.3 Brand Trust

Moreover, AI as a new technology causes considerable debate, particularly regarding people's acceptance of it. According to Kim, Giroux & Lee (2021), individual belief in the precision of AI’s recommendation is vital in shaping brand trust. Therefore, if AI could provide personalized, accurate recommendations, it could enhance customers’ perception of AI accuracy, thereby boosting their trust in the brand that utilizes this service (Cristobal Rodolfo Guerra-Tamez et al., 2024). For instance, according to Cristobal Rodolfo Guerra-Tamez et al., (2024), people will trust an e-commerce company that utilizes AI since they believe AI can enhance the security of the website which mitigates the risk in doing online transactions. Moreover, within the gaming sector, players are more likely to prefer a game that utilizes AI since they believe AI to be fair and competent.

On the other hand, a study by Deniz Lefkeli, Mustafa Karataş & Zeynep Gürhan-Canlı (2023) suggests that people’s trust towards a brand that utilizes AI diminished since people think that AI will share the information they provide to a broader audience which leads to a sense of exploitation. This effect is shown to be stronger for people who prioritize privacy. However, Deniz Lefkeli, Mustafa Karataş & Zeynep Gürhan-Canlı (2023) also believes that in order to gain people's trust towards brands who utilize AI in their service, it is crucial for a brand to gain people's confidence in the brand’s dependability and competence since trust is established based on the expected vulnerability to exploitation.

Considering the significance of trust in the adoption of new technologies, it is imperative for every company intending to integrate AI into their services to ensure the accuracy of their offerings. This is proven that the accuracy of the AI recommendation or service can enhance people's trust in brands who utilize it (Cristobal Rodolfo Guerra-Tamez et al., 2024). Therefore, we believe that examining people's exposure, attitude, and perception towards AI is vital to understand how it will impact people's trust towards brands that utilize AI in their service.

2.4 Attitude and Perception Towards AI

Additionally, the increasing integration of artificial intelligence (AI) into everyday life has become increasingly prominent. AI finds application across diverse domains including medicine (Zhang et al., 2021), art (Bellaiche et al., 2023), business and marketing (Kim, Giroux & Lee, 2021), and so forth. Hence, understanding individuals' attitudes and perceptions towards AI is necessary due to ongoing debates surrounding how the public perceives this technology. According to Pickens (2005), attitude refers to a person's mindset or inclination to behave in a certain manner, influenced by their experiences and personality traits which shape their actions. On the other hand, perception is intricately linked to attitudes. However, perception occurs when an individual encounters a situation or stimuli, leading them to interpret it based on their past experiences.

2.4.1 Attitudes Toward AI

First, let's delve into people's attitudes toward AI. According to Stein et al., (2024), individuals' attitudes toward AI may vary depending on their personality traits. Their study employs the Big Five Model to explore these attitudes, comprising five core personality dimensions: openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism. Stein et al., (2024) propose that individuals who exhibit openness to experience, characterized by traits such as adventurousness, curiosity, and imagination, tend to have positive attitudes toward AI due to their excitement and curiosity towards novel ideas. Furthermore, individuals with extraversion traits, which encompass outgoing, talkative, and sociable tendencies, are less likely to express concerns regarding new technologies, causing them to be more open-minded to innovations like AI. Furthermore, those with high levels of agreeableness, characterized by warmth, cooperativeness, and kindness, may hold positive attitudes toward specific types of AI. Conversely, conscientious individuals, known for their diligence, efficiency, and perfectionism, might have negative attitudes toward AI, as they perceive challenges in comprehending its functionality and foreseeing AI's unpredictable behaviors. Lastly, individuals characterized by neuroticism, exhibiting self-consciousness and shyness, are prone to heightened vulnerability to external stressors. They often struggle to manage impulsive reactions, leading to a predisposition towards negative attitudes concerning specific technologies, such as self-driving cars and limited AI applications.

Moreover, attitudes toward AI vary across different fields. In the realm of art, Chiarella et al., (2022) conducted an experiment where participants were tasked with evaluating two abstract paintings—one labeled as "human-created" and the other as "AI-created." The findings revealed that participants prefer paintings labeled as "human-created," since individuals perceive emotion as a vital element in art, an aspect they believe AI lacks. On the other hand, in public administration, there is a tendency for positive attitudes towards AI. This optimism comes from the belief that AI has the potential to enhance public services by expediting processes and streamlining administrative procedures, thereby mitigating administrative delays (Ingrams, Kaufmann & Jacobs, 2021).

2.4.2 Perception Towards AI

Furthermore, given the pervasive integration of AI across diverse domains, various studies aim to understand the nuanced perceptions held by individuals regarding this technology. For instance, Kelley et al., (2021) conducted a multinational study to explore public perceptions of AI across eight countries. Their investigation revealed four overarching thematic dimensions characterizing public sentiment towards AI: exciting, useful, worrying, and futuristic. Additionally, respondents in their survey often have mixed feelings about AI such as, "A mixture of knowledge and fear. I know that it will help or is already helping in several important areas, but there is always that fear that one of these AIs will become too autonomous and turn against us." This multifaceted response underscores the duality inherent within public perception surrounding AI, wherein both enthusiasm and fear shape societal perception towards this novel technology.

AI has found significant application in diverse domains, including the medical sector. Zhang et al., (2021) investigated patients' perceptions of AI in the context of interpreting radiology imaging data. Their findings indicate that a majority of patients perceive AI tools as useful, more accurate and logical compared to doctors. Nevertheless, patients express a demand for transparency regarding the underlying processes through which AI arrives at its conclusions or recommendations. This insistence on transparency stems from concerns regarding the quality, trustworthiness, and accuracy of AI systems.

Similarly, Kim, Giroux, and Lee (2021) highlight the superior accuracy and precision of algorithmic judgments rendered by AI systems, particularly in light of the vast datasets they can analyze. This capability not only facilitates deeper insights for enterprises but also enables greater personalization, thereby enhancing user experiences. However, despite the demonstrated performance and accuracy of statistical models, skepticism towards AI persists among individuals. According to Seegebarth et al., (2019), this skepticism arises from people's tendency to consider the level of risk and uncertainty associated with adopting novel technologies.

On the other hand, people's perception of AI varies depending on the nature of the decision-making processes involved. According to Huang and Rust (2018), people believe that AI demonstrates proficiency primarily in mechanical and analytical tasks, hence people will most likely believe in AI when it comes to analytical decisions rather than more intuitive judgements. This inclination is reinforced by the perception that mechanical and analytical tasks are inherently characterized by precision, logic, and analytic, thus fostering expectations among individuals that AI will provide more accurate decisions in such domains (Kim, Giroux & Lee, 2021).

3. Theoretical Framework and Hypothesis

This chapter will explain the theoretical underpinning of the study, which is the Technology Acceptance Model (TAM) and Extended Technology Acceptance Model (TAM 2). Additionally, it will provide a detailed explanation of each variable, serving as the foundation for the hypotheses in the conceptual model. Furthermore, the proposed conceptual model will be presented.

3.1 Theoretical Background

In this study, we employ the Technology Acceptance Model (TAM) and Extended Technology Acceptance Model (TAM 2) as our framework. This theory was developed by Davis (1989) during a technological explosion in the 1970s and 1980s and extended by Venkatesh and Davis (2000). This theory has become one of the most used theories to understand an individual's acceptance and adoption of new technology. According to TAM theory, people will most likely be willing to adopt a new technology if they find it to be easy to use and useful. For instance, a study by Pillai et al., (2023) found that perception of ease of use and perception of usefulness played crucial roles in influencing student adoption of AI teacher robots.

Davis (1989) defines the perception of ease of use as an individual's perception of the level of effortlessness when utilizing a new technology. This factor has consistently been linked to users' intentions to adopt and utilize new technologies, particularly if they perceive the technology to be user-friendly, enabling them to achieve their intended outcomes effortlessly, and presenting clear and comprehensive information (Davis, 1989). This perception foster people's positive attitude toward the new technology. Therefore, we suggest that people's attitude towards new technology, which in this context is AI, could explain the perception of ease of use variable in the TAM theory.

Furthermore, the adoption of new technology is also influenced by perceived usefulness, which, as described by Davis (1989), refers to the belief that using a new technology will enhance people's job performance. This factor is crucial in driving the adoption of new technology, as individuals are more likely to perceive a new technology positively if they believe it can improve their task performance, increase efficiency, and simplify processes (Davis, 1989). However, to truly enhance people's job performance, and efficiency, and streamline processes, the new technology must demonstrate accuracy, ensuring it delivers optimal results and reduces both time consumption and unnecessary costs. Therefore, we suggest that individuals' accurate perceptions of new technology, such as AI, could explain the perceived usefulness variable in the TAM theory.

In addition, according to Venkatesh and Davis (2000) in the Extended Technology Acceptance Model (TAM 2), individuals initially rely on others' opinions due to limited knowledge of new technology. However, as they gain direct experience and learn about its strengths and weaknesses, their perceptions and attitudes evolve—a process we refer to as exposure. Increased exposure to new technology makes continued use more likely. Venkatesh and Davis (2000) also argue that perceived usefulness, which we refer to as accuracy perception, changes with experience as individuals rely more on their own sensory information rather than subjective norms. In contrast, perceived ease of use, related to attitudes toward the service, is less stable over time due to the significant role of hands-on experience. Therefore, we believe that exposure to new technology, such as AI, influences attitudes and perceptions, subsequently affecting behavioral intentions to use the technology.

Moreover, Davis (1989) defines behavioral intention as individuals' intention to use a specific technology, while usage behavior refers to their actual utilization of the technology. In this study, our objective is to investigate the impact of AI as a new technology on people's trust in brands that employ it in their services. We assume that individual with high exposure (experience) towards AI are more likely to perceive AI as accurate (useful) and have a positive attitude towards it (easy to use), thus they will be more inclined to have positive behavioral intentions and usage behavior towards the technology which contribute to fostering their trust towards brands that utilize AI in their service. Therefore, we suggest that variables related to brand trust could explain behavioral intention and usage behavior within the TAM and TAM 2 theory.

3.2 Hypotheses Development

To refine the research model proposed by Cristobal Rodolfo Guerra-Tamez et al., (2024) and delve deeper into this phenomenon, this section will outline our hypothesis development. This serves as the foundation for refining the research model.

