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AI vs. Human: Ad Creator Influence

How Ad Creators Shape Consumer Responses and Acceptance of AI in Advertising.

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Title:	AI vs. Human: Ad Creator Influence – How Ad Creators Shape Consumer Responses and Acceptance of AI in Advertising.
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Key terms: Artificial Intelligence, Ad Creator, Anxiety, Attitude, Personality Traits.

Background:

In an era where artificial intelligence (AI) increasingly infiltrates the creative domains traditionally dominated by humans, a critical question arises: How does the believed origin of an advertisement—whether generated by AI or crafted by a human—affect consumer perception and behavior? The integration of AI in advertising has stirred significant academic and practical interest, exploring how AI impacts consumer behavior differently from traditional human-created ads. Recent studies have highlighted varying consumer responses based on the advertised source, be it AI or human, influencing key advertising metrics.

Purpose:

This study aimed to investigate the effects of the belief of AI versus human made ads on consumer behavior dimensions such as Purchase Intention (PI), Ad Evaluation (Eva_M), and Word of Mouth (WOM). It also sought to understand how these effects are mediated by anxiety and moderated by personality traits like agreeableness, extraversion, openness, and demographics age and level of education. Thus, this paper explores the nuanced psychological impacts and behavioral outcomes triggered by the believed source of advertising content, unveiling the subconscious biases and overt responses of consumers to AI versus human creator.

Method:

A comparative analysis involving the same ad in two survey groups (Survey A – marked as AI-generated ad – and Survey B – marked as human-made ad) was conducted, with participants unaware of the believed ad origin variation. The study employed the PROCESS Macro Models 1 and 4 in SPSS to analyze the direct effects and interactions. The level of Anxiety was tested as a mediator and personality traits and demographic factors were tested as moderators to gauge their influence on the effectiveness of AI-generated versus human-made ads.

Conclusion:
The results show that ads believed as AI-generated performed less effectively across Purchase Intention, Ad Evaluation, and Word of Mouth compared to those believed to be human-made. Significant mediation of anxiety and significant moderation effects were found with traits such as agreeableness and extraversion positively influencing ad reception, while higher levels of education tended to buffer negative perceptions of AI-generated ads. These findings suggest that consumer characteristics play a crucial role in the reception and effectiveness of AI-generated advertising, underscoring the need for tailored advertising strategies that consider both the source of the ad and the target demographic's psychological and demographic profiles.

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This thesis has demonstrated the significant impact of the creator on its creation. On a personal level, it has highlighted something beyond scientific measurement – the importance of the people around you. As the creators of this thesis, we would therefore like to express our gratitude to our muses.

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Last but certainly not least, we want to thank our parents. We love you.

Yours,

Louisa Horgby

Daniele Galizzi

Declaration of Ethical AI Use

We hereby declare that this thesis represents our own work.

We declare that we have obtained the necessary ethical approval (e.g., GDPR) and acknowledged our obligations and the rights of the participants/respondents in the research. We have read and applied the Jönköping University's current research ethics guidelines with regards to the use of artificial intelligence (AI) tool in this work as presented in the Course Guide. During the preparation of this work the authors used the following AI tools and the purpose for their use.

Dall-E for generating an Image for the ad used in the experiment.

DeepL to translate texts.

ChatGPT and **Consensus** to get an overview of subject areas, analyzing data, and to improve the writing.

As authors, we have reviewed and edited the content as needed and take full responsibility for the content of the thesis.

Louisa Horgby

Daniele Galizzi

17. Mai 2024

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List of Abbreviations

AI – Artificial Intelligence
Et al. – and others

H1.1a – Hypothesis 1.1a
H1.1b – Hypothesis 1.1b
H1.1c – Hypothesis 1.1c…

RQ1 – Research Question one
RQ2 – Research Question two
RQ3 – Research Question three

Survey A – Survey with Advert marked as AI-generated
Survey B – Survey with Advert marked as human-made

1. Introduction

In this chapter, we delve into the evolving role of artificial intelligence (AI) in advertising. We introduce how the believed ad creator—whether human or AI—influences consumer responses. Thereby a significant research gap emerges, which leads to the research questions. The purpose of this chapter is to explore these dynamics, highlighting the necessity of understanding consumer responses and acceptance of AI in advertising.

1.1. Background

Content created by employing AI algorithms, also known as synthetic content, promises to radically change the advertising and marketing landscape in the coming decades, presumably for the better (Arango, Singaraju, & Niininen, 2023). Before promoting widespread use, it is essential for marketing scientists and practitioners to have a solid understanding of how synthetic content is perceived by consumers.

As the boundaries between human creativity and artificial intelligence (AI) blur in the advertising industry, it is crucial to assess how the identity of the ad creator – whether AI or human – affects consumer responses. The reliability and perceived authority of an ad creator are instrumental in cultivating consumer trust and driving effective persuasion within marketing campaigns (Thompson & Malaviya, 2013). Thus, the creator of an advertisement significantly influences consumer acceptance and behavior, highlighting the importance of transparency in advertisement origination, as this can greatly affect the overall effectiveness of marketing campaigns.

Studies have shown that the perceived origin of content, whether human or technological, markedly influences both the cognitive and emotional responses of consumers, which in turn impacts their willingness to engage with and react to advertisements (Wu & Wen, 2021; Singh, 2023). This underscores the crucial role of the advertisement creator in shaping consumer perceptions and acceptance (Ismagilova, Slade, Rana, & Dwivedi, 2020). As AI continues to proliferate in marketing, understanding consumer acceptance of AI-generated advertisements has become a key focus in contemporary research and practice.

Copywriting and the creation of visual illustrations and representations – traditionally seen as the exclusive domain of human creativity and understanding – is undergoing a significant transformation as AI and machine learning technologies begin to play a crucial role in this field (Yilmaz, 2023). The production and distribution of advertising materials has traditionally relied on human labor and analogue tools. However, technological innovations have provided the advertising industry with digital and automatic tools that allow advertisers to automate many advertising processes, i.e. advertising whose content is based on the artificial and automatic generation and modification of data (Campbell, 2021). This means, that with AI many things become possible. The question that remains as a marketer is – should it be done?

1.2 Research Problem and Research Questions

With the rise of AI, ambivalent acceptance has echoed through various industries. The discourse around the application of AI in marketing communication reveals a wide spectrum of scholarly opinions, reflecting the nuanced perspectives on its impact from a customer viewpoint, highlighting both the positive and negative aspects. On one hand, proponents argue that AI enhances marketing communication through personalized experiences and increased efficiency, pointing to the technology's capacity to analyze consumer data for tailored interactions (Merisavo et al., 2007). On the flip side, critics raise concerns about the ethical implications and potential risks to privacy, asserting that AI could erode consumer trust and underscore a lack of human touch in digital interactions (Gonçalves et al., 2023). This divergence in viewpoints highlights the complex relationship between technological advancement and consumer satisfaction presented by AI in advertising.

How consumers response to the use of AI in advertising is still unclear. Recent studies have investigated AI acceptance in advertising from a company perspective, yet the consumer perspective remained unclear to a large extend (Wu & Wen, 2021). Same holds for the understanding of why consumers respond differently to AI usage (Wu & Wen, 2021; Arango et al., 2023).

Generally, consumers are uneasy about robots (Song et al., 2023). This is a double-edged sword when it comes to how they react to AI-generated advertising. AI advertising could both enhance their appreciation of advertising by activating the positive machine heuristic and jeopardize this appreciation by making them perceive AI advertising as creepy (Wu & Wen, 2021). Thus, 'AI anxiety' became recently a new field of research (Kaya et al., 2024). It is therefore important for advertisers who want to use AI to create adverts to know whether AI-generated adverts are received differently from human-created adverts and, if so, what triggers their target customers' discomfort with the use of AI.

Previous studies on AI artwork have shown a negative bias towards art generated by AI. People tend to judge artworks less favorably when they are labelled as artworks generated by AI (Elgammal et al., 2017; Chamberlain et al., 2017). Visual adverts in their original form are also created solely by humans and can therefore also be understood as "works of art" in a broader sense. If we apply these insights on AI art perception to the perception of visual advertisements, the following research questions emerges given the generally mixed levels of anxiety and attitudes of consumers towards AI:

- **RQ1: Does believing a visual ad is made by AI or a human affect the consumer response?**
- **RQ2: Does anxiety mediate how consumers response to ads depending on whether they are believed to be AI or human made?**
- **RQ3: What factors influence consumer response to AI-generated ads?**

The aim of this study is to examine whether consumers evaluate adverts differently when they are generated by AI or created by a human (RQ1) and, if so, which factors influence the different evaluation (RQ3). Furthermore, this study investigates how consumer responses may differ based solely on the believed creator of the ad. Thus, anxiety and its potential mediation will be measured (RQ2). From this, the effects of AI-generated advertising on consumer responses are to be derived, leading to valuable managerial implications, such as whether the use of AI should be "concealed" or not.
Furthermore, the research aims to contribute to the existing literature by highlighting the consumer perspective on AI-generated advertising images. This study further aims to fill a gap in the current advertising literature, which is that AI in advertising has been

predominantly studied from the perspective of advertisers or advertising professionals (Wu & Wen, 2021). Although scholars have proposed several directions for future research on AI in advertising, the consumer perspective has not yet been sufficiently emphasized (Li, 2019). However, consumers are the final judges of advertising effectiveness. Therefore, their overall appreciation of AI-generated advertising should be an important consideration in this area of research (Wu & Wen, 2021).
Thus, the study may provide insights into the transformative potential of AI in the advertising industry and help practitioners and academics understand the impact of AI on consumer responses in this context.

In this study 'consumer response' serves as a collective term for the evaluation of an advertisement, the resulting purchase intent, and its subsequent word of mouth.

1.3 Purpose

Visual advertising is crucial for communicating brand messages and engaging consumers, and its importance is becoming even greater in today's digital landscape where consumer attention is highly fragmented. With advances in AI, visual advertising has evolved to enable personalized and targeted messages through sophisticated analysis of consumer data, which can increase engagement and response rates (Merisavo et al., 2007). Thus, many practitioners have already applied AI in their marketing strategies.

Spotify uses AI to personalize music recommendations, but it extends this technology to advertising as well (Kaput, 2024). By analyzing users' listening habits, Spotify can offer highly targeted ads that are relevant to the individual's mood or interests. This strategy has increased the effectiveness of ads and enhanced user satisfaction. However, the integration of AI also raises ethical concerns, particularly in relation to privacy and the authenticity of digital communications, which could undermine trust and compromise the effectiveness of advertising (Gonçalves et al., 2023). Considering these issues, further research is needed to understand consumer responses to AI-generated advertising and investigate potential biases that may influence perceptions in AI-generated visuals. This research is crucial for optimizing marketing strategies that balance human creativity with AI efficiency and consider the wider impact of AI on our interactions with technology.

Considering the varied research outcomes on consumer reactions and acceptance towards AI and its increasingly important role in advertising, it is particularly relevant and interesting to investigate consumer acceptance of AI in this context. The exploration of consumer acceptance of AI is crucial given its substantial potential to transform marketing practices. AI significantly enhances marketing by streamlining processes, reducing costs, and automating workflows (Kalicanin et al., 2019). Thus, traditional marketing techniques can be effectively innovated, and the overall quality of marketing development can be improved when AI and marketing technology are combined (Yilmaz, 2023). Smaller enterprises or startups that struggle to find the budget to work with an advertising agency can do these tasks themselves with the help of AI. Advertising agencies that work for larger companies, on the other hand, can also integrate AI into their work processes to increase effectiveness. Thus, Reshetkova (2019) concludes that AI has the potential to increase the effectiveness of advertising generally. But does increasing the effectiveness of content creation in advertising through AI also increase customer purchase intent? Or could it even have a negative impact on it because the customers are afraid of the ad generator?

Given the significant potential of AI as a tool in advertising, it is important for marketing professionals to explore how awareness of AI usage affects consumer perceptions of the advertising of products and brands, as well as their response. This is in line with the research call by Wu and Wen (2021), who focused on the overall perception of AI-powered advertising in their study. According to Wu and Wen (2021), future research should compare human-created adverts with AI-generated adverts and investigate which factors influence the different consumer responses, which this study aims to answer.

1.4 Definitions

Artificial Intelligence

In this study, AI is defined as a technology that simulates human intelligence and, through flexible adaptation enabled by learning, unlearning, and relearning, provides added value (Bock et al., 2020; Qin & Jiang, 2019). As an advanced technology that can sift through extensive customer data and derive insights from it, AI can learn and gain intelligence from the process (Ford et al., 2023). Consequently, the use of AI in advertising can complement the advertisers' intelligence in deciphering structured and unstructured customer data to gain insights (Mogaji et al., 2021). Thus, AI can generate and deliver advertisements based on consumer interests and preferences (Ford et al., 2023).

Visual Advertisement

Visual advertising refers to the strategic use of visual elements, such as images, colors, symbols, and videos, to communicate advertising messages and persuade the target audience (Ye et al., 2019). In this study we will focus on images mainly. Visual advertising leverages the power of visual rhetoric, which involves the use of visual figures and elements as rhetorical devices to effectively convey messages and evoke desired responses from viewers (Vu, 2017). It plays a crucial role in influencing consumer behavior, enhancing brand awareness, and driving engagement by making complex ideas more accessible and memorable through visual representation (Mitchell & Olson, 1981).

Purchase Intent

The purchase intent measures the likelihood of consumers purchasing a product after being exposed to an advertisement. Research indicates that advertising influences purchase intent directly by shaping consumer attitudes and preferences (Duffett, 2015).

Ad Evaluation

Ad evaluation refers to the process of assessing and measuring the effectiveness of advertising campaigns based on specific criteria such as ethicality, likeability, humor, and informational content (Massey et al., 2015).

Word of Mouth

Word of mouth (WOM) involves the sharing of product information by consumers with others, which can significantly amplify the reach and impact of an advertisement. Graham and Havlena (2007) discuss the strong link between advertising and positive WOM, indicating that effective advertisements can enhance brand advocacy and significantly influence purchase decisions through increased WOM (Graham & Havlena, 2007).

1.5 Study Overview

This explorational study will focus on how the believed ad creator—whether AI or human—affects consumer responses. To guide this analysis, we will utilize the Theory of Reasoned Action (TRA) by Ajzen and Fishbein (1980) and the Big Five Personality Traits by Costa and McCrae (1992), which provides a framework for understanding the influences on behavioral intentions. The research employs a quantitative approach, collecting data from two distinct groups of participants, each comprising around 140 individuals, through online surveys conducted via Qualtrics. These groups will evaluate an advert, with one group being informed that the advert was generated by AI and the other being told that it was created by humans. This research design is intended to eliminate biases such as brand awareness and personal preferences so that the focus is solely on the impact of the believed origin of the advertising on consumer response.

The study will investigate the mediating effect of anxiety concerning AI in advertising creation, while also exploring the moderating effects of attitude towards AI, personality traits, and demographic characteristics. The quantitative analysis will include independent samples t-tests, regression analyses, and moderated mediation analysis, aiming to understand the nuanced effects of knowing an ad's creator on consumer behavior. This methodology allows us to systematically assess and compare the effectiveness and reception of AI-generated content in the advertising domain, contributing valuable findings to the discourse on AI's role in creative industries.

2. Literature Review

This chapter presents a review of existing literature related to the purpose of this study. It lays the theoretical framework for investigating the impact of AI in advertising. Through a structured literature review and the integration of theories, we formulate hypotheses to guide our empirical inquiry. This theoretical framework sets the stage for rigorous analysis, aiming to understand the broader implications of AI-generated advertising on consumer response.

The integration of AI in advertising is a transformation that promises significant changes to the landscape of marketing communications (Yilmaz, 2023). This literature review examines interdisciplinary perspectives on how consumers perceive and react to AI-generated content in advertising, utilizing a blend of marketing, psychology, technology, and ethics studies to offer a comprehensive overview.

2.1 Visual Advertisement – From Posters to Personalization

Visual advertising has changed dramatically over the centuries, from the simple shop signs of ancient civilizations to complex digital ads that can now be created by AI itself (Huh et al., 2023). Initially, visual advertising flourished through physical media such as billboards and printed illustrations in newspapers and magazines in the 19th and early 20th centuries (Ford et al., 2023).

As the 20th century progressed, television became a dominant medium, heralding the golden age of television advertising from the 1950s to the 1980s. By the 1990s, however, the market was saturated with visual advertising, leading to a desensitization of consumers and a noticeable decline in the effectiveness of traditional advertising methods (McGuigan, 2019). This saturation was exacerbated by the digital revolution of the 2000s, which introduced new advertising platforms such as banner ads and video adverts on websites. The digital space quickly became cluttered, fueling consumer ad fatigue and the emergence of ad blocking technologies (Barnes & Hair, 2009).

The effectiveness of visual advertising continued to decline until the late 2010s - when social media became “a thing”. Social media platforms have become a dominant space for visual advertising due to the high engagement levels and the ability of these platforms to integrate seamlessly into the daily lives of users (Bellman, Robinson, Wooley, & Varan, 2017). Advertisements on social media are not only prevalent but also highly targeted, leveraging data to personalize ads to user preferences, which increases their effectiveness (Alalwan, 2018). The demand of personalized advert emanating from social media started to be met through the strategic use of AI – and is still going on. Artificial intelligence's ability to analyze vast amounts of consumer data enabled unprecedented levels of ad personalization, making visual advertising more relevant and less intrusive (Huh et al., 2023). Modern programmatic buying - where ads are automatically served based on their likelihood to appeal to specific people - has helped revitalize the effectiveness of visual ads by reducing redundancy and increasing relevance.

Thus, the advertising ecosystem has radically changed in the last two decades (Donthu et al., 2022). With new technology and the explosion of digital media, advertising has evolved from traditional forms such as newspapers, billboards, radio and television to various new and exciting media and platforms. Modern advertising media uses artificial intelligence to increase the effectiveness of advertising and optimize ad delivery (Ford et al., 2023).

