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Abstract

As artificial intelligence (AI) becomes an increasingly integrated innovation in the digital world, its impact on the consumer perception and behavior has drawn interest, academically and in industry. This thesis investigates the effectiveness of AI-powered advertising on Generation Z's trust, attitudes, and purchasing intentions. This study will use the Technology Acceptance Model (TAM) with a few additions, such as: AI literacy, perceived AI accuracy, and perceived AI reliability. These variables are put in place to examine their level of influence on functional and emotional perception in AI on Generation Z. By exploring how AI-powered advertising affects the consumer-brand relationship within this demographic, this study will contribute to the academic understanding of technology acceptance and guide marketers in leveraging this new technology without hurting their relationship with these new and upcoming consumers.

Keywords: AI-powered advertising, Generation Z, Technology Acceptance Model, Consumer Trust, Advertising Perception, AI Perception

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1 Introduction

In an ever evolving digital era, society has been introduced to a new stage of technological advancement, marked by the beginning of artificial intelligence (AI) (Damioli et al., 2024). This innovative technology enables machines to think and act like humans, able to process vast amounts of data to perform tasks that are traditionally carried out by people. Tasks include recognizing patterns, making informed decisions, and passing judgement in ways that imitate human cognitive functions (Pattam, 2021). Since the release of OpenAI's ChatGPT in 2022, AI-powered programming has begun to revolutionize a range of industries, including advertising. The impacts of AI have shown an influence specifically on the consumer-brand relationship, especially among Generation Z, who have been spearheading this technological shift (Shevchyk, 2024). As AI continues to reshape industries and transform the dynamics of the consumer-brand relationship, it will influence this notable generation. This demographic is deeply immersed in technology. However, they also seek authenticity and other key values, valuing genuine connections in this rapidly evolving digital landscape (Neufeld-Wall, 2023) and have now emerged into the marketplace as young consumers (Thangavel et al., 2022).

In tandem with technological advancements, this generation is reshaping the consumer landscape in ways that impacts all socioeconomic groups that reach beyond Generation Z. This results in the generation influencing the entire demographic spectrum. The opportunities presenting themselves to companies are both transformational and demanding. Businesses are in need of reevaluating how they create value for their consumers, finding a balance between large-scale production and personalization. Companies also need to display integrity in their marketing and work ethics. This will ensure that the companies' values, transparency, and authenticity will align (Francis & Hoefel, 2018).

As the first generation to mature in a world shaped by technology, this generation has become well-acquainted with rapid shifts in the digital landscape, which differentiate them from the generations that preceded them (ALBESCU, 2022). Unlike the previous generations, Generation Z displays unique consumer behaviors that will differentiate themselves and highlight the interactions made in the marketplace. Consumer behavior refers to the actions and decisions individuals make when selecting, purchasing, or using products and services. Consumer behavior is especially relevant when considering Generation Z because their decisions are heavily influenced by their technology-driven environment and distinct preferences (Radu, 2023).

Among the distinct consumer behaviors exhibited by Generation Z, trust has been revealed as a particularly crucial factor in significantly influencing their purchasing decisions (Priporas et al., 2017). This generation, known for their discerning nature and reliance on digital information, values authenticity and transparency when choosing to interact with a brand. Where information is easily accessible and consumer skepticism is high, this generation seeks for an open and honest consumer-brand relationship that stays true to their promises (Kirnosova, 2021). For Gen Z, trust plays an essential role in shaping not only their purchasing decisions, but also their loyalty and commitment to a brand (Guerra-Tamez et al., 2024).

Trust has become a critical factor in influencing purchasing decisions among Gen Z (Singh, 2024). Moorman, Deshpande, and Zaltman (1993) defined trust as “a willingness to rely on an exchange partner in whom one has confidence,” while Morgan and Hunt (1994) defined it as a trustor’s “confidence in an exchange partner’s reliability and integrity.” Both of these definitions align with Rotter’s (1967) foundational concept that interpersonal trust is an “expectancy held by an individual or a group that the word, promise, verbal or written statement of another individual or group can be relied upon.” For Gen Z, trust is crucial to their decision-making process when choosing the companies or brands they engage with, driven by their discerning nature and expectation for transparency and authenticity (Guerra-Tamez et al., 2024).

Artificial intelligence has begun to make waves in the consumer landscape, generating both excitement and apprehension among marketers and consumers alike (Qi et al., 2024). As AI continues to advance and grow in its presence, it is becoming a greater topic of interest for many industries. However, despite its growing presence, there remains a significant knowledge gap regarding the broader implications of AI in advertising, especially when understanding the specific impacts on consumer groups (Suraña‑Sánchez & Aramendia‑Muneta, 2024). In particular, one key area that remains to be thoroughly underexplored is the effects AI-powered advertising has on factors, such as: trust, consumer attitudes, and purchasing behaviors among Generation Z, a demographic known for digital savviness and discerning nature (Guerra-Tamez et al., 2024) (Bonner, n.d.).

Generation Z is highly connected (Francis & Hoefel, 2018) and has established an unique approach to interacting with brands, creating an importance of understanding how they respond and accept new technologies, like AI in the advertising space. This research seeks to address this knowledge gap by examining the relationship between AI-driven advertising and consumer behavior within this unique demographic (Bonner, 2023). By doing so, this research will contribute valuable insights regarding the ways in which AI influences brand perception and consumer decision making among this younger generation that is influencing the future of the marketplace (Koulopoulos & Keldsen, 2016).

The purpose of this research is to explore the effects of using AI-powered content in an Instagram advertisement on Generation Z's trust, consumer attitudes, and purchasing intentions. Specifically, this study will apply a modified version of Davis' Technology Acceptance Model

(TAM) to examine how AI-powered creative influences Gen Z's attitudes, perception, and purchasing intentions. AI literacy, perceived accuracy of AI, and perceived reliability of AI will be integrated into Davis' TAM framework, expanding on the concepts of perceived ease of use and perceived usefulness. Investigating these relationships, this research aims to determine whether AI can be effectively used as a technological tool to enhance advertising efforts, without adverse effects on the consumer-brand relationship among this emerging demographic.

Just as a well-crafted advertisement resonates with consumers (Jamal & Khan, 2025), AI holds potential to strengthen brand connections through personalized, relevant experiences or risk alienating consumers if the messaging is perceived as impersonal or overly automated. In a time when digital interactions are increasingly impacting consumer behavior (Yoesoep Edhie Rachmad, 2024), it is critical to understand how Gen Z responds to AI-powered content in advertising. Whether this new technology can be accepted without undermining trust or consumer attitudes is a key concern for the advertising industry in navigating the complexities of modern advertising and a rapidly evolving digital world.

The findings of this study will provide valuable insights for marketers seeking to leverage AI as an effective tool for crafting more personalized and impactful advertising campaigns. Understanding how AI can enhance or hinder the consumer-brand relationship with Gen Z will be pivotal for brands aiming to build stronger connections with this demographic. By exploring how AI affects trust, attitudes, and purchasing decisions, this research offers guidance for safeguarding brand reputation and consumer loyalty. Understanding the unique aspects and values of Gen Z, and how their shared experiences shape their consumer behaviors, will be essential for brands in maintaining relevance and fostering relationships with this emerging generation and today's digital marketplace.

1.1 Contribution of the Current Study

This study offers several significant contributions to both academic research and the advertising industry. First, AI-powered advertising presents an unique opportunity to leverage Ai as a tool for enhancing creativity. By utilizing AI, companies and brands can upgrade their content creation processes, but also increase operational efficiency (Yang, et al., 2017) by producing more engaging and relevant advertising content at a faster rate. While the potential benefits of AI-powered advertising are substantial, there are also powerful considerations regarding its impact on consumer-brand relationships.

As AI-generated content becomes more acclimated to, it is important to understand how it influences consumer trust and perceptions of authenticity. The concerns about data privacy and the need for transparency in how personal data is collected, processed, and used for marketing purposes are also important aspects to understand as marketers (J. Wulf & Seizov, 2020). These issues must be carefully addressed to maintain a healthy and strong relationship between brands and their consumers within this young demographic.

Second, Gen Z is a demographic that matured in a fully digital environment, establishing them as true “digital natives” (Bhalla, et al., 2021). This generation is highly tech-savvy (Bonner, 2023) and constantly connected to various digital platforms and tools (Francis & Hoefel, 2018). Gen Z is characterized by a strong emphasis on authenticity (Francis & Hoefel, 2018), transparency (Guerra-Tamez et al., 2024), and reliability (Witt & Baird, 2018, p. 55) when interacting with brands. They are highly selective in their purchasing (Guerra-Tamez et al., 2024), not only evaluating products based on quality and price but also considering brand values, corporate responsibility (Salam, et al., 2024), and transparency (Guerra-Tamez et al., 2024). As such, Gen Z’s purchasing behavior is influenced by the authenticity (Francis & Hoefel, 2018) of the brands they support.

Third, trust plays a pivotal role in fostering consumer purchasing decisions (Priporas, et al, 2017), particularly among Gen Z. Trust is crucial in building and maintaining strong consumer-brand relationships in a landscape dominated by digital interactions (Guerra-Tamez et al., 2024). For Gen Z, trust is not easily given, but must be earned through consistent, authentic communication and transparent business practices (Guerra-Tamez et al., 2024). Given their expectations for authenticity, Gen Z is highly sensitive to missteps or perceived disingenuous behavior from companies and brands. In the context of new technology and AI adoption, trust becomes more important to consumers (Guerra-Tamez et al., 2024). As AI technology becomes more embedded in the advertising industry, brands must work to ensure that the use of AI in their messaging aligns with Gen Z's values, while maintaining consumer trust in the brand's intentions and practices.

Fourth, the Technology Acceptance Model (TAM) provides a valuable framework for understanding how individuals adopt and interact with new technology. TAM emphasizes two key factors: perceived usefulness and perceived ease of use, as primary determinants of technology acceptance (Davis, 1989). In the content of AI acceptance, these factors are crucial in determining how consumers, particularly Gen Z, engage with AI-powered content. However, beyond traditional TAM constructs, this study introduces additional dimensions, such as: AI literacy (Lee & Park, 2023), accuracy (Nussberger et al., 2022), and reliability (Witt & Baird, 2018, p. 55), which are essential for shaping how users interact with and trust AI technologies. Gen Z, with their digital fluency (Lee & Park, 2023), is likely to place importance on these aspects when evaluating AI-powered advertising and content. Understanding the role AI literacy, perceived AI accuracy, and perceived AI reliability play will be key in navigating user acceptance and fostering valuable interactions with AI-powered tools in advertising. These insights will contribute to both academic understanding of technology adoption and offer practical guidance for brands seeking to wisely manage the complexities of AI integration into their marketing strategies.

2 Literature Review

In the context of the theoretical framework, the primary objective of this section is to thoroughly review and explore the key concepts for explaining the relationship between AI-powered advertising and Gen Z's consumer behavior. To achieve this, the study will examine the complex interplay between several critical concepts: AI advertising, Generation Z, consumer trust, and AI perception. These concepts are hypothesized to be interconnected in their influence in how Gen Z interacts with and responds to AI-powered advertisements. A deeper understanding of these relationships is essential for evaluating the impacts of AI-generated content, specifically in the context of Instagram ads, has on Gen's trust and broader consumer behavior.

By investigating these interconnections, this study aims to uncover the mechanisms through which AI influences consumer attitudes and purchasing intentions within this particular demographic. Additionally, gaining a deeper understanding of how Gen Z perceives and accepts AI, while understanding how their perceptions influence their trust of brands. This offers valuable insights for marketers looking to effectively leverage AI in their advertising strategies and messaging. This knowledge will overall help gauge whether AI-powered content can foster positive consumer relationships, or risk undermining the trust and attitudes among Gen Z.

2.1 AI Advertising

The quick developments in AI technology in recent years have led to growing applications across a wide range of industries, driving significant changes in fields like: advertising, media, e-commerce, education, and beyond (Gao, 2023; Gao & Huang, 2021; Kietzmann et al., 2018; Murgai, 2018). The rise of AI has established a strong technical foundation for intelligent operations within the advertising industry (Lai, 2021). In particular, AI is now being widely utilized in key areas, such as: content creation (Bhatt, 2021; Campbell, Plangger, Sands, & Kietzmann, 2021).

Artificial intelligence (AI) is revolutionizing the content creation space, offering new tools and capabilities to enhance efficiency, creativity, and personalization. Recently, AI technologies, such as: machine learning algorithms and natural language processing, have made significant strides in automating the process of generating text, visuals, and multimedia (Nasser & Erafy, 2023). These advancements allow brands, marketers, and content creators to produce high-quality content at a faster rate and with greater precision, while tailoring their messaging to meet the preferences of specific audiences (Nasser & Erafy, 2023). AI-powered content creation tools, such as GPT-3 and image generation models, offer brands the opportunity to effectively leverage advanced technologies to craft more personalized and impactful advertising campaigns, allowing them to provide tailored content that resonates with consumer preferences and enhancing the overall relationship between brands and the consumer (Nasser & Erafy, 2023). However, while AI offers numerous benefits, it also raises concerns about authenticity, transparency, and ethical implications of using machines to generate content (Lehtimäki, 2024). This section will explore the growing role of AI in advertising, impacts on the creative process, and the opportunity of increased concerns. While examining the concerns of data privacy and effects on the consumer-brand relationship.

2.1.1 AI Created Creative

Predictive analysis has been a common practice in the advertising industry to anticipate future consumer behavior and optimize marketing strategies. This type of analysis helps marketers make informed decisions, such as targeting specific groups with personalized ads and predicate campaign performance. Predictive analytics uses data, algorithms, and machine learning to forecast future outcomes based on past behavior (Enache, 2020). Building on the foundations of predictive analytics, AI technology has further expanded the capabilities of the advertising industry (Kumar et al., 2024).

AI has progressively been integrated into multiple facets of the advertising process, including areas like ad design, content creation, and copywriting (Kumar et al., 2024). The incorporation of AI into the advertising industry holds the potential to significantly transform and streamline these processes, allowing them to be more efficient and effective (Kumar et al., 2024). The primary goal of introducing AI into the industry is to enhance the level of personalization and precision within the creative aspects of the advertising process, increasing the probability of content being tailored to better meet the preferences and behaviors of the target audience (Qin & Jiang, 2019). The application of AI in advertising has been previously explored in various studies, such as the work of Yang, Liu, and Zhang (2017), where they compared traditional advertising design methods and those used in smart advertising powered by AI technology. Their study revealed that AI-powered advertising techniques are not only more efficient, but also more cost-effective and user friendly.

This revelation highlights how AI holds the ability to optimize ad creation, reduce the time and resources required, and produce content that resonates more effectively with consumers (Lehtimäki, 2024). As we look toward the future, AI is poised to play a prominent role in navigating the complexities of the digital era (Kumar et al., 2024). It provides a valuable tool for reaching target audiences (Kumar et al., 2024), particularly Gen Z, who have been recognized for their digital fluency and discerning nature when identifying personalized and authentic brand efforts (Lee & Park, 2023). AI stands to revolutionize the advertising landscape, offering the potential for more dynamic, innovative, and impactful campaigns (Kumar et al., 2024).

While AI holds great potential for transforming industries like advertising, it also brings forth ethical and economic challenges, particularly in creative sectors. Hagendorff's study (2024) sheds light on these ethical issues, in particular the impacts on artists' rights and the authenticity of their work, illustrating the complex balance between innovation and responsibility that AI requires to continue to evolve. Hagendorff's study (2024) highlights the attention brought to the economic challenges faced by artists in light of the rise of mass-produced synthetic art generated by AI. A prominent concern raised in the study is the financial loss artists endure as their work is increasingly used in the training of AI models without authorization, recognition, or compensation. This practice undermines the value of artists' original work and raises ethical questions regarding intellectual property rights in the digital era. While some critics argue that AI-generated content lacks genuine creativity and innovation, viewing these models as replicas rather than true artistic expression, others declare that AI has the potential to enhance and accelerate the creative process, creating a positive effect (Hagendorff, 2024). Proponents of AI in the creative space believe that, when approaching responsibility, these tools can serve as valuable aids in artistic exploration, helping in expanding the boundaries of creativity and inspire new forms of expression (Hagendorff, 2024). Despite differing perspectives on the matter, it is clear that the intersection of AI and art present both opportunities and challenges, particularly when it comes to protection of artists' rights and the authenticity of creative work.

This intersection of opportunity and challenge becomes additionally more complex when considering the impacts of AI on societal norms, such as beauty standards, where AI-generated content can reflect and amplify existing ideals, often shaped by cultural biases (Bendell, 2023). AI-generated imaging often reflects and reinforces prevailing beauty standards, which are rooted in societal preferences and often influenced by Western ideals (Bendell, 2023).

These beauty standards typically emphasize specific physical features, such as youthfulness and attractiveness, which are traditionally associated with health and reproductive advantages (Jones et al., 2021). With the rise of image-generating technologies, new and artificial beauty traits are being introduced. These new traits can have a varied response, being either embraced or rejected based on user feedback (Bendell, 2023). This AI-driven process suggests that as the technology becomes more widely used, they could gradually shape and redefine the concept of beauty into a synthetic form, giving rise to new standards that may differ from existing ones (Bendell, 2023). The effects of AI-generated ideals can be particularly profound for individuals, who may feel an increasing pressure to conform to the beauty standards set by machines. These possible expectations, driven by the widespread AI content creation of images, could potentially aggravate body image concerns and reinforce unrealistic beauty norms (Bendell, 2023).

The growing influence of AI in impacting societal standards, particularly in the realm of beauty, parallels the increasing role of AI in various industries, including advertising, where it has been harnessed to increase the effectiveness and efficiency of content creation. In 2016, Alibaba, China's largest e-commerce platform, introduced the Luban System through its AI lab, which integrates advanced AI technology into the ad design process. Initially designed for posters for Alibaba's own Taobao.com and TMall Marketplace, the system revealed its potential by dramatically enhancing the efficiency and effectiveness of the advertising content (Qin & Jiang, 2019). In 2016, the Luban System generated 170 million posters for Alibaba's November 11 discount campaign, leading to a 100% increase in the click-through-rate (CTR) on Taobao (Qin & Jiang, 2019). The following year, the system expanded its capabilities, producing 400 million posters for the same campaign, equivalent to approximately 8,000 posters per second

(Qin & Jiang, 2019). By 2018, Alibaba had opened the platform to third-party users, assisting in the creation of six million posters for over 200,000 Taobao vendors during the annual discount event (Qin & Jiang, 2019).

The trend of AI-driven innovation began picking up speed as it continued with other major players in the e-commerce and advertising industries. Qihoo 360 launched the Leonardo Da Vinci Canvas System in 2017, a smart ad design tool catering to around 20,000 online vendors, while Kuizi Tech developed the Smart Creation System to enhance ad design abilities (Qin & Jiang, 2019). In 2018, JD, another Chinese e-commerce giant, introduced the Shakespear system, a copywriting tool designed to automate the generation of product descriptions and ad copy. By analyzing search keywords entered by users, Shakespeare generates corresponding ad content, adapting based on user interaction and prioritizing more relevant descriptions in future searches. The system contains self-adaptive learning capabilities, which allows it to evolve and improve over time (Qin & Jiang, 2019).