3.2.1 AI Exposure and Brand Trust

Various studies across different sectors confirm the influence of AI exposure on brand trust. For instance, in the hospitality industry, trust in AI-enhanced marketing systems notably impacts consumers' intentions to make bookings, underscoring the importance of trust (Cristobal Rodolfo Guerra-Tamez et al., 2024). Conversely, trust in AI is shaped by how consumers perceive its benefits—like improved security and the credibility of platforms—as well as their familiarity with the AI systems in use (Cristobal Rodolfo Guerra-Tamez et al., 2024). Moreover, the relationship between AI exposure and brand trust involves several layers and is influenced by factors such as the perceived reliability and accuracy of the AI systems, individual attitudes toward AI, and previous experiences with such technologies. These elements suggest that greater exposure to AI can enhance brand trust, thereby affecting consumer buying behavior (Cristobal Rodolfo Guerra-Tamez et al., 2024).

In the AI Powered Profile Building context, people who have high exposure to AI are more likely to understand the sophistication of AI such as providing personalized interactions and predicting preferences. Therefore, we assume that people who have a high exposure towards AI are more likely to trust a brand that employs AI in their service. Based on this, we propose a hypothesis:

H1: There is a positive relationship between individuals' exposure to AI and their trust in brands that integrate AI into their services.

3.2.2 AI Exposure and Attitude Towards AI

On the other hand, people's exposure to AI also significantly influences their attitudes toward this technology. For instance, as indicated by Stein et al., (2024), women and the elderly may tend to hold more negative attitudes towards AI. This could be attributed to factors that women may have less interest in high-tech domains than men in general. Similarly, elderly people might have limited access to AI due to the difficulties in understanding rapid technological advancements. In contrast, according to Kim et al., (2024), who investigated worker self-efficacy in AI utilization, individuals with extensive exposure to AI are more likely to have high self-efficacy which enables them to adopt and effectively utilize AI in their work, leading to positive attitudes towards AI. As a result, it reduces their concerns about job displacement by AI.

In the context of AI-Powered Profile Building, individuals' attitudes towards the service may vary depending on their exposure to AI. Given that this service is designed to assist users in improving their profiles for the job market, we assume that users generally hold a positive attitude towards the service. Based on this, we propose a hypothesis:

H2: There is a positive relationship between individuals' exposure to AI and their positive attitude towards AI-powered profile building.

3.2.3 Attitude Towards AI and Brand Trust

As previously described, individuals with high exposure to AI tend to hold more positive attitudes toward it. This is supported by Zhang et al., (2021) study, where the majority of participants viewed AI as useful. One participant expressed enthusiasm, stating, "I like the idea. I like the concepts. I've no problem using it. It's gonna happen no matter what. We're all just in for a future of a lot more AI interaction. I am actually looking forward to it." However, despite this optimism and excitement, trust remains a crucial factor for technology adoption. According to Seegebarth et al., (2019), new technologies are often associated with complexity and uncertainty which require people's confidence and trust for the adoption. Additionally, Zhang et al., (2021) emphasize the importance of trust-building processes to encourage the adoption of new technology.

In the context of AI-Powered Profile Building, individuals may exhibit positive attitudes toward the service if they perceive it as useful. Therefore, trust becomes pivotal for brands that are introducing new technology adoption. According to Ling et al., (2023), people are inclined to choose brands that alleviate uncertainties, bolster confidence, and provide a sense of security during the purchasing process. Based on this, we propose a hypothesis:

H3: There is a positive relationship between individuals' positive attitude towards AI-powered profile building and their trust in brands that integrate this service.

3.2.4 AI Exposure and Perception of AI

Additionally, a study by Wei et al., (2024) highlights the pivotal role of public perception in shaping individuals' comprehension of the world and subsequently influencing their behavior. Their findings suggest that individuals with significant exposure to AI tend to acknowledge its utility, thereby fostering a favorable perception of the technology. In contrast, those with limited exposure to AI are more prone to skepticism and have negative perceptions towards it.

In the context of AI-Powered Profile Building, individuals may hold diverse perceptions regarding its utility and accuracy, particularly considering its provision of personalized headlines and descriptions based on the user's experience, skills, and interests. However, according to the perception of usefulness in TAM theory (Davis, 1989), if users perceive this service as useful for profile creation and could enhance their profile accurately, they are more inclined to adopt it. Based on this, we assume that people with high exposure towards AI are more likely to recognize the utility and the accuracy of the service, increasing their propensity to adopt it. Therefore, we propose the following hypothesis:

H4: There is a positive relationship between individuals' exposure to AI and their perception of the accuracy of AI-powered profile building.

3.2.5 Perception of AI and Brand Trust

Furthermore, according to a study by Kim, Giroux & Lee (2021) which discusses consumer trust in AI recommendation, the accuracy of information that AI provides critically influences people's perception towards AI. This accuracy significantly impacts individuals' confidence in the credibility of the product or service, as people generally prefer precise information. Moreover, according to Cristobal Rodolfo Guerra-Tamez et al., (2024), if AI could provide personalization and accurate recommendation, it would enhance customer perception of the technology. Furthermore, Kim, Giroux & Lee (2021) argue that the perception of AI providing accurate information strengthens people's trust in the technology, leading to favorable responses toward companies that utilize it.

In the context of AI-Powered Profile Building, if AI could offer precise recommendations for constructing a user's profile which helps to enhance their personal branding, individuals would have a positive perception of the service, leading to trust in the brand employing it. Therefore, we propose the following hypothesis:

H5: There is a positive relationship between individuals' perception of AI-powered profile building as accurate and their trust in brands that offer this service.

3.3 Conceptual Model

Based on the literature review, we have developed our conceptual model, drawing from previous studies conducted by Cristobal Rodolfo Guerra-Tamez et al., (2024). Hence, based on our findings from various literature which discuss about exposure towards AI, attitude towards AI, and perception towards AI, we propose a new model:

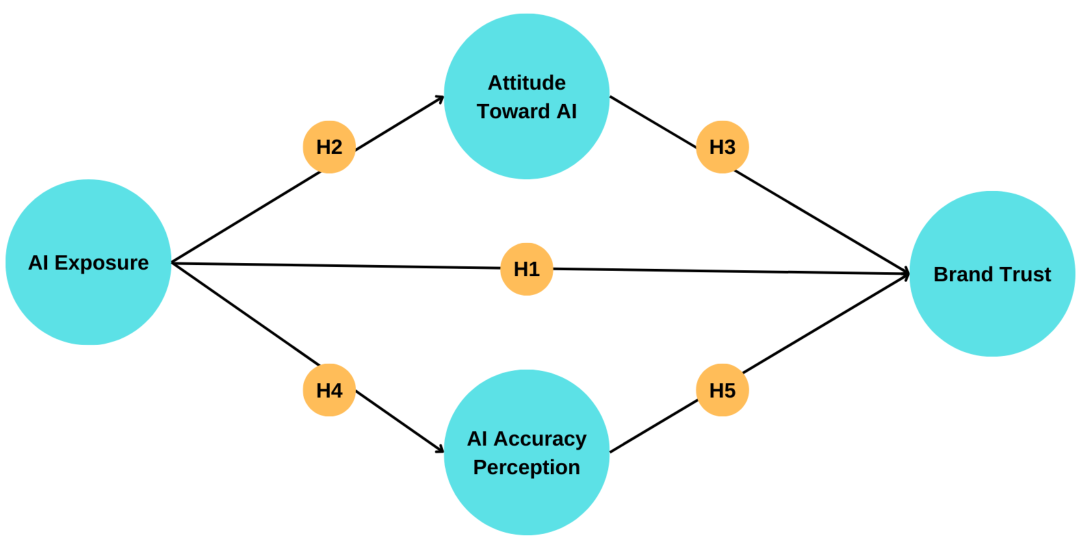

Figure 1 Conceptual Model

H1: There is a positive relationship between individuals' exposure to AI and their trust in brands that integrate AI into their services.
H2: There is a positive relationship between individuals' exposure to AI and their positive attitude towards AI-powered profile building.
H3: There is a positive relationship between individuals' positive attitude towards AI-powered profile building and their trust in brands that integrate this service.
H4: There is a positive relationship between individuals' exposure to AI and their perception of the accuracy of AI-powered profile building.
H5: There is a positive relationship between individuals' perception of AI-powered profile building as accurate and their trust in brands that offer this service.

3.4 Chapter Summary

AI-based algorithms, particularly through recommender systems, are a new technology that significantly impacts user interactions by providing personalized suggestions based on user characteristics and preferences (Cabiddu et al., 2022). According to Cabiddu et al., (2022), when these systems offer useful and human-like interactions, they can enhance user trust and integration into decision-making processes. Additionally, Cristobal Rodolfo Guerra-Tamez et al., (2024) suggest that AI exposure which refers to the extent and frequency of interactions with AI, affects consumer behavior, shaping how they engage with brands and make purchasing decisions. Positive initial experiences with AI can foster ongoing trust in these technologies, which are also influenced by user attitudes and perceptions.

On the other hand, accurate and personalized recommendations by AI can influence users' attitudes and perceptions towards AI, which is crucial in forming trust in brands utilizing it (Cristobal Rodolfo Guerra-Tamez et al., 2024). Individuals' attitudes towards AI vary by personality traits, with openness to experience correlating with positive attitudes, while conscientiousness may lead to skepticism (Stein et al., 2024). Furthermore, public perception of AI varies by field. In art, people show negative attitudes towards AI because they believe it lacks emotions which is crucial in artwork (Chiarella et al., 2022). However, in public administration, AI is viewed positively for its potential to improve services and reduce delays (Ingrams, Kaufmann & Jacobs, 2021).

In this study, we employ the Technology Acceptance Model (TAM) by Davis (1989) and its extended version (TAM 2) by Venkatesh and Davis (2000) to explain AI adoption through perceived ease of use, perceived usefulness, experience, and behavioral intention. Positive attitudes towards AI are linked to ease of use, while perceived usefulness explains people's perceptions of AI accuracy. Furthermore, experience refers to individuals' direct interactions with the new technology, which we refer to as exposure. Lastly, behavioral intention, which we refer to as trust, is defined as people's intention to use the technology. We assume if people believe the technology is useful, they are more likely to use it and trust the brands that employ it in their services.

In examining the relationship between AI Exposure, Attitudes Towards AI, Accuracy Perception of AI, and Brand Trust, we used AI-Powered Profile Building by LinkedIn as our study context. AI-Powered Profile Building is a tool designed to help LinkedIn users create their headlines and descriptions based on their expertise and experience (T., 2023), enhancing their personal branding and professional network. In this study, we aim to examine whether high exposure to AI can help form people's trust in brands such as LinkedIn, given that LinkedIn employs AI-Powered Profile Building in their service. Additionally, we want to investigate if people are more likely to have positive attitudes towards AI-Powered Profile Building if they perceive it as useful for building their profiles. Furthermore, we seek to determine if users perceive AI-Powered Profile Building as accurate since it provides recommendations based on their experience and expertise. Finally, we want to explore whether people may develop greater trust towards brands that utilize AI in their services if they have positive attitudes towards AI and perceive it as accurate.