AI in marketing can be seen as a set of breakthrough technologies that enable machines to solve problems, facilitate decision-making, and perform tasks associated with humans and their intelligence (Qin & Jiang, 2019; Copeland, 2021). AI has made advertising more competent, personalized, targeted, and intelligent by automating and facilitating key functions of advertising, such as consumer information discovery, media planning, purchasing, ad creation and impact evaluation (Chen et al., 2019; Deng et al., 2019; Li, 2019).

2.2 The Importance of the Ad Source

With an ever-improving AI, the question arises as to whether the origin of an advert is relevant if customers cannot easily recognize that the advert was created by an AI. - Yet we argue that the origin of an advertisement does matter.

The origin of marketing communication plays a pivotal role in influencing the attitudes and behavioral intentions of customers. This is underpinned by several communication and persuasion theories, including the Elaboration Likelihood Model (Petty & Cacioppo, 1983), the Heuristic-Systematic Model (Chaiken, 1980), and research on source credibility (Pornpitakpan, 2004; Biswas et al., 2006). These theories and empirical studies emphasize that the effectiveness of communication in marketing to influence consumer attitudes and behaviors depends not only on the content of the message but also significantly on the characteristics of the source delivering it. Furthermore, the study of O'Cass and Grace (2004) explores the impact of both marketer-controlled and marketer-uncontrolled communications on consumers' feelings and attitudes towards service brands. Their findings highlight the crucial role that the origin of marketing communications plays in shaping consumer responses, especially in service settings like retail stores and banks.

Similarly, the study of Yilmaz et al. (2011) shows that the likability and credibility of the advertising source have a direct impact on effectiveness of print advertisements, influencing attitudes toward the ad, the brand, and the willingness to purchase. The impact varies across different levels of consumer involvement and product category knowledge, highlighting the need to consider source characteristics carefully in marketing communications (Yilmaz et al., 2011).

Furthermore, research suggests that a likeable source in an advertisement will generate increased attention to the advertisement and positive feelings towards the brand, which will then be reflected in the likelihood of purchase (Callcott & Phillips, 1996). The more credible the source, the more likely it is that consumers will be influenced by the message (Petty & Wegener, 1998; Pornpitakpan, 2004). Thus, the credibility and the general acceptance of the advertisement creator or generator has an impact on the performance of the ad and consumer responses to it.

2.2.1 Understanding Consumer Perceptions of AI-Generated Content

A study by Wu and Wen (2021) reveals that consumers' acceptance of AI-generated advertisements is influenced by their perceived objectivity of the advertisement creation process. This perception positively affects the machine heuristic—consumers' belief that machines are more secure and trustworthy than humans—which in turn enhances appreciation for AI-generated ads. However, Wu and Wen (2021) point also out that the perceived creepiness of AI advertising can negatively impact consumer appreciation, highlighting the dual effects of AI's role in advertising.

Similarly, the study by Arango, Singaraju, and Niininen (2023) explores how consumer perceptions are shaped by AI-generated content in the context of charitable advertising. The study investigates how potential donors react to AI-created images of children used in charity ads, revealing that knowledge of the AI involvement impacts donation intentions negatively. This effect is mediated by reduced feelings of empathy and altered emotion perception, suggesting that consumers may feel less emotionally connected and more skeptical when they are aware that the content is artificially generated. The research underscores a crucial consideration for nonprofits using AI in their advertising strategies: the importance of maintaining transparency and ethical standards to ensure that the use of AI does not undermine the authenticity or effectiveness of their fundraising efforts. The authors recommend a cautious approach to employing synthetic content, emphasizing that charities should clearly communicate their ethical motives when using AI to mitigate potential adverse reactions from the public.

Furthermore, Adhikari and Singh (2023) discusses the role of AI in enhancing personalization in eCommerce advertising, which can lead to improved consumer experiences. However, the paper also warns of significant concerns regarding data privacy and biases in AI algorithms, which are pivotal in maintaining consumer trust. Thus, YouTube faced significant challenges with its AI-driven ad placement system when major brands discovered their ads were being displayed next to videos containing hate speech and extremist content: Despite the platform's intent to align ads with viewer preferences and relevant content, this misalignment led to a backlash from advertisers, many of whom paused their spending (Solon, 2020). The incident underscored the risks of relying solely on automated systems, prompting YouTube to enhance its content policies, improve its AI algorithms, and increase human oversight to ensure more appropriate ad placements and safer monetization practices. These insights call for a balanced view of AI's capabilities and its potential pitfalls.

2.2.2 Interdisciplinary Insights on AI in Advertising

Chuan, Tsai, and Yang (2023) provide a comprehensive overview of AI in advertising, focusing on the ethical and sociopolitical consequences of hyper-personalization and commercial surveillance. Their work advocates for stricter regulations and corporate digital responsibility to ensure the ethical use of AI in marketing communications and emphasizes the need for AI literacy among advertisers. Holbrook and Batra (1987) delve into the emotional aspects of consumer behavior, proposing models that assess how emotions mediate the effects of advertising on consumer responses. These models are increasingly relevant in analyzing responses to AI-generated content, where emotional engagement can differ significantly from traditional human-created ads (Holbrook & Batra, 1987).

Building on these perspectives, examining the attitude towards AI and personality traits in general are essential for understanding consumer reactions to AI-driven advertising.

2.3 Study Design

This experimental study is structured to investigate the impact of the ad creator (AI vs. Human) on various outcomes, specifically advertisement evaluation, purchase intent, and word of mouth. The ad creator serves as the independent variable, while the outcomes mentioned function as the dependent variables. These dependent variables are pivotal as they help ascertain the effectiveness of the advertisement and its subsequent influence on consumer response.

This quantitative approach is inspired by the work of Hong and Curran (2019) on "Artificial Intelligence, Artists, and Art: Attitudes Toward Artwork Produced by Humans vs. Artificial Intelligence" and shall extend this inquiry into the realm of advertising. Our research focuses on comparing consumer evaluations of advertisements based on their believed origins: generated by AI versus created by human creativity. This study design is based on the following hypothesizes.

H1a: *Ads believed as AI-generated ads will score lower in Purchase Intention than ads believed as human-made.*
H1b: *Ads believed as AI-generated ads will score lower in Ad Evaluation than ads believed as human-made.*
H1c: *Ads believed as AI-generated ads will score lower in WOM than ads believed as human-made.*

Furthermore, the study incorporates a mediator, anxiety, which will be assessed to understand how it influences the relationship between the believed ad creator and the outcomes. Anxiety in this context refers to the emotional response of participants in general but is primarily examined in relation to AI-generated content compared to human-generated content (see *Figure 1*).

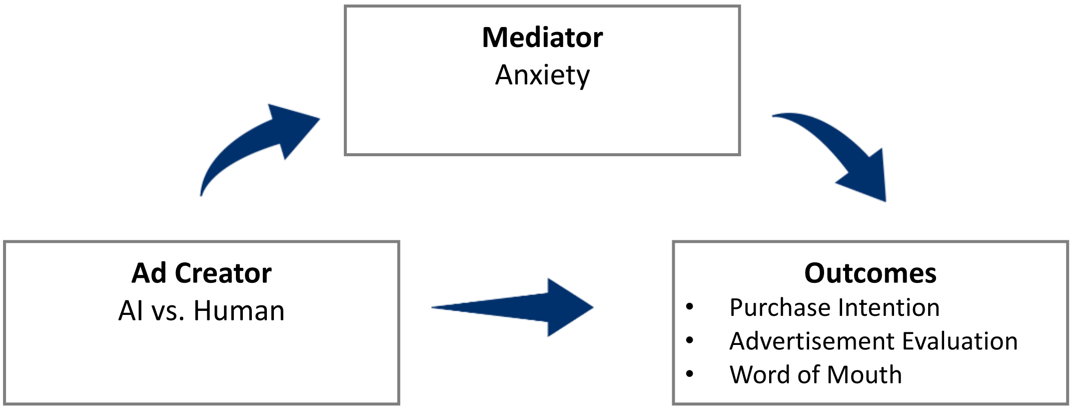

Figure 1 - Study Design with Mediator Anxiety
Source: Authors' illustration

The study also includes several moderators that could influence the interaction between the independent variable and the dependent variables. These moderators include:

- **Attitude (TRA)**: This refers to the Theory of Reasoned Action, suggesting that an individual's behavior is driven by their intention, which in turn is influenced by their attitude toward the behavior and subjective norms.

- **Openness to Experience**: This personality trait could affect how participants perceive and react to innovations like AI in advertising.
- **Extraversion**: The impact of extraversion might be significant in terms of how participants engage with and respond to the ads.
- **Agreeableness**: This could influence how positively participants view and evaluate the ads, affecting their reported purchase intent and willingness to engage in word of mouth.
- **Demographics**: Factors such as age and level of education are included as moderators to explore how different demographic groups perceive and are influenced by AI versus human-created ads.

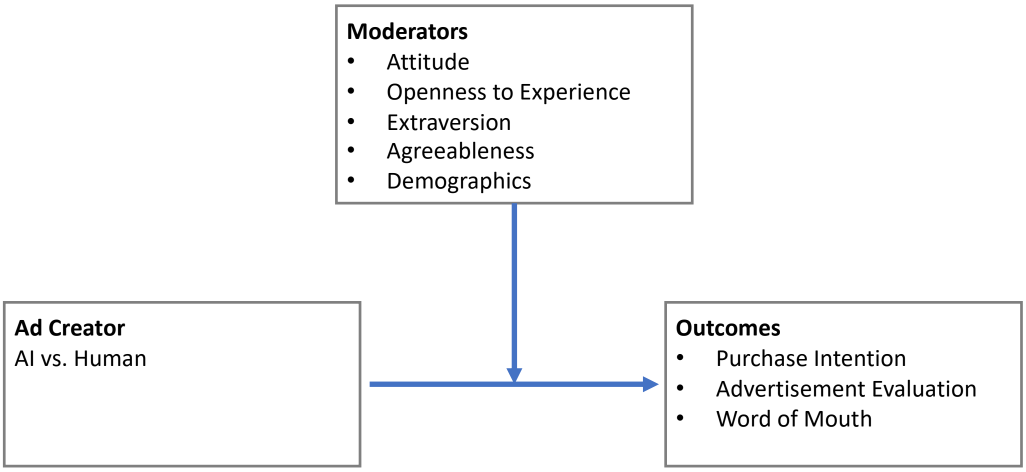

Figure 2 - Study Design with Moderators

Source: Authors' illustration

This design allows the study to comprehensively assess the direct effects of the ad creator on consumer responses and how these effects are potentially modified by individual differences and psychological factors (see *Figure 2*). This approach not only enriches the understanding of advertising dynamics but also provides nuanced insights into consumer behavior in the context of technological advancements in advertising. Based on the TRA, the study offers a quantitative analysis approach that ensures a comprehensive evaluation of consumer responses. By using an ad with a fictitious brand and product, possible distortions due to brand recognition are eliminated, ensuring high internal validity. Thus, this design is strategically suited to decipher the psychological interplay between advertiser perceptions and consumer responses in the digital advertising landscape.

2.4 Anxiety as a Mediator

Anxiety is a multifaceted construct that manifests in various forms, including apprehensions about learning new technologies and fears of being replaced by automation (Johnson & Verdicchio, 2017). Thus, people have concern that AI will affect the labor market, since it will make many human jobs redundant. This fear is not unfounded, as this is already a trend in call centers, assembly lines and the fast-food industry. Creative work, such as creating adverts, is another area where AI appears to be outperforming humans (Hong & Curran, 2019). There are concerns about AI as such, but also about the usage of AI.

AI technology brings challenges such as job losses, privacy and transparency concerns, algorithmic biases, growing socio-economic inequalities and unethical actions (Green, 2020). These challenges can lead to disruption, which manifests itself in the form of anxiety (Kaya et al., 2024). Thus, it is not surprising that scientist specify this form of anxiety as “AI anxiety” most recently. According to Kaya et al. (2024) AI anxiety can be defined as excessive fear of problems resulting from changes in personal or social life caused by AI technologies.

General anxiety traits can predispose individuals to higher levels of AI Anxiety, suggesting a correlation between general anxiety levels and specific anxieties related to new technologies. This is supported by research showing that individuals with higher general anxiety are more likely to exhibit fear or apprehension towards AI and its applications in various fields (Johnson & Verdicchio, 2017).

In the context of our study, which examines the acceptance of AI-generated advertisements, anxiety serves therefore as a pertinent mediator. It captures the nuanced psychological barriers that may influence an individual’s receptivity to AI. This relevance is twofold: first, the anxiety studied here encompasses the fear and dislike of learning and mastering AI technology. Secondly, anxiety here includes fear about the potential impact of AI, particularly on the workplace.

By incorporating anxiety as a mediator, this study recognizes and measures these underlying anxieties, providing a clearer picture of how they may dampen the acceptance of AI-driven advancements in the advertising sector. This approach is fitting because it allows us to isolate and understand the indirect effects of these anxieties on the relationship between the ad creator (AI vs. Human) and consumer outcomes.
This leads to these Hypothesizes:

H2a: *The Ad Creator (AI vs. Human) mediates through the level of anxiety the Purchase Intent.*
H2b: *The Ad Creator (AI vs. Human) mediates through the level of anxiety the Ad Evaluation.*
H2c: *The Ad Creator (AI vs. Human) mediates through the level of anxiety WOM.*

2.5 Theory of Reasoned Action (TRA)

The Theory of Reasoned Action (TRA) by Ajzen and Fishbein (1980) is one of the most popular theoretical frameworks for understanding behavior based on attitudinal and social factors (see *Figure 3*). The TRA encompasses an individual's intention to perform a behavior, attitudes towards the behavior and subjective norms, whereby an individual's intentions to perform the behavior in question are determined by attitudes towards the behavior and subjective norms (Ajzen & Fishbein, 1980; Fishbein & Ajzen, 1975).

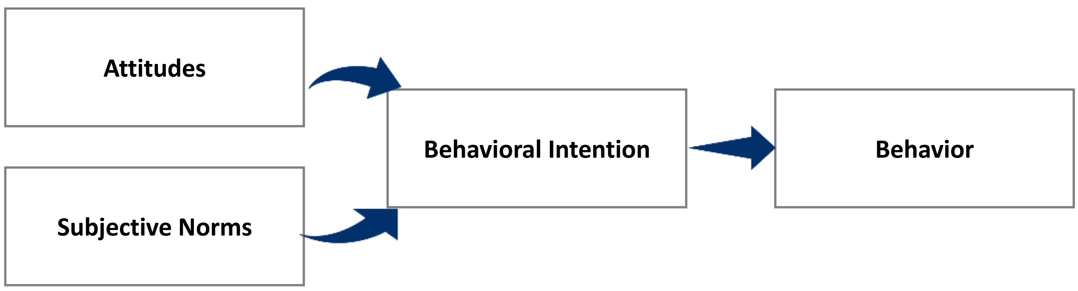

Figure 3 - Theory of Reasoned Action (TRA)
Source: Authors' illustration based on the TRA by Ajzen and Fishbein (1980).

In the TRA by Ajzen and Fishbein (1980) attitudes and social norms are two distinct components that influence an individual's intention to perform a specific behavior:

Attitudes refer to the individual's positive or negative evaluations of performing a behavior. These evaluations are based on the individual's beliefs about the outcomes of the behavior and the value they place on those outcomes.
Social Norms relate to the perceived social pressure to perform or not perform the behavior. This perception is influenced by the individual's beliefs about whether people important to them think they should engage in the behavior and their motivation to comply with these expectations.

According to Ajzen and Fishbein (1980) attitudes are formed based on personal beliefs and evaluations about the consequences of a behavior. They reflect an individual's assessment of the benefits and drawbacks of engaging in the behavior. While Social Norms are shaped by the individual's perception of the expectations of others. These norms are not about personal beliefs regarding the behavior's outcomes but about the individual's understanding of what significant others belief and their willingness to align with these beliefs. Thus, attitude and subjective norms influence the behavior intent differently according to Ajzen and Fishbein (1980).

In the context of AI-generated vs. human-created ads, the visual elements become a ground for consumers to evaluate the creativity, innovation, and even the ethical implications of the AI usage in advertising. These evaluations are deeply tied to attitudes and the perceived social norms, as they reflect broader societal attitudes towards technology, creativity, and automation. Thus, this theory is particularly suiting for understanding the dynamics of consumer reactions to advertisements, where the identity of the ad creator—either AI or human—can significantly influence attitudes and perceived norms.

2.5.1 TRA Adaptation

In this study we focus solely on attitudes rather than subjective norms. This is justified by the nature of consumer decision-making in advertising contexts. Attitudes are directly relevant because they involve personal evaluations and reactions to stimuli (in this case, the advertisements), based on the perceived qualities of the ads themselves (Shimp, 1981). These evaluations are what we aim to measure and compare. Subjective Norms would not provide the same level of insight into personal cognitive and affective reactions to the ads but would instead reflect how individuals belief others think they should react. This involves perceived social pressures or expectations, therefore, subjective norms are less controllable in this isolated setting, as they depend more on broader social contexts and interactions that are not being directly manipulated in this study.

Furthermore, attitude towards the behavior is directly related to the individual's positive or negative evaluation of the behavior. The adoption of innovative technologies, such as AI in advertising, is often influenced more by personal beliefs and attitudes towards the technology than by social pressures or norms (Rogers, 2003). Given that AI in advertising represents a relatively new and evolving area, individual attitudes towards AI-generated content might be more salient than the perceived social pressure or norms regarding its acceptance.

Since the core objective of the study is to compare consumer evaluations based on the perceived origins of advertisements, attitudes are likely to have a more immediate and measurable impact on the likelihood of purchasing the product advertised. This direct link suggests that attitudes could be a more powerful predictor of behavior intentions than subjective norms in the context of advertising evaluation. Thus, the focus on attitudes allows not only a simpler and more focused analysis but suits better to our study design – the direct manipulation of perceived ad creator, which targets individual cognitive and emotional responses – core components of attitude. This results in the adaptation of the TRA to our study design shown in *Figure 4*.

Figure 4 - Adaption of TRA to Study Design

Source: Authors' illustration based on the TRA by Ajzen and Fishbein (1980).