Additionally, known advertising agencies, such as: Leo Digital Network and Dentsu Aegis Network have now progressed in developing their own smart copywriting systems, leveraging AI to create adaptive content (Qin & Jiang, 2019). AI technologies in advertising have been evolving over time, as noted by Chen (2017) and Liao (2017), creating a transformation in the industry. The integration of AI has introduced the idea of reshaping key advertising processes, including research, media planning, creative development, copywriting, and performance evaluation (Chen, 2017; Liao 2017). Despite these advancements, it remains essential to explore how AI is altering the traditional advertising processes and how it is reshaping content creation and overall advertising creativity. Further investigation will be crucial for understanding the full impact of this new technology on the advertising industry.

2.1.2 Increased Efficiency

Advertising efficiency, as defined by Luo and Donthy (2001) and Pergelova, Prior, and Rialp (2010), refers to the ratio of a firm's advertising inputs to its corresponding outputs. This concept highlights the optimization of advertising resources in a way that maximizes the return on investment (ROI), primarily by increasing brand awareness among the target audience and influencing their purchasing intentions (Cheong et al., 2014; Luo & Donthu, 2001; Pergelova et al., 2010). Essentially, it involves strategically managing advertising efforts to increase sales and profitability. The effective management of advertising, the use of suitable platforms, and technology can significantly impact a firm's financial success driving higher returns and a stronger market position (Manala-O & Atienza, 2020; Rahman, Rodríguez-Serrano, & Hughes, 2021). By optimizing the advertising process, companies can enhance their ability to build a strong consumer-brand relationship, foster engagement, and increase their financial performance (Al-Gamrh & Rasul, 2024).

The application of AI technology in the traditional advertising process has notably enhanced efficiency, a benefit that is apparent in various stages of the workflow (Qin & Jiang, 2019). The advancements in AI technology have also enhanced the efficiency of key workflows across media production as well, from content creation to post-production tasks (Nasser & Erafy, 2023). This allows creative professionals to redirect their focus toward more innovative and impactful aspects of advertising, further amplifying the transformative effects of AI on the advertising industry (Nasser & Erafy, 2023).

According to Yang et al. (2017), the integration of AI into the ad design process has made it more efficient, cost-effective, and user friendly. However, efficiency is not limited to just one or two steps in the advertising process driven by AI. Instead, it has the potential to be a defining characteristic of the entire workflow, offering a comprehensive improvement that positively impacts the overall effectiveness of the advertisements (Yang et al., 2017). An AI-driven approach enables real time, accurate, and efficient operations, which significantly enhances the outcome of advertising campaigns.

The structure of advertising costs are typically measured through metrics, such as cost per action (CPA) or cost per sale (CPS), which also feel the benefits from AI's efficiency. CPA is based on specific consumer actions, such as: signing up, adding items to a shopping cart, or engaging with content, while CPS directly correlates with actual sales, making it an efficient and performance driven metric (Qin & Jiang, 2019). This analysis leads to the conclusion that AI may not completely overhaul the traditional advertising process, however it has transformed it into a more synchronized, tool-driven, and highly efficient system. Powered by data and advanced algorithms, the new process has improved key aspects of advertising, including cost, quality, service, and speed (Qin & Jiang, 2019). In their study, Yang, Liu, and Zhang (2017) further observed that AI technology shortens design cycles, streamline customer communication, reduce labor and economic costs, and enhance overall management. This demonstrates the far-reaching benefits of AI in modern advertising.

According to a study conducted by Lehtimäki (2024), the integration of artificial intelligence into creative processes in advertising has proven to enhance both efficiency and productivity in various stages of design and content creation. AI plays an important role in three primary areas: supporting creativity, streamlining the initial phases of design, and automating repetitive tasks (Lehtimäki, 2024). Respondents from the study that are in industry studies have highlighted that AI, particularly in the automation of tasks like editing images into multiple formats without the need for manual intervention, has positively impacted job satisfaction (Lehtimäki, 2024). In addition to automating routine tasks, AI tools like ChatGPT, have been embraced as valuable brainstorming partners and assistants, aiding generate more effective prompts for other AI-powered tools. This makes AI useful in the early stages of the creative process, such as: quickly generating prototypes and layouts (Lehtimäki, 2024).

However, despite its strengths in these initial phases, the technical quality of AI-generated materials, along with ongoing concern about copyright, still currently restrict its application in final products (Lehtimäki, 2024). While AI can save valuable time during the early stages of creation, producing a quality final product typically still requires traditional methods like organizing photography sessions. While economic savings are achievable, they may not be as significant as anticipated, as high-quality results continue to demand both human ingenuity and manual effort (Lehtimäki, 2024).

AI technology has the potential to enhance overall efficiency of the workplace by increasing productivity and improving output. AI programming simplifies time-consuming processes, including performance monitoring, ad placement, and optimization (Singh et al., 2021). This improvement in efficiency and productivity lowers the possibility of human mistakes and overall simplifies the advertising process, which will ultimately encourage marketers to spend money more wisely (Singh et al., 2021). As AI continues to enhance efficiency and productivity in advertising (Singh et al., 2021), it also brings important considerations regarding privacy to the forefront, which must be carefully managed to maintain consumer trust and compliance with regulations (Nabb & Peterson, 2024).

2.1.3 Privacy

Overall personalization, efficiency, and productivity improvement is aided by AI integration in the advertising process. However, there is the issue of data privacy to be aware of.

The advancement of technological marketing capabilities has raised significant ethical concerns, particularly regarding the need to prioritize data privacy and security (Kumar et al., 2024). As these technologies evolve, it becomes increasingly important to implement safeguards to protect consumer's sensitive information. Ensuring integrity and confidentiality of data is essential not only for maintaining consumer trust, but also for upholding ethical standards within marketing practices (Stahl & Wright, 2018). Without these ethical measures, the potential for misuse of personal information can undermine the credibility and ethical foundation of marketing strategies (Kumar et al., 2024). In this context, Hagendorff (2020) defines privacy as safeguarding personal information and ensuring the right to confidentiality in the creation and use of AI technology, further emphasizing the importance of these ethical considerations in the evolving landscape of digital marketing.

Significant advancements have been made in enhancing privacy, fairness, and explainability in terms of AI systems. For instance, various privacy preserving techniques have been implemented to secure data sets and learning algorithms (Hagendorff, 2020). These methods include approaches where AI systems "visibility" is obscured utilizing cryptographic techniques, differential privacy, or stochastic privacy (Ekstrand et al., 2018; Baron & Musolesi, 2017; Duchi et al., 2013; Singla et al., 2014). However, despite these advancements, a notable contradiction arises due to AI's rapid development, largely being driven by the availability of vast amounts of personal data. This data is collected by privacy invasive entities, such as: social media platforms, smartphone applications, and Internet of Things devices equipped with numerous sensors (Hagendorff, 2020).

In result, it can be argued that the current AI boom aligns with the rise of a post-privacy society. In various respects, this post-privacy era also mirrors the characteristics of a "black box" society (Pasquale, 2015), where, despite technical and organizational efforts to enhance transparency, explainability, and accountability, large areas of opacity persist. The lack of transparency is a result of the inherent complexity of technological systems and the strategic decisions made by organizations to limit openness (Hagendorff, 2020).

The ongoing debate surrounding privacy in the context of AI is often revolving around finding the balance between individuals' right to privacy and the advantages that companies gain from accessing user data, such as improved service personalization, increased profitability, and the creation of regulatory frameworks that ensure optimal outcomes (Elliott & Soifer, 2022). Experts in the field have highlighted the importance of fostering consumer trust, while also emphasizing the need for clear guidelines and the development of secure algorithms (Forbes Technology Council, 2023). For instance, it has been argued that when consumers fully understand the benefits of AI applications, they are more likely to share personal information in exchange for rewards and incentives (Wang et al., 2021). Additionally, there are calls for regulators to strengthen oversight to increase consumer trust and ensure privacy protection (Kumar et al., 2024).

AI systems process vast amounts of data, and when that data is anonymized or not linked to specific individuals, it may not directly infringe on personal privacy (Elliott & Soifer, 2022). Companies or brands have the ability to take advantage of this data by developing algorithms that do not require identifying the individuals behind the data (World Economic Forum, 2022). This can be achieved through databases that use anonymous identifiers, ensuring that personal identification is not possible (Kumar et al., 2024). For instance, in the retail industry, AI systems can be designed so that purchasing data does not directly correspond to individual customer profiles. Instead, the purchasing habits recording can be linked to an identifier, allowing retailers to analyze product popularity without compromising consumer privacy (Kumar et al., 2024). Similarly, anonymous surveys can be used to collect customer feedback, with incentives provided to participants (Kumar et al., 2024).

While anonymous identifiers are a common and effective method of maintaining privacy, they can still present risks. For example, if an identifier is linked to high-risk purchasing behavior, the system may flag that identifier as a high-risk customer, potentially influencing future decisions, like credit approvals (Kumar et al., 2024). Even though the initial data collection did not link purchases to specific individuals, AI may later use this anonymized data to impact credit decisions, thus revealing potential privacy concerns (Kumar et al., 2024).

Furthermore, when privacy concerns intersect with the use of AI, there are situations where using personal information may be unavoidable, though there are numerous secure, non-invasive methods to manage it. Techniques like data encryption and access controls can prevent authorized access to sensitive data, and homomorphic encryption allows computations on encrypted data without exposing the information (Ren et al., 2021). Additionally, device processing and federated learning enable data processing directly on users' devices, reducing the need to transfer data (Li et al., 2020). Data retention policies ensure that data is only stored as long as necessary and securely deleted afterward.

The accountability aspect of data privacy also extends beyond simple compliance with data protection regulations. For companies and brands, this means implementing systems to protect data and taking responsibility for the decisions made using the data (Kumar et al., 2024). With AI's role in data collection and analysis, the traditional boundaries of human accountability become less clear, requiring new strategies for transparency and explainability within AI systems (Collina et al., 2023). This is critical in ensuring that accountability remains clear in AI-powered processes (Kumar et al., 2024). Wirtz et al. (2023) highlight the concept of corporate digital responsibility (CDR) and emphasize the importance of businesses developing a strong culture around CDR (Kunz & Wirtz, 2023). An example of accountability challenges is Meta's $51 million settlement in Canadian class-action lawsuit regarding AI-driven marketing strategies (CBC/Radio Canada, 2024). In this case, Facebook used users' images in AI-generated ads without explicit consent, underscoring the need for responsible data practices and the potential consequences of failing to uphold privacy standards (CBC/Radio Canada, 2024)

According to Nabb and Peterson (2024), a common concept mentioned in interview responses is uneasy regarding privacy violation, data exploitation, discrimination, obligation of advertisers to prioritize transparency, user consent, and data security. Marketers hold the responsibility to ensure consumers understand how the data used is being collected and utilized, while obtaining permission from users before targeting them with personalized advertising to follow ethical principles (Nabb & Peterson, 2024).

2.1.4 Effects on Consumer Relationship

In digital marketing, research has found that strong brand-consumer relationships build positive consumer responses, such as purchase intentions, brand loyalty, and brand preferences (Cheng & Jiang, 2021). Since COVID-19 and the years following it, a new trend emerged for consumers to rely on online communication to seek information and make purchasing decisions. With the fast-paced implementation of AI chatbots, consumers have already begun to rely on online tools. The adoption of AI could enhance the relationships between brands and consumers through marketing activities (Cheng & Jiang, 2021).

AI has become a crucial component in managing consumer relationships, playing a pivotal role in enhancing how businesses engage with customers (Mishra & Mukherjee, 2019). As consumers increasingly familiarize themselves with the benefits that AI can offer, they are experiencing improvements in their overall user interactions. AI-powered customer relationship management (CRM) systems have revolutionized the way marketers analyze vast amounts of consumer data, providing deeper insights and more precise targeting (Jain & Kumar, 2024).

Research on CRM has shown that with the integration of big data from multiple sources, marketers can create a well-structured and efficient data infrastructure (Jain & Kumar, 2024). This infrastructure allows for a quick implementation of advanced consumer analytics, which fosters stronger consumer relationships (Kitchens et al., 2018). Additionally, Chatterjee et al. (2021) highlights that organizational agility enhances the ability to successfully adopt AI-powered customer service systems, ensuring long-term and positive consumer relationships. Furthermore, studies have also explored how combining Internet of Things with relationship marketing strategies can boost business performance and strengthen sustainable consumer relationships (Lo & Campos, 2018).

In today's competitive marketplace and brands increasing at an high rate, many contemporary companies are aiming to establish lasting, meaningful relationships with their consumers, recognizing the importance of mutual and long-term engagement (Morgan-Thomas et al., 2020). These brand-consumer relationships go beyond simple transactions, influencing key factors, such as: consumer satisfaction, trust, and commitment, which are crucial for brand loyalty (Chung et al., 2018; Zehir et al., 2011; Zhang & Bloemer, 2008). For example, fashion brands increasingly utilize chatbots to provide customers with reliable, real-time information, while reducing uncertainty and enhancing consumer satisfaction (Mimoun et al., 2017). In result, this has a positive effect on the quality of communication and fosters trust between users and the chatbots they interact with (Yagoda & Gillan, 2012). The growing consumer preference for chatbots should not be ignored, as AI-powered shopping assistants are becoming a natural part of the purchasing journey (Klaus & Zaichkowsky, 2020). When consumers' experience consistent, positive interactions with AI-powered assistants, it builds trust in the tools and the providing brand, strengthening the overall relationship between the consumer and the brand (Klaus & Zaichkowsky, 2020).

AI-powered analytical tools provide companies and brands with the ability to make data-driven decisions for future strategies and operational improvement, utilizing insights drawn from past patterns and trends (The Upwork Team, 2023). These AI tools can aid in analyzing various aspects of consumer behavior, such as: purchasing habits, engagement levels, and preferences, offering a deeper and detailed understanding of marketing effectiveness (Kumar et al., 2024). By leveraging this advanced AI analysis, marketers can modify their campaigns to better align with the unique needs and desires of individual consumers. Furthermore, by continuously monitoring real-time consumer feedback and sentiments, companies can foster stronger, more personalized relationships with their audience (Kumar et al., 2024). This approach can enhance consumer satisfaction and give businesses an advantage over competitors in a crowded marketplace (Kumar et al., 2024).

The advertising industry's growing opportunity to use AI could revolutionize the digital market by aiding in content creation (Nasser & Erafy, 2023) and efficiency (Singh et al., 2021), which resonates with Generation Z's tech-savvy, value driven, and authenticity seeking nature (Bonner, 2023). Gen Z, having grown up in a digital landscape saturated with technology, is highly adaptable at navigating and engaging with artificial intelligence (Francis & Hoefel, 2018). They are particularly drawn to brands that reflect their values of transparency and responsibility (Collina et al., 2023), and are increasingly using digital tools to make informed, cautious purchasing decisions (Brand et al., 2022).

2.2 Generation Z

Generational cohorts are not scientifically defined by specific age ranges; rather, they include “groups of people born during the same time period and living through similar life experiences and significant emotional events during their formative years….[will thus] leave individuals within each group with similar values, attitudes, and beliefs that set them apart from other cohort groups” (Brosdahl & Carpenter, 2011, p. 459). Rather than relying on scientific criteria, the delineation of generational cohorts is shaped by national or world events. This leads to the cohorts being determined by analytical perspectives and a fluid understanding of where one generation ends and another begins (Munsch, 2021). The post-millennial generation, commonly referred to as Generation Z or Gen Z, includes individuals 18-24 in the year 2025 (Rabia Hameed et al., 2025). Generation Z exhibits a notably higher purchasing power, driven by higher disposable income compared to previous generations, making them a key target for marketers (Brand et al., 2022). Given their unique characteristics, Gen Z has grown up as digital natives in an environment that influences their consumer behavior and interactions with technology (Chang & Chang, 2023).

Although Gen Z may be relatively young, they are a powerful and influential consumer group. Gen z has a remarkable impact on household purchasing decisions, contributing to an estimated $200 billion in annual purchases (Autotrader & Kelly Blue Book, 2016). As a result, companies and brands are increasingly focused on targeting Gen Z consumers, whose shopping habits are actively shaping new business strategies (Chang & Chang, 2023). For example, Etsy invested $1.62 billion to acquire Depop, a UK-based secondhand fashion platform, in response to increased demand for shopping sustainable options (BBC, 2021), a particular concern for Gen Z. Similarly, Unilever has committed to reducing its plastic usage by incorporating more recycled materials and exploring alternative sustainable options (BBC, 2019). Researchers and industry professionals alike emphasize the importance of understanding Gen Z's preferences and behaviors, as recognizing these generational differences is essential for creating effective marketing strategies and fostering long-term consumer relationships (Chang & Chang, 2023).

2.2.1 Gen Z as Digital Natives

Generation Z (Gen Z), often referred to as true digital natives, has grown up surrounded by technology and the internet, creating a familiarity with digital tools from an early age (Chang & Chang, 2023). According to Chao, Hsy, Liu, and Cheng (2021), digital natives are defined as individuals who were born and ‘‘have spent their entire lives surrounded by and using computers [and they] are all native speakers of the digital language of computers, video games, and the Internet’’ (Chao et al., 2021). This generation has had continuous access to the internet, social media platforms, and mobile technologies throughout their lives (Chang & Chang, 2023). According to Wikia (2013), a prominent digital media company, a significant portion of Gen Zers, 25%, are already online within the first five minutes of waking up, while 73% are connected within the first hour of their day (Wikia, 2013). This constant connectivity highlights their deep integration with the digital world, shaping their behaviors, preferences, and daily routines (Chang & Chang, 2023).

This generation has been immersed on the internet, social networks, and mobile technology since early youth (Francis & Hoefel, 2018). Growing up in a technology-saturated environment has equipped Gen Z with unique comfort in navigating global imperatives and accessing information on an unprecedented scale (Rehman, 2017). As a result of Gen Z's upbring in this digital age, they have cultivated both comfort with technology and a strong ability to engage and adapt to a range of digital applications. The extensive exposure to vast amounts of data and graphics on the internet has fostered a familiarity among Gen Z with navigating diverse digital environments and engaging with a variety of digital applications. Growing up in this digital era has instilled a higher level of confidence in technological sources in comparison to other generational cohorts (Wijerathne & Peter, 2023).

Digital natives and digital immigrants refer to the differing perspectives and behaviors toward technology across generations (Chao et al., 2021). Digital natives are individuals who have matured in a world fully immersed in technology, having been surrounded by computers, video games, digital music, cell phones, and other digital tools from an early age (Chao et al., 2021). For Gen Z, digital natives, technology is second nature, having the ability to navigate it effortlessly as it is an intrinsic part of their lives. On the other hand, digital immigrants are those born before the digital era, and while they may adopt new technology due to personal interest or professional needs, their relationship with these technologies is often less intuitive (Chao et al., 2021). As a result, younger generations, particularly digital natives, naturally embrace and adapt to technological advancements more seamlessly. Their early and continual exposure to emerging technology, including AI, results in them being more familiar with these innovations and more comfortable integrating them into their daily lives (Chao et al., 2021).

Digital natives approach work**,** information consumption, and entertainment quite differently from digital immigrants (Palfrey & Gasser, 2008). While digital immigrants were accustomed to consuming information in a linear and traditional format, like reading books, digital natives have matured in an entirely digital world (Kirk et al., 2015). This world is a place where access to information is highly interactive, the information they seek is available instantly, often at the touch of a button, and mobile devices are frequently used, often away from their computers (Choi et al., 2008).