4. Methodology

This chapter outlines the methodological framework used for this study. It starts with an overview of the underlying research approach, progresses through the research philosophy and design, and delves into the data collection methods, questionnaire development, and data analysis techniques. The chapter wraps up with an examination of the study's reliability and validity, while also addressing its limitations and ethical considerations.

4.1 Research Approach

This study adopts a quantitative approach to assess the influence of AI on individuals' trust in AI-powered brands. According to Rana, Gutierrez & Oldroyd (2021), quantitative methods are effective for predicting phenomena using numerical data. Generally, quantitative studies follow a deductive approach to elucidate specific phenomena within a broader context, often employing surveys to provide numerical descriptions of the sample under investigation, with findings typically generalizable to a wider population (Rana, Gutierrez & Oldroyd, 2021). Thus, in this study, we aim to quantify the effects and correlations of Exposure to AI, Attitude towards AI, and Accuracy Perception of AI on individuals' trust in AI technologies, utilizing AI-Powered Profile Building by LinkedIn as the context.

4.2 Research Philosophy

The philosophical underpinnings of a researcher form the cornerstone of any scholarly investigation, encapsulating deep-seated beliefs about existence, reality, and knowledge (Easterby-Smith et al., 2021). Research philosophy comprises a framework of beliefs concerning the approach to data research, which is pivotal for defining research objectives and shaping the research design (Easterby-Smith et al., 2021). Such philosophical grounding not only aids researchers in enhancing the robustness of their study designs but also fosters innovation and creativity (Easterby-Smith et al., 2021). Therefore, in the methodology chapter of this thesis, we will delve into the philosophical approaches adopted—specifically ontology and epistemology—to lay a solid groundwork for the methodology employed in this study.

4.2.1 Ontology

Ontology, a branch of philosophy, deals with the researcher's fundamental assumptions about the nature of reality (Easterby-Smith et al., 2021). Goertz and Mahoney (2012) state that most concepts or measurements are created to reflect phenomena that truly exist in the empirical world. Ontology encompasses a spectrum of positions including realism, internal realism, relativism, and nominalism (Easterby-Smith et al., 2021). For the purposes of this study, internal realism is deemed most appropriate. This philosophical stance posits that a singular truth exists independently of human thought, although it acknowledges that this truth can only be understood indirectly because concrete facts are not always directly observable (Easterby-Smith et al., 2021). Thus, in this research, the dynamics among AI exposure, attitude towards AI, accuracy perception of AI and brand trust are seen as manifestations of an underlying reality, albeit one that is challenging to comprehend fully. We recognize that knowledge is constrained and context-dependent, and its validity may vary based on different experiences and situations. Consequently, this study will attempt to approximate reality as closely as possible by indirectly accessing the truth through the observation and collection of real-world phenomena. Therefore, internal realism serves as the most suitable ontological perspective for this investigation, guiding the exploration of the research questions.

4.2.2 Epistemology

Epistemology is concerned with the study of knowledge and the methods used to explore the nature of the world (Easterby-Smith et al., 2021). It involves understanding what constitutes acceptable knowledge within a specific field of study (Saunders, Lewis & Thornhill, 2009). According to Easterby-Smith et al., (2021), epistemological approaches can broadly be divided into positivism and social constructionism. Positivism asserts that the social world can be understood through objective measurements. In contrast, social constructionism argues that the real world is shaped by individual perceptions and experiences.

Given the internal realism ontology adopted for this research, positivism is more appropriate for our purposes. This approach allows for an objective examination of phenomena, which is preferable to subjective interpretations that rely on personal feelings or thoughts. Positivism is particularly adept at examining human and social behaviors (Easterby-Smith et al., 2021), which aligns well with our study's focus on the influence of artificial intelligence (AI) on brand trust.

Positivism supports a systematic and objective approach to research, which is essential for quantitatively measuring variables and establishing clear, causal relationships. This makes it a suitable foundation for the quantitative methods employed in our study, facilitating a structured investigation into the impacts of AI on brand trust. Therefore, adopting a positivist epistemological framework ensures a rigorous and measurable analysis, making it an ideal choice for this study.

4.3 Research Design

Bell, Bryman, and Harley (2019) emphasize the importance of a research design as a structured plan used to gather and analyze data through various methods. This design serves as a blueprint that guides the selection of appropriate data collection tools and techniques, tailored to meet the specific needs and questions of the study.

In this study, a research design is conceived following the principles laid out by Easterby-Smith et al., (2021), which involves a systematic framework for collecting and analyzing data. This framework supports the clear definition of methods and techniques employed throughout the research process. The design of this research is shaped to facilitate the examination of how AI influences brand trust among consumers.

To achieve this, the study utilizes a deductive approach to quantitative research, as defined by Burns and Burns (2008). This approach ensures that the research is conducted systematically, allowing for the collection of measurable and quantifiable data. Details regarding the methods of data collection, the tools used, the planning of data collection activities, and the determination of sample size are meticulously planned to align with the overarching research objectives. This structured approach ensures that the research design adequately addresses the research questions and aligns with the established methodological principles.

4.3.1 Deductive Reasoning

The relationship between theory and research often involves selecting between deductive and inductive methodologies (Bell, Bryman & Harley, 2019). Deductive reasoning, as explained by Burns and Burns (2008), begins with a general theory from which specific hypotheses are derived and tested through the collection of data, following a top-down approach. This is in contrast to inductive reasoning, where theories are developed from the ground up, starting with detailed observations that lead to broader generalizations (Burns & Burns, 2008).

Bryman and Bell (2011) and Easterby-Smith et al., (2021) note that while inductive reasoning builds theories through observations and pattern analysis, deductive reasoning uses existing theories to generate hypotheses which are then empirically tested. This method is particularly prevalent among researchers who adopt a positivist stance, as they seek to verify theories through systematic and empirical investigation.

For our study on the influence of AI on brand trust, a deductive approach is deemed most suitable. The vast body of existing literature provides a solid theoretical foundation from which specific hypotheses regarding AI exposure, accuracy perception, and user attitudes can be formulated. These hypotheses are then empirically tested, allowing for conclusions about the relationships between these variables to be drawn. This deductive, top-down approach ensures that the research questions are addressed effectively, making it the appropriate choice for achieving the objectives of the study.

4.3.2 Cross-Sectional Design

In the realm of research design, data can be collected through either cross-sectional or longitudinal methods (Burns & Burns, 2008). A cross-sectional study collects a significant amount of data at a single point in time from various cases to examine relationships among different variables (Bell, Bryman & Harley, 2019). This is contrasted with longitudinal designs, which collect data over extended periods to observe changes and trends (Bell, Bryman & Harley, 2019).

This research employs a cross-sectional design due to its efficiency in terms of time and cost compared to longitudinal studies (Burns & Burns, 2008). In this approach, data are collected simultaneously from respondents at one specific point, allowing for immediate comparison and analysis within the sample. Cross-sectional studies are often utilized in social survey research, as they provide a snapshot of variables at a single moment, unlike longitudinal studies where data on the same variables are collected repeatedly over time (Bryman & Bell, 2011; Easterby-Smith et al., 2021).

For this particular study, a cross-sectional design was deemed necessary and most practical. After distributing the questionnaire on social media platforms, responses were gathered almost concurrently, ensuring that all data concerning the variables of interest were obtained simultaneously. This method was particularly suitable given the time constraints of the study and the need to analyze all variables and indicators within the same timeframe.

4.4 Data Collection Method

Following the establishment of the research approach and design, the method for data collection was selected. Data collection is essential for gathering the empirical data necessary to address research questions. For this study, primary data was chosen due to the lack of existing data relevant to our specific needs. Primary data collection allows for tailored control over the research process, particularly in the design of questionnaires and sampling strategies (Easterby-Smith et al., 2021).

The primary data for this research was collected using an online survey, selected for its cost-effectiveness, rapid data collection capabilities, and ability to reach a broad geographical audience. Online surveys also automate data collection, reducing errors and data loss, and allow for the implementation of screening questions that help in filtering out ineligible responses (Bryman & Bell, 2011).

The survey was created on yonsurvey.com, a platform known for its user-friendly interface, enhancing the overall experience and quality of data collected. The sampling process involved defining the appropriate population, selecting the sampling method, and determining the sample size to ensure the accuracy and reliability of the research outcomes.

4.4.1 Target Population

The study will focus on selecting participants who are both familiar with AI technologies and active LinkedIn users. This group will include fresh graduates actively seeking job opportunities and experienced workers aiming to elevate their personal branding and professionalism. Focusing on individuals engaged in enhancing their professional image and career prospects through LinkedIn's AI-driven tools will provide valuable insights into how these features influence their trust and reliance on AI technologies. This approach allows for a targeted examination of the relationship between AI familiarity and trust among users who leverage AI for professional advancement. Participants will be recruited through various online channels, including social media and LinkedIn, to ensure a representative sample of this generational group.

4.4.2 Sampling Technique

Before distributing the survey to the broader target population, a pilot study was conducted with a small group to pre-test and refine the survey instrument. This preliminary step, as suggested by Malhotra, Nunan, and Birks (2017), is crucial to ensure the survey's clarity, comprehensibility, and error-free nature, which are essential for obtaining accurate and honest responses from participants.

Although probability sampling is preferred for its ability to provide clearer insights into the representativeness of a sample relative to the target population, thus reducing sampling bias (Easterby-Smith et al., 2021), this study utilized non-probability sampling methods due to constraints related to time and cost. Non-probability sampling can still offer valuable insights for exploratory research and is characterized by techniques such as convenience sampling, snowball sampling, and quota sampling (Bryman & Bell, 2011). Specifically, this research employed convenience and snowball sampling strategies, which are recognized for their efficiency, ease of implementation, and cost-effectiveness (Burns & Burns, 2008), making them suitable choices given the study's logistical limitations.

4.4.3 Sample Size

Quantitative and deductive research typically requires a large number of respondents to enable statistically valid generalizations (Easterby-Smith et al., 2015). Nevertheless, determining the appropriate sample size is influenced by various factors, including the research design's demands and constraints related to time and cost (Bell, Bryman, & Harley, 2019). While there is no one-size-fits-all solution for deciding sample size, practical considerations often guide this decision.

Roscoe (1975) suggests that for most research scenarios, a sample size ranging from 30 to 500 is suitable, and for studies involving multivariate analyses, such as multiple regression, it is advisable to have at least ten times as many respondents as the number of variables being studied. This guideline was considered in the planning and execution of this study to ensure the reliability and validity of the results.