2.5.2 Attitude towards AI

Attitudes towards AI are crucial as they directly influence an individual's intention to use AI technologies or to accept the usage of it. Since positive attitudes lead to stronger intentions to adopt and accept (Ajzen & Fishbein, 1980), positive attitudes towards AI could lead to stronger intentions to accept the usage of AI in advertising. Aiming to compare consumer responses to advertisements presumed to be generated by AI versus those presumed to be human-made, the following hypotheses, can be proposed:

H3a: *A positive attitude towards AI leads to higher purchase intent for AI-generated ads.*
H3b: *A positive attitude towards AI leads to more favorable evaluations of AI-generated ads.*
H3c: *A positive attitude towards AI leads to greater WOM for AI-generated ads.*

These hypotheses suggest that if individuals hold negative attitudes towards advertisements believed as generated by AI - perhaps due to concerns over creativity, authenticity, or privacy - such attitudes are likely to negatively influence their purchase intentions, the ad evaluation and its followed WOM. It embodies the TRA's assertion that a person's negative evaluation of performing a behavior (in this case, engaging with AI-generated ads) diminishes their intention to engage in that behavior (purchasing the advertised product).

2.6 The Big Five Trait Taxonomy

The Big Five personality traits, also known as the Five-Factor Model, are a widely accepted framework for understanding human personality. Each of the Big Five dimensions captures a broad domain of human personality and behavior. They are based on the research of many psychologists over the years, including seminal works by Costa and McCrae (1992) who developed the Revised NEO Personality Inventory (NEO-PI-R) which assesses the Big Five traits. According to their work the personality traits can be defined as followed:

- **Openness to Experience:** This trait features characteristics such as imagination, creativity, and a willingness to try new things. Individuals high in this trait tend to be open to new experiences, curious, and artistically sensitive. They are more likely to engage in creative and abstract thinking.

- **Conscientiousness:** Conscientiousness includes high levels of thoughtfulness, good impulse control, and goal-directed behaviors. Highly conscientious individuals are organized, mindful of details, and careful. They plan and think about how their behavior affects others, which typically leads to success in school and work environments.

- **Extraversion:** This dimension is characterized by excitability, sociability, talkativeness, assertiveness, and high amounts of emotional expressiveness. Extraverts enjoy interacting with people and are often perceived as full of energy. They tend to be more positive and are often motivated by social engagement.

- **Agreeableness:** This trait reflects individual differences in general concern for social harmony. Agreeable individuals value getting along with others. They are generally considerate, friendly, generous, helpful, and willing to compromise their interests with others. Agreeableness is also associated with trust and altruism.

- **Neuroticism:** Often referred to as emotional instability, this trait involves the tendency to experience frequent and intense negative emotions such as anger, anxiety, or depression. Individuals high in neuroticism are emotionally reactive and vulnerable to stress. They are more likely to interpret ordinary situations as threatening and minor frustrations as hopelessly difficult.

The Big Five structure by Costa and McCrae (1992) does not mean that personality differences can be reduced to just five traits. Rather, these five dimensions represent personality at the broadest level of abstraction, and each dimension summarizes a large number of different, more specific personality traits (John & Srivastava, 1999). This constrains the depth of research but also provides good structure.

Utilizing the Big Five model in research offers several distinct advantages. Firstly, it is supported by a robust body of empirical evidence that attests to its validity and reliability across different cultures and demographic groups (McCrae & Costa, 2008). Thus, the universal applicability makes the Big Five a valuable tool for comparing results across studies and populations, enhancing the generalizability of research findings. Secondly, the model's broad categories are interpersonally relevant and predict important life outcomes, such as academic and career success, interpersonal relationships, and psychological well-being (Ozer & Benet-Martínez, 2006). Thus, the adoption of the Big Five model ensures a theoretically and empirically sound framework that facilitates both breadth and depth in personality assessment. This approach not only contributes to the clarity and comparability of research results, but also improves the ability to develop interventions and applications based on a sound understanding of personality structure.

2.7 The Big Five Trait Taxonomy Adaptation

In this study we investigate only the personality traits Openness to Experience, Extraversion, and Agreeableness. The exclusion of Neuroticism and Conscientiousness is substantiated by findings from Kaya et al. (2024), who observed that Conscientiousness did not significantly predict attitudes toward AI, showing only a weak correlation with negative AI anxiety. Similarly, Emotional Stability was found to have a weak and inconsistent impact on AI attitudes. These trends are supported by other research, such as Park & Woo (2022) and Schepman & Rodway (2022), which also report nonsignificant relationships between these traits and technology adoption. This approach streamlines the research focus, omitting traits with lesser impact on the core objectives of our study.

Within the context of advertising and AI acceptance Openness to Experience, Extraversion, and Agreeableness stand out for their relevance and potential impact on how consumers engage with and respond to AI-generated content (Kaya et al., 2024). These traits provide a psychological lens through which individual differences in the reception of AI-driven advertising can be assessed. By focusing on these traits, the research promises to unearth insights into the acceptance of AI in advertising, offering a clear contribution to our understanding of how personality influences consumer responses to technological advancements in advertising. In the following, the scientific relevance to investigate the personality traits Openness to Experience, Extraversion and Agreeableness regarding AI acceptance will be outlined.

2.7.1 Openness to Experience

Sindermann et al. (2020) found that openness to experience enables people to think and act positively towards AI. More broadly, other research suggests that openness to experience can increase the perceived practicality and usability of technologies, including smartphones, PCs, AI-powered applications, and internet use (Hawi & Samaha, 2019; McElroy et al., 2007; Na et al., 2022; Svendsen et al., 2013; Zhou & Lu, 2011). This results in these hypotheses:

H4.1a: *Individuals high in Openness to Experience are more likely to have higher Purchase Intent for AI-generated ads.*
H4.1b: *Individuals high in Openness to Experience are more likely to evaluate AI-generated ads more favorably.*
H4.1c: *Individuals high in Openness to Experience are more likely to engage in WOM for AI-generated ads.*

2.7.2 Extraversion

Schepman and Rodway (2022) found a negative correlation between extroversion and attitudes towards AI, suggesting that the more introverted people are, the more positive their attitudes towards AI. Technologies that facilitate social interactions like extroverted people, while AI technologies can help reduce social interactions (Schepman & Rodway, 2022, Yuan et al., 2022), which can benefit introverted people. In contrast, other the study of Devaraj et al. (2008) shows that extroversion can promote the adoption of technology in individuals. There is evidence that extroversion is one of the key traits that consolidates behavioural intentions and actual use of technology (Barnett et al., 2015; Svendsen et al., 2013; Wang et al, 2012; Zhou & Lu, 2011). This conflicting study environment not only makes researching the relationship between extroversion and AI particularly intriguing but also forms the basis for our hypotheses 4.2:

H4.2a: *Extroverted individuals are more likely to have higher Purchase Intent for AI-generated ads.*
H4.2b: *Extroverted individuals are more likely to evaluate AI-generated ads more favorably.*
H4.2c: *Extroverted individuals are more likely to engage in WOM for AI-generated ads.*

2.7.3 Agreeableness

Agreeable individuals have a more tolerant attitude towards the negative aspects of AI (Kaya et al., 2024). For example, agreeable individuals tend to be warm, pleasant, and friendly to others, which enables them to get along more efficiently with those around them and be more accommodating (Gosling et al., 2003; McCarthy et al., 2017). These traits could activate a cognitive set that facilitates better adaptation to changes in daily life brought about by technological innovations such as AI (Kaya et al., 2024). Previous research also indicated a significant relationship between agreeableness and negative attitudes towards technology/AI (Barnett et al., 2015; Charness et al., 2018; Schepman & Rodway, 2022) and a non-significant relationship with positive attitudes towards AI (Park & Woo, 2022; Schepman & Rodway, 2022). This leads to hypotheses 4.3:

H4.3a: *Agreeable individuals are more likely to have higher Purchase Intent for AI-generated ads.*
H4.3b*: Agreeable individuals are more likely to evaluate AI-generated ads more favorably.*
H4.3c: *Agreeable individuals are more likely to engage in WOM for AI-generated ads.*

2.8 Demographic Moderators

Demographic factors such as age, and education level are pivotal in moderating the acceptance of AI-generated advertisements. They are key to dissecting the demographic nuances influencing the integration of AI in advertising.

2.8.1 Age

There are contradictory findings regarding the relationship between attitudes towards AI technology and age. Park et al. (2022) found that people of older age have a higher acceptance of intelligent information technologies supported by AI and adopt new technologies with increasing age to stay up to date. However, much of the literature suggests that younger people have a more positive attitude towards AI (European Commission & Directorate-General for Communications Networks, Content & Technology, 2017; Gillespie et al., 2021). This leads to the hypotheses 5.1:

H5.1a: *The younger the better the Purchase Intent of the AI-generated ads.*
H5.1b: *The younger the better the Ad Evaluation of AI-generated ads*
H5.1c: *The younger the better the WOM of the AI-generated ads.*

2.8.2 Level of Education

Previous research has shown that a higher level of education increases the likelihood of a positive attitude towards AI in general (Gnambs & Appel, 2019; Zhang & Dafoe, 2019). For example, Masayuki (2016) found that in companies where employees had a higher level of education, there was a much more positive attitude towards AI than in companies where employees had a lower level of education. This results in the 5.2 hypotheses:

H5.2a: *The higher the level of education the better the Purchase Intent of the AI-generated ads.*
H5.2b: *The higher the level of education the better the Ad Evaluation of the AI-generated ads.*
H5.2c: *The higher the level of education the better the WOM of the AI-generated ads.*

3. Methodology

This chapter outlines our methodology for investigating. It begins by detailing our experimental study design, which involves presenting identical ads as either marked as AI-generated or human-created, followed by the measurement of key response variables through a structured online survey. The chapter further discusses our use of anxiety as a mediator and various moderators like attitude, personality traits, and demographics to deepen our understanding of the psychological factors influencing ad acceptance. Ethical considerations are rigorously maintained to ensure the integrity of our findings.

3.1 Study Method

This methodology section provides a comprehensive outline for our experimental study aimed at understanding consumer responses to AI-generated versus human-made advertisements, employing a rigorous quantitative analysis approach. Grounded in the Theory of Reasoned Action, this quantitative research explores the impact of the believed ad creator identity on key outcomes such as ad evaluation, purchase intent, and word of mouth. Participants, a diverse cohort of internet users, are methodologically surveyed to capture a comprehensive data set, assessing variables like ad relevance, overall impression, and persuasive power through a structured online survey.

Methodologically, we employ a dual approach: initially presenting the same advertisement marked either as AI-generated or human-created to eliminate preconceived biases, and subsequently measuring response variables through statistical analyses to gauge differences in consumer reactions. Responses were measured using a five-point-Likert scale to offer insights into the relationship between the ad creator, the consumer responses and its mediating and moderating effects involved.

This rigorous approach is complemented by ethical adherence to voluntary participation and anonymity, ensuring the integrity of our findings. Our comprehensive analysis extends beyond simple comparative metrics, using regression analyses to explore deeper interrelations between ad evaluations and individual differences among participants. This layered investigation not only enhances our understanding of advertising dynamics in the context of technological advances but also aims to provide nuanced insights into how the perceived origin of an ad – AI-generated versus human-made – affects consumer responses (see *Figure 5*).

Introduction Text for Survey

Survey A:

This is a visual ad for a pot is generated from AI.

Survey B:

This is a visual ad for a pot created by an employee of an advertising agency.

Figure 5 - Ad used in Survey

Source: Authors' illustration generated by DALL-E.

Materials

The survey was divided into five main sections, with each addressing different variables of interest:

1. **Ad Evaluation**: Respondents viewed one advertisement – either marked as AI-generated or as created by a human – and rated it on various aspects such as relevance, overall impression, persuasiveness, word-of-mouth, and purchase intention.
2. **Measuring Mediator Anxiety**: The survey used the Anxiety Subscale of the Hospital Anxiety and Depression Scale (HADS-A) to assess respondents' current emotional states, which could mediate their responses to the advertisements.
3. **Measuring Extra Moderators**: Personality traits such as extraversion, agreeableness, and openness were measured using a Likert scale to understand how these traits might moderate the relationship between ad type and consumer responses.

4. **Attitudes toward AI**: This section employed the general attitudes towards Artificial Intelligence Scale to gauge participants' perceptions of AI, which could influence their responses to the AI-generated advertisement.
5. **Demographics**: Basic demographic information was collected to analyze the data across different population segments and control for potential confounding variables.

   The whole survey can be found in Appendix 1.

The Ad itself – Why a pot?

The choice to use a visual advertisement featuring a pot in our study was driven by several key considerations linked to the objectives of the research and the survey method employed.

A pot is a universally recognized item, avoiding biases associated with more niche or culturally specific products. This neutrality supports broad applicability across diverse demographic groups in our survey sample. Furthermore, using a product with low emotional engagement, like a pot, is advantageous when examining the mediation of anxiety and moderation by personality traits. It minimizes extraneous emotional reactions that might obscure the specific impacts of ad creator type on anxiety levels and personality-driven responses. This clarity is essential for accurately assessing how these psychological factors interact with perceptions of AI-generated content.

By focusing on a practical, emotionally neutral item, the study effectively isolates and evaluates the influences of ad origin on consumer behavior, providing clearer insights into the roles of anxiety and personality traits in advertising effectiveness.

Procedure

Participants were recruited online and given access to the survey, which was hosted on Qualtrics. They were welcomed with an introduction that outlined the survey's general purpose (master thesis) and structure. Upon agreeing to participate and providing informed consent, each participant was then presented with the same advertisement which was either described as “generated from AI” or “created by an employee of an advertising agency”. Following the viewing of each advertisement, they responded to the questions related to ad evaluation, their emotional state, personality traits, attitudes toward AI, and finally, demographic questions. The survey was designed to be completed in approximately seven minutes.

Sampling Method

The study employed a convenience sampling technique, specifically utilizing a snowball sampling approach, to recruit participants for an online survey. Thus, the survey did not specify a target demographic for participant recruitment, aiming instead for a diverse sample of students and internet users. This method was chosen to efficiently gather a diverse range of respondents by leveraging networks of individuals who then recruit future respondents from among their acquaintances. This approach is particularly useful for quickly obtaining a broad and varied sample, though it may introduce some biases related to the social and professional networks from which participants are drawn. The surveys were conducted in from March to Mai in 2024.

	Gender					**Age**			**Education Level**	
	Quantity	Female	Male	Third/Non -Binary	Prefer not to say	Quantity	Mean	Min- Max	Quantity	Mean
AI Survey A (total 143)	141	58	82	0	1	133	27.1278	18-73	142	2.62
Non-AI Survey B (total 140)	139	71	67	1	0	131	27.084	19-66	139	2.78

Table 1 - Demographics of Survey Participants

Survey Participants

The initial response to the online survey comprised 360 individuals. After careful screening and exclusion of unfinished responses and those with missing data, a total of 283 valid responses were retained for analysis. These responses were divided between two survey conditions: Survey A, which participants were led to belief featured an AI-generated advertisement, and Survey B, which was presented as containing a human-made advertisement.

The final sample for Survey A consisted of 143 participants, while Survey B had 140 participants. The demographic breakdown across the surveys highlighted slight differences in gender composition. Survey A included 58 females and 82 males, whereas Survey B comprised 71 females, 67 males, and 1 individual identifying as Third Gender/Non-Binary. This distribution indicates a diverse gender representation, providing a broad perspective on consumer responses to the advertisements.

3.2 Ethical Considerations

Our research methodology was rigorously designed to adhere to the highest ethical standards, ensuring that the integrity of the study and the welfare of the participants were maintained throughout the process. Below, we elaborate on the challenges and risks associated with these ethical goals and describe the measures implemented to meet these challenges and mitigate these risks.

Anonymity and Confidentiality

Maintaining participant anonymity is crucial to protect their privacy but can be challenging, especially when collecting potentially sensitive information, such as questions about anxiety and personality traits, through online platforms. It comes with a risk of accidental disclosure of identities or personal data due to data breaches or improper handling of data.

To ensure anonymity, all identifying information was separated from survey responses as soon as they were collected. Data were coded with unique identifiers that do not reveal the participant's identity. Furthermore, we utilized secure, encrypted platforms for data collection and storage (Qualtrics and Dropbox), minimizing the risk of unauthorized access.

Voluntary Participation and Informed Consent

Ensuring that all participants clearly understand the scope of the study and the nature of their involvement can be challenging, particularly in online settings where miscommunication may occur. Participants might feel coerced or might not fully understand their rights and the study's demands, leading to ethical breaches in consent.

Therefore, we provided an informed consent form at the beginning of the survey, which clearly outlined the study's purpose, the nature of their participation, and the structure of the questions rubrics before the questions started.

Data Security

Protecting stored data from unauthorized access or loss is a significant challenge, especially with the increasing sophistication of cyber threats. Potential data breaches could lead to exposure of confidential participant information. Data security is essential, especially due to the high sensitivity of the data associated with questions about personality and anxiety. Thus, we used cybersecurity measures to safeguard the data collected. This included using secure servers with up-to-date firewalls and encryption protocols. Access to the data was restricted to the authors of the study.

By addressing these challenges and implementing robust strategies to mitigate the associated risks, our research methodology has not only complied with ethical guidelines but has also improved the trustworthiness and integrity of the study results.

3.3 Data Analysis Method

3.3.1 Data Import and Cleaning

The data collected from the online survey platform, Qualtrics, was imported into SPSS for analysis. Initial data cleaning involved several steps:

Firstly, we checked for any missing or incomplete responses. Missing data were handled using appropriate imputation methods where feasible, or by excluding cases with substantial missing values from the analysis to maintain the integrity of the dataset. Responses that were nonsensical or fell outside the expected range were identified and removed to ensure the quality of the dataset. Furthermore, adjustments were made for reverse-scaled questions to align all scales in the same direction, facilitating accurate analysis.

Secondly, descriptive statistical analyses were performed to summarize the data. This included calculating central tendency and dispersion, such as means, maximums, minimums, and standard deviations. They were computed for each variable to understand the distribution and central tendencies of the responses.