In general, digital natives possess a higher level of familiarity with the internet, and this experience plays a crucial role in their approach to interacting with online content. This level of internet experience influences how individuals respond to interactivity (Kirk et al., 2015). For example, less experienced users may find interactivity features too complex and lead to a decrease in satisfaction, though they may experience heightened levels of arousal (Kim et al., 2012). However, excessive levels of arousal can become overwhelming, causing users to reject digital media altogether (Fiore et al., 2005). Furthermore, the effects of interactivity vary depending on the situation and the user's experience level (Kirk et al., 2015). Under high-involvement circumstances, like when students work on assignments or individuals seek medical information, experienced users tend to respond more positively to interactivity. In contrast, for less experienced users, it may come with a cognitive cost, leading to less favorable attitudes (Liu & Shrum, 2009).

A key characteristic of this generation is their passion for content creation (Dye, 2007). With easy access to the internet and personal cloud storage, they have the ability to gather material from countless sources and use a wide array of tools and platforms to produce content (Smith, 2017). This creative, resourceful environment has led many digital natives to favor jobs that allow for innovation and self-expression (Dye, 2007). According to Matson (2016), nearly half of digital natives aspire to become entrepreneurs and become their own boss (Matson, 2016).

Gen Z, as digital natives, are commonly attracted to online communities, where they are able to communicate with others about various topics or connect with others who share similar interests and passions (Dye, 2007). This behavior can also be seen in their interactions with brands and companies (Williams et al., 2012). Gen Z desires to participate in the creative process, influence products and brands, and voice their opinions online (Smith, 2017). As a target consumer, they not only create content, but also hold the power to spread marketing messages at a rapid pace (Smith, 2017). Their constant connectivity creates an expectation for instant results (Jones et al., 2010). For Gen Z, waiting for an app to load for a few seconds can feel like a long time. Digital natives are accustomed to immediate access to information and feedback through the internet, particularly when interacting with brands online (Smith, 2017). Gen Z also prefers visuals over text. While the brain typically processes images faster than text, digital natives are especially skilled at interpreting visual content (Palfrey & Gasser, 2008).

Despite Gen Z's preference for fast responses, digital natives can maintain long attention spans for certain stimuli, like computer games, where interactivity holds their focus (Smith, 2017). Through extensive gaming, Gen Z has developed "attentional deployment", which is the ability to multitask and respond quickly to both anticipated and unexpected events (Prensky, 2001). In the context of shopping, digital natives expect a seamless experience that integrates both online and offline worlds, with a smooth flow of information and products. This applies to advertising as well (Smith, 2017). This seamless integration of online and offline experience in the context of shopping extends to Gen Z's brand preferences, where their awareness and expectations play a crucial role in their purchasing decisions (Gillespie et al., 2021).

2.2.2 Personalization

Personalization can be defined as the practice of delivering tailored advertisements to individuals based on their specific preferences and behaviors (Li, 2016). Companies and brands use this approach to enhance their marketing efforts and strengthen the consumer-brand relationship across various platforms, such as social media and email (Montgomery & Smith, 2009). An advantage of personalization in the digital age lies in the wealth of data that companies and brands can collect. This data can include insights into consumer's shopping habits, online activities, and personal preferences (Elrizal & Astuti, 2024). This extensive information allows companies to analyze patterns and construct detailed consumer personas, enabling them to target their marketing messaging more effectively and meet the precise needs of their audience (Elrizal & Astuti, 2024).

A positive perception of personalized advertising can greatly improve how consumers view a brand, fostering stronger loyalty and elevating their overall opinion and attitude towards the brand (DelVecchio et al., 2006; Fetscherin & Heinrich, 2015). When consumers encounter advertisements that align with their interests or passions, they are more inclined to interact with that brand and make repeated purchases (Elrizal & Astuti, 2024). This increased engagement can increase brand loyalty, and strengthen long-term consumer relationships (Elrizal & Astuti, 2024). By utilizing data analytics and consumer insights, companies and brands can refine their personalization strategies over time, ensuring they remain responsive to shifting consumer preferences (Elrizal & Astuti, 2024). Ultimately, personalization can drive sales and deepen connections between consumers and brands, resulting in mutually beneficial outcomes for both parties.

Although Gen Z values marketing communication that caters to their specific needs, many brands fail to deliver the level of personalization Gen Z desires, which often leads to consumer frustration (Abraham et al., 2019; Ahora et al., 2021; Chandra et al., 2022; Li & Liu, 2017). This frustration partly originates from Gen Z's lifelong exposure to digital communications, which has made them skillful in recognizing when brands' messaging are generic or fail to account for their unique preferences and experiences (McKee et al., 2023). As a result, this mismatch increases the likelihood that the Gen Z consumers will ignore or avoid these marketing efforts altogether (Djafarova & Bowes, 2021; Schmidt & Maier, 2022). While Gen Z may be willing, but hesitant, to share personal data in exchange for a more tailored experience (Forbes, 2022), they are also more likely to employ a variety of tactics to avoid unwanted marketing. Research shows that Gen Z consumers frequently use tools, like digital blocking software, private browsing modes, and the disabling of geolocation tracking, especially when they feel that the brand's personalization efforts fall short of their expectations (Brinson et al., 2018; Latvala et al., 2022). For example, Wielki (2020) found that the use of ad-blocking software increases when a brand's messaging does not align with their values or lifestyle (Wielki, 2020).

This ambiguity in the effectiveness of personalization is consistent with the personalization-privacy calculus, a framework in which consumers weigh the perceived privacy risks against the benefits of personalized marketing (Chen et al., 2022; Cloarec et al., 2022; Hayes et al., 2021; Jahari et al., 2022). With the growing concerns about privacy and mistrust of digital tracking technology (Gironda & Korgaonkar, 2018; Li & Liu, 2017), Gen Z consumers increasingly take measures to limit tracking, which can undermine the ability of marketers to deliver effective personalized experiences (Cloarec et al., 2022; Latvala et al., 2022). When consumers are unwilling to share personal data or take protective steps to restrict tracking, marketers are left with limited information (McKee et al., 2023). Limited information then reduces the marketers' capacity to create highly personalized marketing content (Ackermann et al., 2022; Wanjugu et al., 2022). This lack of information within data access leads to the delivery of non-personalized digital communications, further increasing consumer frustration and resulting in detachment from the brand (Anaza et al., 2021).

In the context of the fourth industrial revolution, the hallmark of modern marketing and advertising is hyper-personalization (Jeffrey, 2021). This can be made possible with AI's ability to extract valuable insights from massive amounts of behavioral, emotional, and psychological data that is generated by individuals (Jeffrey, 2021). This level of personalization is highly useful to marketers, as it creates an opportunity to foster closer connection with its audience. As a result, there has been a shift in how digital and physical retail operations are structured, with a focus on leveraging vast amounts of personal data to engage each individual on a deeper level (Turow, 2017, 9–10). Reflecting on AI's impact on the advertising industry, Urban et al. (2020) note, "It isn't difficult to imagine a day when companies will be able to integrate a wide array of databases to discern what consumers want with greater sophistication and analytic power and then leverage that information for market advantage" (Urban et al., 2020, 71). This insight underscores the idea that AI is a powerful tool that has the ability to enhance marketing strategies by providing a deeper understanding of consumer behaviors and preferences (Jeffrey, 2021).

AI has the power to craft a marketing strategy centered around hyper-personalization, which lies in the ability to offer benefits across the entire consumer engagement lifecycle (Korzeniowski, 2018, p. 32). While the concept of personalization in marketing is not new, the level of personalization now achievable with data analytics and AI is a recent development. For the advertising industry, the ability to gain access to highly contextualized data about individuals within your target audience's digital behaviors, normally gathered by self-learning systems, provides advantages beyond traditional tracking and recommendation engines (Jeffrey, 2021). These AI systems enable marketers to tailor experiences and offers that align with individual preferences and psychographic personas (Turow, 2017, p. 11). These advanced AI algorithms are designed to "activate brand interactions across touch points" (Del Rowe, 2016, p. 15), enhancing the overall consumer journey through highly relevant and personalized engagements (Jeffrey, 2021). However, research suggests that the relationship between personalization and brand outcomes may be curvilinear, with overlay personalized experiences sometimes resulting in consumer discomfort or privacy concerns. This can ultimately harm brand perception (Cloarec, 2020).

2.2.3 Gen Z Value Authenticity and Transparency

Authenticity has become a fundamental aspect of human identity, as it allows individuals to form connections based on shared similarities, common interests, and trust (Kazanina, 2024). In today's digital era, authenticity is a crucial component of an online identity, shaping how individuals perceive both themselves and others (Kazanina, 2024). According to Ebster and Guist (2005), authenticity is context-dependent and subjective, which makes it difficult to objectively measure. Thus, it is driven by personal ideology and not easily confined to a fixed framework. This complexity leads to the nuanced nature of authenticity, where different individuals or groups may interpret its meaning in different ways (Kazanina, 2024). However, In the context of marketing, authenticity is defined as the perception of a brand or content being genuineness that leads to deeper connections and trust (Jones, 2018).

In the advertising industry, authenticity has become essential for creating effective campaigns (Kazanina, 2024). Today's consumers increasingly seek authentic digital content that resonates with them personally, preferring it over idealized, polished images (Rixom & Rixom, 2023). According to Morhart, Malar, Guevremont, Girardin, & Grohmann (2015), brand authenticity is defined at the extent to which consumers perceive a brand as being true to itself and its customers, while also aiding consumers stay true to their own values and identities. Brands that manage to successfully portray authenticity through their digital content often experience higher levels of brand loyalty and trust (Kazanina, 2024). Stackla's 2021 survey highlights the significance of authenticity, with 86% of consumers stating that authenticity influences their brand choices. Additionally, 60% of consumers prefer content that feels genuine over perfect imagery. However, 53% feel that most brands fail to meet their authenticity expectations (Stackla, 2021). These statistics underscore the growing importance of authenticity in building consumer trust and brand loyalty.

The value of a brand's authenticity has emerged as a crucial factor for Gen Z as they actively search for the truth in brand messaging and value individual expression (Francis & Hoefel, 2018). Being digital natives, Gen Z has developed an awareness of advertising strategies and is increasingly frustrated by manipulative messaging, believing that authenticity is ideal (Fromm & Read, 2018).

Gen Z's skepticism toward traditional advertising has led them to gravitate toward brands that emphasize authenticity and transparency. This generation values straightforward, honest communication and authentic engagement over carefully curated advertisements (Prasanna & Priyanka, 2024). For Gen Z, brands that openly share their stories, values, motivations, and engage in sincere and meaningful conversations with their audience are more likely to foster trust within the consumer (Prasanna & Priyanka, 2024). For advertising campaigns to truly connect and resonate with their Gen Z audience, demonstrating authenticity is no longer optional. It is a crucial element that influences their perception and support of a brand (Prasanna & Priyanka, 2024).

Gen Z seeks advertising that reflects their own experiences, preferring genuine representation over filtered or idealized portrayals of life (GWI, 2022, p. 44,). With this insight, to effectively engage this audience, marketers must adopt an authentic approach to reach Gen Z, who values authenticity and reliability in their brand's content and messaging (GWI, 2022). Building on their desire for authenticity, Gen Z's consumer behaviors are also influenced by their unique experience during their formative years marked by economic uncertainty. This context has fostered a cautious approach to spending, making Gen Z highly selective in their purchasing decisions.

Transparency is more than an abstract idea; it has become an essential requirement in the digital era. Gen Z's growing demand for transparency reflects their broader call for accountability and authenticity in business operations from companies and brands (Bergstrand &

Åradsson, 2024). According to Bergstrand and Aradsson (2024), transparency plays a pivotal role in shaping positive consumer attitudes. For Gen Z, the desire for transparency goes beyond surface-level expectations; it is connected to their wider values of social responsibility and corporate ethics (Bergstrand & Åradsson, 2024). This generation expects companies and brands to demonstrate openness, not only in their products and services, but also in their overall approach to ethical conduct and social impact (Bergstrand & Åradsson, 2024).

2.2.4 Gen Z are Cautious Purchasers

Generation Z has demonstrated a reluctance to embrace risk in their purchasing decisions (Brand et al., 2022). Gen Z grew during the 2008 recession, which resulted in the loss of nine million jobs and eight million homes due to foreclosure (Reisenwitz, 2021). They have developed a cautious approach to spending and as a result they tend to enter the market with a mindset focused on saving rather than spending, making them both practical and frugal (Brand et al., 2022). Gen Z exhibits a higher level of caution and risk aversion in comparison to the generation before, particularly when it comes to financial decisions (Iqbal, 2018).

Unlike Generation Y, members of Gen Z are more proactive in building their wealth and preparing for their financial future from an early age (Hoffower, 2019). This cautious approach is also evident in their attitudes toward student loan debt. Gen Z is consciously trying to avoid student loan burdens that their parents have faced (Reisenwitz, 2021). As a result, Gen Z shows a trend to view risk-taking as a potential path to failure, disappointment, and harm, which can lead to a preference for more secure and stable financial choices (McQueen, 2015).

Gen Z also prefers to make purchasing decisions based on their natural in-depth analysis through digital contents on products and brands. They achieve this by exploring web pages, reviews, ratings, opinions, and shopping experiences shared on social media (Brand et al., 2022). The COVID-19 pandemic has significantly altered Gen Z’s purchasing behaviors, leading post COVID-19 shoppers to adopt a more “social and sensible” approach, in contrast to the earlier "individualistic and materialistic" mindset prevalent before the pandemic (Agrawal, 2023, p. 14,).

Gen Z also places a strong emphasis on sustainability when making purchasing decisions. As this focus on eco-friendliness has gained traction within this new demographic, greenwashing has emerged as a trend. Greenwashing refers to the deceptive practice, in which brands mislead consumers with claims about their environmental impact. This led Gen Z to become increasingly wary of a brand's authenticity and legitimacy, prompting them to reevaluate their purchasing when comforted with vague or misleading information in a brand's messaging (Liu & Hei, 2021).

When faced with unfamiliar tasks, like purchasing a car, Gen Z tends to approach decisions with caution and through research (Chang & Chang, 2023). In these cases, this generation is likely to seek out relevant information from a variety of sources, such as: manufacturers, dealerships, and third-party websites (Chang & Chang, 2023. Furthermore, digital media plays a role in shaping Gen Z's decision-making process. For example, if they are exposed to digital content that focuses on the risks associated with distracted driving, this will become a prioritized factor for them. In this context, they could prioritize factors like safety features and advanced technology in their car buying decision (Autotrader & Kelly Blue Book, 2016). The information they encounter through digital platforms is perceived as useful, reinforcing the social influence of digital media on this generation (Chang & Chang, 2023).

Generation Z's cautious approach to risk-taking in the workplace reflects the growing influence of "safetyism" on their behavior and decision-making process (Henrique, 2025). According to Henrique (2025), a quantitative analysis revealed that 60% of surveyed employees preferred to avoid high risk projects unless they were guaranteed support and provided clear, detailed guidelines. Interviews further explained this trend, with many participants indicating a strong preference for structured environments where expectations are clearly defined, as opposed to situations that are ambiguous or high-pressure (Haidt, 2024; Haidt & Lukianoff, 2018).

This heightened risk aversion, while ensuring a sense of security, has broad consequences for creativity and innovation (Henrique, 2025). For example, a manufacturing company reported a noticeable decrease in innovation proposals from younger employees, attributing to the trend of failure and reluctance to high-risk projects that carry the potential for disappointment (Scheuch et al., 2021). This shift in mindset through the generations has the potential for long-term effects on the ability of organizations to foster an environment of experimentation and new ideas (Henrique, 2025).

Gen Z's cautious and risk-averse mindset significantly influences their purchasing and workplace behaviors (Henrique, 2025). Maturing in the aftermath of economic uncertainty, Gen Z prioritizes financial security, taking a more practical and frugal approach than the generations before (Brand et al., 2022). Their purchasing decisions are guided by careful research and digital content, reflecting a preference for informed and stable choices in their shopping process (Chang & Chang, 2023). Overall, Gen Z's have a risk-averse nature, and it shapes their financial, consumer, and professional decisions in a way that reflects their desire for security and stability.

2.3 Trust

Building on consumer behavior literature and various social research studies (Deutsch, 1958; Moorman et al., 1993; Morgan & Hunt, 1994; Sorrentino et al., 1995), Sirdeshmukh et al. (2002), presents a conceptual model that shifts from the traditional behavioral definition of trust, being described as the 'willingness to rely on an exchange partner in whom one has confidence' (Moorman et al., 1992; Ganesan, 1994; Mayer et al., 1995), and moves toward a cognitive and evaluative perspective, which considers trust as the 'extent of confidence in the exchange partner's reliability and integrity' (Morgan & Hunt, 1994; Doney & Cannon, 1997).

A factor that plays a crucial role in influencing consumer purchase intentions is trust

(Marka & Arumsari, 2022). In the context of online transactions, trust refers to the consumer's confidence in a company's commitment to privacy, as well as the perceived quality of its products or services (Marka & Arumsari, 2022). This sense of trust from consumers contributes to a consumer's willingness to engage in transactions, fostering a sense of security and assurance. According to Leeraphong and Mardjo (2013), trust has a strong, positive impact on purchase intention, demonstrating its critical role in driving consumer decisions to make purchases (Leeraphong & Mardjo, 2013). Trust reflects a consumer's reliance on a brand to fulfill their expressed needs and wants (Chaudhuri & Holbrook, 2001). It also represents the level of confidence consumers have in a brand's ability to meet their specific expectations (Chaudhuri & Holbrook, 2001).

Power and Whelan (2008) indicate that higher levels of consumer trust enhance a brand's perceived attractiveness, which in turn fosters greater consumer attachment. Similarly, Pennanen et al. (2007) identify trust as a crucial factor in cultivating positive consumer-brand relationships. A recent study that focuses on Generation Z consumers highlights that brand experience and trust serve as mediators in the relationship between social media marketing efforts and brand value (Rahmawati & Hidayati, 2023).

According to Sheth and Parvatiyar (1995), a brand's longevity often depends on consumer trust, particularly when direct interactions between consumers and brands are limited. A significant barrier to online transactions is consumer's lack of trust in a brand's content, which restricts their engagement with the brand (Rios & Riquelme, 2008). This distrust can arise from various issues, including concerns about: security and privacy, fraud, and misleading information (Tarapata, 2024). Given the risks of privacy violations and misinformation, trust is essential for fostering meaningful consumer participation on social media. Consequently, consumers must feel confident in the digital information they encounter on social media

(Shahbazi & Bunker, 2024).

2.3.1 Trust in Advertising

Trust in advertising is fundamentally defined as the confidence individuals have in its reliability as a source of information about products and services, as well as their willingness to act based on that information (Soh et al., 2009). This aligns with earlier conceptualizations of trust, which encompass cognitive, emotional, and behavioral dimensions (Lewis & Weigert, 1985).

Trust involves not only beliefs and feelings, but also the readiness to use that knowledge as a basis for action (McAllister, 1995). Johnson and Grayson (2005) indicate that both affective processes and behavioral intentions, alongside cognitive beliefs, are essential for trust to exist. Trust arises from perceptions of trustworthiness (McAllister, 1995). Importantly, while beliefs in trustworthiness may exist, a lack of willingness to rely on signals limits actual trust (Moorman et al., 1993). This implies that trust in advertising often reflects behavioral intent rather than actual behavior (Soh et al., 2009).

Previous literature has also suggested that trusting behaviors without a corresponding confidence in trustworthiness may stem from situational factors rather than genuine trust (Lewis & Weigert, 1985). In the advertising context, a lack of alternative information sources may compel consumers to depend on the information provided in ads. Consequently, their willingness to act based on advertising can be viewed as a more accurate indicator of trust in advertising than their actual trusting behavior (Soh et al., 2009). This reliance on advertising as a primary information source highlights the intricate relationship between consumer trust and advertising effectiveness.