For our study, utilizing a non-probability sampling technique meant that the generalizability of the findings would be somewhat limited. The aim was to gather responses from more than 100 participants to ensure a robust analysis. Ultimately, we received responses from 104 participants, but 2 entries were identified as error data and excluded from the analysis. Therefore, 102 respondents completed the survey, aligning with the target.

4.5 Questionnaire Design

In this study, we utilized a questionnaire administered through yonsurvey.com to gather our data. The survey was conducted in English to ensure accessibility to LinkedIn users across various countries. It commenced with an introduction outlining the study's purpose and provided information on respondent protection in accordance with the General Data Protection Regulation (GDPR). On the second page, a video and description were provided to explain AI Powered Profile Building, offering respondents insight into how the feature operates.

The survey comprised six sections: the type of LinkedIn account held by respondents, aimed at distinguishing their expectations, as AI Powered Profile Building is currently available only to premium users. It was anticipated that their expectations might vary accordingly. Subsequent sections included demographic questions, respondents' exposure to AI in general, their attitudes toward AI Powered Profile Building, their perception of its accuracy, and their trust in brands using AI.

In addition, the questions were adapted from the research of Cristobal Rodolfo Guerra-Tamez et al., (2024) and tailored to suit the context of this study. Participants responded to a total of 17 questions, excluding demographic questions.

4.5.1 Variable

The variables used in the study are described in Table 1.

Table 1 Research Variables

Variable	Variable Category
AI Exposure	Independent Variable
Attitude Towards AI	Mediating Variable
Accuracy Perception of AI	Mediating Variable
Brand Trust	Dependent Variable

In this study, AI Exposure serves as the independent variable, influencing the dependent variable which is brand trust. According to Navarro & Foxcroft (2022), the independent variable (IV) explains phenomena, while the dependent variable (DV) is what is being explained. In simpler terms, the IV acts as the predictor, and the DV is the outcome. Furthermore, MacKinnon, Fairchild & Fritz (2007) argue that a mediator variable exists in a causal sequence between two other variables, potentially influencing how one variable affects the other. In this study, attitude towards AI and accuracy perception towards AI serve as mediating variables that can influence people's trust towards brands utilizing AI.

4.5.2 Measurement

We intend to gather data using the same scale item as the previous study which is Likert Scale. This is because the Likert scale is widely recognized and respected in social science research for its simplicity and effectiveness (Taherdoost, 2019). In the Likert Scale, participants are asked about their opinion about a statement by stating their agreement from strongly agree to strongly disagree. By employing the Likert Scale, we aim to establish a reliable and easily interpretable measure of participants' opinions (Taherdoost, 2019).

Furthermore, some studies opt for a 5-point scale to minimize participant confusion. However, Taherdoost (2019) suggests that respondents generally prefer higher option scales, such as 7 points, to express nuanced feelings. Additionally, according to Taherdoost (2019), a 7-point scale is believed to better capture participants' true evaluations. Therefore, in this study, we will use a 7-point Likert scale to allow participants to express their opinions more comprehensively.

4.5.3 Survey Questions

To ensure the validity and reliability of the data, this study employs measurement and statements from previous study which is outlined in Table 2.

Table 2 Survey Items

Measurement Variables	**Source**	**Sample of Statements**	**Scale**
AI Exposure	Cristobal Rodolfo Guerra-Tamez et al., (2024)	I often interact with AI-powered devices or services.	Likert Scale: Please rate how much you agree with the following statement:
		AI is a central part of my daily life.	
		I frequently use AI in	

		shaping my online presence.	(1 = Strongly Disagree, 2 = Disagree, 3 = Somewhat Disagree 4 = Neither Agree or Disagree 5 = Somewhat Agree 6 = Agree 7 = Strongly Agree
		I am familiar with AI technology in my daily life	
AI Accuracy Perception		I expect the recommendations provided by AI-Powered Profile Building to be accurate.	
		I expect the suggestions from AI-Powered Profile Building to be highly appropriate for me.	
		I expect that AI Powered Profile Building information aligns with my experience and skill	
		I expect AI Powered Profile Building to understand my expertise	
Attitude towards AI		I expect to feel comfortable	

		interacting with AI-Powered Profile Building while creating my profile.	
		I expect to trust the suggestions provided by AI-Powered Profile Building	
		I expect AI-Powered Profile Building to accurately provide recommendations for my profile.	
		I expect AI-Powered Profile Building to enhance my profile	
Brand Trust		I trust brands that utilize AI services (such as LinkedIn utilizing AI-Powered Profile Building).	
		Brands using AI provide reliable services (such as LinkedIn providing AI-Powered Profile Building to enhance user profiles).	

		I trust AI recommendations (such as writing suggestions from AI-Powered Profile Building in LinkedIn).	
		Knowing that a brand utilizes AI reassures me (such as LinkedIn's utilization of AI-Powered Profile Building).	

4.5.4 Questionnaire Distribution

In this study, the questionnaire was distributed online through friends lists and group chats on WhatsApp, which included friends, classmates, and teachers. Moreover, since the study concentrated on profile-building platforms, the questionnaire was also shared directly on LinkedIn to more effectively reach the target population. Alternatively, the snowball sampling method involves the researcher initially contacting a few individuals relevant to the study and then leveraging their networks to expand the sample (Bryman & Bell, 2011). In this context, participants were encouraged to refer colleagues who use LinkedIn and are interested in personal branding within professional sectors. This method proved to be a time-efficient strategy to accelerate the survey distribution.

4.6 Data Analysis Method

Data analysis will begin with descriptive statistics to gain insight into the sample characteristics and their initial attitudes toward AI on LinkedIn. Descriptive analysis is an essential initial step in research, providing an overview of the data before conducting inferential statistical comparisons (Kaur, Stoltzfus & Yellapu, 2018). In our study, Jamovi will be utilized as the software of choice. Jamovi is a free and open statistical platform and is chosen for its intuitive and user-friendly interface.

Initially, to verify the association between the survey items and their corresponding factors, Confirmatory Factor Analysis (CFA) was conducted. This approach was chosen over exploratory factor analysis because the items used to measure each variable were based on prior research.

In addition, the fit of the overall model will be evaluated using fit indices such as the Chi-Square test, Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), and Root Mean Square Error of Approximation (RMSEA). Finally, linear regression was performed to analyze the mediation role and the direct or indirect relationships between variables, based on the method described by Baron and Kenny (1986).

4.7 Validity and Reliability

Validity assesses how accurately an instrument measures the intended concept using the appropriate method (Bougie & Sekaran, 2020). Common types of validity include Content Validity, Criterion-Related Validity, and Construct Validity.

4.7.1 Validity

In this research, Construct Validity is employed to demonstrate how well the results align with the theoretical frameworks underlying the study. Factor Analysis, a multivariate technique, is utilized to confirm the dimensions of the concept and establish construct validity, highlighting the most suitable items for each dimension (Bougie & Sekaran, 2020).

Confirmatory Factor Analysis (CFA) specifically measures validity and supports hypothesis testing by verifying the theoretical predictions associated with the constructs. CFA ensures the robustness of the factor structure across different data sets, utilizing the chi-square distribution to test the adequacy of the factor structure against the data (Burns & Burns, 2008; Sallis et al., 2021). A Factor Loading value threshold of 0.6 is applied to gauge validity (Hair et al., 2006).

Following the validity assessment, model fit is evaluated to determine how well the theoretical model corresponds with the observed data. Metrics used include the chi-square to degree of freedom ratio ($\chi 2$/df), Comparative Fit Index (CFI), Tucker Lewis Index (TLI), and Root Mean Square Error of Approximation (RMSEA), with specific threshold values outlined in Table 3.

Table 3 Model Fit Indices

Model Fit Indices	Recommended Value	Source
NC = $\chi 2/df$	1 < NC <3	Kline (2016)
CFI	≤ 0.90	Bentler (1990)
TLI	≤ 0.90	Bentler and Bonett (1980)
RMSEA	≤ 0.08	McDonald and Ho (2002)

While validity is crucial, it alone does not fully ensure accurate measurement. Both validity and reliability are required for consistent results, which leads to a discussion on reliability in section 5.4.2.

4.7.2 Reliability

Reliability concerns the consistency and stability of measurement results, particularly how free they are from random error. It is essential to ensure that measurements are consistent over time and across variables (Malhotra, Nunan & Birks, 2017). In this study, internal consistency reliability was utilized, which is appropriate for surveys where multiple items measure variables in a summated scale.

To assess reliability, Cronbach's Alpha and McDonald's Omega were employed, which evaluate the average intercorrelations among scale items. Reliability scores below 0.60 are deemed poor, around 0.70 are acceptable, and above 0.80 are considered good (Bougie & Sekaran, 2020; Navarro

& Foxcroft, 2022). Therefore, this study set the minimum acceptable threshold for internal consistency at 0.70, ensuring the reliability of the measurements.

4.8 Limitations

The limitations of this study primarily stem from the choice of a quantitative approach over a qualitative one. While the quantitative method allowed us to collect data from a larger sample and minimized human error (Bell, Bryman & Harley, 2022; Malhotra, Nunan & Birks, 2017), it lacked the ability to provide in-depth insights that could explain the survey results more comprehensively. A qualitative study could have offered a deeper understanding of the reasoning behind consumer perspectives.

Additionally, our study faced constraints due to the lack of access to premium LinkedIn users who already had experience with AI features in profile building. We were compelled to continue our survey by including some basic LinkedIn users, informing them about the AI features, and gathering their expectations regarding these features. Although these methods were still relevant, they were not ideal for our research objectives. Furthermore, the use of random convenience sampling restricted our ability to follow up on actual consumer behavior. This limitation means we could not provide detailed insights into the actual behaviors of consumers post-survey, which would have enriched our findings.

4.9 Chapter Summary

This chapter outlines the methodological framework used for assessing the influence of AI on individuals' trust in AI-powered brands, focusing on LinkedIn's AI-Powered Profile Building. A quantitative approach was adopted, utilizing a deductive reasoning method to empirically test hypotheses derived from existing theories. Data was collected through an online survey distributed to LinkedIn users, specifically targeting fresh graduates and experienced professionals. Non-probability sampling methods were employed due to constraints in time and cost, resulting in 102 valid responses.

Data analysis involved descriptive statistics and Confirmatory Factor Analysis (CFA) to verify associations between survey items and factors. The mediation role of variables such as attitude towards AI and accuracy perception of AI was analyzed using linear regression based on the Baron and Kenny (1986) method. This approach allowed for the examination of both direct and indirect relationships between variables, providing a comprehensive understanding of how AI exposure influences brand trust. Reliability and validity were ensured through robust measures such as Cronbach's Alpha and CFA, with the study recognizing limitations in depth due to its quantitative nature and the use of convenience sampling.