Additionally, Cronbach's Alpha was calculated for each multi-item scale to assess internal consistency. The threshold for acceptability was set at an alpha value of 0.7, following standard practice in psychological and social research. The same instruments were used to measure constructs across both surveys.

3.3.2 Inferential Statistical Analysis with PROCESS Macro

Mediation Analysis

Using the PROCESS macro (Model 4), we explored the role of anxiety as a mediator in the relationship between the type of advertisement (AI-generated vs. human-made) and various dependent variables (Purchase Intention, Ad Evaluation, Word of Mouth). The analysis provided estimates of direct effects - the direct impact of the independent variable on the dependent variables – and indirect effects – the effect mediated by anxiety, along with significance testing to determine the mediation effect's strength.

Moderation Analysis

We employed the PROCESS macro (Model 1) to assess the impact of attitudes towards AI, personality traits (Extraversion, Agreeableness, Openness), and demographics (Age & Level of Education) as moderators in the relationship between advertisement type and dependent variables. This analysis involved: Focusing on the significance of interaction terms to determine the influence of moderators and the calculation of conditional effects at various levels of the moderators to examine how these relationships change across different moderator values.

3.3.3. Interpretation, Reporting, and Justification of the Chosen Approach

Results from both mediation and moderation analyses were detailed, highlighting significant effects and interactions. The findings were discussed in terms of their practical and theoretical implications. Limitations of the study were acknowledged, including potential biases in self-reported data, the representativeness of the sample, and limitations inherent to the survey method.

The use of the SPSS PROCESS macro for mediation and moderation analysis is particularly apt for addressing our research questions:

For RQ1 ("Does believing a visual ad is made by AI or a human affect the consumer response?"), the PROCESS macro is particularly suited as it allows for the analysis of direct and indirect effects of the independent variable (Ad Creator) on the dependent variables (Purchase Intention, Ad Evaluation, WOM). This enables us to not only examine the straightforward impact of who creates the ad, but also how this impact might be mediated or moderated by other variables such as attitudes towards AI. The macro's capability to handle both simple and conditional process models allows us to test for potential mediators (e.g., attitude towards AI) that explain the mechanism through which Ad Creator influences consumer responses, and moderators (e.g., demographic variables) that might alter the strength or direction of this influence.

For RQ2 ("Does anxiety mediate how consumers respond to ads depending on whether they are believed to be AI or human made?"), the PROCESS macro is ideal due to its robust handling of mediation models. This capability allows us to investigate whether anxiety mediates the relationship between the Ad Creator and consumer response. By doing so, we can determine if the effect of believing an ad is AI-generated versus human-made on consumer responses is partially or fully explained by the consumers' anxiety levels.

For RQ3 ("What factors influence consumer response to AI-generated ads?"), PROCESS is again the ideal tool due to its robust handling of multiple moderators in a single model. The macro facilitates the exploration of interactions between the Ad Creator and various personal traits such as openness to experience, agreeableness, and other demographics. By employing this approach, we can systematically dissect how different audience segments perceive AI-generated content differently, providing deeper insights into consumer psychology and market segmentation.

Furthermore, our quantitative approach, employing validated scales for measuring attitudes and personality, ensures that the data collected are robust and reliable, allowing for generalizable and valid conclusions within the quantitative research paradigm. The choice of advanced statistical methods for analyzing interactions and mediating effects provides a comprehensive view of the complex dynamics at play, which is essential for making informed marketing decisions and theoretical advancements.

3.4 Scales

3.4.1 Hospital Anxiety and Depression Scale (HADS)

To measure anxiety the Hospital Anxiety and Depression Scale (HADS), developed by Zigmond and Snaith (1983), is a widely used and validated scale. The HADS is designed to assess anxiety and depression in individuals with physical health problems, making it especially useful in medical settings. However, its simplicity and focus on psychological symptoms rather than physical symptoms have also made it popular in various other contexts, including research and general population assessments (Bocéréan & Dupret, 2014; Herrero et al., 2003).

The HADS consists of 14 items, with 7 items related to anxiety (HADS-A) and 7 related to depression (HADS-D). Each item is scored on a scale from 0 to 3, with the total score for each subscale ranging from 0 to 21. Higher scores indicate greater levels of anxiety or depression. As our study only measures the level of anxiety and not the level of depression of the participants, we will only include the HADS-A in our study. This approach has proven successful in previous studies that do not originate from the psychological field (Bocéréan & Dupret, 2014; Herrero et al., 2003).

Anxiety Subscale (HADS-A)

The anxiety subscale includes questions that assess generalized anxiety symptoms, such as restlessness, worries, and fears. Items are designed to measure the psychological aspects of anxiety to avoid confounding with physical health conditions.

To apply the HADS-A, respondents were asked to indicate their emotional state. The response options range from 0 (e.g., "Not at all") to 3 (e.g., "Most of the time"), depending on the item. The scale is straightforward and can be completed in a few minutes, making it convenient for both clinical and research settings. Thus, this scale provides a useful tool for quickly assessing anxiety.

3.4.2 General Attitudes towards Artificial Intelligence Scale (GAAIS)

For measuring Attitude towards AI, the "General Attitudes towards Artificial Intelligence Scale (GAAIS)" by Schepman and Rodway (2020) is used as it provides a comprehensive instrument. The GAAIS underwent initial statistical validation revealing two subscales: Positive and Negative attitudes towards AI. These subscales capture emotions in line with their valence, where the positive subscale reflects societal and personal utility, and the negative subscale encompasses concerns related to AI. The GAAIS has shown good psychometric properties including convergent and discriminant validity, making it a suitable tool for gauging general attitudes towards AI.

To apply the GAAIS in our research, we used seven items about AI where participants rated their agreement or disagreement on a five-point-Likert scale. This included statements like "Artificially intelligent systems can help people feel happier." (positive) or "I think Artificial Intelligence is dangerous." (negative).

3.4.3 The Big Five Inventory (BFI)

The Big Five Trait Taxonomy and the Big Five Inventory (BFI) are related but distinct concepts in the study of personality. The BFI elaborated by John and Srivastava in 1999, is a specific psychological assessment tool developed to measure the five broad dimensions outlined in the Big Five Trait Taxonomy. While the Big Five Trait Taxonomy provides the conceptual framework for understanding personality structure, the BFI is a practical tool that operationalizes this framework, allowing researchers and practitioners to assess individual differences in these traits efficiently. John and Srivastava's contribution with the BFI was to create a reliable and valid instrument that could be easily used to measure the theoretical constructs of the Big Five Taxonomy, making the abstract dimensions of personality accessible and measurable in empirical research.

The inventory of BFI was designed to be a concise, yet comprehensive, measure for research purposes, providing a practical way to evaluate the broad dimensions of personality proposed by the Big Five model. It is used in a variety of contexts, including psychological research, clinical settings, and even in organizational environments for purposes such as employee selection and career counseling (Soto & John, 2017). Thus, we used BFI to measure the three important personality traits of our study.

The BFI consists of 44 items that respondent rate on a five-point-Likert scale, which assess their agreement with statements that reflect aspects of each of the five traits. We used three items for each personality trait to measure it in our study.

3.5 Rigor of Research

The quantitative methodology employed in this study ensures the validity of the findings by meticulously measuring the intended constructs and relationships. The inclusion of attitude towards AI as a moderator in the mediation and moderation analyses adds depth, enabling a nuanced understanding of how participants' views may shape their reactions. By incorporating multiple measures and advanced statistical techniques, this study rigorously evaluates the hypothesized relationships, providing robust evidence for the proposed theoretical framework.

Our data has a value of 0.697 according to Cronbach's Alpha (Appendix 2). While this value is slightly below the .7 mark, which is often cited as a minimum standard for basic research, it is still within an acceptable range, especially in social science research where slightly lower reliability may be tolerable depending on the complexity and nature of the constructs being measured. A score near .7 suggests that the items have a moderate level of internal consistency for a scale consisting of multiple items measuring a single construct or related constructs. However, it's argued that even lower alpha values can still be acceptable since the use of alpha should be contextualized rather than relying on a universal threshold for acceptability (Taber, 2017).

The survey includes a relatively large number of items (29). In general, the more items a survey has, the more likely it is that the survey can accurately measure the variability of responses. A larger number of items can therefore help to compensate for inconsistencies or measurement errors that may arise from individual items.

In summary, while the Cronbach's Alpha is slightly below the ideal threshold, the reliability of the data can be argued as adequate for exploratory studies and sufficient to draw preliminary conclusions, especially given the complexity likely inherent in a scale with 29 diverse items.

3.6 Addressing Methodology Limitations

While our methodology is robust, it is also critical to acknowledge its limitations within the paradigms it operates. For instance, while TRA provides a useful framework for understanding the influence of attitudes on behaviors, it does not account for other psychological factors such as cognitive biases or previous experiences that may also influence consumer behavior. Similarly, the Five-Factor Model, while comprehensive, does not capture all aspects of personality that might impact ad perception, such as cultural influences or situational variables.

By recognizing these limitations, we ensure that our research conclusions are drawn with caution and highlight areas for further study, such as incorporating qualitative measures to capture more nuanced consumer insights or extending the model to include additional psychological or contextual factors.

In conclusion, our selected research approach offers critical insights into the psychological processes underlying consumer responses to new advertising formats, providing valuable contributions to both academic knowledge and practical marketing strategies.

4. Findings

The findings chapter introduces the analysis of the recorded data retrieved from the online survey. It details the preparation and execution of data analysis, examines the results, and discusses the validity and reliability of the survey measures.

4.1 Survey Comparison Analysis

In an in-depth analysis of the descriptive statistics from the Surveys A (marked as AI-generated) and B (marked as human-made), we observe distinct differences that highlight variations in response patterns, possibly influenced by the marked content creator or demographic differences in the survey populations.

In Survey B, the Purchase Intention scores ranged from 1 to 5 with a mean of 3.44, significantly higher than Survey A, which ranged from 1 to 4 with a mean of 2.03. Survey B participants rated ads more favorably in terms of Ad Evaluation (Eva_M), with scores reaching up to 5 and an average of 3.5196, compared to Survey A's maximum of 4.50 and an average of 2.2832. The mean score for WOM in Survey B was 3.04, significantly higher than Survey A's 1.87. After T test independent sample test, a p-value of less than 0.001 in both one-tailed and two-tailed tests is shown for Purchase Intentions, Ad evaluation, and WOM. This indicates a significant difference, providing strong evidence against random variation or chance.

Anxiety

Levels of Anxiety were notably different, with Survey A reporting a higher average (mean = 2.6092) compared to Survey B (mean = 2.0418) (Appendix 3).

Attitudes towards AI

Both surveys showed a positive attitude towards AI, with Survey A slightly higher (mean = 3.4060) than Survey B (mean = 3.2990) (Appendix 3). This metric, although slightly in favor of Survey A, does not align with the overall better performance seen in Survey B, suggesting other factors at play affecting the acceptance and effectiveness of AI-generated ads.

Personality Traits

Scores for Extraversion, Agreeableness, and Openness were all higher in Survey B, which could correlate with the higher scores observed in Ad Evaluation and WOM.

In conclusion, the data analysis shows that Survey B outperforms Survey A across most evaluated metrics (see *Table 2*). This consistent pattern across different measures suggests a general trend where respondents in Survey B are more receptive to the advertisements presented, which could be influenced by lower levels of anxiety and higher levels of certain personality traits. The detailed statistical analysis underscores the need to consider both psychological and demographic factors in evaluating ad campaign effectiveness.

	Purchase Intentions		Ad Evaluation		WOM	
	Mean	Significance	Mean	Significance	Mean	Significance
AI (Survey A) Sample:143	2.03	Yes p<0.001	2.2832	Yes p<0.001	1.87	Yes p<0.001
Non-AI (Survey B) Sample:140	3.44		3.5196		3.04	

Table 2 - Survey Comparison with Means Values

4.2 Interpretation of the Survey Comparison

Participants were generally less inclined towards purchasing the advertised product of Survey A (marked AI-generated) then B (marked human-made). The notably less favorable evaluation of the Purchase Intention, Ad Evaluation, and Word of Mouth could have been influenced by many potential factors, which may indicate different demographic profiles that found the ads more attractive. However, the age, gender, and nationality range of the two surveys differ not much, suggesting that it must be another influence of the lower performance of the Ad in Survey A.

The differences of the participants personality traits could have also influenced the evolution, since Extraversion, Agreeableness, and Openness are higher in Survey B. These characteristics typically correlate with more positive interactions and a greater receptiveness to new experiences, which can enhance the effectiveness of advertising. Particularly, the higher Agreeableness and Openness scores could align with the increased willingness to evaluate ads more favorably and engage in sharing them. If this were the case, the measured attitude towards AI would also be higher – if these personality traits alone lead to a higher willingness to evaluate things more favorable the attitude towards AI must also be ranked higher in Survey B. However, the general attitude towards AI got ranked even less favorable on the GAAIS in Survey B. This suggest that the participants personality traits alone did not affect the lower ranking of the advertisement.

Given that the primary distinction between the two surveys was the identification of the believed ad's creator – AI versus human – it is logical to conclude that this factor significantly influenced the differing outcomes observed. The attribution of the ad's origin as either AI-generated or human-created in Survey A appears to have had a notable impact on its effectiveness. This assumption is supported by the observed variance in performance metrics such as Purchase Intention, Ad Evaluation, and Word of Mouth between the survey groups.

Moreover, the consistency in methodology and variables between the two surveys, except for the ad source attribution, strengthens the argument that the source of the ad is a pivotal factor. This focused change isolates the source as the primary variable influencing the observed differences in outcomes, providing a clear causative linkage between the ad creator attribute and the survey results.

Thus, the provided data from the survey comparisons supports hypotheses H1a, H1b, and H1c. The results indicate that ads perceived as AI-generated consistently perform worse across key metrics such as Purchase Intention, Ad Evaluation, and Word of Mouth when compared to ads perceived as human-made. The poorer performance of the ad in Survey A can be attributed largely to the negative predispositions or lower perceived authenticity and emotional resonance when participants are aware that the content is generated by AI rather than humans. This highlights the significant impact of source credibility in advertising, where human-created content still tends to be perceived as more reliable and connected to genuine human experience compared to AI-generated content.

	Attitude	Openness	Extraversion	Agreeableness	Age	Education	Anxiety
Purchase Intention	Yes p = .0012	No p = .0802	No p = .3226	No p = .1270	No p = .1272	No p = 0.1779	Yes p = .0000
Ad-Evaluation	Yes p = .0044	Yes p = .0055	No p = .2286	Yes p = .0391	Yes p = .0034	Yes p = 0.0192	Yes p = .0000
Word Of Mouth	Yes p = .0173	No p = .3620	No p = .8587	No p = .7972	Yes p = .0005	No p = 0.3135	Yes p = .0000

Table 3 - Moderation and Mediation Results

4.3 Mediation Effects of Anxiety

In evaluating the role of anxiety as a mediator in the relationship between the perceived creator of advertisements (AI-generated vs. human-made) and consumer responses, we performed a mediation analysis with a sample of 280 participants, using both surveys, the data of the manipulated and the control group. The detailed tables can be found in Appendix 4.

The mediation model consisted of the following:

- *Independent Variable (X):* AI_H, indicating whether the ad was perceived as AI-generated (coded as 1) versus human-made (coded as 0).
- *Mediator (M):* Anx_M, representing the individuals' anxiety levels.
- *Dependent Variables (Y):* PI (Purchase Intention), Eva_M (Ad Evaluation), and WOM (Word of Mouth).

Anxiety as a Mediator for Purchase Intention (PI)

The results show that AI-generated advertisements directly decrease purchase intentions (AI_H coefficient: -1.1115, $p < .0000$). Additionally, while the study observed a significant correlation between higher levels of pre-existing anxiety and reduced purchase intentions, anxiety did not originate from exposure to AI-generated content. Instead, anxiety served as a pre-existing condition that exacerbated the negative reception of AI advertisements. The indirect effect of anxiety was significant (-.3100, BootLLCI: -.4510, BootULCI: -.1926), suggesting that individuals with higher anxiety levels are particularly sensitive to AI-generated ads, which in turn lowers their likelihood to purchase. This underscores the importance of considering consumer psychological profiles when deploying AI-driven marketing campaigns.

Anxiety as a Mediator for General Evaluation (Eva_M)

The analysis revealed that individuals with higher levels of pre-existing anxiety are significantly more affected by AI-generated advertisements (AI_H coefficient: .5673, $p < .0000$). The direct effect of AI on general evaluation was significantly negative (-.8841, $p < .0000$), indicating that AI ads are evaluated less favorably. The mediation analysis showed a significant indirect effect (-.3713, BootLLCI: -.5113, BootULCI: -.2472), demonstrating that the negative evaluation of AI-generated content is partly due to higher pre-existing anxiety levels among respondents.

Anxiety as a Mediator for Word of Mouth (WOM)

Similarly, individuals predisposed to higher anxiety levels reported increased discomfort with AI-generated ads (AI_H coefficient: .5673, $p < .0000$). The direct negative impact of AI on the likelihood of sharing these ads was substantial (-.9520, $p < .0000$). Furthermore, the mediation effect of anxiety was significant (-.2123, BootLLCI: -.3459, BootULCI: -.1053), indicating that pre-existing anxiety contributes to a reduced tendency to discuss or recommend AI-generated ads.

Discussion of Hypothesis and Conclusion

The findings from this study support Hypotheses H2a, H2b, and H2c, demonstrating that anxiety acts as a significant mediator in the relationship between the believed ad creator (AI vs. Human) and essential advertising outcomes – Purchase Intent, Ad Evaluation, and Word of Mouth. The analysis indicated that AI-generated advertisements tend to elevate anxiety levels, which negatively impacts consumer responses in a sequence aligned with the hypothesized order (see *Figure 1*). Specifically, the increased anxiety elicited by AI ads leads to lower Purchase Intent, poorer Ad Evaluations, and diminished Word of Mouth activity.