Earlier research has revealed that trust plays a crucial role in shaping consumers' perceptions of value (Sirdeshmukh et al., 2002), influencing their purchasing decisions (Erdem

& Swait 2004), and strengthening brand commitment and loyalty (Chaudhuri & Holbrook 2001). These research insights highlight the importance for marketers to cultivate and reinforce trust in their relationship with consumers, often through trust focused advertising appeals (Li & Miniard, 2006).

Examples of these trust focused appeals include a Reynolds Wrap advertisement stating, “Trust every delicious morsel to Reynolds,” a Pfizer Inc. advertisement that declares, “U need sleep? Trust UNISOM,” and an Arm & Hammer campaign emphasizing its 150-year legacy of consumer trust. Similarly, Duracell’s tagline stated, “Trusted Everywhere,” while EDS ads reinforce the notion that “Trust is not given, it’s earned, and EDS earns that trust a million times a day” (Li & Miniard, 2006). However, the two key perspectives challenge this value. First, previous research has revealed that consumers tend to be skeptical of advertising (Fry & McDougall 1974; Greyser & Bauer 1966). This general distrust may diminish the impact of explicit claims of trustworthiness or trigger psychological reactance (Brehm, 1966), potentially leading consumers to develop a more negative perception of the advertised brand.

Trust also plays a critical role in a brand’s success, as evidenced by a strong influence on key factors, such as: brand equity (Ballester & Munuera‐Alemán, 2005), brand loyalty (Atulkar, 2020; Chaudhuri & Holbrook, 2001), purchase intention (Chaudhuri & Holbrook, 2001; Dam, 2020), and positive referrals (Becerra & Badrinarayanan, 2013).

Alongside brand affect, trust is a driving force behind brand commitment, shaping consumers’ decision-making process when choosing between competing brands within the same product category (Chaudhuri & Holbrook, 2002). According to Fritz et al. (2014), an understanding of trust in the context of brands is essential for them to strengthen customer-brand relationships and optimize marketing strategies. Ultimately, examining trust, particularly from the consumer’s perspective, is crucial for assessing and enhancing a brand’s success across a range of key performance indicators (Heim et al., 2024).

2.3.2 Trust in Technology

Previous research in trust originally emerged in the context of interpersonal relationships, where the trustee was a human being. Most information systems (IS) trust research has centered on web vendors or virtual team members. This means that the trustee has typically been a person or an organization composed of people (Li et al.,2008). However, recent research covering information systems has shifted focus to trust in technology. This is where the trusted entity is technology, such as a recommendation agent or an information system (Corritore et al., 2003; McKnight, 2005; Wang & Benbasat, 2005). In this context, trust has been defined similarly to interpersonal trust, highlighting the trustor's willingness to "behaviorally depend on a piece of software (e.g., a statistical system) to do a task" (McKnight, 2005).

Models of trust and technology acceptance have been applied to human-technology interactions, particularly in the case of recommendation agents (Komiak & Benbasat, 2006; Wang & Benbasat, 2005). Empirical findings support the validity of these models, showing a strong association between trusting beliefs, benevolence, competence, integrity, and technology acceptance constructs (Wang & Benbasat, 2005).

Research within the Computers are Social Actors (CSA) paradigm provides a strong foundation for applying trust to technology. Laboratory studies summarized by Nass and Moon (2000) reveal that individuals engage with computers in a social manner, even though they recognize that they are non-human. Participants inhibited behaviors, such as: politeness, stereotyping, and preference for similarity in their interactions with computers (Li et al., 2008). While trust research recommendation agents have used anthropomorphic interfaces with computer generated speech and animation, many CSA studies elicited social responses from users through simple text-based interfaces (Li et al., 2008). Humans tend to anthropomorphize technology even when it lacks human-like features, like a voice or embodiment (Nass et al., 1995). These findings suggest that trust in an information system is a meaningful concept (McKnight, 2005) and that models of initial trust formation can be effectively applied to technology.

Research demonstrates that trust is crucial for helping users navigate perceptions of risk and uncertainty when adopting new technologies (Gefen et al., 2003). Studies on technology adoption reveal that the factors influencing initial acceptance differ from those driving continued use (Agarwal & Prasad, 1997). Specifically, users' pre-implantation expectations significantly shape their post-implementation experiences with a new system (Ginzberg, 1981). From the diffusion of innovations perspective, users actively seek information about a new technology, which directly impacts their attitudes toward it (Li et al., 2008).

Initial perceptions of a technology's characteristics influence the decision to adopt (Moore & Benbasat, 1991). Users are less likely to explore new technologies if they perceive a considerable risk in exploring them (Agarwal & Prasad, 1997). Moreover, the initial exposure to a system is critical, as it is during this phase that adaptation and learning are most likely to occur (Tyre & Orlikowski, 1994).

The connection between initial technology adoption and initial trust has been well documented (Li et al., 2008). Trust is a dynamic concept that evolves over time, and research has highlighted the significance of initial trust, where users must overcome feelings of risk and uncertainty before engaging with the technology (McKnight et al., 2002). Literature on trust in organizational contexts has shown that individuals often form trusting beliefs before having direct experience with another party (Berg et al., 1995), and while elevated levels of trust can be present this trust can be nurtured over time. Initial trust differs from trust developed through familiarity, as users lack direct experience to inform their early trusting beliefs (Gefen, 2004). Understanding the dynamics of initial trust is essential, as it can impact later phases of the user technology relationship (McKnight & Chervany, 2006).

Given the foundational insights into initial trust and its evolution, it is key to explore how these dynamics apply specifically to trust in artificial intelligence (AI) (Omrani et al., 2022). As users engage with AI technologies, they encounter unique challenges related to uncertainty and perceived risks, which can significantly influence their initial trust levels (Omrani et al., 2022). Understanding the nuances of initial trust in the context of AI not only sheds light on user adoption but also highlights the ongoing need to foster and sustain trust as users gain more familiarity with these systems (Omrani et al., 2022).

2.3.3 Trust in AI

Although the pursuit of AI dates back centuries (Nilsson, 2009), only in recent years have AI systems begun delivering effective results. AI is commonly characterized as an anthropomorphized process that mimics human reasoning (Omrani et al., 2022). In today's digital era, AI models can approximate human cognitive abilities across various domains and possibly surpass human performance in some areas. This has enabled the beginning of full automation of tasks, including tasks that require complex decision making and specialized skills (Omrani et al., 2022).

Trust plays an important role in human-AI interactions, particularly when dependence is involved (Shareef et al., 2021) and when said dependence carries inherent risks (Komiak & Benbasat, 2006). The inherent risks are largely due to the complexity and unpredictability of AI behavior (Glikson & Woolley, 2020). These risks arise because decisions made by AI agents can impact society and pose greater consequences for the companies responsible for their deployment (Saif & Ammanath, 2020).

The success of AI adoption hinges on trust, as it influences how users engage with and rely on these technological systems (Sullivan et al., 2022). Ribeiro, Singh, and Guestrin (2016) supported this by stating that "if the users do not trust a model or a prediction, they will not use it." (Ribeiro et al., 2016, p. 1135-1144). They also highlighted the distinction between two dimensions of trust. Trust in an individual prediction versus trust in the overall AI model. The former relates to using AI-generated outcomes for decision making, while the latter pertains to evaluating an AI model's reliability before deployment (Omrani et al., 2022).

AI's appeal lies in its ability to outperform human capabilities, particularly in processing vast amounts of complex data in a short amount of time. However, if humanity were to encounter a hypothetical super-intelligent extraterrestrial life, there might be some hesitation to delegate decision making to it with questions to its intentions (Omrani et al., 2022). Similarly, AI systems offer no theoretical guarantees of correctness in every scenario, even though it is human made (Omrani et al., 2022). While those familiar with AI training processes may expect the systems to perform well in familiar situations, uncertainty remains regarding how it would handle unprecedented cases. The fundamental difference between biological and AI (Korteling et al., 2021) underpins the skepticism surrounding AI's trustworthiness.

Consequently, AI adoption is closely tied to trust, which in this context, defines the relationship between humans and automation (Lee & See, 2004). In previous academic literature, two major research streams on trust in automation have emerged. First, the focus on trust in technology and innovation (Ghazizadeh et al., 2012; Lee & Moray, 1994; Lee & See, 2004; Zuboff, 1988). Second, trust in the firms driving the innovation and their communication strategies (Brock, 1965; Chiesa & Frattini, 2011; Ram & Sheth, 1989; Sternthal et al., 1978). According to Hengstler et al. (2016), trust in AI is influenced by trust in the underlying technology, which evolves based on these three dimensions: performance, process, and purpose information (Hengstler et al., 2016). Performance refers to operational effectiveness and data security. Processes are specifically focusing on cognitive compatibility and usability. Lastly, the purpose refers to the application context and design (Omrani et al., 2022).

While the majority of the discussion surrounding technology acceptance has been broad, rather than AI specific (Hooks et al., 2022), studies on robots in domestic settings and elder care have explored factors that influence public acceptance. Previous research has examined socio-demographic characteristics, national technological, and economic development indicators (Omrani et al., 2022). The findering reveal that broader contextual factors fail to fully explain attitudes toward robots. However, age, gender, and place of residence have been how to play a role (Vu & Lim, 2021; Carradore, 2021).

Further examining trust in AI, Oksanen et al. (2020) investigated how people assign different levels of trust to human, robotic, and AI-based agents. Their study utilized a trust game in which participants decided how much fictitious money to entrust to either an AI-based agent or a robot, while testing whether the agent's name influenced trust levels. The results showed that the highest level of trust was placed in a robot with a non-human name, while the least trusted entity was an unspecified control named "Michael," where it was unclear whether the agent was human or artificial (Oksanen et al., 2020). It was concluded that trust in advanced AI is higher when it is perceived as reliable in cognitive performance and fairness. Additionally, personality traits from the Big Five model (McCrae & Costa, 1987) played a role in trust attribution, openness was positively correlated with trust, whale conscientiousness was negatively correlated. The study also suggested that higher education levels, prior to exposure to robots, and greater confidence in interacting with AI may increase trust in these technologies (Oksanen et al., 2020).

Research indicates that trust is a vital predictor of users' willingness to adopt various AI systems (Lockey et al., 2021). Given the significant role of trust in fostering relationships, it is crucial to understand the factors that influence trust in AI. When exploring cognitive trust in AI, researchers often measure users' willingness to act on factual information or advice, as well as reliability and their perceptions of the technology's helpfulness, competence, and usefulness (Glikson & Woolley, 2020).

To bridge the discussion of trust in AI with the perspectives of different user demographics, it is essential to consider how generational attitudes, particularly those of Gen Z, influence trust dynamics. As digital natives who have grown up with technology, Gen Z's experiences and expectations shape their approach to trust in AI systems (Guerra-Tamez et al., 2024). Understanding the unique factors that foster or hinder trust among this generation can provide valuable insights into how AI technologies can be effectively designed and implemented to meet their needs.

2.3.4 Gen Z Trust

Building trust is a process that evolves over time. This generation is particularly discerning, having grown up in a fast-paced digital landscape that shapes their expectations for authenticity and transparency. Brands are expected to approach their consumer relationships with intentionality, being mindful of the unique needs and desires of this audience. If a brand fails to show palpable commitment or authenticity, Gen Z will seek alternatives that resonate more closely with their expectations (Witt & Baird, 2018).

Trust is a vital factor for all consumers, and Gen Z is no exception. However, positioning a brand as an authority does not resonate well with this generation; instead, trust must be earned through authentic engagement. By fostering trust, brands can lower the barriers to acceptance and create a safe environment for Gen Z, encouraging them to choose the brand over its competition (Witt & Baird, 2018). To effectively build trust with Gen Z, brands must also consider how trust interacts with technology acceptance, as understanding the factors influencing technology adoption is crucial in today's digital landscape.

A recent study focusing on Gen Z consumers (Rahmawati & Hidayati, 2023, p. 665) revealed that both brand experience and brand trust serve as critical mediators in the relationship between social media marketing efforts and brand value. These findings support the importance of fostering positive brand interactions and building consumer trust to enhance perceived brand value (Tarapata, 2024), particularly in the digital era where social media plays a central role in consumer engagement.

Furthermore, research by J.N. Sheth and A. Parvatiyar (1995, p. 397-418) highlights that a brand's longevity and success are largely dependent on consumer trust, especially in a situation where direct transactions between consumers and companies are not feasible. This supports the idea that the ability to reach and resonate with Gen Z is important because they are the upcoming consumer in the marketplace (Thangavel et al., 2022). In such cases, trust becomes the foundation of consumer-brand relationships, reinforcing the significance of strategic marketing efforts that prioritize authenticity and reliability, values of Gen Z, to cultivate lasting consumer confidence (Tarapata, 2024).

According to Binti Rali's (2024) research, their findings indicate that positive online reviews significantly enhance consumer trust, which leads to a higher likelihood of impulsive purchasing behavior (Binti Rali, 2024). This aligns with previous studies that highlight the critical role of trust in the online shopping environment, particularly among Gen Z and digital natives because they are heavily influenced by user-generated content and peer opinions (Christin, 2023; Hilal, 2022).

The study, which focused on Gen Z, further highlights that as consumer trust in online reviews increases, so does the probability of making spontaneous purchases. This suggests that e-commerce platforms, such as Shopee, can strategically leverage this relationship to foster greater consumer confidence within Gen Z (Binti Rali, 2024). By promoting authentic and credible user reviews, these platforms can strengthen trust among Gen Z shoppers, ultimately driving higher engagement and boosting sales (Binti Rali, 2024).

Among Gen Z, attitudes toward AI are key factors in shaping trust. As a tech-savvy demographic (Bonner, 2023), Gen Z holds distinct perspectives on this technology that influence their trust in brands leveraging AI technologies. Previous research in e-commerce and viral marketing has demonstrated that consumers' perceptions of AI, its advantages and applications, directly affect their trust in online vendors and brand messaging (McLean et al., 2021; Marjerison et al., 2022). Similarly, in industries like airlines, the approach that is used to present AI through marketing channels significantly impacts trust and purchase decisions (Tussyadiah & Miller, 2019). These findings highlight that Gen Z's trust in brands is shaped by factors like AI's perceived accuracy, and their previous experiences with it (Guerra-Tamez et al., 2024).

2.4 Theoretical Background – Technology Acceptance Model

2.4.1 Factors that Impact AI Perception

Perceptions of artificial intelligence (AI) are shaped by diversity of end users and contextual factors (Taherdoost, 2018; Sindermann et al., 2021). One illustrative example comes from the field of automated driving, where Awad et al. (2018) applied Foot's Trolley Dilemma (Foot, 1967) to examine public preferences regarding whether an AI-controlled vehicle should respond to an unavoidable crash scenario. The study concluded that AI behavior in such contexts, should be guided by an integration of public perception, ethical considerations, and societal expectations (Awad et al., 2018).

In another study, Araujo et al. (2020) explored the perceived usefulness of AI across three domains, media, healthcare, and law. Unlike the automated driving study, their study revealed a widespread public concern about AI risks, fairness, and overall societal impact. This suggests that for AI technology to gain broad acceptance, it is essential to consider how individuals and society as a whole assess its risks and benefits.

An important aspect influencing AI perception is its domain of implementation (Brauner et al., 2023). Philipsen et al. (2022) investigated how people perceive AI's role in different contexts and what design elements contribute to fulfilling expected roles. The study found that while users generally did not desire AI to take on personal roles, like a friend or partner, their level of trust in AI's data handling influenced their openness to such possibilities (Philipsen et al., 2022). People who believed in a more dangerous world were more inclined to accept AI in subordinate roles, like a servant, rather than an equal or superior entity. However, the assignment of roles didn't necessarily correlate with the willingness to use AI. The study noted that perceptions of AI's intelligence, morality, and control were only slightly different from perceptions of human intelligence, supporting the idea that initial impressions of AI can shape long-term evaluations and adoption (Philipsen et al., 2022).

As AI continues to be integrated into everyday life, whether through personal assistants like Alexa or Siri (Burbach et al., 2019), large language models like ChatGPT, or smart home and shopping technologies (Rashidi & Mihailidis, 2013), understanding user perceptions and evaluations are being increasingly important (Wilkowska et al., 2018**;** Kelly et al., 2023). As AI technologies become more sophisticated, it has the potential to bring transformative changes at an individual, organization, and societal level (Bughin et al., 2018; Liu et al., 2021; Strich et al., 2021). Therefore, ongoing research surrounding AI's implementation, ethical considerations, and public trust are critical for ensuring its responsible and beneficial integration into various aspects of life (Brauner et al., 2023).

According to Du, Sun, Jiang, Islam, and Gu (2024), AI literacy directly influences how individuals perceive AI's role in social good, their confidence in learning AI, and their awareness of AI-related ethical considerations. Additionally, it indirectly affects their willingness and intention to engage in AI learning (Du et al., 2024). Additionally, trust and positive perception was characterized as a combination of perceived reliability, perceived accuracy, and familiarity with the content (Wilts, 2024). This perspective aligns with the Technology Acceptance Model (TAM), which suggests that perceived ease of use and perceived usefulness contribute to trust, perception, and adoption of technology (Venkatesh & Davis, 2000).

Moreover, participants in Wilts' (2024) study emphasis on accuracy reflects a strong expectation for precision and correctness, reinforcing the role of accurate information in fostering trust and a positive perception. Additionally, the need for familiarity, as expressed by some participants, supports the idea that trust and perception is often rooted in prior knowledge and recognition, serving as a validation mechanism for credibility (Wilts, 2024).

This research applies the Technology Acceptance Model (TAM) to the context of artificial intelligence. TAM is a foundational theory in the information system that explores how consumers accept and utilize technology (Suhir et al, 2014). It predicts user acceptance based on two key factors: perceived usefulness and perceived ease of use (Davis, 1989).

Building on this, purchase intention reflects the consumer's evaluation and the response to technology acceptance. Purchase intention emerges from the learning processes and cognitive evaluations that shape consumer perception. This intention serves as a motivational driver, prompting consumers to engage with products or services (Filieri et al., 2018). When consumers fulfill their needs, their actual experiences align with their initial expectations, reinforcing the cycle of acceptance and usage. (Marka & Arumsari, 2022).

2.4.2 Technology Acceptance Model

The Technology Acceptance Model (TAM) was first developed by Davis in 1989. This model examines user behaviors in the adoption of new technologies. The technology acceptance model, TAM, is fundamentally based on two key elements: 'perceived usefulness' and 'perceived ease of use' (Davis, 1989). This model effectively predicts an individual or group of people's willingness to accept a specific technology, as demonstrated in various contexts such as: internet usage, social media, and mobile marketing (Sarp, 2023). Davis posits that both 'perceived usefulness' and 'perceived ease of use' will significantly influence consumer's attitudes and behavioral intentions toward technology adoption.

People's willingness to adopt an application often hinges on their belief that it will enhance their job performance, a concept known as perceived usefulness (PU). Defined as "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989, p. 320), perceived usefulness stems from the notion of being advantageous in its application. In organizational settings, individuals are motivated by performance-based rewards such as raises, promotions, and bonuses (Pfeffer, 1982; Schein, 1980; Vroom, 1964). Consequently, when users perceive a system as highly useful, they are more likely to believe in a positive correlation between its use and their performance outcomes, reinforcing their motivation to adopt the technology (Davis, 1989).