5. Data Analysis

This chapter outlines the statistical analysis of the data collected and discusses the results in relation to the hypotheses set forth earlier. The analysis begins with preparatory steps and initial tests, followed by a comprehensive evaluation. The chapter concludes with a synopsis of the findings related to the proposed hypotheses.

5.1 Introduction to Data Analysis

After the data collection was completed, it was systematically prepared for detailed analysis. The initial step involved conducting descriptive statistics to summarize the dataset's characteristics. This process helped in identifying patterns, trends, and potential outliers within the data. Subsequently, a Confirmatory Factor Analysis (CFA) was carried out to evaluate the model's fit and to confirm the validity of the constructs used in the study. Additionally, the reliability of the scales was assessed using Cronbach's Alpha, ensuring the consistency of the measures employed.

An independent sample (two-tailed) T-test was then run to assess the differences between responses to each survey, exposure to AI and its relationship to AI accuracy perception, attitude towards AI, and brand trust testing hypotheses (H1, H2, H4). Finally, a mediation analysis was performed to assess whether AI accuracy perception and Attitude towards AI have a mediating effect on the relationship between AI Exposure and Brand trust (H3, H5).

5.2 Data Preparation

Data collection was efficiently executed using the YON Platform, which facilitated the direct export of responses into a Microsoft Excel Sheet. After data collection was complete, the responses were imported into Jamovi, where a thorough visual inspection was conducted to verify the accuracy of the data transfer and to ensure there were no missing values or outliers (Bell, Bryman & Harley, 2022). The survey design mandated responses to all questions, which significantly reduced the likelihood of incomplete responses and minimized non-response errors (Malhotra, Nunan & Birks, 2017).

For analysis, the collected data was processed using Jamovi software version 2.5.4, a tool built on the R programming language known for its user-friendly Graphical User Interface (GUI). This interface simplifies complex data analyses, offering flexibility and ease of use (Ahmed & Muhammad, 2021). During data pre-processing in Jamovi, demographic questions were categorized as nominal data types, while responses to survey questions using a Likert scale were treated as continuous data types. Among the 102 responses collected, all required fields were completed, reflecting the effective design of the questionnaire.

5.3 Descriptive Statistics

The following descriptive statistics are used to provide insight into the survey population, central tendencies, correlation, and frequency of results.

5.3.1 Survey Populations

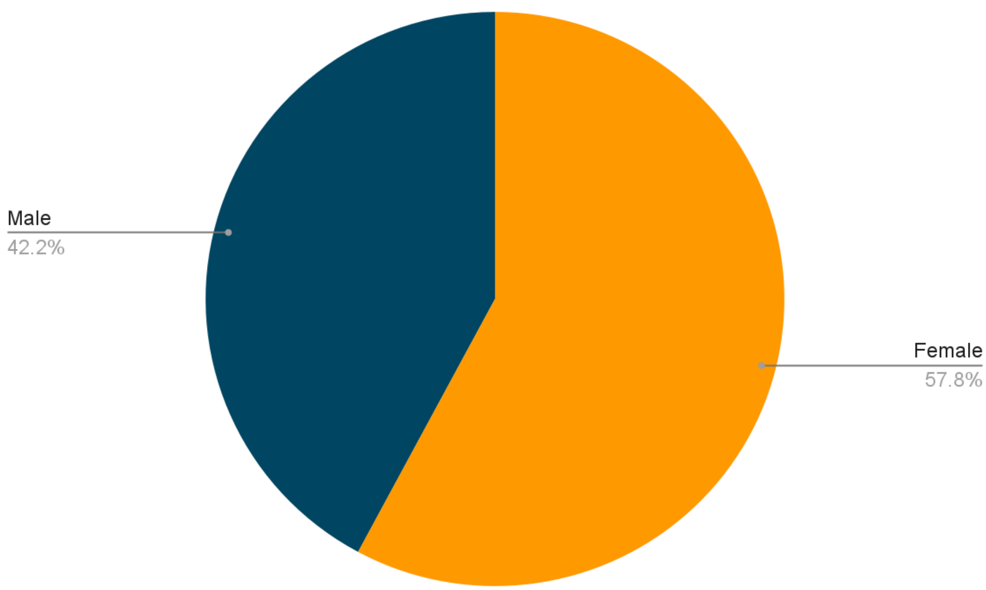

Figure 2 Gender of Survey Respondents

The initial descriptive analysis of the dataset is represented in the pie chart above. The gender distribution in this study predominantly consists of female participants, who account for 57.8% of the sample with 59 female respondents, compared to 43 male respondents (42.2%).

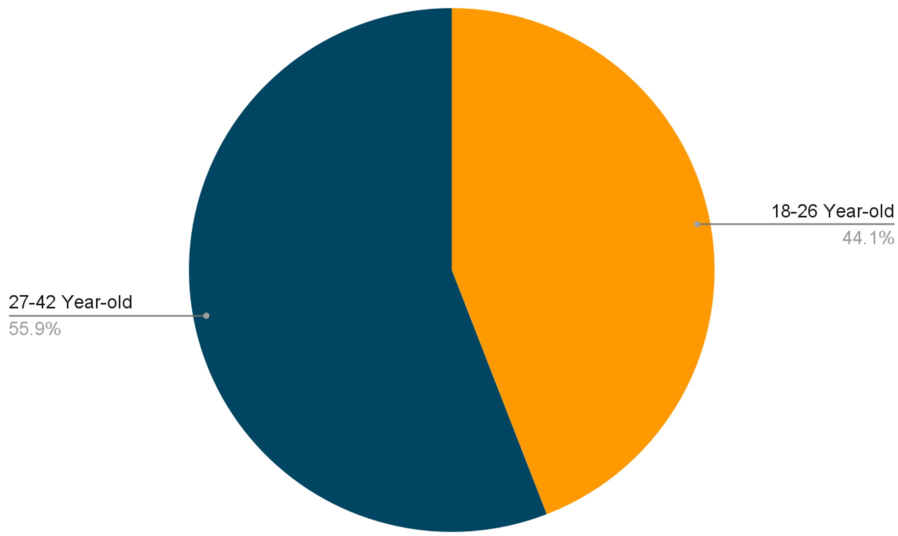

Figure 3 Age of Survey Respondents

The age distribution of the respondents was relatively balanced, with the 18-26 age group constituting 44.1% of the sample (45 respondents - Gen Z), and the 27-42 age group making up 55.9% (57 respondents - Gen Y). This distribution was expected given that the survey was conducted online, where these two age groups are predominant among internet users (Statista, 2023b). The age profile of the respondents aligns well with the target demographic of this study, which focuses on LinkedIn users and who are familiar with AI technologies.

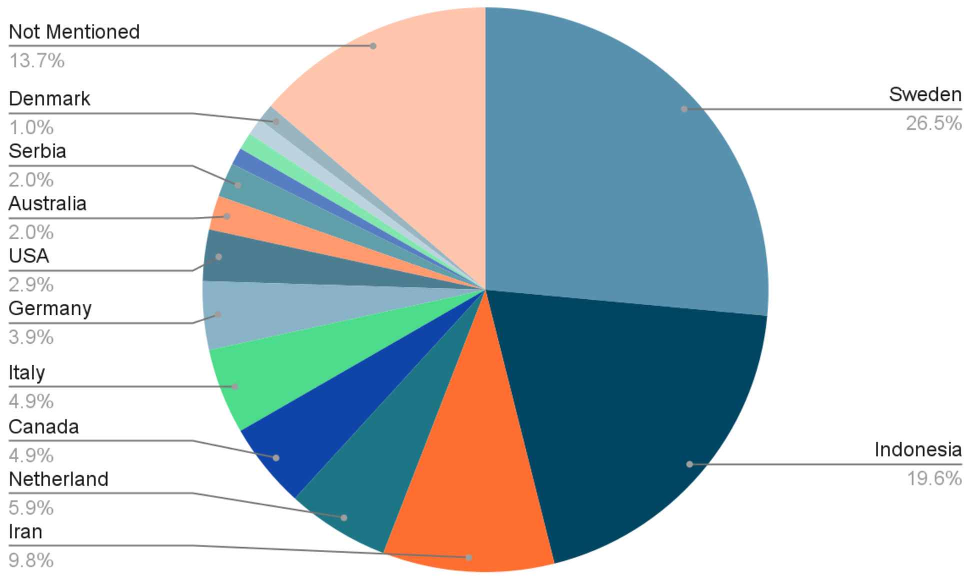

Figure 4 Country of Residence of Survey Respondents

Fourteen countries were represented in this study, with the most dominant presence being Sweden (27 respondents, 26.5%), Indonesia (20 respondents, 19.6%), and Iran (10 respondents, 9.8%). 14 respondents have not mentioned their living country (13.7%). Receiving respondents from diverse backgrounds helps the generalizability of the study.

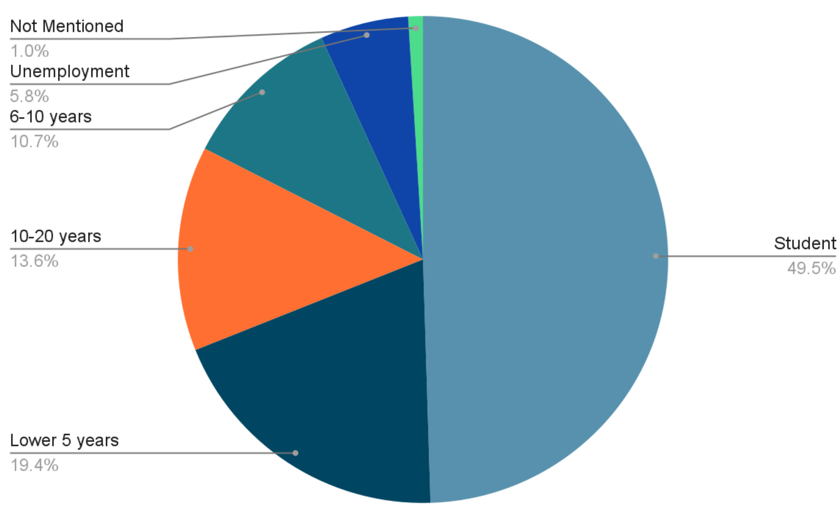

Figure 5 Occupational Status of Survey Respondents

Regarding “Occupational Status”, half of the respondents were students (51 persons), employees with less than 5 years of experience (20 respondents, 19.4%), employees with 10-20 years of experience (14 respondents, 13.6%), employees with 6-10 years of experience (11 respondents, 10.7%), and unemployment users (6 respondents, 5.8%).