This mediation effect implies that the adverse consumer responses to AI-generated content are significantly influenced by the heightened anxiety that such advertisements tend to provoke, rather than merely the origin of the content itself. Consequently, this highlights the critical role of managing consumer anxiety in advertising strategies that incorporate AI-generated content. Addressing the psychological impact of these advertisements is essential for mitigating negative perceptions and enhancing the overall effectiveness of advertising campaigns involving AI. This approach will not only help in improving consumer reception but also in leveraging AI capabilities to enhance ad personalization and engagement without alienating potential customers.

4.4 Moderation Effects of Attitude

The investigation into the moderating effects of attitudes on consumer responses to AI-generated advertisements uncovers significant interactions across all outcomes. The detailed tables for all moderation effects can be found in Appendix 5.

Purchase Intention (PI)

Attitude significantly moderates the impact of AI-generated advertisements on Purchase Intention. The interaction term (AI_H * Atti_M) yielded a coefficient of .8204 ($p = .0012$), underpinning the variance in PI scores by .0242 (R^2 change). At lower levels of attitude, the adverse effect of AI on PI is pronounced (-1.7533), and although this effect softens with increasing attitude levels, it remains negatively significant even at higher levels (-1.0502). This moderation suggests a continuum where a more favorable attitude towards AI can buffer, but not completely offset, the negative predispositions toward AI-generated advertisements.

Ad Evaluation (Eva_M)

The pattern is consistent in Ad Evaluation, with the interaction term (AI_H * Atti_M) presenting a coefficient of .6505 ($p = .0044$). The change in R^2 is .0188, marking a substantive alteration in evaluations based on attitudes. Starting from a deficit (-1.5263) with less favorable attitudes, the evaluation of AI-generated content improves with increasingly positive attitudes. However, the ratings remain below average compared to their human-generated counterparts.

Word of Mouth (WOM)

Word of Mouth responses also indicate that attitudes play a moderating role, albeit to a lesser extent, with an interaction coefficient of .6246 ($p = .0173$) and a R^2 change of .0153. This suggests that while attitudes do influence the likelihood of discussing AI-generated content, the effect is less pronounced compared to PI and Ad Evaluation.

Discussion of Hypothesis and Conclusions

The findings corroborate Hypotheses H3a, H3b, and H3c, indicating that the source of the ad (AI vs. human) significantly influences Purchase Intent, Ad Evaluation, and WOM through the mediator of attitudes toward AI. The analysis reveals a clear trend: negative effects are pronounced for AI-generated ads across all examined outcomes, but these effects are lessened by more positive attitudes toward AI.

Across the measures, the recurring theme is the mitigating influence of positive attitudes on the otherwise negative reception of AI-generated content. However, while the interaction effects are significant, the coefficients indicate that even with the most favorable attitudes, AI-generated content does not reach parity with human-made content in terms of Purchase Intention, General Evaluation, or Word of Mouth: While a more positive attitude towards AI may lead to better ratings for AI-generated content, these ratings are still not on par with those for human-generated content. This suggests that it is difficult for AI to achieve a similar level of acceptance to human efforts and highlights the importance of managing public perceptions and attitudes towards AI technologies.

In conclusion, while positive attitudes toward AI can improve consumer responses, they do not entirely neutralize underlying reservations. These findings could inform marketers about the challenges in AI adoption and underscore the need for strategies that build consumer trust and highlight the human-AI collaboration in creating content.

4.5 Moderation Effects of Openness

While openness does influence consumer attitudes to some extent, its impact as a moderator is not uniformly significant across all measures of consumer response to AI-generated content.

Purchase Intention (PI)

In assessing the Purchase Intention, openness displayed a non-significant main effect with a coefficient of .1919 ($p = .0667$), suggesting only a marginal inclination for open individuals to have stronger purchase intentions. The interaction between AI-generated advertisements and openness (Int_1) was likewise not significant ($p = .0802$), implying that openness does not substantially influence the way consumers' purchase intentions are affected by the source of advertisement creation.

Ad Evaluation (Eva_M)

For Ad Evaluation, openness showed a significant main effect (.2281, $p = .0108$), indicating that individuals with higher openness scores are generally more favorable in their evaluation of advertisements. The interaction term (Int_1) had a coefficient of .3105 ($p = .0055$), which signifies that openness significantly moderates the effect of AI-generated content on Eva_M, with higher levels of openness correlating with a lesser negative impact.

Word of Mouth (WOM)

With Word of Mouth, openness presented a significant main effect (.2282, $p = .0362$), indicating that more open individuals are more likely to share their views on advertisements. This means people who score higher on the Openness to Experience trait are generally more willing to talk about advertising and share their opinions about it. This is evidenced by the significant main effect of openness on WOM.

However, the interaction between openness and AI-generated content (Int_1) did not reach statistical significance ($p = .3650$), which suggests that openness does not alter the likelihood of sharing information about AI-created advertisements compared to those created by humans:

When looking at the specific type of advertising (AI-generated vs. human-generated), individuals' openness has no significant effect on the likelihood that they share information about AI-generated advertising compared to human-generated advertising. This means that regardless of whether an ad is believed to be AI-generated or human-made, the impact of an individual's openness on their propensity to share information about the ad remains the same – openness increases sharing regardless of the origin of the ad.

Discussion of Hypothesis and Conclusions

The results from the analysis align with hypotheses H4.1a, H4.1b, and H4.1c, demonstrating that the personality trait of openness to experience influences the impact of ad creator type (AI vs. Human) on Ad Evaluation, Purchase Intent, and Word of Mouth (WOM), albeit with varying degrees of significance.

Openness to experience significantly moderates the effect of the ad creator on Ad Evaluation ($p = 0.0055$), suggesting that individuals with high levels of openness are more receptive and less critical of AI-generated ads. This attribute likely leads to more favorable evaluations of such content, as open-minded individuals are typically more accepting of new technologies and innovations. This supports H4.1b.

In terms of Purchase Intent, while openness to experience is associated with a more favorable outlook, it does not significantly moderate the relationship between the ad creator type and purchase intentions ($p = 0.3620$). This indicates that while openness influences general perceptions and potential willingness to engage with AI-generated content, it does not distinctly alter the intent to purchase based on the origin of the ad. Similarly, for Word of Mouth, openness to experience does not show a significant moderation effect ($p = 0.8587$). Open individuals may be more likely to discuss and share information about advertisements in general, but this trait does not significantly differentiate their likelihood to share information specifically about AI-generated ads versus human-created ads. Thus, H4.1a and H4.1c are not fully supported.

Openness to experience appears to serve as a buffer that reduces the negative impact of AI-generated advertising. People who score higher on this trait appear to be more open-minded and less critical of AI-generated content, which has a positive impact on their ratings, purchase intentions and likelihood to recommend the products. This suggests that targeted or customised marketing strategies that include AI-generated advertising could be more effective if they consider the personality traits of the target audience, particularly their openness to new experiences.

However, while openness is associated with more favorable evaluations and a tendency to share information, its role as a moderator between the perception of AI-originating content and consumer responses is less clear. Notably, while it does significantly influence the ad evaluation of such content, its impact on purchase intentions and word of mouth is not significantly modulated by whether the content is AI-generated or not.

4.6 Moderation Effects of Extraversion

Across all tested outcomes—Purchase Intention, General Evaluation, and Word of Mouth—the findings consistently reveal that extraversion does not significantly influence how consumers react to AI-generated advertisements.

Purchase Intention (PI)

Extraversion exhibited a compelling influence on PI as a main effect, denoted by a coefficient of .4173 ($p = .0002$), indicating that individuals with higher extraversion levels displayed a propensity for increased Purchase Intention. The significant positive relationship between Extraversion and PI can be understood through the lens of the psychological traits associated with extraversion, as it encapsulates qualities such as sociability, assertiveness, and emotional expressiveness. Thus, extraverts are often more responsive to external stimuli (Fishman et al., 2011), including marketing and advertisements. Their tendency to engage more intensely with their environment can lead to a higher likelihood of noticing and reacting positively to marketing efforts.

However, the interaction between AI-generated content (AI_H) and extraversion (Extr_M) did not significantly alter PI ($p = .3226$), as evidenced by a negligible R^2 change of .0020. This intimates that while extraversion may elevate the likelihood of purchase intent, its effect remains constant irrespective of whether the advertisement is AI-generated or human-made.

Ad Evaluation (Eva_M)

For Ad Evaluation, extraversion's main effect was again pronounced (.4432, $p < .0001$), underscoring that more extraverted individuals tend to appraise advertisements more favorably. The interaction term, albeit suggestive of a trend (.1539), did not achieve statistical significance ($p = .2286$), with a minute R^2 change of .0028. Consequently, the inclination of extraverted individuals to evaluate advertisements more favorably was not distinctly moderated by the AI origin of the content.

Word of Mouth (WOM)

Word of Mouth, the propensity to share information about the advertisements, similarly showcased a significant main effect of extraversion (.4645, $p < .0001$). However, the interaction with AI-H was not significant, as mirrored in the negligible R^2 change (.0001) and p-value of .8587. Extraverted participants were likely to share information about the ads, but this likelihood was not influenced by whether the ad was AI-generated.

Discussion of Hypothesis and Conclusions

The hypothesis H4.2a, H4.2b, and H4.2c are not fully supported. While extraversion positively influences Ad Evaluation, Purchase Intent, and WOM across both AI and human-created ads, it does not act as a significant moderator in how the ad creator (AI vs. Human) affects these outcomes. Extraversion enhances these consumer responses regardless of whether the ad is AI-generated or created by humans, but it does not significantly alter the relationship between the type of ad creator and the consumer responses examined.

Extraversion emerged as a consistent predictor of more favorable Purchase Intention and General Evaluation, as well as greater Word of Mouth communication, yet these relationships were not significantly influenced by the nature of the ad's creator, AI or human. This consistency across outcomes illustrates extraversion’s robust impact on consumer behavior, independent of AI involvement.

Future research could delve deeper into the nuanced ways in which personality traits like extraversion interact with technological advancements in advertising, potentially considering longitudinal data to track changes over time as individuals become more accustomed to AI in various domains.

4.7 Moderation Effects of Agreeableness

Agreeableness does influence consumer attitudes to some extent, however, its impact as a moderator is not uniformly significant across the tested measures of consumer response to AI-generated content.

Purchase Intention (PI)

Within the realms of Purchase Intention, agreeableness showcased a positive main effect, with a coefficient of .3354 ($p = .0043$), indicating individuals with higher levels of agreeableness are inclined towards stronger purchase intentions. The interaction of AI-generated content with agreeableness (Int_1), however, displayed a coefficient of .2189, which did not reach the conventional levels of statistical significance ($p = .1270$), suggesting that while agreeableness influences PI, it does not significantly modulate the effect based on the AI or human origin of the content.

Ad Evaluation (Eva_M)

For Ad Evaluation, the agreeableness main effect was substantial (.4669, $p < .0001$), affirming the role of agreeableness in the positive appraisal of advertisements. The interaction effect (Int_1) of agreeableness with AI-generated advertisements was noteworthy (.2400, $p = .0391$) and induced an R^2 change of .0071. The moderating effect of agreeableness in this context is statistically significant, albeit modest, hinting that as agreeableness intensifies, the negative perceptions associated with AI-generated content in terms of evaluation are attenuated.

Word of Mouth (WOM)

In terms of Word of Mouth, agreeableness emerged as a strong main effect (.4975, $p < .0001$), underscoring that more agreeable individuals are more likely to share information about advertisements. The observed strong main effect of agreeableness on WOM suggests that individuals with higher agreeableness scores are more inclined to share information about advertisements. This outcome is likely due to sociability.

Agreeableness is fundamentally linked to sociability, empathy, and a cooperative disposition (Haas et al., 2015). People high in agreeableness tend to be more sympathetic and less competitive, which might make them more likely to share positive experiences, including advertising content, as a means of fostering connections and goodwill with others.
Yet, the interaction between AI-generated content and agreeableness (Int_1) did not significantly influence WOM ($p = .7972$), indicating that the sharing of information about AI-generated content does not vary by levels of agreeableness.

Discussion of Hypothesis and Conclusions
The investigation into the hypotheses H4.3a, H4.3b, and H4.3c offers partial validation regarding the impact of agreeableness on the relationship between ad creator type (AI vs. Human) and consumer responses. Agreeableness positively influences Ad Evaluation, Purchase Intent, and Word of Mouth (WOM); however, its role as a moderator is evident only in the context of Ad Evaluation.

While agreeableness positively correlates with Purchase Intent, enhancing overall consumer engagement, it does not significantly moderate the impact based on whether the ad is AI-generated or created by humans ($p = 0.1779$). This suggests that the agreeable personality's propensity to favorably view ads is uniform across different types of ad creation.
Similarly, agreeableness does not demonstrate a significant moderation effect for WOM between AI and human-created ads ($p = 0.3135$). Agreeable individuals are generally more likely to share information about ads, but this inclination does not vary significantly depending on the ad's origin. Thus, the hypotheses H4.3a and H4.3c are not fully supported.

In contrast, agreeableness significantly moderates Ad Evaluation ($p = 0.0192$), indicating that agreeable individuals may evaluate AI-generated ads more favorably than less agreeable ones. This distinction underscores a specific moderating effect of agreeableness in how consumers assess AI versus human-generated content, aligning agreeableness with a more critical role in the evaluation process specifically tailored to the nature of the ad creator. This supports H4.3b.

Agreeableness, as a personality trait, appears to consistently predict more favorable consumer reactions in terms of Purchase Intention and Ad Evaluation, and a higher propensity to engage in WOM. Nevertheless, its moderating role is more pronounced in the domain of Ad Evaluation of AI-generated advertisements, less so in Purchase Intention, and non-existent in WOM.

4.8 Moderation Effects of Age

The data of the analysis of age as a moderator underscores the varying influence of age on how consumers perceive and react to AI-generated content across different advertising outcomes.

Purchase Intention (PI)

The interaction between age and the type of ad creator showed a non-significant effect ($\beta = .0206$, $p = .1272$), suggesting that age does not significantly alter the impact of AI-generated content on purchase intentions. The minimal R^2 change (.0055) further supports this lack of moderation. Across different ages, the effect of AI on purchase intention remains consistently negative, though the magnitude slightly decreases with age, indicating a somewhat lesser negative impact among older individuals.

Ad Evaluation (Eva_M)

Contrary to purchase intention, age significantly moderated the relationship between ad creator type and ad evaluation ($\beta = .0359$, $p = .0034$). This suggests – against our expectations – that older individuals might evaluate AI-generated ads more favorably than younger ones. At lower ages, AI ads significantly suffer in evaluations, but as age increases, these evaluations become less negative. For example, at age 22, the effect is -1.5053, improving to -1.2326 by age 29.6.

Word of Mouth (WOM)

Age shows a significant moderating effect on the relationship between AI-generated ads and WOM ($\beta = .0460$, $p = .0005$). This finding points to an age-dependent difference in how likely individuals are to share information about AI-generated ads. Younger individuals show stronger negative responses, with the negative impact gradually lessening with age. For instance, the impact at age 22 is -1.5211, decreasing to -1.1716 by age 29.6.

Discussion of Hypothesis and Conclusions

Ad Evaluation and Word of Mouth show that older age groups tend to respond less negatively to AI-generated ads compared to younger individuals, contrary to the hypotheses that younger individuals would rate these ads more favorably. Hypotheses H5.1a, H5.1b, and H5.1c are not supported. Contrary to expectations, age does not significantly alter the impact of AI-generated content on Purchase Intent. Younger individuals do not exhibit higher Purchase Intent for AI-generated ads compared to older individuals. Surprisingly, older individuals evaluate AI-generated ads more favorably than younger ones. Younger individuals show more negative evaluations of AI-generated ads. Furthermore, younger individuals are also less likely to engage in Word of Mouth for AI-generated ads compared to older individuals. Older individuals show a lesser negative impact and are more likely to share information about AI-generated ads.

The findings suggest that the hypotheses H5.1a, H5.1b, and H5.1c should be reconsidered or refined, given that the data indicates older individuals may respond more favorably or less negatively to AI-generated ads than younger individuals. Specifically, older individuals tend to have fewer negative reactions to AI-generated ads, both in terms of evaluation and willingness to engage in word-of-mouth. These findings not only contradict our expectations, but also suggest a generational gap in receptivity to AI in advertising, where younger consumers may be more skeptical or critical compared to older ones. Older people may be less critical of the use of AI in advertising and instead appreciate the novelty or effectiveness of this advertising.

4.9 Moderation Effects of Level of Education

The role of educational attainment in influencing responses to AI versus human-generated advertisements was examined to understand how educational background might affect perceptions and behaviors towards different ad sources.

Purchase Intention (PI)

Education as a moderator revealed a non-significant interaction effect with AI-generated content in influencing purchase intentions ($\beta = .1781$, $p = .1779$). The R^2 change was also minimal (.0041), suggesting that educational attainment does not significantly alter the impact of AI on purchase intentions. Despite the non-significant interaction, it is noted that higher levels of education mildly cushion the negative impact of AI on purchase intentions. However, the moderation by education is not statistically significant, indicating that educational differences do not meaningfully change the baseline negative perception induced by AI.

Ad Evaluation (Eva_M)

In contrast to PI, education significantly moderated ad evaluations ($\beta = .2774$, $p = .0192$), reflected in a noticeable R^2 change (.0124). This suggests that individuals with higher educational levels may possess a more nuanced perception or critical evaluation skills that slightly mitigate the negative bias against AI-generated ads. The effect of AI on ad evaluations becomes less negative with increasing levels of education, indicating a moderating effect of education where higher-educated individuals might evaluate AI-generated ads more favorably.

Word of Mouth (WOM)

The analysis did not show a significant interaction effect for education on WOM ($\beta = .1364$, $p = .3135$). This suggests that educational attainment does not significantly influence how likely individuals are to talk about AI-generated ads. Although not statistically significant, there is a trend where higher education levels correlate with a less negative impact on the likelihood of spreading WOM about AI-generated ads. However, like with PI, the changes are not substantial enough to constitute a significant moderation.