Perceived ease of use (PEOU), in contrast, is defined as "the degree to which a person believes that using a particular system will be free of effort" (Chang & Tung, 2007, p. 74,). This aligns with the definition of "ease," which denotes a lack of difficulty or significant effort (Davis, 1989). Since effort is a limited resource that individuals allocate among various activities (Radner & Rothschild, 1975), an application that users perceive as easier to navigate is more likely to gain acceptance.

The use of TAM instead of alternative frameworks is favorable because of its specific emphasis on user perception and behavioral intentions regarding technology adoption (Utomo & Yasirandi, 2024). This framework is a well-suited option to examine the acceptance of AI among Generation Z. Unlike more complex models, such as the Unified Theory of Acceptance and Use of Technology (UTAUT), TAM offers a more streamlined approach. This simplicity is not a limitation but rather an advantage, as it provides a greater flexibility in application, making it more adaptable for studying intricate dynamics of technology implementation and user behavior (Utomo & Yasirandi, 2024).Gen Z, as digital natives, tend to be highly instrumental in their technology use. They focus on practical benefits and ease of use, which aligns well with TAM's constructs (Onjewu et al., 2024). In comparison to UTAUT, which incorporates a broader range of variables and external influences, TAM remains more focused. TAM allows a clearer analysis of the key factors that drive technology adoption decisions (Utomo & Yasirandi, 2024).

Since its inception, TAM has undergone numerous refinements and expansions to enhance its applicability. A specific development of note included the incorporation of additional variables, like perceived enjoyment and perceived social influence (Venkatesh et al., 2003; Venkatesh & Davis, 2000). This accounts for broader motivational and social factors in technology adoption (Otto et al., 2024). Furthermore, TAM has been extended through frameworks like the Theory of Planned Behavior (TPB) and the Contextual Model of Technology Acceptance (C-TAM) (Andrina Granić, 2023; Legris et al., 2003). These integrate additional psychological and contextual elements into the model (Otto et al., 2024). Despite these expansions, the core assumptions regarding the impact of perceived usefulness and perceived ease of use on technology acceptance remain fundamental and unchanged.

Empirical research consistently reinforces the validity of TAM, with numerous studies affirming that PU and PEOU are key determinants in predicting technology adoption and usage (Venkatesh et al., 2003; Legris et al., 2003). These findings highlight the model's robustness in explaining behavior across various technological contexts.

In the context of this study, which examines the acceptance of AI in advertising, it is crucial to acknowledge the unique attributes of AI technologies that may influence adoption. Factors, such as the complexity of AI systems and concerns related to privacy, could impact users' perceptions of ease of use and usefulness, thereby shaping their willingness to embrace this technology (Otto et al., 2024). On the other hand, AI's capability to generate personalized and relevant advertisements may enhance its perceived usefulness, ultimately fostering greater acceptance (Otto et al., 2024). This underscores the importance of adapting TAM to accommodate the distinct characteristics of AI-powered technology when assessing their adoption and integration into the advertising industry and other technological environments.

Beyond these core components of TAM, factors such as: literacy, accuracy, and reliability also play influential roles in shaping an individual's attitude towards technology acceptance (Lee & Park, 2023; Wilts, 2024; Hoff & Bashir, 2015). Building on the principles of TAM, the concept of AI literacy emerges as a crucial factor in understanding users' interactions with the AI chatbot and an individual's overall acceptance of ChatGPT (Lee & Park, 2023).

2.4.3 AI Literacy

Traditionally, the concept of literacy has been understood as the ability to read, write, and communicate effectively using written language (Long & Magerko, 2020). The promotion of literacy has historically had profound political and emancipatory effects. This ends up expanding access to knowledge and empowering individuals to share and exchange ideas (Paulo Freire, 1972).

Over time, the notion of literacy has evolved to encompass skill sets in a variety of disciplines that enable expression, communication, and access to information (Long & Magerko, 2020). Some examples include: digital literacy, which refers to the ability to effectively use computational devices (Bawden et al., 2008); computational literacy, which is defined as "an appreciation of the nature, aims, and general limitations of science, coupled with some understanding of the more important scientific ideas" (Laugksch, 2000); and data literacy, which is described as "the ability to read, work with, analyze, and argue with data as part of a broader process of inquiry into the world" (D'Ignazio, 2017). Similarly, AI literacy can be defined as a set of competencies that enable individuals to critically assess AI technology, collaborate and communicate effectively with AI, and utilize AI as a tool in various settings (Long & Magerko, 2020). This can include online environments, households, and workplaces (Long & Magerko, 2020).

AI literacy is closely linked to other established literacies in related fields. A key relationship is with digital literacy, which serves as a prerequisite for AI literacy, as individuals must first be able to use computers to engage with AI technology (Long & Magerko, 2020). However, computational literacy is not a necessary requirement for AI literacy, even though it may be beneficial. Although programming skills can enhance an individual's understanding and are essential for AI developers, they also pose a possible barrier to AI literacy for general users. Most individuals interact with AI in their daily lives and do not need programming expertise to understand or effectively use AI (Long & Magerko, 2020). Similarly, scientific literacy can contribute to AI literacy, particularly in understanding machine learning principles and methodologies (Shaprio et al., 2018). However, like computational literacy, it is not a mandatory prerequisite (Long & Magerko, 2020).

AI literacy refers to a comprehensive skill set that develops an understanding of AI across three key dimensions: learning about AI, understanding how AI functions, and adapting to life with AI (Long & Magerko, 2020; Miao et al., 2021). The first dimension, learning about AI, emphasizes the acquisition of fundamental concepts and techniques associated with AI. This includes the ability to identify which platforms, tools, and systems use AI technologies and distinguish them from those that do not (Otero et al., 2023). Developing this foundational knowledge enables individuals to navigate the increasingly AI-driven technological landscape with confidence.

The second dimension, learning how AI works, focused on the understanding of mechanisms behind AI technologies. This involves grasping the principles of machine learning, data processing, and decision-making algorithms, allowing users to interact more effectively with AI-powered applications (Otero et al., 2023). Comprehension skills of AI's operational framework empowers individuals to use this technology more efficiently and make more informed decisions when engaging with them (Otero et al., 2023).

The third dimension, adapting to life with AI, highlights the societal and ethical implications of AI. This aspect encourages individuals to critically assess AI's impact on various aspects of life. This includes employment, privacy, and decision-making processes (Otero et al., 2023). By fostering an awareness of how AI influences daily activities and broader societal structures, individuals can develop a responsible and ethical approach to AI adoption and usage (Otero et al., 2023). Together, these three dimensions form a holistic approach to AI literacy, equipping individuals with the necessary skills to navigate, understand, and critically evaluate AI technologies in both personal and professional contexts.

ChatGPT is an advanced AI chatbot and has garnered a great deal of attention for its ability to comprehend complex languages, generating personalized, human-like responses (Ma & Huo, 2023). Notably, it stands out as the first user-friendly AI interface accessible to the general public. According to Lee and Park (2023), ChatGPT literacy is positively linked to user satisfaction, a crucial predictor for both user intention and learning effectiveness. Similar to digital literacy, ChatGPT literacy is poised to become a key determinant in shaping individuals' perceptions and interactions with the rapidly evolving digital landscape.

While ChatGPT's advanced capabilities and user-friendly interface have made it a popular choice, understanding the importance of accuracy in its responses is critical for user navigating information in a digital age.

<u>2.4.4 Perceived AI Accuracy</u>

Perceived AI accuracy refers to the user's assessment of how correct AI-generated recommendations are (He et al., 2019; Shin, 2020). Rather than focusing on the complex algorithms and mechanisms that create these recommendations, users tend to prioritize the perceived accuracy of the outputs (Pal at al., 2023). Since most individuals lack direct knowledge of the intricate processes behind the AI decision making process, their trust in AI systems is largely shaped by how well the recommendations align with their expectations and needs (Pal et al., 2023).

A higher perceived accuracy of AI-generated recommendation systems can significantly enhance users' overall evaluations and acceptance of these systems (Pal et al., 2023). When AI consistently provides recommendations that users find relevant and precise, it fosters confidence in the technology. This ultimately increases its adoption and usage (Pal et al., 2023). Conversely, if users perceive AI-generated recommendations to be frequently inaccurate or misleading, trust in the system diminishes, potentially leading to skepticism or disengagement (Pal et al., 2023).

Even in the absence of detailed explanations, individuals may still perceive automated decisions as accurate due to a general human tendency to trust expert systems (Dijkstra, 1999; Dzindolet et al., 2003). This trust originates from the assumption that technology, particularly AI-powered systems, operated with a level of precision and objectivity that surpasses human judgement (Aoki et al., 2024). However, the opposite effect is also a possible occurrence, particularly in cases where individuals have developed "algorithmic aversion." This is a psychological phenomenon that describes a preference for human-generated predictions over computer-generated ones, even if the evidence suggests that the AI-powered predictions are more accurate (Simmons, 2018, p. 1090–1091). Algorithmic aversion often arises when users overreact to an error made by an algorithm. The user is perceiving minor mistakes as indication of fundamental flaws in the system's reliability (Dietvorst et al., 2015).

In these cases, users can inherently trust or be skeptical of AI. Both cases also provide an explanation of how the system's decision making process can play an important role in influencing perceptions of accuracy. When users are given insight into how AI reaches conclusions, they are better equipped to understand the logic behind the recommendations (Aoki et al., 2024). This reduces the uncertainty and enhances confidence in the system's outputs (Aoki et al., 2024). Additionally, explanations can serve a functional purpose for system developers and other stakeholders by enabling them to review the AI's knowledge base, reasoning processes, and decision pathways (Adadi & Berrada, 2018).

This transparency allows for continuous monitoring, debugging, and refinement of AI systems (Aoki et al., 2024). This also ensures that errors can be identified and corrected effectively (Adadi & Berrada, 2018). As a result, explanations not only increase user trust in AI, but it also reinforces the belief that automated decisions are subject to correction and improvement. This fosters a perception of accuracy by demonstrating that AI systems are not rigid or infallible, but rather dynamic tools capable of learning, adapting, and improving over time (Aoki et al., 2024).

ChatGPT is the most advanced chatbot currently available, demonstrating remarkable proficiency in language and producing human-like writing. However, this technology has notable limitations. When presented with more complex questions, the risk of generating inaccurate responses increases. The responses may seem plausible to users, potentially leading them to accept false information as truth. Additionally, the data provided by ChatGPT may not always be current, lacking the real-time updates that can be found on websites and social media platforms (Ulusoy et al., 2023). This limitation underscores the importance of accuracy in AI interactions. This limitation highlights the critical need for reliability in AI technologies.

Additionally, the efficiency of technology varies by task, making task characteristic a critical factor in fostering cognitive trust in AI (Hancock et al., 2011). High machine intelligence enhances AI performance in traditional technology-related tasks and expands the range of tasks that can be undertaken. As the capabilities of AI expand, the influence of task characteristics on developing cognitive trust becomes increasingly intricate and less predictable.

Prior research highlights that one of the central challenges in establishing trust in AI revolves around the accuracy of AI systems (Lockey et al., 2021). Trust in AI is not solely based on its functionality, but it is also heavily influenced by the user's perception of reliability (Pal et al., 2023). Therefore, ensuring and communicating high levels of accuracy in AI-driven recommendations is a key factor in fostering user trust and encouraging long-term reliance on AI technology.

2.4.5 Perceived AI Reliability

Reliability is defined as "the extent to which an experiment, test, or measuring procedure yields the same results on repeated trials" (Merriam-Webster, 2019). Unlike trustworthiness, which involves relationships with both trusted entities, reliability pertains to the consistency of a system's performance. AI, as a systematic set of techniques, lacks the capacity for trust or emotional connection (Ryan, 2020). Concerns about ChatGPT's reliability have emerged, particularly regarding its use of questionable journals as information sources (Mehdi Dadkhah et al., 2023), raising significant doubts about the accuracy and dependability of its outputs. Given the concerns surrounding ChatGPT's reliability, it is essential to examine the broader context in which this technology is being applied, especially in fields like advertising and digital marketing.

Reliability, defined as exhibiting the same and expected behavior over time, is essential for establishing trustworthiness (Hoff & Bashir, 2015). However, assessing reliability in AI can be challenging, particularly in systems with high machine intelligence, where learning from data may cause the technology to exhibit varying behaviors, even if its core objectives remain unchanged. The relationship between AI reliability and trust is often more complex in high intelligence systems compared to low-intelligence ones and can differ across various AI applications (Glikson & Woolley, 2020). Early theoretical models of trust in automation primarily emphasized attributes related to the system's technical performance, such as reliability (Malle & Ullman, 2023). In these models, trust was closely tied to the system's ability to perform tasks competently and reliably (Malle & Ullman, 2023). As AI evolves, understanding the complex link between reliability and trust will be key to understanding AI acceptance and trust in AI.

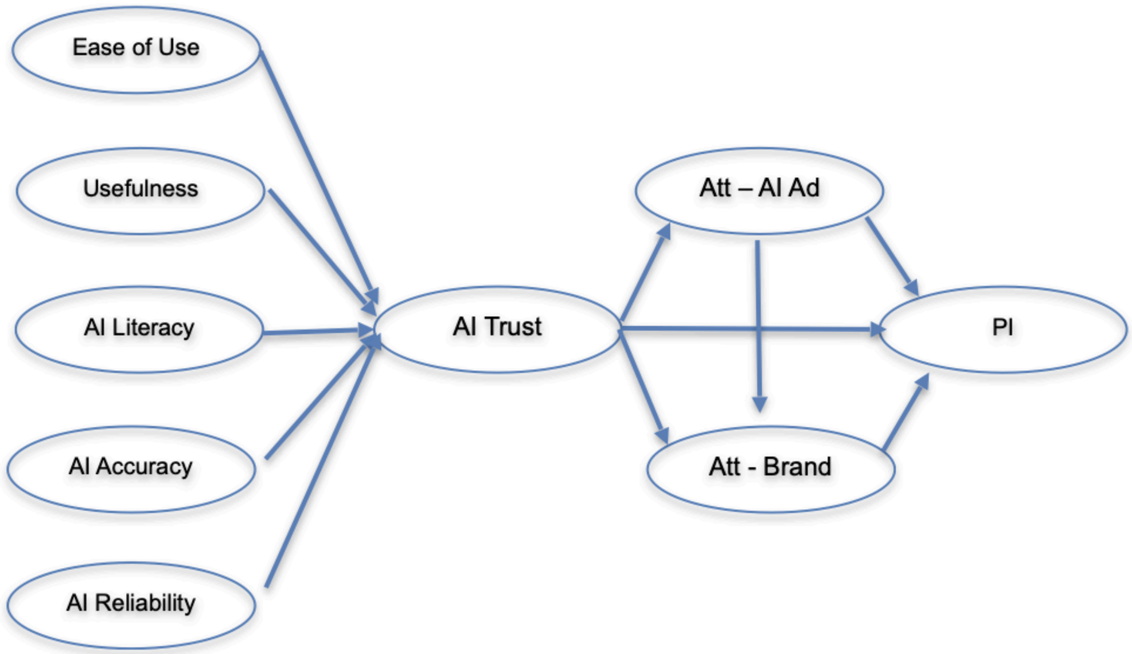
Reliability is widely recognized as a fundamental aspect of trust, particularly in the context of automated systems (Lee & See, 2004). Previous research has consistently demonstrated that the reliability of a system significantly influences user's trust in its functionality (Seo et al., 2024). For example, studies on warning systems have revealed that when a system is perceived as reliable, users are more likely to trust and act upon its alerts and recommendations (Chen et al., 2018).

Several researchers have further highlighted the critical role that reliability plays in fostering trust in automation (Seo et al., 2024). Dzindolet et al. (2003) found that providing users with contextual information about the reason automated system's decisions matter can enhance their trust in the system. This suggests that trust is a function of a system's accuracy and how well users understand its decision-making process. Similarly, in a study conducted by Chancey et al. (2017), participants inhibited significantly higher trust in a system with high reliability compared to one with lower reliability. These results indicate that users develop trust based on their perception of how consistently and effectively an AI system performs its intended function.

Beyond reliability itself, research has explored how different types of errors made by AI systems influence user trust (Seo et al., 2024). Kocielnik et al. (2019) found that user reactions to AI-generated mistakes were largely shaped by their overall perception of the system's reliability. This means if an AI system is generally reliable, users may be more forgiving of occasional errors, whereas frequent inconsistencies can erode trust.

2.5 Model

Building upon the insights gained from the previous literature review, this current study introduces a comprehensive model designed to explain multiple key relationships in the context of AI-powered advertising. Specifically, this model aims to investigate: first, the role of technology perceptions in shaping Generation Z's attitude toward AI-powered advertising creative, their overall brand attitude, and their purchasing intentions. Second, the mediating effects of AI trust in the relationship between technology perceptions and Gen Z's attitudes, align with their purchasing behaviors. By exploring these dynamics, this study seeks to provide a deeper understanding of how technological perceptions and trust in AI influence consumer attitudes and their decision making processes within this digitally native generation.



H1. Perceived ease of use is positively associated with AI trust.
H2. Perceived usefulness is positively associated with AI trust.
H3. AI literacy is positively associated with AI trust.
H4. Perceived AI accuracy is positively associated with AI trust.
H5. Perceived AI reliability positively is associated with AI trust.
H6. AI trust is positively associated with attitude toward AI-powered ads.
H7. AI trust is positively associated with attitude toward brand.
H8. Attitude toward AI-powered ads is positively associated with attitude toward brand.
H9. AI trust is positively associated with purchasing intention.

3 Methodology

This study uses a quantitative experimental approach to investigate Generation Z's psychological responses to AI-powered advertising. The decision to focus on Generation Z in this study is motivated by their unique characteristics briefly described in the previous literature review. Some of these characteristics include their purchasing behaviors and profound connection to digital technology. As true digital natives, Gen Z matured in an era where artificial intelligence (AI) is increasingly integrated into various aspects of life, including advertising and brand interactions. Their familiarity with and reliance on digital platforms make them a crucial demographic for understanding how AI-powered advertising influences consumer perception, trust, attitude, and purchasing decisions.

By examining this generation's response to AI in advertising, this study uncovers critical insights into the evolving digital landscape and its impact on consumer-brand relationships. More specifically, it will explore how Gen Z's perceptions of AI shape their attitudes toward brands, their level of trust in AI-powered marketing efforts, and their ultimate purchasing intentions.

This research is justified by its ability to systematically examine Gen Z psychological response to AI-powered advertising through a quantitative experimental approach. Given Gen Z's deep integration with digital technology, an online survey with embedded stimuli was the most effective method for reaching this demographic, ensuring accessibility and engagement. The randomized experimental design, in which participants were assigned to view either a human-made or AI-generated advertisement, allows for a controlled comparison for consumer responses while minimizing potential biases. The decision to use two visually similar Instagram ads, only the AI-generated ad labeled as such, ensures that the differences in consumer attitudes, trust, and purchasing intentions can be directly attributed to the AI factor rather than other variables. Additionally, the use of established measurement scales and Structural Equation Modeling strengthens the study's validity by enabling robust statistical analysis of the relationships between Ai perceptions, brand attitude, and purchasing behaviors. By employing a rigorous, data-driven methodology, this study contributes to the academic understanding of AI in advertising and provides practical insights for marketers seeking to leverage AI-generated content effectively within digital marketing strategies.