Finally, based on the data on "LinkedIn Account Type," it is evident that the vast majority of respondents possess a basic LinkedIn account (93 respondents, 91.2%). This suggests that a significant portion of our sample lacks direct exposure to LinkedIn's AI features. To address this gap, we provided an introductory clip about LinkedIn's AI features at the beginning of our survey, aimed at informing respondents and eliciting their expectations regarding these features. Conversely, 8.8% of respondents reported having a premium account. This minority group possesses firsthand experience with LinkedIn's AI features, thus enabling them to offer more nuanced and precise feedback based on their actual usage. It's worth noting that the proportion of premium users in our dataset reflects the lower rate of premium users within the broader LinkedIn user base. This distribution is considered reasonable and representative of our user demographic.

5.3.2 Measures of Central Tendency Figure

Table 4 Central Tendency Measures

Descriptives

	N	Missing	Mean	Median	Mode	SD	Minimum	Maximum
AE1	102	0	4.96	5.00	5.00	1.54	1	7
AE2	102	0	4.05	4.00	5.00	1.64	1	7
AE3	102	0	3.65	4.00	4.00	1.80	1	7
AE4	102	0	4.84	5.00	5.00	1.53	1	7
AAP1	102	0	4.87	5.00	5.00	1.35	2	7
AAP2	102	0	4.88	5.00	5.00	1.44	1	7
AAP3	102	0	5.04	5.00	5.00	1.29	1	7
AAP4	102	0	4.80	5.00	6.00	1.44	1	7
ATA1	102	0	5.19	5.00	5.00	1.39	1	7
ATA2	102	0	4.77	5.00	5.00	1.50	1	7
ATA3	102	0	4.98	5.00	5.00	1.50	1	7
ATA4	102	0	5.20	5.00	5.00	1.31	1	7
BT1	102	0	4.66	5.00	5.00	1.33	1	7
BT2	102	0	4.69	5.00	4.00	1.34	1	7
BT3	102	0	4.53	5.00	5.00	1.41	1	7
BT4	102	0	4.41	4.50	5.00	1.56	1	7

The chart above shows the measures of central tendency as related to each of the survey items. Below, is a chart separating the measures by survey, to show the differential between those who have premium accounts and basic accounts. Since a 1-7 scale was used for this study, the risk of outliers skewing the results is slim.

5.4 Inferential Statistics

Inferential statistics were used to assess the reliability of survey items and the model. The results are presented below:

5.4.1 Confirmatory Factor Analysis

To verify the association between the survey items and their corresponding factors, Confirmatory Factor Analysis (CFA) was conducted instead of exploratory factor analysis. This approach was chosen because the items used to measure each variable were based on prior research.

Table 5 CFA Factor Loadings

Factor Loadings

Factor	Indicator	Estimate	SE	Z	p	Stand. Estimate
AI Exposure	AE1	1.096	0.142	7.73	<.001	0.714
	AE2	1.414	0.140	10.08	<.001	0.868
	AE3	1.282	0.165	7.78	<.001	0.715
	AE4	0.903	0.150	6.02	<.001	0.592
AI Accuracy Perception	AAP1	1.080	0.112	9.60	<.001	0.801
	AAP2	1.230	0.115	10.73	<.001	0.860
	AAP3	1.101	0.103	10.69	<.001	0.858
	AAP4	1.271	0.113	11.26	<.001	0.885
Attitude Towards AI	ATA1	1.085	0.116	9.33	<.001	0.784
	ATA2	1.285	0.119	10.78	<.001	0.860
	ATA3	1.391	0.112	12.40	<.001	0.935
	ATA4	1.143	0.103	11.09	<.001	0.875
Brand Trust	BT1	1.168	0.104	11.18	<.001	0.882
	BT2	1.237	0.102	12.13	<.001	0.926
	BT3	1.173	0.115	10.18	<.001	0.835
	BT4	1.250	0.129	9.72	<.001	0.807

In this study, five factors were quantified using their designated survey items. The relationships between these items and their factors are detailed in the table provided. All 12 items displayed a significant p-value (p<.001) and a Z-value greater than zero, indicating that each item effectively contributes to the model (Navarro & Foxcroft, 2022). Eleven of these items show an ideal fit with standard estimates greater than 0.700, while the remaining one item is considered to have an acceptable fit with standard estimates greater than 0.500. The uniform p-values of <.001 further confirm the robustness with which these items represent their respective factors (Tavakol & Wetzel, 2020).

Factor Estimates

Table 6 Factor Covariances

Factor Covariances

		Estimate	SE	Z	p	Stand. Estimate
AI Exposure	AI Exposure	1.000 [a]				
	AI Accuracy Perception	0.507	0.0887	5.72	<.001	0.507
	Attitude Towards AI	0.431	0.0948	4.55	<.001	0.431
	Brand Trust	0.600	0.0768	7.81	<.001	0.600
AI Accuracy Perception	AI Accuracy Perception	1.000 [a]				
	Attitude Towards AI	0.920	0.0249	36.90	<.001	0.920
	Brand Trust	0.734	0.0547	13.40	<.001	0.734
Attitude Towards AI	Attitude Towards AI	1.000 [a]				
	Brand Trust	0.781	0.0477	16.38	<.001	0.781
Brand Trust	Brand Trust	1.000 [a]				

The standard estimates presented in the factor covariances table above are indicative of the correlation coefficients (r). Values below the absolute threshold of |.80| are considered ideal, as coefficients higher than this may indicate that the variables are too closely correlated to be considered independent of each other (Taylor, 1990). In this survey, most of the variables displayed correlation coefficients well under the |0.80| threshold, indicating no significant concerns regarding their independence. However, there appear to be some issues with AI Accuracy Perception and Attitude towards AI (r= 0.920>0.80), as their correlation coefficient is 0.920, which exceeds the 0.80 threshold.

5.4.2 Model Fit

Table 7 Test for Exact Fit

Test for Exact Fit

χ^2	df	p
160	98	<.001

A p-value of less than .001 in a test for exact fit significantly reduces the likelihood of a Type 1 error in the theoretical measurement model (Sallis et al., 2021).

Table 8 Fit Measures

Fit Measures

			RMSEA 90% CI	
CFI	TLI	RMSEA	Lower	Upper
0.954	0.943	0.0786	0.0558	0.100

The Comparative Fit Index (CFI) and Tucker Lewis Index (TLI) scores, at .954 and .943 respectively, suggest a suboptimal fit, as they meet the generally accepted threshold for a good fit (>.95). Additionally, the Root Mean Square Error of Approximation (RMSEA) value at .0786 also indicates a less than ideal fit, as optimal RMSEA values are below .06. Both the lower and upper confidence interval values exceed the ideal fit threshold, suggesting that achieving an ideal RMSEA in future runs is unlikely (Hu & Bentler, 2009; Navarro & Foxcroft, 2022).

To ensure accurate results, we have excluded AE4 values below 0.5 and present the table below. Our analysis indicates that the measures for model fit analysis remain consistent whether including or excluding AE4. Therefore, we have decided to include AE4 in subsequent analyses.

Table 9 Fit Measures (without AE4)

Fit Measures

			RMSEA 90% CI	
CFI	TLI	RMSEA	Lower	Upper
0.964	0.955	0.0732	0.0471	0.0971

5.4.3 Internal Consistency Reliability Analysis

Table 10 Cronbach's Alpha Loadings by Factor

Item Reliability Statistics

	If item dropped	
	Cronbach's α	McDonald's ω
AI Exposure	0.904	0.908
AI Accuracy Perception	0.794	0.816
Attitude Towards AI	0.791	0.802
Brand Trust	0.801	0.836

This type of reliability analysis computes a statistic that assesses the internal consistency of each item in measuring key constructs. As indicated in Table 10 above, both Cronbach's alpha and McDonald's omega coefficients achieve excellent scores, exceeding the minimum recommended threshold of 0.7 as suggested by Bougie and Sekaran (2020) and Navarro and Foxcroft (2022). These outcomes validate a satisfactory model. This indicates substantial intercorrelations among the items, reflecting high consistency and stability, and low susceptibility to changes in conditions. The internal reliability test results for each construct are detailed in Table 10.

Cronbach's Alpha measures the consistency of responses among items within a factor. Acceptable scores range from 0.7 to 0.95, and for all factors measured in this study, the scores fall within this range. These satisfactory scores reflect strong internal consistency among the items of each factor, though not to the extent that the items could be seen as overly similar (Tavakol & Dennick, 2011). The outcomes of this test demonstrate robust internal consistency for the items used in this study.

5.5 Descriptive Statistics and Psychometrics Properties

Table 11 presents the descriptive statistics and psychometric properties of the marketing variables. The mean values provide an average of respondents' reactions on the specified scales, serving as a measure of the data's central tendency. The results show that the majority of the values fall between 4.38 and 5.03, indicating that most respondents feel neutral or agree with the variables being measured.

Table 11 Descriptive Statistics and Psychometrics Properties

Descriptives

				Skewness		Kurtosis	
	Mean	SD	Variance	Skewness	SE	Kurtosis	SE
AI Exposure	4.38	1.31	1.71	0.0338	0.239	–0.3593	0.474
AI Accuracy Perception	4.90	1.23	1.51	–0.4175	0.239	0.1735	0.474
Attitude Towards AI	5.03	1.28	1.64	–0.3993	0.239	–0.0644	0.474
Brand Trust	4.57	1.26	1.60	–0.0484	0.239	–0.0204	0.474

Additionally, skewness and kurtosis are critical for understanding the shape of the distribution. This study found that three variables have negative skewness, indicating a slight leftward skew in the distribution, with values ranging from -0.0484 to -0.4175.

5.6 Testing Mediation Using Baron and Kenny's Method

Baron and Kenny's (1986) method provides a systematic approach for testing mediation effects in a model with multiple mediators. The method involves three sequential steps, as outlined below:

Step One: Establishing a Relationship between the Independent and Dependent Variables

The first step in testing mediation is to establish a significant relationship between the independent variable (X) and the dependent variable (Y). This is achieved by conducting a linear regression analysis with Y as the dependent variable and X as the independent variable. The coefficient (C) obtained from this analysis should be significantly different from zero in the expected direction, indicating a direct relationship between X and Y.

$Y = i\,1 + c\,X + e1$

Step Two: Assessing the Relationship between the Independent Variable and the Mediator

After confirming the direct relationship between X and Y, the next step is to assess the relationship between the independent variable (X) and the mediator (M). This is accomplished by conducting a linear regression analysis with M as the dependent variable and X as the independent variable. The coefficient (a) obtained from this analysis should be significantly different from zero, suggesting that X influences M1.