Discussion of Hypothesis and Conclusions

Hypothesis H5.2b is supported. Higher levels of education are associated with better Ad Evaluation of AI-generated ads. Hypotheses H5.2a and H5.2c are not supported. Higher levels of education do not significantly improve Purchase Intent or the likelihood of spreading Word of Mouth for AI-generated ads.

This mixed response suggests that while education significantly moderates how ads are evaluated in relation to their AI or human origin, it does not significantly impact purchase intentions or the likelihood of spreading WOM. Notably, higher education levels tend to buffer the negative perceptions associated with AI-generated ads, potentially due to better critical thinking and information processing capabilities that come with higher educational attainment. This finding suggests that advertisers might need to consider educational backgrounds when targeting their ads, as more educated audiences might respond differently to AI-generated content compared to less educated ones.

5. Discussion

This chapter highlights the empirical findings by further discussing the findings, managerial implication, limitations, and further research.

The findings of our study underscore the significance of the believed origin of an advertisement in shaping consumer responses. It appears that consumer perceptions are influenced not by the actual method of ad creation but by what they belief about the ad's origin. Despite the advertisement in our experiment being generated by AI, participants responded more favorably when they believed it was created by a human. This discrepancy highlights a critical managerial implication: consumer beliefs about AI involvement in advertising can significantly impact ad evaluation and overall performance.

The implications are clear: companies need to carefully manage consumer perceptions regarding the use of AI in advertising. Even if a company does not use AI, the mere belief among consumers that AI is involved can lead to negative outcomes. This finding suggests that transparency about the ad creation process, coupled with efforts to build trust in AI technologies, is crucial for maintaining favorable consumer responses. The perceived authenticity and emotional connection associated with human-created ads seem to enhance consumer acceptance, indicating that the believed origin of an advertisement indeed matters.

5.1 Summary of Findings

Anxiety was a significant mediator in how AI-generated ads affected Purchase Intention, General Evaluation, and Word of Mouth. The presence of anxiety worsened consumer reactions to AI-generated ads, leading to lower intentions to purchase, poorer evaluations of the ads, and a reduced likelihood of recommending or talking about the product. The direct effects of AI on these outcomes were still significant after accounting for anxiety, indicating that other factors besides anxiety contribute to the negative reactions against AI-generated ads.

Attitudes played a significant moderating role in the relationship between ad type (AI vs. human) and outcomes such as Purchase Intention, General Evaluation, and Word of Mouth. The negative effects of AI-generated ads on these outcomes lessened as attitudes toward AI became more positive. This indicates that improving consumer attitudes toward AI could mitigate some of the adverse reactions to AI-generated content.

Extraversion did not significantly moderate the impact of AI-generated ads on any of the outcomes, which suggests that whether a person is introverted or extraverted does not influence their reaction to the type of ad creation.

Agreeableness significantly moderated the relationship between AI-generated ads and Ad Evaluation, but not Word of Mouth or Purchase Intent. Higher agreeableness was associated with a less negative response to AI-generated ads, implying that agreeable individuals may be more accepting or less critical of AI-generated content.

Openness was found to be a significant moderator for Ad Evaluation, with higher openness linked to a less negative impact of AI-generated ads. However, openness did not significantly moderate the relationship with Purchase Intention and Word of Mouth. This suggests that open-minded individuals may respond more favorably to new technologies like AI in advertisements, at least in terms of their buying intentions and evaluations.

The analysis of age as a moderator revealed that older individuals tended to evaluate AI-generated ads more favorably and were more likely to share information about them, compared to younger individuals who exhibited stronger negative responses.

The level of educational also plays a critical role in moderating consumer responses to AI-generated ads. While education did not significantly impact purchase intentions, it did significantly influence ad evaluations, with higher education levels associated with more favorable evaluations of AI-generated ads. However, education did not significantly affect word of mouth, despite a trend suggesting higher education correlated with a less negative impact.

Consumers' responses to AI-generated ads are complex and influenced by their emotional states, their personal traits, and their demographics. Positive attitudes toward AI and higher levels of agreeableness and openness can buffer the negative responses typically associated with AI-generated ads. Meanwhile, increased anxiety due to AI-generated ads consistently mediates negative consumer reactions across multiple outcomes, underscoring the need to address and reduce anxiety-provoking elements in such ads.

5.2 Discussion of Research Questions

RQ1: Does believing a visual ad is made by AI or a human affect the consumer response?

The findings confirm that the perceived origin of an advertisement significantly affects consumer responses. Ads identified as AI-generated are evaluated more negatively compared to those believed to be created by humans. This suggests that transparency regarding the use of AI in ad creation can influence consumer trust and acceptance.

RQ2: Does anxiety mediate how consumers respond to ads depending on whether they are believed to be AI or human-made?

Anxiety significantly mediates consumer responses to AI-generated ads, exacerbating negative reactions such as lower purchase intentions, poorer ad evaluations, and reduced word of mouth potential. This mediation suggests that beyond the initial bias against AI, the anxiety provoked by AI ads plays a crucial role in shaping the overall consumer reaction. Addressing this anxiety, perhaps by humanizing AI processes or enhancing transparency about how AI is used, could improve consumer responses.

RQ3: What factors influence consumer response to AI-generated ads?

Several factors influence consumer reactions to AI-generated ads. Firstly, attitudes towards AI play a crucial moderating role; more positive attitudes can lessen the negative impacts of AI-generated ads. Personality traits also modulate responses, where traits like agreeableness and openness lead to more favorable evaluations of AI-generated ads. Moreover, demographic factors like age and level of education influences these responses, with older and more educated individuals showing more acceptance and less negative bias towards AI-generated ads. Further Research might study more factors that this study did not cover.

5.3 Managerial Implications

5.3.1 Trigger Warning: Anxiety!

AI-generated advertising is received differently by consumers. One "trigger" of the target customers' discomfort is anxiety. Our results show that fear mediates between the ad creator and consumer behavior for all outcomes examined (purchase intention, ad evaluation, and WOM). This confirms Wu & Wen's (2021) assumptions derived from their research on consumer reactions to AI-generated advertising, showing that feelings of creepiness and discomfort towards robots can undermine the appreciation of advertising, suggesting that fear influences consumer reactions to AI-generated content. As AI continues to permeate the advertising sector, understanding and mitigating anxiety – and more particular AI Anxiety – is critical to developing marketing strategies that promote positive consumer engagement rather than discomfort. This is particularly relevant for products that are associated with high stakes or personal well-being.

This is a valuable insight for marketers as it can be inferred that the use of AI as a content generator may not be advisable in anxiety-ridden marketing contexts, such as pharmaceutical products or insurance. This is in line with the findings of Arango, Singaraju & Niininen (2023) on the impact of the use of AI on donation intentions. They found that potential donors reacted negatively to children's faces when they knew they had been generated by AI, with the negative effects mediated by reduced empathy and anticipatory guilt. This underscores that in scenarios requiring deep emotional engagement, AI-generated content may fall short of effectiveness.
Since anxiety mediates negative responses to AI ads, strategies to familiarize consumers with the role of AI in content creation or emphasizing the reliability and creativity of AI may help reduce anxiety and improve ad reception.

This research could be pivotal since consumer acceptance of AI in marketing and advertising is marked by a dichotomy: while AI's ability to offer personalized and efficient experiences is viewed positively (Merisavo et al., 2007), ethical concerns, privacy risks, and a preference for human interaction present notable challenges (Gonçalves et al., 2023). Thus, balancing the opportunities for enhanced personalization with the need to address anxiety and concerns is crucial for fostering consumer acceptance of AI in these fields.

In conclusion, the findings highlight the complex interplay of individual differences and psychological responses in shaping how consumers react to AI-generated versus human-generated advertisements. Marketers need to consider these factors when integrating AI into creative processes to enhance effectiveness and acceptance. By incorporating these strategies, marketers can more effectively deploy AI in advertising efforts, ensuring that the adoption of this technology leads to enhanced consumer engagement and satisfaction.

5.3.2 Personality Traits based Target Groups

Big Five personality traits can help in identifying target groups to create effective marketing campaigns. Kobayashi, Ishikawa, and Minamikawa (2019) studied how the Big Five personality traits influence ad targeting and creative design. They found that personality-based ad targeting can predict users' receptiveness to ads, tailoring ad creative to better suit individual personality traits. Their study found that personalization significantly improves the effectiveness of marketing campaigns by increasing ad receptivity and interaction rates. Given the possibility of personalizing advertising through AI, our findings can be used to identify people with higher AI acceptance based on their personality.

The intersection of AI-driven advertising and consumer personality traits provides a fertile ground for exploring how individual differences shape responses to technologically generated content. The Big Five personality traits—Openness, Agreeableness, and Extraversion—are particularly relevant in predicting and understanding these responses.

Openness to Experience denotes a person's receptivity to new ideas, creativity, and change (Rubinstein & Strul, 2007). Our study suggests that individuals with high levels of openness are more positively inclined towards AI-generated advertisements. This could be attributed to their appreciation for novel and innovative approaches, including the utilization of new technologies like AI in advertising (McCrae & Costa, 1992). They are likely to perceive AI-driven content as more interesting and engaging, which enhances their overall evaluation of the ads.

Target groups with high openness are ideal for marketing strategies that emphasize creativity, novelty, and sophisticated information; they tend to be more responsive to products and services that offer new experiences or innovative approaches (Rubinstein & Strul, 2007). This could be e.g.: early adopters of technology, art and culture enthusiasts, or travelers seeking unique experiences. Marketers targeting audiences characterized by high openness might find success in campaigns that emphasize the innovative and creative aspects of AI. This approach could involve showcasing how AI can tailor creative content to individual preferences or introduce unexpected and engaging elements into advertising.

Agreeableness reflects a person's propensity towards altruism, trust, and cooperation (McCrae & Costa, 1992). Our results indicate that agreeableness positively influences responses to AI-generated advertising. Individuals high in agreeableness may be more accepting and less critical of the intentions behind AI-generated ads, leading to more favorable evaluations and stronger purchase intentions. They may be more interested in products and services that promote health and well-being, not just for themselves but for their family and community. This includes e.g.: wellness programs, holistic health services, and community health initiatives.
For advertisers, understanding the impact of agreeableness can guide the tone and message of AI-generated content. Ads that emphasize trustworthiness, community benefits, and ethical assurances could resonate well with agreeable audiences.

Extraversion is associated with sociability, assertiveness, and a preference for social interaction. Extraverts responded more positively to AI (Attitude towards AI), likely due to their general openness to engaging experiences and content that can be shared socially. Interestingly, our findings did not show a significant interaction between extraversion and the source of the ad (AI vs. human), suggesting that while Extraverts are generally more responsive, their attitudes do not significantly differ based on the ad’s origin.

Incorporating the Big Five personality traits into the analysis of AI-driven advertising reveals significant insights into consumer behavior. Openness, Agreeableness, and Extraversion each play distinct roles in how individuals perceive, evaluate, and react to AI-generated advertisements. These traits not only predict individual differences in ad reception but also offer practical pathways for marketers to tailor their AI-driven campaigns to better meet the psychological profiles of their target audiences.

5.3.3 Pre-Testing

The analysis of how personality traits, attitudes towards AI, and anxiety influence responses to AI-generated content provides valuable insights for marketers looking to integrate AI more effectively in advertising strategies. Though pre-testing of visual ads performances is commonly used in advertisement pre-testing regarding personalities could be done to improve ad performances. Before fully launching an AI-generated campaign, pre-testing content across different personality profiles can help understand varying responses and adjust strategies accordingly. This would ensure that the final versions are refined to appeal across a broader range of personalities or are targeted to specific segments.

5.3.4 Attitude Shift toward AI – Older People like AI too!

According to our findings attitudes towards AI significantly affect how ads are received. Informative campaigns that educate consumers about the benefits and safety of AI can help improve attitudes, reducing negative biases. Large and influencing Companies (e.g. Google) could run a series of informational ads explaining how AI helps tailor search results. Recommendations on YouTube to user preferences cold also help to educate the mass audience, emphasizing transparency and control over data to build trust and positive attitudes.

The surprising finding from the study—that older people tend to be more acceptive towards the usage of AI in adverting—presents an intriguing dimension to our understanding of consumer reactions to AI-generated advertisements. Contrary to the common hypothesis and prevailing literature suggesting that younger individuals, typically more tech-savvy and accustomed to AI technologies, would be more receptive to AI-generated ads (Gillespie et al., 2021), our analysis indicates a shift in this pattern. Older individuals might evaluate AI-generated ads more favorably than their younger counterparts. This finding aligns with Park et al. (2022), who found that older people have a higher acceptance of AI-supported intelligent information technologies and adopt new technologies with increasing age to stay up to date. The unexpected moderating role of age in the evaluation of AI-generated advertisements highlights the nuanced ways in which different demographics interact with technology.

5.4 Theoretical Implications: Expansion of TRA Model

The Theory of Reasoned Action (TRA) posits that an individual's behavior is driven by their intentions, which are in turn influenced by their attitudes towards the behavior and subjective norms. When applying TRA to the findings related to attitudes towards AI and their influence on advertising effectiveness, several nuanced theoretical implications emerge:

The TRA traditionally considers attitudes towards a behavior as being influenced by beliefs about the outcomes of the behavior and evaluations of these outcomes (Ajzen & Fishbein, 1980). In the context of AI-generated advertising, this model should be expanded to include attitudes towards the technology itself.

The findings from our study suggest that an additional factor ‘Awareness of Origin’ of the advertisement should be included to extend the TRA. Thus, the extended TRsA model could enhance its applicability in contexts where the (believed) source of information plays a crucial role, such as in advertising by AI versus humans (see *Figure 6*).

Figure 6 - Expansion of TRA Model: Incorporating Awareness of Origin
Source: Authors’ illustration generated

Our analysis indicated significant differences in the evaluation of advertisements based on whether the ad was believed as AI-generated or human-made. When participants knew an ad was generated by AI (Awareness), their attitudes and, consequently, their intentions and behaviors were negatively influenced. This was evident in lower scores in Purchase Intention, Ad Evaluation, and Word of Mouth in Survey A compared to Survey B, where the origin was either not disclosed or attributed to humans. This suggests that merely being aware of the ad's AI origin triggers a set of biases or skepticism that impacts consumer response. Thus, integrating 'Awareness of Origin' into the TRA model could help explain additional variance in how attitudes are formed and how they influence subsequent behaviors.

The extension of the TRA model by integrating Awareness of Origin and its impact on consumer responses metrics like Purchase Intention, Ad Evaluation, and Word of Mouth, is supported by several pieces of data and findings:

It was consistently observed that Survey B, where the ad was not identified as AI-generated or were attributed to human creators, had higher means across Purchase Intention, Ad Evaluation, and Word of Mouth compared to Survey A, where the ad was explicitly marked as AI-generated. This suggests that awareness of an ad's AI origin negatively impacts consumer responses. Respondents in Survey B, believing the ad to be human made, showed more favorable reactions.

While discussing anxiety, it became evident that knowing an ad is AI-generated might heighten anxiety, which in turn affects ad evaluation negatively. Although the anxiety discussed was a general state, not directly caused by AI, the correlation between higher anxiety levels and lower ad effectiveness in the context of AI ads supports the notion that awareness (or misperceptions about AI) could be influencing anxiety levels.

Furthermore, the explicit mention of AI as the ad creator serves as a moderating variable influenced the traditional pathways of TRA – attitude to behavioral intention to action. The statistical evidence showed significant differences in consumer reactions based solely on the source attribution of the ad, pointing towards the necessity of including 'Awareness of Origin' in the TRA model. Moreover, our findings suggesting that personality, age, and education might interact with awareness in complex ways that TRA traditionally doesn't account for.

These data points collectively support the argument that awareness of an ad’s origin as AI-generated introduces biases or skepticism that influence the cognitive and affective processes stipulated by the TRA model. This theoretical extension suggests that TRA could be enhanced by considering the roles of awareness about the ad's origin to better predict and understand consumer attitudes and behaviors in the context of AI-generated content.

Incorporating these factors into the TRA model would not only broaden the theoretical understanding but also enhance the model's practical relevance, particularly in digital marketing and online advertising contexts. This expanded model could assist marketers in strategizing more effectively by considering how awareness and knowledge of an ad's origin influence consumer reactions. For instance, marketers might find it advantageous to be transparent about an ad's AI origin in demographics that exhibit higher levels of acceptance and understanding of AI capabilities.

5.5 Limitations and Further Research

Future research should focus on empirically testing this expanded TRA model across different contexts and consumer segments to validate the proposed theoretical adjustments. Additionally, studies could explore the thresholds of AI acceptance in advertising, determining how much awareness are necessary to turn AI-generated content into a competitive advantage rather than a drawback.

The sample size and selection process may not adequately represent the target population, which limits the generalizability of the findings. Self-selection bias could also skew results if individuals with particular attitudes towards AI are more likely to participate. Relying on self-reported data introduces the potential for bias. The accuracy and reliability of the constructs measured depend on respondents' perceptions and honesty, which are subjective and can be influenced by social desirability.

While anxiety was identified as a mediator, other emotional or cognitive factors such as trust, privacy concerns, or perceived usefulness of AI could also mediate the relationships explored. Additionally, moderators other than the personality traits could influence the outcomes, including demographic variables or past experiences with AI. Furthermore, the lower Purchase Intention and Ad Evaluation scores in the AI group might not only reflect anxiety or negative attitudes towards AI but could also be a manifestation of a broader resistance to change or a preference for human touch in services and advertising.

As the field of artificial intelligence continues to expand and evolve, the need for further investigation into mediators becomes increasingly important. Anxiety and particularly AI anxiety is a significant and growing concern as more individuals and organizations integrate AI systems into their daily operations and decision-making processes. Understanding the nuances of this anxiety, its causes, and its impacts is crucial. Therefore, comprehensive research into various mediators that could alleviate or enhance AI anxiety is essential for developing effective strategies to address and manage this modern challenge.

The data suggest a cautious approach is warranted when integrating AI into consumer-facing functions. While there is an evident potential for anxiety reduction strategies to enhance receptivity to AI-generated content, there also lies an opportunity to educate and acclimate consumers to the benefits and reliability of AI through strategic communication and transparency.