3.1 Data Collection

Given Gen Z's prior familiarity with digital platforms and their ease of navigating technology, an online survey incorporating a stimulus was conducted via the Qualtrics platform as the primary method of data collection. This approach aligns with the digital nature of the target demographic, participants ages 18-24, ensuring accessibility and convenience for respondents. This survey was distributed through the University of Oklahoma's email system and various social media platforms, maximizing reach and engagement. The data collection period spanned one month (March 2025), during which responses were actively gathered. This study gained a sample size of 210 qualified respondents.

To maintain a focused and methodologically sound approach, strict inclusion criteria was applied in defining the research sample. The target respondents were individuals belonging to Generation Z, specifically those aged between 18 and 24 during the data collection period (March 2025), corresponding to birth years between 2001 and 2007. This age-based criteria is essential for ensuring the study accurately reflects the perspectives and behaviors of this generational cohort. To verify eligibility, screening questions were implemented in the survey, ensuring qualified participants were being recorded.

Participants were invited through a combination of social media outreach and university email distribution. An initial call for respondents was posted on platforms, such as: Instagram, LinkedIn, Facebook, Reddit, explicitly stating that the survey is intended for individuals within the Generation Z demographic. The recruitment messaging also emphasized the voluntary nature of participation, ensuring respondents feel comfortable engaging with the study.

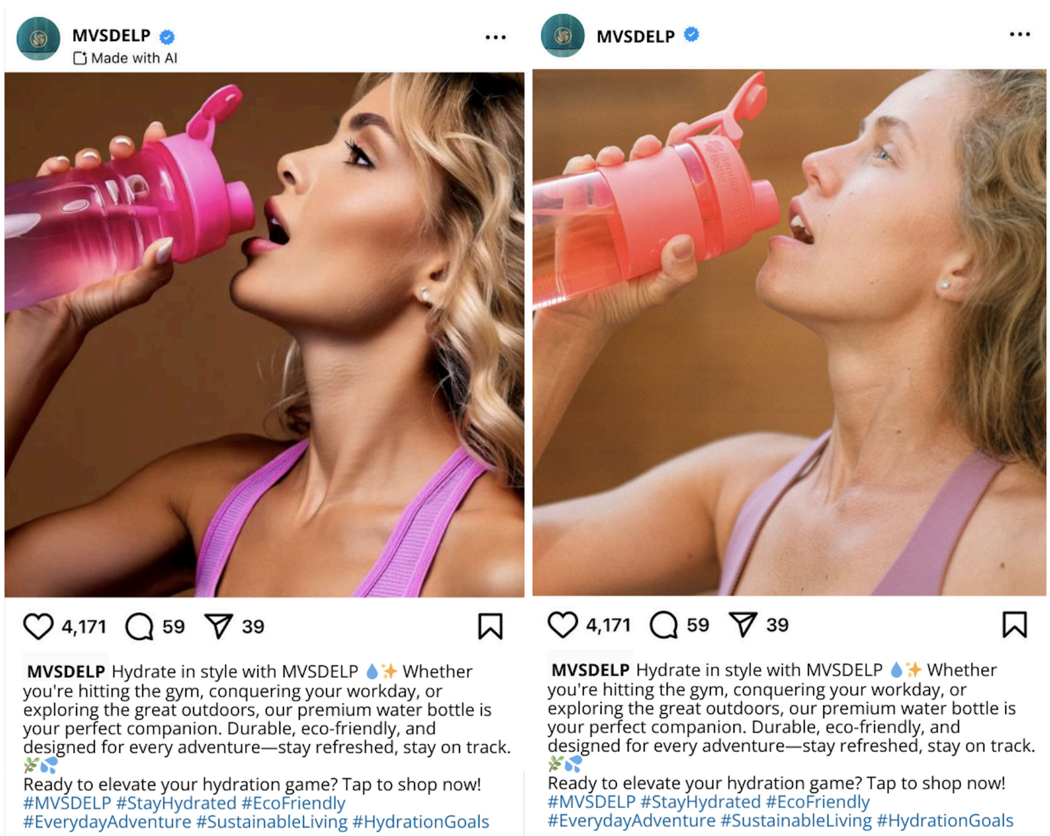
Furthermore, to uphold ethical research standards and protect participants confidentiality, all personal information was securely stored and anonymized. This study received Institutional Review Board (IRB) approval (Approval Number: 18261).The questionnaire began with a consent question, ensuring that all participants voluntarily agreed to take part in the research. If the respondent selected “No” for the consent, they were automatically disqualified and exited from the survey, ensuring that only willing participants were included in the data collection process. Similarly, a screening question was implemented to confirm that respondents were 18 years or older. Those who did not meet this age requirement were also disqualified and removed from the survey, maintaining the integrity of the study’s demographic. This approach upheld ethical research standards by prioritizing informed consent and participant autonomy. By implementing these measures, this study collected high-quality data while fostering a secure and trustworthy research environment.

3.2 Stimulus

The current study aimed to explore Gen Z’s psychological responses to AI-powered advertising by examining how they perceive and react to advertisements created by AI versus those designed and feature humans. Given Gen Z’s digital fluency and their increasing exposure to AI-powered content, understanding their attitudes, trust levels, and perceptions with AI-generated advertising is crucial for marketers and researchers alike.

To achieve this, this study utilized two fake Instagram advertisements as a stimulus. The two stimuli were similar Instagram ads, showcasing a woman with a water bottle. The first stimuli was human-made and showcased a human woman. On the other hand, the second stimulus was a fully AI-generated image that resembles the human-made image. The AI-generated ad includes a clear label that reads “*Made with AI.”* This ensures that participants are aware of its origin. To assess whether participants notice and acknowledge this notification, a manipulation check is incorporated into the survey, verifying their awareness of the AI attribution. By maintaining consistency in the product, branding, and visual elements, this approach will allow for a controlled examination of how AI-generated content influences consumer perceptions differently from human-created advertising. Participants' reaction to these ads was measured through various psychological and behavioral indicators, including: trust, brand attitude, and purchase intention.

This methodology provides valuable insights into the role of AI in shaping advertising effectiveness and consumer trust. By comparing audience responses between AI and human-generated advertisements, this study uncovers the underlying factors that drive consumer attitudes toward AI-powered advertising. These findings can contribute to the growing body of research on AI in advertising, while offering practical implications for brands seeking to integrate AI-powered creative into their marketing strategies.



3.3 Measurement

This study's framework employs an interval level of measurement to assess participants' responses regarding brand trust, attitudes, purchasing intentions, and perceptions of AI. Using an interval scale, like a Likert scale or a semantic differential scale, ensures that the differences between scale points remain consistent, enabling precise measurement of key variables and facilitating robust statistical analysis.

Perceptions of AI were assessed using five key constructs, each measured with a 7-point Likert scale derived from established literature. Participants' awareness of AI was measured using a 7-point Likert scale from Gillespie, Lockey, and Curtis (2021). A factor analysis presented that all items are loaded to a single factor (Eigenvalue = 2.031, 67.6% variance explained, Cronbach α = .759). AI familiarity was measured using a 7-point Likert scale adopted from Byungura, Hansson, Muparasi, and Ruhinda (2018). A factor analysis presented that all items are loaded to a single factor (Eigenvalue = 2.003, 66.8% variance explained, Cronbach α = .751).

Perceived ease of use and perceived usefulness were measured using a 7-point Likert scale adopted from Davis (1989), assessing how intuitive and beneficial participants find AI-powered advertising. A factor analysis showed that all items are loaded to a single factor for perceived ease of use (Eigenvalue = 1.469, 49% variance explained, Cronbach α =.701). A factor analysis presented that all items are loaded to a single factor for perceived usefulness (Eigenvalue = 2.262, 72% variance explained, Cronbach α =.802).

AI literacy was measured using a 7-point Likert scale adopted from Lee and Park (2023), evaluating participants' previous knowledge and understanding of AI technologies. A factor analysis presented that all items are loaded to a single factor (Eigenvalue =2.082, 69.4% variance explained, Cronbach α = .776). AI accuracy is measured with a 7-point Likert scale based on Aini, Sembring, Setiawan A., Setiawan I. and Rahardja (2023), assessing perceptions of how precisely AI generates and delivers. A factor analysis presented that all items are loaded to a single factor (Eigenvalue = 1.846, 61.5% variance explained, Cronbach α = .682).

Perceived AI reliability is evaluated using a 7-point Likert scale adopted from Kim, Kang, and Moon (2015), measuring trust in AI's dependability. A factor analysis presented that all items are loaded to a single factor (Eigenvalue = 2.041, 68% variance explained, Cronbach α = .764). AI Trust used a likert scale adopted from Choung, David, and Ross (2022). A factor analysis presented that all items are loaded to a single factor (Eigenvalue = 2.477, 82.6% variance explained, Cronbach α = .893).

In addition to AI perception metrics, this study measures attitudes and purchasing behavior using well-established scales. Attitude toward AI is using a 7-point Likert scale, adopted from Spears and Singh (2004). A factor analysis presented that all items are loaded to a single factor (Eigenvalue = 3.335, 83.4% variance explained, Cronbach α = .933). Attitude toward advertisement and attitude toward the brand is assessed using a 7-point semantic differential scale, adopted from Spears and Singh (2004) to gauge participants' emotional and cognitive responses toward AI-generated content and its impact on brand attitude. A factor analysis presented that all items are loaded to a single factor for attitude toward advertisements (Eigenvalue = 3.537, 88.4% variance explained, Cronbach α = .956). A factor analysis presented that all items are loaded to a single factor for attitude toward brand (Eigenvalue = 3.627, 90.7% variance explained, Cronbach α = .966). Purchasing intention is measured using a 7-point Likert scale, also adopted by Spears and Singh (2004), to determine the likelihood of participants making a purchase based on their exposure to AI-powered advertisements. A factor analysis presented that all items are loaded to a single factor (Eigenvalue = 1.807, 90.3% variance explained, Cronbach α = .892).

3.3.1 Analysis

To comprehensively examine the relationships among the variables in this model, the collected data was analyzed using the Statistical Package for the Social Sciences (SPSS). A series of t-tests was used to examine the difference between human-based and AI-based advertising, and a series of regression was used to find the associations among variables.

4 Results

The analysis revealed several notable findings directly related to the research questions. The data demonstrate meaningful patterns and significant outcomes that contribute to understanding the topic under investigation.

4.1 Sample

Of 215 respondents, 5.5% are high school graduates or GED holders, 42.8% currently have some college education, 6.2% have an associate degree, 35.9% have a bachelor's degree, 6.2% have a masters degree, and 3.4% have a doctorate degree. This data indicates that a majority of the respondents have completed or currently enrolled in a higher education program. In addition to their educational status, the respondents had an average age of 24, which indicates that they are a part of Gen Z.

In terms of gender representation, the respondents identify as 77.9% female, 19.3% male, with 0.7% opting to not say, and 2.1% identifying as non-binary. Concerning their residency, 60.4% currently reside in Oklahoma, 31.3% in Texas, and few other states with small percentages: Arkansas with 0.7%, Florida with 1.4%, Georgia with 0.7%, Indiana with 0.7%, Kansas with 1.4%, Louisiana with 0.7%, Michigan with 0.7%, Missouri with 0.7%, Ohio with

0.7%, and Oregon with 0.7%.

4.2 Manipulation Check

The first manipulation check, which asked respondents to identify whether the ad was created by AI or human, in the AI-generated ad group (M=1.92, sd=0.268) were significantly higher than the first manipulation check in the human-made group (M=1.30, sd=0.461; t = 10.136, df = 143, p < 0.001). However, the second manipulation check, which measured how realistic the person featured in the ad appeared, in the AI-generated ad group (M=65.39, sd=23.198) were lower than those in the human-made group (M=74.320, sd=22.050; t = -2.364, df = 142, p = .722). The manipulation check for ad realism was also correlated with attitude toward the ad (r(67)=.271, p =.024).

4.3 Statistical Comparison of Participant Responses to AI and Human-Created Ads

In this study, respondents were randomly assigned to one of two advertising stimuli: a human-made ad or a similar AI-generated ad. Both groups were asked the same set of questions. An independent-samples t-test was calculated to determine whether ease of use, usefulness, AI literacy, AI reliability, AI accuracy, AI trust, attitude toward the ad, brand attitude, and purchasing intentions of subjects were statistically different.An independent t-test was conducted to examine whether responses differed statistically between the two conditions.

An independent-samples t-test was calculated comparing the mean score of participants who viewed the AI-generated ad to the mean score of participants who viewed the human made ad in perceived ease of use. No significant difference was found (t =1.594, df = 165, p = .712). The mean of the AI-generated group (M = 4.4457, sd = .77077) was not significantly different from the mean of the human made group (M = 4.2489, sd = .82034) for perceived ease of use. An independent-samples t-test was calculated comparing the mean score of participants who viewed the AI-generated ad to the mean score of participants who viewed the human made ad in perceived usefulness. No significant difference was found (t =.971, df = 162, p = .618). The mean of the AI-generated group (M = 4.6479, sd = 1.32226) was not significantly different from the mean of the human made group (M = 4.4489, sd = 1.28924) for perceived usefulness.

An independent-samples t-test was calculated comparing the mean score of participants who viewed the AI-generated ad to the mean score of participants who viewed the human made ad in AI literacy. No significant difference was found (t =.714, df = 160, p = .173). The mean of the AI-generated group (M = 4.0575, sd = 1.27509) was not significantly different from the mean of the human made group (M = 3.9022, sd = 1.49451) for AI literacy. An independent-samples t-test was calculated comparing the mean score of participants who viewed the AI-generated ad to the mean score of participants who viewed the human made ad in perceived AI accuracy. No significant difference was found (t =-.190, df = 153, p =.717). The mean of the AI-generated group (M = 4.2691, sd = 1.07252) was not significantly different from the mean of the human made group (M = 4.2361, sd = 1.08689) for perceived AI accuracy. An independent-samples t-test was calculated comparing the mean score of participants who viewed the AI-generated ad to the mean score of participants who viewed the human made ad in perceived AI reliability. No significant difference was found (t =1.094, df = 153, p =.729). The mean of the AI-generated group (M = 3.1024, sd = 1.23379) was not significantly different from the mean of the human made group (M = 2.8889, sd = 1.18678) for perceived AI reliability.

An independent-samples t-test was calculated comparing the mean score of participants who viewed the AI-generated ad to the mean score of participants who viewed the human made ad in AI trust. No significant difference was found (t =.072, df = 149, p =.221). The mean of the AI-generated group (M = 4.0338, sd = 1.38222) was not significantly different from the mean of the human made group (M = 4.0185, sd = 1.21530) for AI trust. An independent-samples *t*-test comparing the mean scores of the AI-generated and human made groups found a significant difference between the means of the two groups in brand attitude (t =-4.034, df = 144, p =< .001). The mean of the AI-generated group was significantly lower (M=3.4049, sd=1.53763) than the mean of the human made group (M=4.2574, sd=.87670).

An independent-samples *t*-test was calculated comparing the mean score of participants who viewed the AI-generated ad to the mean score of participants who viewed the human made ad in ad attitude. No significant difference was found (t =-3.937, df = 145, p =.054), however it was just above 0.05. The mean of the participants that viewed the AI-generated ad (M=3.4840, sd=1.50018) was not significantly different from the mean of the participants that viewed the human made ad (M=4.3841, sd=1.23787) for ad attitude. An independent-samples *t*-test was calculated comparing the mean score of participants who viewed the AI-generated ad to the mean score of participants who viewed the human made ad in purchasing intention. No significant difference was found (t =-2.826, df = 143, p =.434). The mean of the AI-generated group (M = 2.3077, sd = 1.42389) was not significantly different from the mean of the human made group (M = 2.9627, sd = 1.35208) for purchasing intention.

4.4 Pearson Correlation Results for AI and Human-Made Advertising

For the AI-generated ad group, Pearson correlation coefficients were calculated to examine relationships between AI-related factors and participants' attitudes, brand perceptions, and purchasing intentions. Significant relationships were found between AI usage and AI trust ($r(76)$=.436, p <.001), AI familiarity and AI trust ($r(77)$=.471, p <.001), AI attitude and AI trust ($r(77)$=.570, p <.001), AI reliability and AI accuracy ($r(80)$=.572, p <.001). Significant positive correlations and are significant relationships were found between perceived AI usefulness and AI trust ($r(77)=.767$, $p<.001$), AI reliability and AI trust ($r(76)=.628$, $p<.001$), and AI accuracy and AI trust ($r(77)=.825$, $p<.001$).

Regarding attitudes and brand perceptions, AI awareness was negatively correlated with both attitude toward the ad ($r(76)=-.256$, $p = 0.024$) and brand attitude ($r(76)=-.267$, $p=.018$), but were significant. AI usage was positively correlated with attitude toward the ad ($r(75)=.242$, $p=.034$), while AI attitude was strongly correlated with both attitude toward the ad ($r(76)=.555$, $p<.001$) and brand attitude ($r(76)=.598$, $p<.001$). Additionally, AI usefulness showed a positive relationship with both attitude toward the ad ($r(76)=.355$, $p=.001$) and brand attitude ($r(76)=.378$, $p<.001$). AI reliability was positively correlated with attitude toward the ad ($r(76)=.348$, $p=.002$) and brand attitude ($r(76)=.407$, $p<.001$), while AI accuracy was also positively associated with attitude toward the ad ($r(76)=.253$, $p=.025$) and brand attitude ($r(76)=.339$, $p=.002$). AI trust demonstrated a significant positive correlation with both attitude toward the ad ($r(75)=.316$, $p=.005$) and brand attitude ($r(75)=.345$, $p=.002$).

For purchasing intentions, AI attitude was significantly correlated with purchasing intention ($r(76)=.415$, $p<.001$), as were AI usefulness ($r(76)=.310$, $p=.006$), AI literacy ($r(76)=.227$, $p=.046$), AI reliability ($r(76)=.492$, $p<.001$), AI accuracy ($r(76)=.312$, $p=.005$), and AI trust ($r(75)=.287$, $p=.012$). Additionally, attitude toward the ad ($r(76)=.594$, $p<.001$) and brand attitude ($r(76)=.653$, $p<.001$) were both strongly correlated with purchasing intention.

For the human-made ad group, Pearson correlation coefficients were calculated to examine similar relationships. AI usage showed a positive correlation with AI attitude ($r(72)=.301$, $p=.009$), and AI familiarity was strongly correlated with AI attitude ($r(73)=.501$, $p<.001$). Similarly, AI usefulness ($r(73)=.550$, $p<.001$), AI reliability ($r(70)=.389$, $p<.001$), and AI accuracy ($r(70)=.475$, $p<.001$) were all significantly related to AI attitude. AI familiarity and

AI trust also showed a significant correlation ($r(70)=.467$, $p<.001$), as did AI attitude and AI trust ($r(70)=.640$, $p<.001$), perceived AI usefulness and AI trust ($r(70)=.700$, $p<.001$), AI reliability and AI trust ($r(70)=.445$, $p<.001$), and AI accuracy and AI trust ($r(70)=.744$, $p<.001$).

In terms of brand perception, AI awareness was negatively correlated with brand attitude ($r(66)=-.249$, $p=.040$), while AI attitude was positively related to attitude toward the ad ($r(67)=.256$, $p=.034$). AI accuracy showed a strong correlation with both attitude toward the ad ($r(67)=.419$, $p<.001$) and brand attitude ($r(67)=.435$, $p<.001$). AI trust was positively correlated with attitude toward the ad ($r(67)=.327$, $p=.006$) and brand attitude ($r(66)=.292$, $p=.016$), Furthermore, attitude toward the ad was strongly correlated with brand attitude ($r(66)=.768$, $p<.001$). Finally, for purchasing intentions, brand attitude was significantly correlated with purchasing intention ($r(65)=.495$, $p<.001$), though a duplicate correlation ($r(65)=.414$, $p<.001$) was present in the original analysis.

