# THE INFLUENCE OF AD VALUE ON ATTITUDE TOWARDS AI-GENERATED ADS AND CONSUMER PURCHASE INTENTION: A THEORY OF PLANNED BEHAVIOR PERSPECTIVE

A THESIS

SUBMITTED TO ABDULLAH GÜL UNIVERSITY

SOCIAL SCIENCES INSTITUTE

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS

FOR THE DEGREE OF MASTER OF SCIENCE

By

Sevde Ceyda ŞAHİN

December, 2025

Kayseri, TÜRKİYE

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## SCIENTIFIC ETHICS COMPLIANCE

I hereby declare that all information in this document has been obtained in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all materials and results that are not original to this work.

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M.Sc. thesis titled The Influence of Ad Value on Attitude Towards AI-Generated Ads And Consumer Purchase Intention: A Theory of Planned Behavior Perspective has been prepared in accordance with the Graduate Thesis Preparation Guidelines of the Abdullah Gül University, Social Sciences Institute.

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## ACCEPTANCE AND APPROVAL

M.Sc. thesis titled The Influence of Ad Value on Attitude Towards AI-Generated Ads And Consumer Purchase Intention: A Theory of Planned Behavior Perspective and prepared by Sevde Ceyda Şahin has been accepted by the jury in the Data Science Graduate Program at Abdullah Gül University, Social Sciences Institute.

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## ABSTRACT

Artificial intelligence is one of vital technological tools increasingly popular and used by companies in marketing applications such as advertising. This thesis aims to investigate relationship between AI-generated ads and Ad value, attitudes, and purchase intentions, and moderating roles of variables such as gender and self-efficacy. The theoretical framework has been designed in line with Theory of Planned Behavior and Advertising Value Model, which provides a comprehensive perspective on how individuals evaluate and respond to AI-supported promotional content. Data was collected through an online survey from participants aged 18-64 between August and September 2025, yielding 361 responses. IBM SPSS Statistics 25 and Python were used for data analysis. Reliability analyses, Factor Analysis (EFA, CFA) were performed to verify the adequacy and robustness of the measurement tools, and hypotheses were analyzed with Structural Equation Modeling (SEM). According to results perceived ad value positively affects both attitudes toward AI-generated ads and purchase intentions. Attitudes toward AI-generated ads notably affect purchase intentions. Attitudes have a mediating role in the relationship between purchase intentions and perceived advertising value. While gender had no moderating impact on perceived ad value and attitude relations, it moderated ad value and purchase intention relations. Its effect on the relationship between attitude and purchase intention is not statistically significant. Self-efficacy significantly negatively moderates the relationship between attitudes and Ad Value. While it positively strengthens the effect of advertising value on purchase intentions, it negatively affects the effect of attitude on purchase intention. Theoretically, this research advances knowledge in AI-enabled marketing communications by integrating two key moderating individual characteristics into the relationship between value perceptions, attitudinal responses, and behavioral outcomes. Also, it provides managerial benefits by highlighting the importance of personalizing AI ads based on consumer behavior.

Keywords: Theory of Planned Behavior, Advertising Value, Attitudes Toward AI-Generated Advertisements, Purchase Intention.

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Tez Başlığı : Reklam Değerinin Yapay Zeka Tarafından Oluşturulan Reklamlara Yönelik Tutum ve Tüketici Satın Alma Niyeti Üzerindeki Etkisi: Planlı Davranış Perspektifi Teorisi

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## ÖZET

Yapay zeka, reklamcılık gibi pazarlama uygulamalarında şirketler tarafından giderek daha popüler hale gelen ve kullanılan teknolojik araçlardan biridir. Bu tez, yapay zeka tarafından oluşturulan reklamlar ile reklam değeri, tutumlar ve satın alma niyetleri arasındaki ilişkiyi ve cinsiyet ve öz yeterlilik gibi değişkenlerin düzenleyici rollerini araştırmayı amaçlamaktadır. Teorik çerçeve, bireylerin yapay zeka destekli tanıtım içeriğini nasıl değerlendirdikleri ve bunlara nasıl yanıt verdikleri konusunda kapsamlı bir bakış açısı sağlayan Planlı Davranış Teorisi ve Reklam Değer Modeli doğrultusunda tasarlanmıştır. Veriler, Ağustos ve Eylül 2025 arasında 18-64 yaş arası katılımcılardan çevrimiçi bir anket aracılığıyla toplanmış ve 361 yanıt elde edilmiştir. Veri analizinde IBM SPSS Statistics 25 ve Python kullanılmıştır. Ölçüm araçlarının yeterliliğini ve sağlamlığını doğrulamak için güvenilirlik analizleri, faktör analizleri (EFA, CFA) yapılmış ve hipotezler yapısal eşitlik modellemesi (SEM) ile analiz edilmiştir. Sonuçlara göre, algılanan reklam değeri hem yapay zeka tarafından oluşturulan reklamlara yönelik tutumları hem de satın alma niyetlerini olumlu yönde etkilemektedir. Yapay zeka tarafından üretilen reklamlara yönelik tutumlar, satın alma niyetlerini önemli ölçüde etkilemektedir. Tutumlar, satın alma niyetleri ile algılanan reklam değeri arasındaki ilişkide aracılık rolü oynamaktadır. Cinsiyet, algılanan reklam değeri ile tutum arasındaki ilişkide düzenleyici bir etkiye sahip değilken, reklam değeri ile satın alma niyeti arasındaki ilişkide düzenleyici etki göstermiştir. Tutum ile satın alma niyeti arasındaki ilişkiye etkisi istatistiksel olarak yeterince anlamlı değildir. Öz yeterlilik, tutumlar ile reklam değeri arasındaki ilişkiyi önemli ölçüde olumsuz yönde etkilemektedir. Reklam değerinin satın alma niyetleri üzerindeki etkisini olumlu yönde güçlendirirken, tutumun satın alma niyeti üzerindeki etkisini olumsuz yönde etkilemektedir. Teorik olarak, bu araştırma, değer algıları, tutumsal tepkiler ve davranışsal sonuçlar arasındaki ilişkiye iki temel düzenleyici bireysel özelliği entegre ederek yapay zeka destekli pazarlama iletişimindeki bilgiyi ilerletmektedir. Ayrıca, tüketici davranışına göre yapay zeka reklamlarının kişiselleştirilmesinin önemini vurgulayarak yönetimsel faydalar sağlamaktadır.