Moreover, considering the personality traits that seem to moderate consumer responses to AI, targeted marketing strategies could be developed to align with the psychological profiles of consumers. However, this strategy must navigate the complexity of individual differences, cultural contexts, and the evolving nature of AI itself.

Future research could expand upon these findings by employing longitudinal designs, more diverse samples, and investigating additional variables that may influence consumer perceptions and behaviors in the context of AI. Furthermore, research could explore additional factors that might influence the reception of AI-created ads, such as cultural differences in the perception of AI, the type of products being advertised, or the complexity of the ad content created by AI.

6. Conclusion

This chapter concludes the findings of the study.

The comparative study of Surveys A (marked as AI-generated) and Survey B (marked as human-made) illustrates a clear consumer bias towards human-made advertisements over AI-generated ones. This bias is influenced by a complex interplay of personality traits, attitudes towards AI, and the mediating effect of anxiety on consumer responses. To leverage AI effectively in advertising, it is essential to address these psychological and emotional factors directly. Marketers need to develop nuanced strategies that consider these elements to enhance the acceptance and effectiveness of AI-generated content. This could lead to a paradigm shift in how AI is perceived in the creative domains, ultimately enabling AI to reach its full potential in marketing and advertising.

The study answers the three research questions, highlighting a definitive impact of ad creator identity on consumer behavior and identifying key factors that influence the evaluation of AI-generated advertisements. The comparative analysis of Surveys A and B provides a robust framework to understand how the identification of an advertisement's creator—whether AI or human—affects consumer responses across various dimensions, including purchase intention, ad evaluation, and word of mouth. This analysis not only delineates the differences in consumer responses between the two surveys but also delves into the psychological underpinnings such as personality traits, attitudes towards AI, and the mediating role of anxiety.

Thus, the results of the comparative analysis of Surveys A and B offer key insights to help advance business and policy theory and practice, particularly in the areas of entrepreneurship, ownership, and renewal. By focusing on the dynamics of consumer behavior in response to AI versus human-made content, this study sheds light on how new technologies can influence market dynamics and consumer decision-making. These findings are both relevant for start-ups and established companies looking to innovate their advertising strategies and product offerings.

Entrepreneurs and business owners can use the results of this study to better understand the readiness of the market for AI-generated content. This knowledge will enable them to shape their business models and marketing strategies to better meet consumer expectations and embody the principle of entrepreneurship.
The study highlights the significant impact of advertiser identity (AI vs. human) on consumer behavior and underlines the importance of innovative approaches in advertising. For entrepreneurs and business owners, this finding is critical as it suggests that the integration of AI can be a key differentiator in the marketplace. However, the entrepreneurial application of AI in advertising needs to be imaginative and action-orientated, exploring new ways to combine AI capabilities with human creativity to improve advertising effectiveness and customer engagement.
Ownership in the context of AI-driven advertising requires a strategic renewal of traditional advertising paradigms. Organizations need to proactively adopt new technologies while ensuring that these technologies align with the core values and expectations of their target audiences. This could be done by incorporating personality traits-based target groups. However, it still requires a continuous re-evaluation and adjustment of business strategies to responsibly incorporate AI and ensure that these technologies are used to truly enhance the customer experience and brand value.

The implications of the study go beyond local markets and offer insights that can be applied globally. The **international perspective** is crucial, as consumer acceptance of AI can vary greatly across cultures and markets. Companies that take an international perspective can better tailor their AI strategies to different consumer groups, increasing their global reach and relevance.

This research also promotes an **entrepreneurial mindset** by emphasizing the importance of innovation in the use of AI in advertising. Embracing AI in advertising represents a clear entrepreneurial opportunity, but it requires creativity, passion, and a readiness to act. Entrepreneurs must not only implement AI technologies but also innovate in how these technologies are applied, ensuring that AI-driven solutions are both effective and captivating to consumers. This proactive approach can lead to the development of more personalized, engaging advertising content that resonates with a diverse consumer base.

The study also emphasizes the importance of **ethical considerations and social impact** when using AI technologies. The study's indication that anxiety mediates consumer response to AI-generated ads highlights the need for ethical consideration in AI deployments. Businesses must ensure that their use of AI in advertising is transparent and ethically sound, prioritizing consumer well-being and trust. This involves educating consumers about AI's role and addressing any concerns related to privacy and data security. By championing transparency and ethical practices in the use of AI, companies can position themselves as responsible leaders in the industry. This commitment to ethics helps to build trust and credibility with consumers and ensures that advances in AI are made with consideration for its wider impact on society.

In summary, the comparative analysis not only enhances our understanding of how AI influences consumer responses, but also aligns with the mission of Jönköping's International Business School to advance business and policy through insights that encourage entrepreneurship, ownership, and renewal. By heeding the principles of international at heart, entrepreneurial thinking and responsible action, organizations can navigate the complexities of AI integration in advertising with an ethical, effective, and globally focused strategy. Businesses are urged to innovate responsibly, embracing global perspectives and entrepreneurial zeal while ensuring their actions are ethically grounded and culturally sensitive. This holistic approach interconnects the advancement of business theory and practice with the evolving needs of modern entrepreneurship, promoting renewal and sustainable growth in the digital age. It equips future business leaders—whether students or professionals—to drive innovation conscientiously and strategically, ushering in a new era of market engagement that is both progressive and principled. Today's creators shape tomorrow's outcomes.

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Appendices

Appendix 1 - Questionnaire of Survey

Introduction:

Welcome to our survey on Advertising for our master thesis. This brief survey is structured into four key sections. The questions on each section are not building on each other, therefore they differ. Your responses are anonymous and vital for our research. Thank you for your participation. Let's dive in!

Survey A:

The following questions relate to the advertising presented. Please answer.

This is a visual ad for a pot is generated from AI.

Survey B:

Advertisement Questions

Based on the advertisement, how likely are you to purchase the product advertised ?

1 Very unlikely	2 Somewhat unlikely	3 Neither likely nor unlikely	4 Somewhat likely	5 Very likely
○	○	○	○	○

How relevant did you find the product advertised to your needs?

1 Not relevant at all	2 Somewhat not relevant	3 Neither relevant nor not relevant	4 Somewhat relevant	5 Very relevant
○	○	○	○	○

How would you rate your overall impression of the advertisement image you just viewed?

1 Very negative	2 Somewhat negative	3 Neither negative nor positive	4 Somewhat positive	5 Very positive
○	○	○	○	○

How likely are you to consider trying this product?

1 Very unlikely	2 Somewhat unlikely	3 Neither likely nor unlikely	4 Somewhat likely	5 Very likely
○	○	○	○	○

To what extent do you agree with the statement: "The advertisement is persuasive."?

1 Strongly disagree	2 Somewhat disagree	3 Neither agree not disagree	4 Somewhat agree	5 strongly agree
○	○	○	○	○

How likely are you to recommend this product to friends or family?

1 Very unlikely	2 Somewhat unlikely	3 Neither likely nor unlikely	4 Somewhat likely	5 Very likely
○	○	○	○	○

Anxiety Questions

In this section, we ask you to consider your current emotional state. Below, you will find a series of statements. Please indicate to what degree these statements reflect how you feel right now.

I feel tense or 'wound up'

0: Not at all	1: From time to time, occasionally	2: A lot of the time	3: Most of the time
○	○	○	○

I still enjoy the things I used to enjoy:

0: Definitely as much	1: Not quite so much	2: Only a little	3: Hardly at all
○	○	○	○

I get a sort of frightened feeling as if something awful is about to happen:

0: Not at all	1: A little, but it doesn't worry me	2: Yes, but not too badly	3: Very definitely and quite badly
○	○	○	○

I can sit at ease and feel relaxed:

0: Definitely	1: Usually	2: Not often	3: Not at all
○	○	○	○

I get a sort of frightened feeling like 'butterflies' in the stomach:

0: Not at all	1: Occasionally	2: Quite often	3: Very often
○	○	○	○

I feel restless as I have to be on the move:

0: Not at all	1: Not very much	2: Quite a lot	3: Very much so
○	○	○	○

Worrying thoughts go through my mind:

0: Only occasionally	1: From time to time but not too often	2: A lot of the time	3: A great deal of the time
○	○	○	○

Extraversion, Agreeableness, Openness Questions

Below, you will find a series of statements. Please indicate how much you agree with each statement, reflecting on your usual behavior and attitudes towards others.

I see myself as someone who is talkative.

1 Not at all	2 Slightly	3 Moderately	4 Very much	5 Extremely
○	○	○	○	○

I see myself as someone who is full of energy.

1 Not at all	2 Slightly	3 Moderately	4 Very much	5 Extremely
○	○	○	○	○

I see myself as someone who has an assertive personality.

1 Not at all	2 Slightly	3 Moderately	4 Very much	5 Extremely
○	○	○	○	○

I see myself as someone who is helpful and unselfish with others.

1 Not at all	2 Slightly	3 Moderately	4 Very much	5 Extremely
○	○	○	○	○

I see myself as someone who has a forgiving nature.

1 Not at all	2 Slightly	3 Moderately	4 Very much	5 Extremely
○	○	○	○	○

I see myself as someone who is generally trusting.

1 Not at all	2 Slightly	3 Moderately	4 Very much	5 Extremely
○	○	○	○	○

I see myself as someone who is original and comes up with new ideas.

1 Not at all	2 Slightly	3 Moderately	4 Very much	5 Extremely
○	○	○	○	○

I see myself as someone who likes to reflect and play with ideas.

1 Not at all	2 Slightly	3 Moderately	4 Very much	5 Extremely
○	○	○	○	○

I see myself as someone who has an active imagination.

1 Not at all	2 Slightly	3 Moderately	4 Very much	5 Extremely
○	○	○	○	○

Attitude Questions

In this section, we aim to understand your perceptions and feelings about Artificial Intelligence (AI) and its role in society. Please read each statement below and rate how much you agree or disagree with it, based on your own experiences and beliefs.

Organizations use Artificial Intelligence unethically

None at all	A little	A moderate amount	A lot	A great deal
○	○	○	○	○

Artificially Intelligent systems can help people feel happier

Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
○	○	○	○	○

I am impressed by what Artificial Intelligence can do

Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
○	○	○	○	○

I think Artificially Intelligent systems make many errors

Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
○	○	○	○	○

I am interested in using Artificially Intelligent systems in my daily life

Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
○	○	○	○	○

Artificial Intelligence might take control of people

Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
○	○	○	○	○

I think Artificial Intelligence is dangerous

Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
○	○	○	○	○

Demographic Questions

What is your gender?

- ○ Female
- ○ Male
- ○ Non-binary/third gender
- ○ Prefer not to say

How old are you?

What is the highest level of education you have completed?

- ○ Below Highschool graduate
- ○ High school graduate or equivalent
- ○ Bachelor's degree
- ○ Master's degree
- ○ Doctoral degree
- ○ Prefer not to say

What country are you from?

We thank you for your time spent taking this survey.
Your response has been recorded.

Appendix 2 - Reliability Test

Reliability

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	276	97.5
	Excluded[a]	7	2.5
	Total	283	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.697	29

Appendix 3 - Descriptive Statistics & T tests

Suvey A

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
PI	143	1	4	2.03	1.048
Eva_M	143	1.00	4.50	2.2832	1.00274
WOM	143	1	5	1.87	1.027
Anx_M	140	1.00	4.00	2.6092	.74411
Extr_M	143	1.00	4.67	2.7156	.82123
Agre_M	142	1.00	5.00	3.0188	.94346
Open_M	143	1.00	5.00	2.9161	1.03270
Atti_M	139	1.43	4.86	3.4060	.48560
Valid N (listwise)	136				

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Age	133	18.00	73.00	27.1278	8.53106
Valid N (listwise)	133				

Descriptives

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Edu	142	1	5	2.62	.905
Valid N (listwise)	142				

Statistics

Gender

N	Valid	141
	Missing	2

Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Female	58	40.6	41.1	41.1
	Male	82	57.3	58.2	99.3
	Prefer not to say	1	.7	.7	100.0
	Total	141	98.6	100.0	
Missing	System	2	1.4		
Total		143	100.0		

Survey B

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
PI	140	1	5	3.44	.969
AdEva_M	140	1.25	5.00	3.5196	.81304
WOM	140	1	5	3.04	1.042
Anx_M	140	1.00	3.71	2.0418	.61582
Extra_M	140	1.00	5.00	3.0595	.71890
Agree_M	140	1.67	5.00	3.2857	.67568
Open_M	140	1.67	5.00	3.4048	.78024
Atti_M	140	2.43	4.71	3.2990	.45367
Valid N (listwise)	140				

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Age	131	19.00	66.00	27.0840	9.68586
Valid N (listwise)	131				

Descriptives

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Edu	139	1	4	2.78	.877
Valid N (listwise)	139				

Statistics

Gender

N	Valid	139
	Missing	1

Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Female	71	50.7	51.1	51.1
	Male	67	47.9	48.2	99.3
	Non-binary/third gender	1	.7	.7	100.0
	Total	139	99.3	100.0	
Missing	System	1	.7		
Total		140	100.0		

T-Test

T-Test

Group Statistics

	AI_H	N	Mean	Std. Deviation	Std. Error Mean
PI	1.00	143	2.03	1.048	.088
	.00	140	3.44	.969	.082
Eva_M	1.00	143	2.2832	1.00274	.08385
	.00	140	3.5196	.81304	.06871
WOM	1.00	143	1.87	1.027	.086
	.00	140	3.04	1.042	.088

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
PI	Equal variances assumed	.069	.793	-11.787	281	<.001	<.001	-1.415	.120	-1.651	-1.179
	Equal variances not assumed			-11.797	280.101	<.001	<.001	-1.415	.120	-1.651	-1.179
Eva_M	Equal variances assumed	7.966	.005	-11.380	281	<.001	<.001	-1.23643	.10865	-1.45030	-1.02255
	Equal variances not assumed			-11.405	271.618	<.001	<.001	-1.23643	.10841	-1.44986	-1.02299
WOM	Equal variances assumed	1.120	.291	-9.447	281	<.001	<.001	-1.162	.123	-1.404	-.920
	Equal variances not assumed			-9.445	280.645	<.001	<.001	-1.162	.123	-1.404	-.920

Appendix 4 - Mediation Analysis

Anxiety mediation towards Purchase intentions

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : PI
    X  : AI_H
    M  : Anx_M

Sample
Size:  280

**************************************************************************
OUTCOME VARIABLE:
 Anx_M

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .3847      .1480      .4665    48.3030     1.0000   278.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     2.0418      .0577    35.3732      .0000     1.9282     2.1555
AI_H          .5673      .0816     6.9500      .0000      .4067      .7280

**************************************************************************
OUTCOME VARIABLE:
 PI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .6527      .4260      .8764   102.7707     2.0000   277.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     4.5584      .1856    24.5642      .0000     4.1931     4.9237
AI_H        -1.1115      .1212    -9.1685      .0000    -1.3501     -.8728
Anx_M        -.5464      .0822    -6.6458      .0000     -.7082     -.3845


****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
    -1.1115      .1212    -9.1685      .0000    -1.3501     -.8728

Indirect effect(s) of X on Y:
          Effect     BootSE   BootLLCI   BootULCI
Anx_M     -.3100      .0652     -.4510     -.1926

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000

------ END MATRIX -----
```

Anxiety mediation towards Ad Evaluation

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : Eva_M
    X  : AI_H
    M  : Anx_M

Sample
Size:  280

**************************************************************************
OUTCOME VARIABLE:
 Anx_M

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .3847      .1480      .4665    48.3030     1.0000   278.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     2.0418      .0577    35.3732      .0000     1.9282     2.1555
AI_H          .5673      .0816     6.9500      .0000      .4067      .7280

**************************************************************************
OUTCOME VARIABLE:
 Eva_M

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .6963      .4849      .6361   130.3810     2.0000   277.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     4.8559      .1581    30.7166      .0000     4.5447     5.1672
AI_H         -.8841      .1033    -8.5604      .0000    -1.0873     -.6808
Anx_M        -.6545      .0700    -9.3448      .0000     -.7923     -.5166


****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
     -.8841      .1033    -8.5604      .0000    -1.0873     -.6808

Indirect effect(s) of X on Y:
          Effect     BootSE   BootLLCI   BootULCI
Anx_M     -.3713      .0672     -.5113     -.2472

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000

------ END MATRIX -----
```

Anxiety mediation towards Word-Of-Mouth

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : WOM
    X  : AI_H
    M  : Anx_M

Sample
Size:  280

**************************************************************************
OUTCOME VARIABLE:
 Anx_M

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .3847      .1480      .4665    48.3030     1.0000   278.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     2.0418      .0577    35.3732      .0000     1.9282     2.1555
AI_H          .5673      .0816     6.9500      .0000      .4067      .7280

**************************************************************************
OUTCOME VARIABLE:
 WOM

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .5361      .2874     1.0121    55.8507     2.0000   277.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.7998      .1994    19.0547      .0000     3.4073     4.1924
AI_H         -.9520      .1303    -7.3076      .0000    -1.2084     -.6955
Anx_M        -.3742      .0883    -4.2361      .0000     -.5481     -.2003


****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
     -.9520      .1303    -7.3076      .0000    -1.2084     -.6955

Indirect effect(s) of X on Y:
          Effect     BootSE   BootLLCI   BootULCI
Anx_M     -.2123      .0618     -.3459     -.1053

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000

------ END MATRIX -----
```

Appendix 5 - Moderation Analysis

5.1 Attitude

Attitude moderation towards Purchase intentions

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 1
    Y  : PI
    X  : AI_H
    W  : Atti_M

Sample
Size:  279

**************************************************************************
OUTCOME VARIABLE:
 PI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .6134      .3762      .9602    55.2884     3.0000   275.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.9166      .6100     6.4204      .0000     2.7157     5.1175
AI_H        -4.2144      .8493    -4.9622      .0000    -5.8864    -2.5425
Atti_M       -.1436      .1832     -.7839      .4338     -.5043      .2171
Int_1         .8204      .2511     3.2666      .0012      .3260     1.3148

Product terms key:
 Int_1    :        AI_H     x        Atti_M

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0242    10.6709     1.0000   275.0000      .0012
----------
    Focal predict: AI_H     (X)
          Mod var: Atti_M   (W)

Conditional effects of the focal predictor at values of the moderator(s):

     Atti_M     Effect         se          t          p       LLCI       ULCI
     3.0000    -1.7533      .1471   -11.9221      .0000    -2.0429    -1.4638
     3.2857    -1.5189      .1192   -12.7475      .0000    -1.7535    -1.2844
     3.8571    -1.0502      .1739    -6.0402      .0000    -1.3924     -.7079

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

W values in conditional tables are the 16th, 50th, and 84th percentiles.

------ END MATRIX -----
```

Attitude moderation towards Ad Evaluation

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 1
    Y  : Eva_M
    X  : AI_H
    W  : Atti_M

Sample
Size:  279

**************************************************************************
OUTCOME VARIABLE:
 Eva_M

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .6109      .3732      .7806    54.5769     3.0000   275.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.1944      .5500     5.8075      .0000     2.1115     4.2772
AI_H        -3.4779      .7658    -4.5416      .0000    -4.9855    -1.9704
Atti_M        .0986      .1652      .5969      .5511     -.2266      .4238
Int_1         .6505      .2264     2.8729      .0044      .2048     1.0963

Product terms key:
 Int_1    :        AI_H     x        Atti_M

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0188     8.2535     1.0000   275.0000      .0044
----------
    Focal predict: AI_H     (X)
          Mod var: Atti_M   (W)

Conditional effects of the focal predictor at values of the moderator(s):

     Atti_M     Effect         se          t          p       LLCI       ULCI
     3.0000    -1.5263      .1326   -11.5100      .0000    -1.7874    -1.2652
     3.2857    -1.3404      .1074   -12.4759      .0000    -1.5519    -1.1289
     3.8571     -.9687      .1568    -6.1791      .0000    -1.2773     -.6601

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

W values in conditional tables are the 16th, 50th, and 84th percentiles.