4.5 Hypothesis 1-5

Hypotheses 1-5 posits five factors - perceived ease of use, perceived usefulness, AI literary, AI accuracy, and AI reliability - are positively associated with AI trust. The table above presents the R-squared values, demonstrating the proportion of variance explained in AI trust. The R-squared value for AI trust (.743) indicates that 73% of its variance is accounted for by perceived AI accuracy, perceived ease of use, perceived AI reliability, and perceived usefulness.

A regression model was used to predict participants' AI trust based on perceived AI accuracy, AI literacy, perceived ease of use, perceived AI reliability, and perceived usefulness. The results yielded a significant regression equation, $F(5,144)=83.397$, $p<.001$, with an R2 value of .743, indicating that 74.3% of the variance in AI trust is explained by these predictors. The predicted AI trust equation is: AI trust= -.714 -.025 (Ease of Use) +.381(Usefulness)

+.52(AI Literacy) +.050(AI Reliability) +.653(AI accuracy). On average, participants' AI trust increased by 1.579.

The coefficient for perceived ease of use (*B*=-.025, *p* <.728) is not statistically significant, indicating that there is not strong evidence to conclude that ease of use is associated with higher AI trust. The null hypothesis is accepted. Conversely, the regression analysis testing the association between perceived usefulness and AI trust found a significant relationship (*B*=.381, *p* <.001), indicating that higher perceived usefulness is linked to greater AI trust. Since the p-value falls below the conventional .05 threshold, the null hypothesis is rejected, supporting the alternative hypothesis: perceived usefulness is positively associated with AI trust.

A similar analysis tested whether AI literacy is positively associated with AI trust. The coefficient for AI literacy (*B*=.052, *p* =.228) was not statistically significant, providing no strong evidence of an association. Thus, the null hypothesis is retained. However, the regression for perceived AI accuracy is positively associated with AI trust yielded a significant effect (*B*=.653, *p* <.001), demonstrating that greater perceived accuracy is linked to higher AI trust. With a p-value below .05, the null hypothesis is rejected in favor of the alternative. In contrast, for the perceived AI reliability is positively associated with the AI trust hypothesis, perceived AI reliability did not significantly predict AI trust (*B*=.653, *p* =.396), suggesting no strong association, leading to the retention of the null hypothesis.

To ensure the validity of the regression models, multicollinearity was assessed using Variance Inflation Factor (VIF) values. All independent variables, perceived ease of use (VIF=1.064), perceived usefulness (VIF=1.751), AI literacy (VIF=1.149), perceived AI accuracy (VIF=1.714), and perceived AI reliability(VIF=1.714), had VIF values below 5. This indicates that multicollinearity was not a concern. This suggests that each predictor independently contributes to explaining AI trust.

4.6 Hypothesis 6-9

Hypotheses 6-9 posits both direct and indirect effects of AI trust on attitude toward the ad, attitude toward brand, and purchasing intention. The R-squared value for attitude toward the ad (.084) suggests that AI trust explains 8% of its variance, while the R-squared value for brand attitude (.088) also shows that AI trust accounts for 8% of its variance. Regarding purchase intention, the R-squared value (.037) indicates that AI trust explains 3% of its variance. However, when considering AI trust, attitude toward the brand, and brand attitude together, the R-squared value for purchase intention increases to .389, meaning these factors collectively explain 38% of its variance. The value of R square (.088) of brand attitude indicates that 8% is explained by AI trust and the value of R square (.584) of brand attitude suggests that 58% is explained by AI trust and attitude toward the ad.

This regression model predicting participants' attitude toward the ad based on AI trust found a significant relationship, $F(1,144)=13.228$, $p<.001$, with an R2 value of .084, indicating that 8.4% of the variance in attitude toward the ad is explained by AI trust. The predicted equation is: Attitude Toward the Ad= 2.613+.325 (AI Trust), with an average increase of .325. Similarly, a regression predicting participants' brand attitude based on AI trust was significant, $F(1,143)=13.788$, $p<.001$, with an R2 of .088. The equation is: Brand Attitude= 2.556+.312(AI Trust), with an average increase of .312.

A regression predicting purchase intention based on AI trust also yielded significant results, $F(1,142)=5.467$, $p=.021$, with an R2 of .037. The equation is: Purchase Intention= 1.741+.217(AI Trust), with an average increase of .217. When purchase intention was predicted using AI trust, attitude toward the ad, and brand attitude as predictors, the regression model was significant, $F(3,143)=29.735$, $p<.001$, with an R2 of .389, indicating that 38.9% of the variance in purchase intention is explained by these factors. The predicted equation is: Purchase Intention= −.047+.003(AI Trust)+.202(Attitude Toward the Ad)+.488(Brand Attitude), with an average increase of .693.

The coefficient ($B=.325$, $p<.001$) was statistically significant, confirming that higher AI trust is associated with a more favorable attitude toward AI-powered ads. The null hypothesis is rejected in favor of the alternative. The independent, AI trust (VIF=1), variable had VIF values below 5, indicating that multicollinearity was not a concern. Similarly, when examining whether AI trust is positively associated with attitude toward brand, AI trust significantly predicted brand attitude ($B=.312$, $p<.001$). This is supporting the hypothesis that greater AI trust is positively associated with attitude toward AI-powered ads. The independent, AI trust (VIF=1), variable had VIF values below 5, indicating that multicollinearity was not a concern.Additionally, a significant relationship was found between attitude toward AI-powered ads and brand attitude ($B=.678$, $p<.001$), when examining whether attitude toward AI-powered ads is positively associated with attitude toward brand. This suggests that a positive perception of AI-powered ads is associated with a stronger brand attitude. The null hypothesis is rejected in support of the alternative hypothesis.

To ensure the validity of the regression models, multicollinearity was assessed using Variance Inflation Factor (VIF) values. All independent variables, AI trust (VIF=1.080) and attitude toward ad (VIF=1.080), had VIF values below 5. This indicates that multicollinearity was not a concern. This suggests that each predictor independently contributes to explaining brand attitude.

A regression predicting brand attitude based on AI trust and attitude toward the ad was significant, $F(2,142)=99.521$, $p<.001$, with an R2 of .584, indicating that 58.4% of the variance in brand attitude is explained by these variables. The equation is: Brand Attitude= .736+.102(AI Trust)+.678 (Attitude Toward the Ad), with an average increase of .78. These findings highlight the strong influences of AI trust on attitudes toward the ad and brands, along with purchase intentions, with additional contributions from attitude toward the ad and brand attitude.

The hypothesis: AI trust is positively associated with purchasing intention, was examined. In a simple regression, AI trust was a significant predictor (B=.217, p =.021). However, when tested alongside attitude toward the ad and brand attitude, the coefficient for AI trust (B =.003, p =.974) was no longer significant. This suggests that AI trust alone is not a strong predictor of purchase intention when controlling for other factors. As a result, the null hypothesis is retained in this case. To ensure the validity of the regression models, multicollinearity was assessed using Variance Inflation Factor (VIF) values. All independent variables, AI trust (VIF=1.103), brand attitude (VIF=2.403), and attitude toward ad (VIF=2.368), had VIF values below 5. This indicates that multicollinearity was not a concern. This suggests that each predictor independently contributes to explaining brand attitude.

H1	Perceived ease of use is positively associated with AI trust.	Rejected
H2	Perceived usefulness is positively associated with AI trust.	Supported
H3	AI literacy is positively associated with AI trust.	Rejected
H4	Perceived AI accuracy is positively associated with AI trust.	Supported
H5	Perceived AI reliability positively associated with AI trust.	Rejected
H6	AI trust is positively associated with attitude toward AI-powered ads.	Supported
H7	AI trust is positively associated with attitude toward brand.	Supported

H8	Attitude toward AI-powered ads is positively associated with attitude toward brand.	Supported
H9	AI trust is positively associated with purchasing intention.	Rejected

5 Discussion

This study was based on 215 respondents primarily from Oklahoma and Texas with an average age of 24, majority currently enrolled in or had completed higher education, and predominantly identified as female. Participants were randomly assigned to view either a human-made or AI-generated ad, and responses were compared across a variety of AI-related and advertising perception metrics. A significant difference emerged in AI familiarity, manipulation checks, ad attitude, brand attitude, and purchasing intentions. Each of these were notably lower in the AI-generated ad group. A regression analysis revealed that AI trust was significantly predicted by perceived usefulness and perceived AI accuracy, but not perceived ease of use, AI literacy, or perceived AI reliability.

Furthermore, AI trust was positively associated with attitude toward ads and brands, although it was a non-significant predictor of purchase intentions, in the context of brand attitude and ad attitude. Attitude toward the ad emerged as a strong predictor of brand attitude, which then in turn strongly predicted purchase intention. The findings in this study suggest that while AI trust plays a foundational role in shaping perceptions, attitudes toward the ad and brand are more critical drivers of consumer intent, especially in the context of AI-generated advertising.

These findings are significant for several reasons, especially when the use of AI in marketing and advertising grows as a potential advantage. The first reason is that perceptions of AI-generated content matters. The data in this study shows that participants consistently responded more negatively to the AI-generated ad compared to the human-made ad, even though they were very similar and the only difference was that the image was AI-generated. This is on the terms of ad attitude, brand attitude, and purchase intention. This suggests that while AI can replicate creative outputs, audiences may still perceive a lack of authenticity or emotional connection, which can hurt brand perception and consumer behavior. A similar trend is evident in previous literature, which highlights Gen Z's upbringing in a fast-paced, digital-first environment that has shaped their high expectations for authenticity and transparency (Witt & Baird, 2018; Liu & Hei, 2021). This heightened discernment has made Gen Z particularly critical of brand messaging, prompting scholars to emphasize the importance of honest communication and meaningful engagement in building strong, lasting consumer-brand relationships with this generation (Tarapata, 2024; Francis & Hoefel, 2018).

The second reason is AI familiarity and recognition impact effectiveness. The fact that participants in the AI group were less familiar with AI and were more likely to correctly identify the ad as AI-generated indicated that consumers are developing a sense for detecting AI-generated content, and that this awareness might lead to skepticism. This has important implications for brands considering full automation in ad creation. Transparency and audience comfort with AI are crucial.

These findings align with existing literature on the role that familiarity plays in shaping perceptions of AI-generated content. These findings support the notion that familiarity is a crucial factor in fostering initial trust, particularly in contexts of emerging technologies like AI (Gefen, 2004; Omrani et al., 2022). While Gen Z is generally characterized as digital natives and are more comfortable with integrating technology into their lives (Chao et al., 2021), their caution to unfamiliar tasks (Chang & Chang, 2023) and sensitivity to authenticity suggest that mere exposure to AI does not guarantee trust.

Trust is central, but is not significant. While AI trust is positively associated with favorable attitudes toward the ad and the brand, it does not independently influence purchase intentions with strength. This reveals that trust in AI is a foundational element, but emotional and brand-driven attitudes are ultimately what convert interest into intention.

While trust in AI has been recognized as a foundational component of successful human-AI interaction (Lee & See, 2004; Omrani et al., 2022), the findings from this study suggest that trust alone is not the only sufficient to drive consumer action. Although participants who trusted the AI system reported more favorable attitudes toward both the ad and the brand, this trust did not strongly or independently influence their purchase intentions. This distinction aligns with prior research emphasizing that trust in AI is a necessary precondition for engagement (Sullivan et al., 2022; Ribeiro et al., 2016), but not a guaranteed predictor of behavioral outcomes.

The literature outlines AI trust as a multi-dimensional construct that encompasses: performance, process, and purpose (Hengstler et al., 2016). This impacts how users evaluate and rely on technology. However, the emotional and relational aspects of brand perception remain a key aspect in converting interest into action, especially among Gen Z, who value competence and connection in digital interactions (Glikson & Woolley, 2020; Guerra-Tamez et al., 2024). While trust enables initial openness to AI-generated content, it needs to be accompanied by emotion and brand-aligned messaging to influence consumer intention and action.

Another reason is the role that perceived usefulness and accuracy play. The regression analyses showed that perceived usefulness and perceived AI accuracy are strong predictors of AI trust. This is significant because it highlights the specific dimensions of AI performance that marketers can focus on when building consumer trust, especially in AI-powered campaigns.

A similar trend is also seen in previous literature. According to Davis (1989), perceived usefulness (PU), the belief that a system will improve performance, is a major driver of user adoption. In this context, participants who viewed AI-generated content as useful and accurate were more likely to trust the system, which echoes earlier research suggesting that perceived advantages directly influence motivation to engage with new technologies (Pfeffer, 1982; Vroom, 1964). While perceived ease of use has often been highlighted as a factor in technology acceptance (Chang & Tung, 2007), this study underscores that for AI in marketing, consumers place greater value on how well the system performs and supports intended outcomes (Davis, 1989). For marketers leveraging AI-driven tools, these insights offer a strategic path: by emphasizing the usefulness and reliability of AI applications, they can foster trust and, in turn, support more favorable consumer responses.

Emotional engagement outweighs technical perception. Despite statistically significant correlations between various AI-related variables and trust, attitude toward the ad and the brand were stronger predictors of purchasing intent. Thai reinforces a long-held marketing belief, emotional engagement and brand perception matter more than technical competency (Mostafa & Kasamani, 2021), even in a high-technological context.

The last reason is the implications for AI in brand strategy. As companies increasingly investigate using AI tools for consumer-facing roles, this study underscores the importance of humanizing AI content or blending it with human elements to ensure the messaging resonates emotionally with the target audience. Blindly automating creative processes hold the potential of backfiring if the output lacks perceived authenticity or emotional depth.

While AI is lauded for its ability to replicate human cognition and even outperform humans in data-intensive tasks (Omrani et al., 2022), this study highlights a key limitation: the potential absence of emotional resonance and authenticity. Literature suggests that trust in AI is not just technical, but it is relational, involving perceptions of fairness, purpose, and human compatibility (Hengstler et al., 2016; Glikson & Woolley, 2020). As such, the emotional disconnect in fully automated advertising can hinder consumer trust and engagement, especially with digitally savvy audiences like Gen Z, who value transparency and meaningful interaction (Guerra-Tamez et al., 2024) as seen in previous literature.

These findings provide data-driven caution for marketers. While AI can streamline content production (Nasser & Erafy, 2023), consumer trust, emotional connection, and brand perception are still human-centric and must be actively nurtured to resonate with Generation Z.

These findings offer valuable academic and professional insights. Academically, these findings have the possibility to contribute to human-AI communication research, showing that Gen Z evaluates AI-generated content differently than human-made content. This may call for updates to models, such as the Source Credibility Model and ELM to account for AI as a persuasive source. Professionally, these findings suggest marketers should not rely solely on AI-generated ads, as Gen Z consumers may perceive them as less authentic. A blended human-AI approach holds a better chance for effectiveness. Transparency, consumer education, and emotionally intelligent user experiences are key for building trust, while striking a balance between personalization and authenticity is key for maintaining brand connection.

5.1 Limitations

This study did have limitations that may affect the generalizability of the findings. First, although the intended target demographic was individuals aged 18-24, the average age of participants was 24. This skews the sample toward the upper end of the range. This may have influenced responses, as younger Gen Z individuals didn’t have as large of a representation.

Second, geographic representation was limited, with the majority of the participants residing in Oklahoma and Texas. Regional cultural differences may have shaped attitudes toward AI and marketing in ways that don't reflect broader national or global perspectives. Lastly, most participants reported having higher levels of education or are currently enrolled in higher education. This may have contributed to greater familiarity with AI and influenced trust or interpretation of AI-generated content. Future research should aim for a more demographically diverse and geographically balanced sample to strengthen the validity of these insights.

5.2 Future Works

Based on these findings and limitations, future research could explore in depth how emotional engagement influences consumer behavior in AI-generated ads and examine the role transparency plays in trust. Further studies have the opportunity to focus on the impact of age within Gen Z on AI perceptions and expand geographic diversity to understand regional differences in AI acceptance. Additionally, exploring how education level affects AI familiarity and trust could provide valuable insights.

6 Conclusion

This study sheds light on how Generation Z, digital natives, respond to AI-powered advertising. As the first true generation to mature fully immersed in digital technology, Gen Z is uniquely positioned to engage with emerging innovations, in this case artificial intelligence. While AI offers marketers powerful tools for personalization and efficiency, the findings emphasize that Gen Z places high value on trust, authenticity, and emotional connection. Technological advancements are not enough for this generation. These are factors that AI-generated content lack in delivering without human involvement.

This study finds that AI trust is influenced by perceptions of AI's accuracy and usefulness, supporting the application of the Technology Acceptance Model (TAM) in this context. Trust in AI, while influenced by perceptions of accuracy and usefulness, does not singularly drive purchasing decisions. Emotional resonance and brand authenticity still remain vital in creating a strong consumer-brand relationship with this demographic. Even in a technologically advanced landscape, emotion and human-centric appeals continue to play a strong role in shaping consumer attitudes and behaviors.

These insights suggest that brands must approach AI integration thoughtfully, blending technological capabilities with human creativity to maintain consumer trust and relevance in this evolving digital world. This will create a more effective approach in creating advertising that resonates with this generation. The human touch will help preserve the emotional depth and brand authenticity that Gen Z demands. It can also prevent content from being perceived as overly robotic or impersonal.

Overall, this study contributes to the growing body of literature surrounding AI in advertising by exploring its effects specifically on consumer trust, attitudes, and purchasing intention within the Gen Z audience. It also offers practical insights for brands aiming to build stronger and more meaningful connections with Gen Z as they grow into an important consumer group. As Gen Z continues to shape the future of the marketplace, understanding how to use AI as a tool responsibly and meaningfully will be essential for brands that aim to build lasting, consumer-brands relationships with this demographic in a digitally driven world.