$M = i\,2 + a\,X + e2$

Step Three: Examining the Relationship between the Mediator and the Dependent Variable, Controlling for the Independent Variable

Once the relationship between X and M is established, the final step is to examine the relationship between the mediator (M) and the dependent variable (Y) while controlling for the effect of the independent variable (X). This is done by conducting a linear regression analysis with Y as the dependent variable and both X and M as independent variables. The coefficient (b) obtained from this analysis should be significantly different from zero, indicating that M affects Y even after accounting for the influence of X.

$Y = i\,3 + a\,X + b\,M+e3$

Hence, we test our model by following those three steps:

Step One: *Establishing a Relationship between the AI Exposure and Brand Trust*

According to Table 12, a linear regression was conducted to evaluate the effect of AI Exposure (independent variable) with Brand Trust (dependent variable). The results of the regression indicated that the model explained 28.2% of the variance and was a significant predictor of Brand Trust, F(1, 100) = 39.3, p < .001.

These results suggest that AI Exposure (β = 0.531, t(100) = 6.27, p < .001) has a significantly positive relationship with Brand Trust.

Table 12 Linear Regression Analysis - AI Exposure and Brand Trust

Model Fit Measures

				Overall Model Test			
Model	R	R^2	Adjusted R^2	F	df1	df2	p
1	0.531	0.282	0.275	39.3	1	100	<.001

Model Coefficients - Brand Trust

Predictor	Estimate	SE	t	p	Stand. Estimate
Intercept	2.322	0.3740	6.21	<.001	
AI Exposure	0.514	0.0820	6.27	<.001	0.531

Based on this arguments, Hypothesis 1, which suggests that AI Exposure is positively associated with Brand Trust, is confirmed.

Step Two: *Assessing the Relationship between AI Exposure and AI Accuracy Perception and Attitude Towards AI*

According to Table 13, a linear regression was conducted to evaluate the effect of AI Exposure on AI Accuracy Perception (as a mediator). The results of the regression indicated that the model explained 21.8% of the variance and that the model was a significant predictor of AI Accuracy Perception, F(1, 100) = 27.9, p < .001.

These results suggest that AI Exposure (β = 0.467, t(100) = 5.28, p < .001) significantly predicts AI Accuracy Perception.

Table 13 Linear Regression Analysis - AI Accuracy Perception

Model Fit Measures

				Overall Model Test			
Model	R	R^2	Adjusted R^2	F	df1	df2	p
1	0.467	0.218	0.210	27.9	1	100	<.001

Model Coefficients - AI Accuracy Perception

Predictor	Estimate	SE	t	p	Stand. Estimate
Intercept	2.974	0.3801	7.83	<.001	
AI Exposure	0.440	0.0833	5.28	<.001	0.467

Based on the previous arguments, Hypothesis 4, which suggests that AI Exposure is positively associated with AI Accuracy Perception, is confirmed.

According to Table 14, a linear regression was conducted to evaluate the effect of AI Exposure on Attitude towards AI. The results of the regression indicated that the model explained 17.5% of the variance and was a significant predictor of Attitude towards AI, $F(1, 100) = 21.1$, $p < .001$.

These results suggest that AI Exposure ($\beta = 0.418$, $t(100) = 4.60$, $p < .001$) significantly predicts AI Accuracy Perception.

Table 14 Linear Regression Analysis - AI Accuracy Perception

Model Fit Measures

Model	R	R^2	Adjusted R^2	Overall Model Test			
				F	df1	df2	p
1	0.418	0.175	0.166	21.1	1	100	<.001

Model Coefficients - Attitude Towards AI

Predictor	Estimate	SE	t	p	Stand. Estimate
Intercept	3.242	0.4066	7.97	<.001	
AI Exposure	0.410	0.0891	4.60	<.001	0.418

Based on the last arguments, Hypothesis 2, which suggests that AI Exposure is positively associated with Attitude towards AI, is confirmed.

Step Three: *Examining the Relationship between the AI Accuracy Perception and Attitude Towards AI and Brand Trust, Controlling for AI Exposure*

According to Table 15, a linear regression was designed to evaluate the effect of AI Exposure, AI Accuracy Perception, and Attitude Toward AI on Brand Trust. The results of the regression showed that the model explained 61.3% of the variance and was a significant predictor of Brand Trust, $F(3, 98) = 51.7$, $p < .001$.

These results suggest that both AI Exposure ($\beta = 0.256$, $t(98) = 3.601$, $p < .001$) and Attitude Towards AI ($\beta = 0.564$, $t(98) = 4.732$, $p < .001$) significantly predict Brand Trust, while AI Accuracy Perception ($\beta = 0.085$, $t(98) = 0.692$, $p = 0.490$) does not.

Table 15 Linear Regression Analysis - Brand Trust

Model Fit Measures

Model	R	R^2	Adjusted R^2	Overall Model Test			
				F	df1	df2	p
1	0.783	0.613	0.601	51.7	3	98	<.001

Model Coefficients - Brand Trust

Predictor	Estimate	SE	t	p	Stand. Estimate
Intercept	0.2600	0.3605	0.721	0.473	
AI Exposure	0.2479	0.0688	3.601	<.001	0.2562
AI Accuracy Perception	0.0870	0.1258	0.692	0.490	0.0848
Attitude Towards AI	0.5562	0.1175	4.732	<.001	0.5639

Hypothesis 3, proposing that Attitude Towards AI positively influences Brand Trust, is also validated. However, Hypothesis 5, which posits a positive relationship between AI Accuracy Perception and Brand Trust, is not supported by the findings.

5.7 Hypothesis Summary

This study confirmed four hypotheses and rejected one. The results revealed that Attitude towards AI mediates the relationship between AI Exposure and Brand Trust. However, our findings reject the mediation role of Accuracy towards AI in the relationship between AI Exposure and Brand Trust. These findings are summarized in Table 16.

Table 16 Summary of Hypothesis Results

Hypothesis	Results	β	p-values
H1: There is a positive relationship between individuals' exposure to AI and their trust in brands that integrate AI into their services.	Accepted	0.531	< .001
H2: There is a positive relationship between individuals' exposure to AI and their positive attitude towards AI-powered profile building.	Accepted	0.418	< .001
H3: There is a positive relationship between individuals' positive attitudes towards AI-powered profile building and their trust in brands that integrate this service.	Accepted	0.564	< .001
H4: There is a positive relationship between individuals' exposure to AI and their perception of the accuracy of AI-powered profile building.	Accepted	0.467	< .001
H5: There is a positive relationship between individuals' perception of AI-powered profile building as accurate and their trust in brands that offer this service.	Rejected	0.085	0.490

5.8 Result Discussion

Firstly, our findings indicate the necessity of revisiting and potentially revising the previous model that governed research in this domain. The discrepancy between our results and the assumptions of the established model underscores the need for a paradigm shift in understanding the dynamics of AI integration in marketing strategies. By demonstrating the inadequacy of the previous model, our research aligns with its primary aim: to prompt a critical reassessment of prevailing theories and frameworks.

Moreover, the non-significant influence of AI accuracy uncovered in our study poses a fundamental challenge to the existing body of literature. Contrary to prior assumptions, our findings suggest that the relationship between AI accuracy and brand trust may be more nuanced than previously believed. This discrepancy prompts us to critically evaluate the factors contributing to the observed deviation in outcomes. Possible explanations may include contextual variations, methodological differences, or unaccounted-for variables that warrant further investigation.

Furthermore, our research sheds light on the overlooked role of AI attitude and perception as crucial mediators in shaping consumer trust. The discovery that higher AI accuracy leads to lower brand trust among customers suggests a complex interplay between technological advancements and human-centered values. Companies focusing solely on the accuracy aspect of AI may overlook the importance of maintaining a human element in their interactions with consumers, potentially eroding trust in their brands. This finding underscores the need for a more holistic approach to AI integration in marketing strategies which considers both technological capabilities and human values.

5.9 Chapter Summary

This chapter embarks on a comprehensive exploration of the integration of artificial intelligence (AI) in marketing strategies and its repercussions on consumer trust in brands. We commence our inquiry with a meticulous examination of descriptive analysis, followed by inferential statistics encompassing Confirmatory Factor Analysis (CFA), Model Fit, and Internal Consistency Reliability Analysis. Subsequently, we employ Baron and Kenny’s methods to scrutinize the intricate interplay between AI accuracy, consumer perception, and brand trust.

Our investigation yields multifaceted insights that challenge established models and illuminate overlooked variables, necessitating a re-evaluation of prevailing frameworks. Firstly, the empirical evidence underscores a palpable disparity between the assumptions of the existing model and our research findings, advocating for a paradigm shift in understanding AI integration in marketing strategies.

Furthermore, our analysis elucidates the pivotal role of AI attitude and perception as mediating factors in shaping consumer trust. By delineating the intricate interplay between technological advancements and human-centered values, we underscore the imperative of adopting a holistic approach to AI integration that encompasses both technical efficacy and human sensibilities.

In addition, our findings challenge conventional wisdom regarding the presumed relationship between AI accuracy and brand trust. Contrary to prior assumptions, our findings reveal a nuanced dynamic, necessitating a critical reassessment of the factors influencing brand-consumer relationships.

In conclusion, this chapter contributes significantly to the field by challenging existing paradigms, shedding light on overlooked variables, and urging a re-evaluation of established theories. By furnishing valuable insights into the complexities of AI integration and its ramifications for consumer trust, we provide a solid foundation for future research and the development of effective marketing strategies in the era of AI.

6. Conclusion

This chapter will discuss research aims and objectives, followed by theoretical and managerial implications. Finally, we outline the limitations of this study and provide suggestions for future research.

6.1 Research Aims and Objective

This study aims to refine the previous research model by changing the role of accuracy perception and attitude towards AI from independent variables to mediating variables. This shift is based on our belief that mere exposure to AI is not sufficient to make people trust a brand that utilizes AI in its services. Similarly, without exposure to AI, individuals cannot accurately assess the accuracy of AI or form an attitude towards it. Therefore, we aim to examine these relationships and update the model accordingly. To achieve this, we formulated two research questions:

1. What is the relationship between individuals' exposure to AI technology and their trust in brands utilizing AI, and is this relationship directly influenced or mediated by their perceptions and attitudes towards AI?

2. Which factor (individuals' perceptions of AI or their attitudes towards AI) has a stronger influence on their trust in brands employing AI services?