------ END MATRIX -----
```

Attitude moderation towards Word-Of-Mouth

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 1
    Y  : WOM
    X  : AI_H
    W  : Atti_M

Sample
Size:  279

**************************************************************************
OUTCOME VARIABLE:
 WOM

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .5183      .2686     1.0356    33.6627     3.0000   275.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.0763      .6335     4.8559      .0000     1.8291     4.3235
AI_H        -3.2768      .8820    -3.7151      .0002    -5.0132    -1.5404
Atti_M       -.0123      .1903     -.0647      .9485     -.3869      .3622
Int_1         .6246      .2608     2.3948      .0173      .1111     1.1380

Product terms key:
 Int_1    :        AI_H     x        Atti_M

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0153     5.7349     1.0000   275.0000      .0173
----------
    Focal predict: AI_H     (X)
          Mod var: Atti_M   (W)

Conditional effects of the focal predictor at values of the moderator(s):

     Atti_M     Effect         se          t          p       LLCI       ULCI
     3.0000    -1.4031      .1527    -9.1864      .0000    -1.7037    -1.1024
     3.2857    -1.2246      .1237    -9.8961      .0000    -1.4682     -.9810
     3.8571     -.8677      .1806    -4.8056      .0000    -1.2232     -.5123

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

W values in conditional tables are the 16th, 50th, and 84th percentiles.

------ END MATRIX -----
```

5.2 Openness

Openness moderation towards Purchase intentions

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 1
    Y  : PI
    X  : AI_H
    W  : Open_M

Sample
Size:  283

**************************************************************************
OUTCOME VARIABLE:
 PI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .6330      .4007      .9195    62.1711     3.0000   279.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     2.7895      .3641     7.6622      .0000     2.0728     3.5061
AI_H        -1.9875      .4366    -4.5525      .0000    -2.8469    -1.1281
Open_M        .1919      .1042     1.8409      .0667     -.0133      .3971
Int_1         .2285      .1301     1.7560      .0802     -.0277      .4847

Product terms key:
 Int_1    :        AI_H     x        Open_M

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0066     3.0834     1.0000   279.0000      .0802
----------
    Focal predict: AI_H     (X)
          Mod var: Open_M   (W)

Conditional effects of the focal predictor at values of the moderator(s):

     Open_M     Effect         se          t          p       LLCI       ULCI
     2.0000    -1.5305      .1988    -7.6970      .0000    -1.9219    -1.1390
     3.0000    -1.3019      .1217   -10.6941      .0000    -1.5416    -1.0623
     4.3333     -.9972      .1859    -5.3639      .0000    -1.3632     -.6312

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

W values in conditional tables are the 16th, 50th, and 84th percentiles.

------ END MATRIX -----
```

Openness moderation towards Ad Evaluation

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 1
    Y  : Eva_M
    X  : AI_H
    W  : Open_M

Sample
Size:  283

**************************************************************************
OUTCOME VARIABLE:
 Eva_M

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .6756      .4565      .6678    78.1033     3.0000   279.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     2.7429      .3103     8.8408      .0000     2.1322     3.3537
AI_H        -2.0303      .3721    -5.4570      .0000    -2.7628    -1.2979
Open_M        .2281      .0888     2.5678      .0108      .0532      .4030
Int_1         .3105      .1109     2.7993      .0055      .0921      .5288

Product terms key:
 Int_1    :        AI_H     x        Open_M

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0153     7.8359     1.0000   279.0000      .0055
----------
    Focal predict: AI_H     (X)
          Mod var: Open_M   (W)

Conditional effects of the focal predictor at values of the moderator(s):

     Open_M     Effect         se          t          p       LLCI       ULCI
     2.0000    -1.4094      .1695    -8.3170      .0000    -1.7430    -1.0758
     3.0000    -1.0989      .1038   -10.5915      .0000    -1.3031     -.8947
     4.3333     -.6849      .1584    -4.3228      .0000     -.9968     -.3730

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

W values in conditional tables are the 16th, 50th, and 84th percentiles.

------ END MATRIX -----
```

Openness moderation towards Word-Of-Mouth

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 1
    Y  : WOM
    X  : AI_H
    W  : Open_M

Sample
Size:  283

**************************************************************************
OUTCOME VARIABLE:
 WOM

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .5471      .2993      .9946    39.7202     3.0000   279.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     2.2588      .3786     5.9657      .0000     1.5134     3.0041
AI_H        -1.4082      .4541    -3.1015      .0021    -2.3020     -.5144
Open_M        .2282      .1084     2.1048      .0362      .0148      .4416
Int_1         .1228      .1354      .9074      .3650     -.1436      .3893

Product terms key:
 Int_1    :        AI_H     x        Open_M

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0021      .8233     1.0000   279.0000      .3650

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

------ END MATRIX -----
```

5.3 Extraversion

Extraversion moderation towards Purchase intentions

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 1
    Y  : PI
    X  : AI_H
    W  : Extr_M

Sample
Size:  283

**************************************************************************
OUTCOME VARIABLE:
 PI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .6563      .4307      .8735    70.3545     3.0000   279.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     2.1662      .3465     6.2518      .0000     1.4841     2.8482
AI_H        -1.6639      .4398    -3.7833      .0002    -2.5296     -.7981
Extr_M        .4173      .1103     3.7843      .0002      .2002      .6343
Int_1         .1445      .1459      .9908      .3226     -.1426      .4317

Product terms key:
 Int_1    :        AI_H     x        Extr_M

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0020      .9817     1.0000   279.0000      .3226

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

------ END MATRIX -----
```

Extraversion moderation towards Ad Evaluation

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 1
    Y  : Eva_M
    X  : AI_H
    W  : Extr_M

Sample
Size:  283

**************************************************************************
OUTCOME VARIABLE:
 Eva_M

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .6754      .4562      .6681    78.0289     3.0000   279.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     2.1637      .3030     7.1402      .0000     1.5672     2.7603
AI_H        -1.5020      .3846    -3.9050      .0001    -2.2592     -.7449
Extr_M        .4432      .0964     4.5953      .0000      .2533      .6330
Int_1         .1539      .1276     1.2066      .2286     -.0972      .4051

Product terms key:
 Int_1    :        AI_H     x        Extr_M

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0028     1.4558     1.0000   279.0000      .2286

********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

------ END MATRIX -----
```

Extraversion moderation towards Word-Of-Mouth

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 1
    Y  : WOM
    X  : AI_H
    W  : Extr_M

Sample
Size:  283

**************************************************************************
OUTCOME VARIABLE:
 WOM

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .5713      .3264      .9561    45.0694     3.0000   279.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     1.6145      .3625     4.4539      .0000      .9010     2.3281
AI_H         -.9280      .4601    -2.0168      .0447    -1.8338     -.0222
Extr_M        .4645      .1154     4.0265      .0001      .2374      .6916
Int_1        -.0272      .1526     -.1782      .8587     -.3276      .2732

Product terms key:
 Int_1    :        AI_H     x        Extr_M

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0001      .0317     1.0000   279.0000      .8587

********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

------ END MATRIX -----
```

5.4 Agreeableness

Agreeableness moderation towards Purchase intentions

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 1
    Y  : PI
    X  : AI_H
    W  : Agre_M

Sample
Size:  282

**************************************************************************
OUTCOME VARIABLE:
 PI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .6604      .4362      .8621    71.6838     3.0000   278.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     2.3408      .3909     5.9879      .0000     1.5712     3.1103
AI_H        -1.9790      .4706    -4.2051      .0000    -2.9054    -1.0526
Agre_M        .3354      .1166     2.8778      .0043      .1060      .5649
Int_1         .2189      .1430     1.5308      .1270     -.0626      .5005

Product terms key:
 Int_1    :        AI_H     x        Agre_M

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0048     2.3432     1.0000   278.0000      .1270

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

------ END MATRIX -----
```

Agreeableness moderation towards Ad Evaluation

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 1
    Y  : Eva_M
    X  : AI_H
    W  : Agre_M

Sample
Size:  282

**************************************************************************
OUTCOME VARIABLE:
 Eva_M

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .7337      .5383      .5649   108.0317     3.0000   278.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     1.9855      .3164     6.2746      .0000     1.3626     2.6084
AI_H        -1.8291      .3809    -4.8014      .0000    -2.5790    -1.0792
Agre_M        .4669      .0943     4.9491      .0000      .2812      .6526
Int_1         .2400      .1158     2.0734      .0391      .0121      .4679

Product terms key:
 Int_1    :        AI_H     x        Agre_M

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0071     4.2989     1.0000   278.0000      .0391
----------
    Focal predict: AI_H     (X)
          Mod var: Agre_M   (W)

Conditional effects of the focal predictor at values of the moderator(s):

     Agre_M     Effect         se          t          p       LLCI       ULCI
     2.3333    -1.2690      .1349    -9.4066      .0000    -1.5346    -1.0035
     3.3333    -1.0290      .0921   -11.1757      .0000    -1.2103     -.8478
     4.0000     -.8690      .1299    -6.6872      .0000    -1.1248     -.6132

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

W values in conditional tables are the 16th, 50th, and 84th percentiles.

------ END MATRIX -----
```

Agreeableness moderation towards Word-Of-Mouth

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 1
    Y  : WOM
    X  : AI_H
    W  : Agre_M

Sample
Size:  282

**************************************************************************
OUTCOME VARIABLE:
 WOM

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .5883      .3460      .9266    49.0338     3.0000   278.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     1.4011      .4053     3.4570      .0006      .6033     2.1989
AI_H         -.9075      .4879    -1.8600      .0639    -1.8680      .0530
Agre_M        .4975      .1208     4.1171      .0001      .2596      .7354
Int_1        -.0381      .1483     -.2572      .7972     -.3300      .2537

Product terms key:
 Int_1    :        AI_H     x        Agre_M

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0002      .0662     1.0000   278.0000      .7972

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

------ END MATRIX -----
```

7.5 Age

Age moderation towards Purchase intentions

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 1
    Y  : PI
    X  : AI_H
    W  : Age

Sample
Size:  264

**************************************************************************
OUTCOME VARIABLE:
 PI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .6213      .3860      .9715    54.4772     3.0000   260.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.9290      .2566    15.3113      .0000     3.4237     4.4343
AI_H        -2.0909      .3841    -5.4428      .0000    -2.8473    -1.3344
Age         -.0168      .0089    -1.8852      .0605     -.0344      .0007
Int_1         .0206      .0134     1.5303      .1272     -.0059      .0471

Product terms key:
 Int_1    :        AI_H     x        Age

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0055     2.3417     1.0000   260.0000      .1272

********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

------ END MATRIX -----
```

Age moderation towards Ad Evaluation

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 1
    Y  : Eva_M
    X  : AI_H
    W  : Age

Sample
Size:  264

**************************************************************************
OUTCOME VARIABLE:
 Eva_M

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .6104      .3726      .7920    51.4654     3.0000   260.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.9182      .2317    16.9109      .0000     3.4620     4.3745
AI_H        -2.2947      .3469    -6.6156      .0000    -2.9777    -1.6117
Age         -.0143      .0081    -1.7763      .0768     -.0302      .0016
Int_1         .0359      .0121     2.9557      .0034      .0120      .0598

Product terms key:
 Int_1    :        AI_H     x        Age

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0211     8.7361     1.0000   260.0000      .0034
----------
    Focal predict: AI_H     (X)
          Mod var: Age      (W)

Conditional effects of the focal predictor at values of the moderator(s):

        Age     Effect         se          t          p       LLCI       ULCI
    22.0000    -1.5053      .1259   -11.9571      .0000    -1.7532    -1.2574
    25.0000    -1.3976      .1125   -12.4230      .0000    -1.6191    -1.1761
    29.6000    -1.2326      .1137   -10.8451      .0000    -1.4563    -1.0088

********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

W values in conditional tables are the 16th, 50th, and 84th percentiles.

------ END MATRIX -----
```

Age moderation towards Word-Of-Mouth

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 ****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 1
    Y  : WOM
    X  : AI_H
    W  : Age

Sample
Size:  264

**************************************************************************
OUTCOME VARIABLE:
 WOM

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .5831      .3400      .9006    44.6551     3.0000   260.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.6431      .2471    14.7453      .0000     3.1566     4.1296
AI_H        -2.5329      .3699    -6.8479      .0000    -3.2612    -1.8045
Age          -.0223      .0086    -2.5993      .0099     -.0393     -.0054
Int_1         .0460      .0129     3.5524      .0005      .0205      .0715

Product terms key:
 Int_1    :        AI_H     x        Age

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0320    12.6194     1.0000   260.0000      .0005
----------
    Focal predict: AI_H     (X)
          Mod var: Age      (W)

Conditional effects of the focal predictor at values of the moderator(s):

        Age     Effect         se          t          p       LLCI       ULCI
    22.0000    -1.5211      .1342   -11.3314      .0000    -1.7855    -1.2568
    25.0000    -1.3832      .1200   -11.5297      .0000    -1.6194    -1.1469
    29.6000    -1.1716      .1212    -9.6676      .0000    -1.4103     -.9330

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

W values in conditional tables are the 16th, 50th, and 84th percentiles.

------ END MATRIX -----
```

7.6 Education Level

Education Level moderation towards Purchase intentions

```
Run MATRIX procedure:

**************** PROCESS Procedure for SPSS Version 4.2 ****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 1
    Y  : PI
    X  : AI_H
    W  : Edu

Sample
Size:  281

**************************************************************************
OUTCOME VARIABLE:
 PI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .6147      .3779      .9610    56.0890     3.0000   277.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     2.9270      .2771    10.5641      .0000     2.3816     3.4725
AI_H        -1.8620      .3750    -4.9648      .0000    -2.6003    -1.1237
Edu           .1869      .0952     1.9637      .0506     -.0005      .3743
Int_1         .1781      .1318     1.3507      .1779     -.0815      .4376

Product terms key:
 Int_1    :        AI_H     x        Edu

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0041     1.8243     1.0000   277.0000      .1779

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

------ END MATRIX -----
```

Education Level moderation towards Ad Evaluation

```
Run MATRIX procedure:

**************** PROCESS Procedure for SPSS Version 4.2 ****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 1
    Y  : Eva_M
    X  : AI_H
    W  : Edu

Sample
Size:  281

**************************************************************************
OUTCOME VARIABLE:
 Eva_M

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .6161      .3795      .7673    56.4774     3.0000   277.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.1572      .2476    12.7521      .0000     2.6698     3.6446
AI_H        -1.9512      .3351    -5.8222      .0000    -2.6109    -1.2915
Edu           .1312      .0850     1.5427      .1240     -.0362      .2986
Int_1         .2774      .1178     2.3544      .0192      .0455      .5093

Product terms key:
 Int_1    :        AI_H     x        Edu

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0124     5.5434     1.0000   277.0000      .0192
----------
    Focal predict: AI_H     (X)
          Mod var: Edu      (W)

Conditional effects of the focal predictor at values of the moderator(s):

        Edu     Effect         se          t          p       LLCI       ULCI
     2.0000    -1.3964      .1336   -10.4542      .0000    -1.6594    -1.1335
     3.0000    -1.1191      .1107   -10.1130      .0000    -1.3369     -.9012
     4.0000     -.8417      .1855    -4.5379      .0000    -1.2068     -.4766

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

W values in conditional tables are the 16th, 50th, and 84th percentiles.

------ END MATRIX -----
```

Education Level moderation towards Word-Of-Mouth

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 1
    Y  : WOM
    X  : AI_H
    W  : Edu

Sample
Size:  281

**************************************************************************
OUTCOME VARIABLE:
 WOM

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .5349      .2862     1.0080    37.0132     3.0000   277.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     2.5081      .2838     8.8382      .0000     1.9494     3.0667
AI_H        -1.4973      .3841    -3.8982      .0001    -2.2535     -.7412
Edu           .1875      .0975     1.9236      .0554     -.0044      .3794
Int_1         .1364      .1350     1.0098      .3135     -.1295      .4022

Product terms key:
 Int_1    :        AI_H     x        Edu

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0026     1.0197     1.0000   277.0000      .3135

********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

------ END MATRIX -----
```