Appendix A: Raw Data

A.1 Table - Sample

		Mean	Count	Column N%
Education	HS Diploma or GED		8	5.5%
	Some College		62	42.8%
	Associate Degree		9	6.2%
	Bachelor's Degree		52	35.9%
	Master's Degree		9	6.2%
	Doctorate Degree		5	3.4%
Age		24		
Gender	Male		28	19.3%
	Female		113	77.9%
	Non-Binary		3	2.1%
	Prefer Not to Say		1	.7%
Location	Arkansas		1	.7%
	Florida		2	1.4%
	Georgia		1	.7%
	Indiana		1	.7%
	Kansas		2	1.4%
	Louisiana		1	.7%
	Michigan		1	.7%
	Missouri		1	.7%
	Ohio		1	.7%
	Oklahoma		87	60.4%
	Oregon		1	.7%

	Texas		45	31.3%

A.2 Table - *T*-Test Group Statistics

		N	Mean	Std. Deviation	Std. Error Mean
AI Awareness	AI	92	4.4891	1.03710	.10813
	Human	77	4.4632	1.31223	.14954
AI Usage	AI	92	3.7337	.78254	.08159
	Human	76	3.6711	.87389	.10024
AI Familiarity	AI	93	4.8674	1.00499	.10421
	Human	77	6.3983	1.25893	.14347
AI Attitude	AI	92	4.0679	1.48162	.15447
	Human	75	3.6411	1.42044	.16402
Ease of Use	AI	92	4.4457	.77077	.08036
	Human	75	4.2489	.82034	.09472
Usefulness	AI	89	4.6479	1.32226	.14016
	Human	75	4.4489	1.28924	.14887
AI Literacy	AI	87	4.0575	1.27509	.13670
	Human	75	3.9022	1.49451	.17257
AI Reliability	AI	83	3.1024	1.23379	.13543
	Human	72	2.8889	1.18678	.13986
AI Accuracy	AI	83	4.2691	1.07252	.11772
	Human	72	4.2361	1.08689	.12809
AI Trust	AI	79	4.0338	1.38222	.15551
	Human	72	4.0185	1.21530	.14322
Manipulative	AI	78	1.92	.268	.030

Check_1					
	Human	67	1.30	.461	.056
Manipulative Check_2	AI	75	65.39	23.198	2.679
	Human	69	74.32	22.050	2.654
Ad Attitude	AI	78	3.4840	1.50018	.16986
	Human	69	4.3841	1.23787	.14902
Brand Attitude	AI	78	3.4049	1.53763	.17410
	Human	68	4.2574	.87670	.10632
Purchase Intention	AI	78	2.3077	1.42389	.16122
	Human	67	2.9627	1.35208	.16518

A.3 Table - Independent *T*-Test- F Values

Construct	**F**	**Sig.**	**t**	**df**
AIaware	3.232	.74	.143	167
AIusage	.001	.978	.490	166
AIfamil	4.428	.037	-8.816	168
AIatt	.006	.941	1.886	165
easeofuse	.136	.712	1.594	165
useful	.250	.618	.971	162
AIliteracy	1.871	.173	.714	160
AIreliable	.120	.729	1.094	153
AIaccur	.132	.717	.190	153
AItrust	1.508	.221	.072	149
Manicheck_1	63.239	<.001	10.136	143

Manicheck_2	.127	.722	-2.364	142
Aad	3.786	.054	-3.937	145
Bad	26.239	0.001	-4.034	144
PI	.617	.434	-2.826	143

A.4 Table - Correlations

AI		**AIaware**	**AIusage**	**AIfamil**	**AIatt**	**easeofuse**	**useful**
AIaware	**Pearson Correlation**	1	0.164	.309**	-0.003	0.044	0.018
	Sig. (2-tailed)		0.12	0.003	0.979	0.678	0.87
	N	92	91	92	91	91	88
AIusage	**Pearson Correlation**	0.164	1	.353**	.364**	-0.048	.316**
	Sig. (2-tailed)	0.12		<.001	<.001	0.654	0.003
	N	91	92	92	91	91	88
AIfamil	**Pearson Correlation**	.309**	.353**	1	.319**	-0.144	.481**
	Sig. (2-tailed)	0.003	<.001		0.002	0.172	<.001
	N	92	92	93	92	92	89
AIatt	**Pearson Correlation**	-0.003	.364**	.319**	1	-0.203	.635**
	Sig. (2-tailed)	0.979	<.001	0.002		0.052	<.001
	N	91	91	92	92	92	89
easeofuse	**Pearson Correlation**	0.044	-0.048	-0.144	-0.203	1	-.253*
	Sig. (2-tailed)	0.678	0.654	0.172	0.052		0.017
	N	91	91	92	92	92	89
useful	**Pearson Correlation**	0.018	.316**	.481**	.635**	-0.253	1
	Sig. (2-tailed)	0.87	0.003	<.001	<.001	0.017	
	N	88	88	89	89	89	89
AIliter	**Pearson Correlation**	.565**	0.089	.336**	0.018	0.03	0.113

	Sig. (2-tailed)	<.001	0.416	0.001	0.865	0.782	0.297
	N	86	86	87	87	87	87
AIreliable	**Pearson Correlation**	-0.09	0.108	.237*	.386**	-0.097	.524**
	Sig. (2-tailed)	0.416	0.336	0.031	<.001	0.383	<.001
	N	83	82	83	83	83	83
AIaccur	**Pearson Correlation**	0.014	.299**	.363**	.494**	-.224**	.648**
	Sig. (2-tailed)	0.9	0.006	<.001	<.001	0.042	<.001
	N	83	82	83	83	83	83
AItrust	**Pearson Correlation**	0.073	.436**	.471**	.570**	-0.189	.767**
	Sig. (2-tailed)	0.523	<.001	<.001	<.001	0.095	<.001
	N	79	78	79	79	79	79
Manipulation_1	**Pearson Correlation**	0.104	0.172	0.074	0.001	-0.188	-0.022
	Sig. (2-tailed)	0.365	0.135	0.518	0.995	0.099	0.849
	N	78	77	78	78	78	78
Manipulation_2	**Pearson Correlation**	-0.125	-0.043	-0.082	0.051	0.89	0.161
	Sig. (2-tailed)	0.285	0.716	0.482	0.666	0.449	0.168
	N	75	74	75	75	75	75
Aad	**Pearson Correlation**	-.256*	.242*	0.05	.555**	0.059	.355**
	Sig. (2-tailed)	0.024	0.034	0.662	<.001	0.608	0.001
	N	78	77	78	78	78	78
Bad	**Pearson Correlation**	-.267*	0.193	0.12	.598**	-0.065	.378**
	Sig. (2-tailed)	0.018	0.093	0.296	<.001	0.569	<.001
	N	78	77	78	78	78	78
PI	**Pearson Correlation**	-0.054	0.205	0.057	.415**	0.025	.310**
	Sig. (2-tailed)	0.637	0.074	0.62	<.001	0.829	0.006
	N	78	77	78	78	78	78

AI	**AIliter**	**AIreliable**	**AIaccur**	**AItrust**	**Manipu_1**	**Manipu_2**	**Aad**	**Bad**	**PI**

AIaware	.565**	-0.9	0.014	0.073	0.104	-0.125	-.256*	-.247*	-0.054
	<.001	0.416	0.9	0.523	0.365	0.285	0.024	0.018	0.637
	6	83	83	79	78	75	78	78	78
AIusage	0.089	0.108	.299**	.436**	0.172	-0.043	.242*	0.193	0.205
	0.416	0.336	0.006	<.001	0.135	0.716	0.034	0.093	0.074
	86	82	82	78	77	74	77	77	77
AIfamil	.336**	.237**	.363**	.471**	0.074	-0.082	0.05	0.12	0.057
	0.001	0.031	<.001	<.001	0.518	0.482	0.662	0.296	0.62
	87	83	83	79	78	75	78	78	78
AIatt	0.018	.386**	.494**	.570**	0.001	0.089	.555*	.598**	.415**
	0.865	<.001	<.001	<.001	0.995	0.449	<.001	<.001	<.001
	87	83	83	79	78	75	78	78	78
easeofuse	0.03	-0.097	-.224*	-0.189	-0.188	0.161	0.059	-0.065	0.025
	0.782	0.383	0.042	0.095	0.099	0.168	0.608	0.569	0.829
	87	83	83	79	78	75	78	78	78
useful	0.113	.524**	.648**	.767**	-0.022	0.065	.355**	.378**	.310**
	0.297	<.001	<.001	<.001	0.849	0.582	0.001	<.001	0.006
	87	83	83	79	78	75	78	78	78
AIliter	1	.265**	0.196	0.194	0.078	0.074	0.022	-0.077	.227*
		0.015	0.076	0.087	0.499	0.532	0.847	0.505	0.046
	87	83	83	79	78	74	78	78	78
AIreliable	.265*	1	.572**	.628**	-0.029	0.068	.348**	.407**	.492**
	0.015		<.001	<.001	0.802	0.564	0.002	<.001	<.001
	83	83	82	78	77	75	78	78	78
AIaccur	0.196	.572**	1	.825**	0.135	0.096	.253*	.339**	.312**
	0.076	<.001		<.001	0.24	0.564	0.025	0.002	0.005
	83	82	83	79	78	75	78	78	78
AItrust	0.194	.628**	.825**	1	0.078	0.096	.316**	.345**	.287*
	0.087	<.001	<.001		0.535	0.417	0.005	0.002	0.012
	79	78	79	79	77	74	77	77	77
Manipulation_1	0.078	-0.029	0.135	0.072	1	-0.169	-0.144	-0.016	-0.07

	0.499	0.802	0.24	0.535		0.149	0.211	0.889	0.544
	78	77	78	77	78	74	77	77	77
Manipulation_2	0.065	0.074	0.068	0.096	-0.169	1	.248*	0.083	0.099
	0.582	0.532	0.564	0.417	0.149		0.033	0.485	0.402
	75	74	75	74	74	75	74	74	74
Aad	0.022	.348**	.253*	.316**	-0.144	.248*	1	.739**	.594**
	0.847	0.002	0.025	0.005	0.211	0.033		<.001	<.001
	78	78	78	77	77	74	78	78	78
Bad	-0.077	.407**	.339**	.345**	-0.016	0.083	.739**	1	.653**
	0.505	<.001	0.002	0.002	0.889	0.485	<.001		<.001
	78	78	78	77	77	74	78	78	78
PI	.227*	.492**	.312**	.287*	-0.07	0.099	.594**	.653**	1
	0.046	<.001	0.005	0.012	0.544	0.402	<.001	<.001	
	78	78	78	77	77	74	78	78	78

	AI	**AIaware**	**AIusage**	**AIfamil**	**AIatt**	**easeofuse**	**useful**
Human							
AIaware	**Pearson Correlation**	1	.283*	.349**	0.171	0.161	0.144
	Sig. (2-tailed)		0.013	0.002	0.143	0.168	0.218
	N	77	76	77	75	75	75
AIusage	**Pearson Correlation**	.283*	1	.239*	.301**	0.054	0.181
	Sig. (2-tailed)	0.013		0.037	0.009	0.648	0.123
	N	76	76	76	74	74	74
AIfamil	**Pearson Correlation**	.349**	.239*	1	.501**	0.065	.576**
	Sig. (2-tailed)	0.002	0.037		<.001	0.579	<.001
	N	77	76	77	75	75	75
AIatt	**Pearson Correlation**	0.171	.301**	.501**	1	-0.181	.550**
	Sig. (2-tailed)	0.143	0.009	<.001		0.12	<.001
	N	75	74	75	75	75	75
easeofuse	**Pearson**	0.161	0.054	0.065	-0.181	1	0.025

	AI	AIaware	AIusage	AIfamil	AIatt	easeofuse	useful
	Correlation						
	Sig. (2-tailed)	0.168	0.648	0.579	0.12		0.832
	N	75	74	75	75	75	75
useful	**Pearson Correlation**	0.144	0.181	.578**	.550**	0.025	1
	Sig. (2-tailed)	0.218	0.123	<.001	<.001	0.832	
	N	75	74	75	75	75	75
AIliter	**Pearson Correlation**	.556**	0.153	0.172	-0.036	0.22	0.102
	Sig. (2-tailed)	<.001	0.192	0.14	0.76	0.058	0.385
	N	75	74	75	75	75	75
AIreliable	**Pearson Correlation**	.242**	.278*	.390**	.389**	0.019	.587**
	Sig. (2-tailed)	0.04	0.019	<.001	<.001	0.877	<.001
	N	72	71	72	72	72	72
AIaccur	**Pearson Correlation**	-0.094	0.106	.281*	.475**	-0.167	.486**
	Sig. (2-tailed)	0.433	0.38	0.017	<.001	0.162	<.001
	N	72	71	72	72	72	72
AItrust	**Pearson Correlation**	0.044	0.115	.467**	.640**	-0.162	.700**
	Sig. (2-tailed)	0.714	0.338	<.001	<.001	0.174	<.001
	N	72	71	72	72	72	72
Manipu_1	**Pearson Correlation**	0.002	0.045	0.226	0.23	-.275*	0.171
	Sig. (2-tailed)	0.989	0.718	0.066	0.061	0.024	0.167
	N	67	66	67	67	67	67
Manipu_2	**Pearson Correlation**	-.246*	0.054	0	0.04	-0.074	-0.011
	Sig. (2-tailed)	0.042	0.661	0.999	0.747	0.544	0.925
	N	69	68	69	69	69	69
Aad	**Pearson Correlation**	-0.149	0.001	0.02	.256*	0.103	0.226
	Sig. (2-tailed)	0.223	0.991	0.869	0.034	0.402	0.062
	N	69	68	69	69	69	69
Bad	**Pearson**	-.249*	0.004	-0.088	0.189	0.1	0.132

	AI	AIaware	AIusage	AIfamil	AIatt	easeofuse	useful
	Correlation						
	Sig. (2-tailed)	0.04	0.974	0.478	0.123	0.419	0.284
	N	68	67	68	68	68	68
PI	**Pearson Correlation**	-0.04	-0.098	0.07	0.179	0.122	0.09
	Sig. (2-tailed)	0.75	0.432	0.572	0.147	0.324	0.471
	N	67	66	67	67	67	67

	AIliter	AIreliable	AIaccur	AItrust	Manipu_1	Manipu_2	Aad	Bad	PI
Human									
AIaware	.556**	.242*	-0.094	0.044	0.002	-.246*	-0.149	-.249*	-0.04
	<.001	0.04	0.433	0.714	0.989	0.042	0.223	0.04	0.75
	75	72	72	72	67	69	69	68	67
AIusage	0.153	.278*	0.106	0.115	0.045	0.054	0.001	0.004	-0.098
	0.192	0.019	0.38	0.338	0.718	0.661	0.991	0.974	0.432
	74	71	71	71	66	68	68	67	66
AIfamil	0.172	.390*	.281*	.467**	0.226	0	0.02	-0.088	0.07
	0.14	<.001	0.017	<.001	0.066	0.999	0.869	0.478	0.572
	75	72	72	72	67	69	69	68	67
AIatt	-0.036	.389**	.475**	.640**	0.23	0.04	.256*	0.189	0.179
	0.76	<.001	<.001	<.001	0.061	0.747	0.034	0.123	0.147
	75	72	72	72	67	69	69	68	67
easeofuse	0.22	0.019	-0.167	-0.162	-.275*	-0.074	0.103	0.1	0.122
	0.058	0.877	0.162	0.174	0.024	0.544	0.402	0.419	0.324
	75	72	72	72	67	69	69	68	67
useful	0.102	.587**	.486**	.700**	0.171	-0.011	0.226	0.132	0.09
	0.385	<.001	<.001	<.001	0.167	0.925	0.062	0.284	0.471
	75	72	72	72	67	69	69	68	67
AIliter	1	.254*	-.247*	-0.059	0.092	-.298*	-0.063	-0.121	0.159
		0.031	0.036	0.622	0.46	0.013	0.605	0.327	0.198
	75	72	72	72	67	69	69	68	67
AIreliable	.254*	1	.411**	.445**	0.095	-0.093	0.18	0.206	0.156
	0.031		<.001	<.001	0.447	0.445	0.139	0.092	0.207

	72	72	72	72	67	69	69	68	67
AIaccur	-.247*	.411**	1	.744**	0.057	0.2	.419**	.435**	0.057
	0.036	<.001		<.001	0.65	0.873	<.001	<.001	0.645
	72	72	72	72	67	69	69	68	67
AItrust	-0.059	.445**	.744**	1	0.179	0.029	.327**	.292*	0.93
	0.622	<.001	<.001		0.148	0.812	0.006	0.016	0.456
	72	72	72	72	67	69	69	68	67
Manipu_1	0.092	0.095	0.057	0.179	1	-.367**	-0.123	-0.066	-0.034
	0.46	0.447	0.65	0.148		0.002	0.321	0.596	0.789
	67	67	67	67	67	67	67	66	65
Manipu_2	-.298*	-0.093	0.02	0.029	-.367**	1	.271*	0.21	-0.113
	0.013	0.445	0.873	0.812	0.002		0.024	0.086	0.363
	69	69	69	59	67	69	69	68	67
Aad	-0.063	0.18	.419**	.327**	-0.123	.271*	1	.768**	.414**
	0.605	0.139	<.001	0.006	0.321	0.024		<.001	<.001
	69	69	69	69	67	69	69	68	67
Bad	-0.121	0.206	.435**	0.292*	-0.066	0.21	.768**	1	.495**
	0.327	0.092	<.001	0.016	0.596	0.086	<.001		<.001
	68	68	68	68	66	68	68	68	67
PI	0.159	0.156	0.057	0.093	-0.034	-0.113	.141**	.495**	1
	0.198	0.207	0.654	0.457	0.789	0.363	<.001	<.001	
	67	67	67	67	65	67	67	67	67

A.5 Table - Regressions

Model Summary						
Model	**Predictors**	**DV**	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	**AIaccur**	**AItrust**	0.862	0.743	0.734	0.66891
	AIliter					
	easeofuse					
	AIreliable					
	useful					

2	**AItrust**	**Aad**	0.29	0.084	0.078	1.3782
3	**AItrust**	**Bad**	0.297	0.088	0.082	1.26788
4	**AItrust**	**PI**	0.193	0.037	0.03	1.40142
5	**AItrust**	**PI**	0.624	0.389	0.379	1.1241
	Aad					
	Bad					
6	**AItrust**	**Bad**	0.297	0.088	0.082	1.26788
7	**AItrust**	**Bad**	0.764	0.584	0.578	0.85967
	Aad					
ANOVA						
Model		**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
1	**Regression**	186.577	5	37.315	83.397	<0.001
	Residual	64.432	144	0.447		
	Total	251.008	149			
2	**Regression**	25.126	1	25.126	13.228	<0.001
	Residual	273.52	144	1.899		
	Total	298.646	145			
3	**Regression**	22.165	1	22.165	13.788	<0.001
	Residual	229.876	143	1.608		
	Total	252.041	144			
4	**Regression**	10.738	1	10.738	5.467	<0.001
	Residual	278.886	142	1.964		
	Total	289.623	143			
5	**Regression**	112.72	3	37.573	29.735	<0.001
	Residual	176.903	140	1.264		
	Total	289.623	143			
6	**Regression**	22.165	1	22.165	13.788	<0.001
	Residual	229.876	143	1.608		

	Total	252.041	144			
7	**Regression**	147.099	2	73.549	99.521	<0.001
	Residual	104.943	142	0.739		
	Total	252.041	144			

A.6 Table - Coefficients

		DV	Unstandardized B	Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	aitrust	-0.714	0.447		-1.599	0.112
	easeofuse		-0.025	0.071	-0.015	-0.349	0.728
	useful		0.381	0.055	0.389	6.958	<0.001
	ailiter		0.052	0.043	0.055	1.21	0.228
	aireliable		0.05	0.059	0.047	0.852	0.396
	aiaccur		0.653	0.067	0.541	9.789	<0.001
2	(Constant)	Aad	2.613	0.379		6.901	<0.001
	aitrust		0.325	0.089	0.29	3.637	<0.001
3	(Constant)	Bad	2.556	0.357		1.17	<0.001
	aitrust		0.312	0.084	0.297	3.713	<0.001
4	(Constant)	PI	1.741	0.394		4.416	<0.001
	aitrust		0.217	0.093	0.193	2.338	0.021
5	(Constant)	PI	-0.047	0.374		-0.125	0.9
	aitrust		0.003	0.078	0.002	0.033	0.974
	Aad		0.202	0.101	0.203	1.998	0.048
	Bad		0.488	0.11	0.455	4.442	<0.001
6	(Constant)	Bad	2.556	0.357		7.17	<0.001
	aitrust		0.312	0.084	0.297	3.713	<0.001
7	(Constant)	Bad	0.736	0.279		2.635	0.009
	aitrust		0.102	0.059	0.097	1.725	0.087
	Aad		0.678	0.052	0.732	13.002	<0.001

Appendix B:References

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