To answer these research questions, we employed the Technology Acceptance Model (TAM) and TAM 2 theory, which are well-known for understanding individual acceptance of new technologies. We chose AI-powered profile building by LinkedIn as our context due to the broad scope of AI and the need to target specific respondents within our limited time and resources.

Our findings revealed that high people's exposure towards AI positively influences their trust towards brands who utilize AI in their service. Moreover, this relationship has proven to be mediated by accuracy perception and attitude towards AI. Furthermore, people's positive attitude towards AI is proven to positively influence brand trust. However, contrary to our expectations, accuracy perception had a low influence on brand trust. We believe this is due to individuals' hesitation towards AI, as some people fear that more accurate AI could potentially replace human roles entirely, leading to lower trust in brands that utilize AI in their services.

6.2 Theoretical Implications

This study aims to deepen our understanding of consumer-brand relationships and technology adoption by introducing an updated research model built upon previous studies. It explores the link between individuals' exposure to AI as the independent variable and its impact on trust toward brands incorporating AI in their services. Additionally, the study incorporates individuals' accuracy perception of AI and attitudes toward AI as mediating variables. We propose that these variables mediate individuals' intention to trust brands utilizing AI in their services, rather than serving as the independent variable. The theoretical framework guiding this research is rooted in the TAM and TAM 2 theories. Furthermore, our findings highlight that prior studies may have overlooked the influence of individuals' attitudes and perceptions in mediating this relationship since our research demonstrates that individuals' positive attitudes and perceptions toward AI play a crucial role in mediating the relationship between their exposure to AI and their trust in the brand. Thus, this study contributes theoretically by presenting an extended research model derived from previous studies, offering fresh insights into consumer-brand relationships, brand trust, and the adoption of AI as a novel technology.

6.3 Managerial Implications

This study offers valuable insights for companies aiming to integrate AI into their services, especially considering the increasing prevalence of AI adoption across industries. Understanding customer acceptance and perception of AI services is essential in today's business landscape. Our findings highlight several noteworthy observations that companies should consider. Firstly, individuals with greater exposure to AI tend to exhibit more positive attitudes and perceptions toward the technology which foster their trust in brands utilizing AI in their services. Additionally, our research indicates that individuals who perceive AI as user-friendly and thus have positive attitudes towards AI are more inclined to trust brands incorporating AI. Interestingly, our findings also suggest a nuanced relationship between the accuracy perception of AI and trust in brands. Contrary to expectations, individuals who perceive AI as highly accurate may exhibit lower trust in brands offering AI-driven services. This unexpected outcome may stem from concerns regarding AI's potential to replace human roles entirely, leading to diminished trust in brands employing advanced AI technologies. In summary, this study provides novel insights for companies seeking to integrate AI into their service offerings. By understanding the nuanced interplay between customer attitudes, perceptions, and trust about AI, businesses can make more informed decisions about leveraging AI effectively while addressing customer concerns and maintaining trust.

6.4 Limitations and Future Research

This study has several limitations that readers and future researchers must consider. First, we used LinkedIn as the context of our research. However, some people might have mixed opinions about LinkedIn as a brand, which could introduce bias into their responses. Hence, future research could consider avoiding specific brands to reduce potential bias.

Second, we are aware that most of our respondents used basic LinkedIn accounts and did not have real experience with AI-powered profile building. To address this, we asked for their expectations rather than their actual experiences. However, some respondents were confused about providing expectations instead of real experiences, which may have led to biased answers. Thus, future research should prioritize capturing real experiences with accessible AI tools.

Lastly, we acknowledge there are different opinions regarding AI-powered profile building between Generation Z and Generation Y. However, due to time constraints and a limited sample size, we couldn't explore this in depth. Therefore, future research could investigate this aspect more thoroughly.

6.5 Chapter Summary

This study aims to refine the previous research model by modifying accuracy perception and attitude towards AI from independent variables to mediating variables. The research questions focus on how exposure to AI influences trust in AI-utilizing brands, mediated by perceptions and attitudes, and which of these factors has a stronger influence on trust. Additionally, this study uses the Technology Acceptance Model (TAM) and TAM 2 as the theoretical foundation and examines AI-powered profile building by LinkedIn as the context.

Key findings reveal that accuracy perception and attitude towards AI positively mediate the relationship between AI exposure and brand trust, which previous research may have overlooked. Surprisingly, our findings reveal that accuracy perception has a low influence on brand trust, which differs from previous research. Therefore, we believe this variable warrants further investigation in the future.

Furthermore, this study offers practical insights for companies integrating AI, emphasizing that higher exposure to AI can foster positive attitudes towards AI and trust in brands that utilize it. However, high accuracy may evoke concerns about human displacement. Therefore, businesses need to address these concerns to maintain customer trust.

The limitations of this study include potential bias from using LinkedIn as the research context, respondents' lack of real experience with AI-powered profile building, and insufficient exploration of generational differences. Future research should consider avoiding specific brands to prevent bias, capturing real AI experiences, and investigating generational perspectives more thoroughly.

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Appendix A: Survey

Survey on the Influence of AI on People's Trust in Brands

Next

Dear Participant,

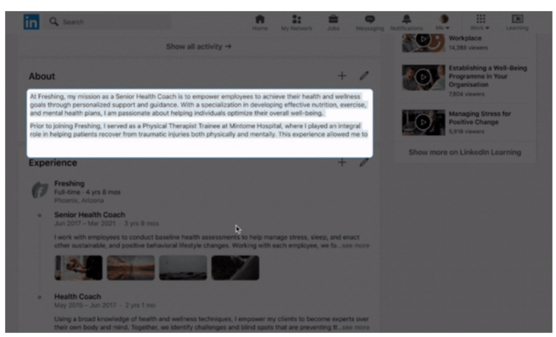
We are master's students studying International Marketing and Branding at Lund University. As part of our research, we are investigating the impact of Artificial Intelligence (AI) on Brand Trust in the context of profile building on LinkedIn. Your insights will greatly contribute to our understanding of how AI recommendations affect Brand Trust in this process. Rest assured, your responses will remain anonymous and confidential, and will only be used for academic research purposes. Once our project is completed, all data will be promptly deleted.

Thank you for your valuable contribution to our study.

Iranaya Dewanti Budi, Ehsan Alinaghian

Introduction of LinkedIn's AI features

Please see below short clip to understand what are the AI features of LinkedIn



To improve individual user experiences, LinkedIn has implemented an AI tool that offers personalized writing suggestions namely AI Powered Profile Building. This feature identifies key skills and experiences and recommends ways to present them in users' **About** and **Headline** sections while respecting each user's unique writing style.

Next

Survey on the Influence of AI on People's Trust in Brands

What type of LinkedIn account do you have?

What type of LinkedIn account do you have? *

- ○ Premium Account
- ○ Basic Account

Next

Survey on the Influence of AI on People's Trust in Brands

Demographic Questions

Gender (Optional)

- ○ Male
- ○ Female
- ○ Prefer not to say

Age (Optional)

- ○ Below 18 years old
- ○ 18-26 years old
- ○ 27-42 years old
- ○ 43-58 years old
- ○ Above 59 years old

Occupation (Optional)

- ○ Student
- ○ Employee (lower than 5 years work experience)
- ○ Employee (6 to 10 years work experience)
- ○ Employee (10 to 20 years work experience)
- ○ Employee (over 20 years work experience)
- ○ Unemployment

Living Country (Optional)
(please write in the box)

Next

Survey on the Influence of AI on People's Trust in Brands

Main Survey

1. I often interact with AI-powered devices or services. *

- 1 (Strongly Disagree)
- 2
- 3
- 4
- 5
- 6
- 7 (Strongly Agree)

2. AI is a central part of my daily life. *

- 1 (Strongly Disagree)
- 2
- 3
- 4
- 5
- 6
- 7 (Strongly Agree)

3. I frequently use AI in shaping my online presence. *

- 1 (Strongly Disagree)
- 2
- 3
- 4
- 5
- 6
- 7 (Strongly Agree)

4. I am familiar with AI technology in my daily life *

- 1 (Strongly Disagree)
- 2
- 3
- 4
- 5
- 6
- 7 (Strongly Agree)

5. I expect the recommendations provided by AI-Powered Profile Building to be accurate. *

- 1 (Strongly Disagree)
- 2
- 3
- 4
- 5
- 6
- 7 (Strongly Agree)

6. I expect the suggestions from AI-Powered Profile Building to be highly appropriate for me. *

- 1 (Strongly Disagree)
- 2
- 3
- 4
- 5
- 6
- 7 (Strongly Agree)

7. I expect that AI Powered Profile Building information aligns with my experience and skill *

- 1 (Strongly Disagree)
- 2
- 3
- 4
- 5
- 6
- 7 (Strongly Agree)

8. I expect AI Powered Profile Building to understand my expertise *

- 1 (Strongly Disagree)
- 2
- 3
- 4
- 5
- 6
- 7 (Strongly Agree)

9. I expect to feel comfortable interacting with AI-Powered Profile Building while creating my profile. *

- 1 (Strongly Disagree)
- 2
- 3
- 4
- 5
- 6
- 7 (Strongly Agree)

10. I expect to trust the suggestions provided by AI-Powered Profile Building *

- 1 (Strongly Disagree)
- 2
- 3
- 4
- 5
- 6
- 7 (Strongly Agree)

11. I expect AI-Powered Profile Building to accurately provide recommendations for my profile. *

- 1 (Strongly Disagree)
- 2
- 3
- 4
- 5
- 6
- 7 (Strongly Agree)

12. I expect AI-Powered Profile Building to enhance my profile *

- 1 (Strongly Disagree)
- 2
- 3
- 4
- 5
- 6
- 7 (Strongly Agree)

13. I trust brands that utilize AI services (such as LinkedIn utilizing AI-Powered Profile Building). *

- 1 (Strongly Disagree)
- 2
- 3
- 4
- 5
- 6
- 7 (Strongly Agree)

14. Brands using AI provide reliable services (such as LinkedIn providing AI-Powered Profile Building to enhance user profiles). *

- 1 (Strongly Disagree)
- 2
- 3
- 4
- 5
- 6
- 7 (Strongly Agree)

15. I trust AI recommendations (such as writing suggestions from AI-Powered Profile Building in LinkedIn). *

- 1 (Strongly Disagree)
- 2
- 3
- 4
- 5
- 6
- 7 (Strongly Agree)

16. Knowing that a brand utilizes AI reassures me (such as LinkedIn's utilization of AI-Powered Profile Building). *

- 1 (Strongly Disagree)
- 2
- 3
- 4
- 5
- 6
- 7 (Strongly Agree)

Submit

Survey on the Influence of AI on People's Trust in Brands

Thank you for completing this survey.