Anahtar Kelimeler: Planlı Davranış Teorisi, Reklam Değeri, Yapay Zeka Tarafından Oluşturulan Reklamlara Yönelik Tutumlar, Satın Alma Niyeti.

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Finally, I would like to emphasize that no artificial intelligence tools were used in the creation of the content or writing of significant portions of this thesis. This means that it is my own original work. The OpenAI GPT-5.1 and Google Gemini Flash 2.5 tools used for proofreading and grammar checks have in no way affected the analysis or originality of the work.

# DEDICATION

To my esteemed family

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## LIST OF ABBREVIATIONS

| | |
|---|---|
| **AI** | Artificial Intelligence |
| **GANs** | Generative Adversarial Networks |
| **HSM** | Heuristic-Systematic Model |
| **SEM** | Structural Equation Modeling |
| **TAM** | Technology Acceptance Model |
| **TPB** | Theory of Planned Behavior |
| **TRA** | Theory of Reasoned Action |

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# 1 INTRODUCTION

## 1.1 Research Problem

The main problem of this thesis is to investigate the impact of advertisements created using artificial intelligence on consumers' purchase intentions and under which conditions this effect becomes stronger or weaker. This research aims to investigate the relationship between artificial intelligence-generated advertisements, advertising value, attitude, purchase intention, and the moderating roles of self-efficacy and gender. AI technologies have rapidly become integrated into marketing practices due to their ability to analyze big data, enhance decision-making efficiency, and improve accuracy in targeting (Huang & Rust, 2020). Today, AI is increasingly utilized in multiple marketing practices from segmentation and recommendation systems to personal assistants and automated delivery systems, and its adoption within advertising practices is growing.

Although existing literature provides valuable insights on the use of AI to assist marketing, operational efficiency, and business performance, studies examining how consumers evaluate AI-generated ads remain insufficient (Huang & Rust, 2020). Existing studies mainly focus on AI ‘role in shaping brand perception and managerial outcomes, but the psychological processes through which AI-generated ads influence consumers’ behavioral intentions are not fully clear.

To address this gap, this research integrates Theory of Planned Behavior and the Advertising Value Model to elaborate how consumers perceive ads value and how their evaluations shape their attitudes that influence behavioral outcomes, purchase intention. The theory of planned behavior (TPB) was chosen because it is a widely accepted theory that explains behavior with intentions and argues that there are dimensions that affect intentions. Artificial intelligence-based advertising is a relatively new subject in literature, and it is known that not every consumer reacts to AI-generated ads in the same way. Recent literature on technology and AI adoption emphasizes the critical role of self-efficacy, defined as individuals' beliefs in their capability to effectively use and evaluate technological systems (Bandura, 1997; Bartsch et al., 2012). Individuals with higher technological or AI-related self-efficacy tend to have more positive evaluations, feel more control during interactions with AI, and show stronger behavioral intentions toward AI-enabled services (Masry Herzallah & Makaldy, 2025; Lin et al., 2025; Shao et al., 2024). Conversely, consumers with low self-efficacy may feel anxious or skeptical, lowering the effectiveness of AI-driven communication (Montag et al., 2023; Hopp & Gangadharbatla, 2016). Therefore, self-efficacy is used as an important moderate variable in this research. It is expected that the positive influence of ad value on attitudes will be stronger for consumers with high self-efficacy. Besides, demographic differences such as gender may affect these responses.

Although studies on AI in marketing are expanding globally, research conducted in Türkiye that integrates AI-generated advertising, perceived advertising value, attitudes toward AI-based ads, self-efficacy, gender, and purchase intentions remains scarce. By addressing this gap, this thesis offers both implications for theoretical and practical. Results are expected to guide marketing professionals when designing more personalized, psychologically grounded and effective AI-generated advertising strategies. Besides, it aims to expand theoretical understanding of how consumers respond to AI-based technologies.

## 1.2 Research Aim and Objectives

This research aimed to examine how perceived advertising value influences customer purchase intention, mediated by consumers' attitudes toward AI-based advertisements and under moderating effects of gender and self-efficacy. This research aims to reach a detailed interpretation of how perceived ad value influences consumer behavior in AI-generated advertising context, and how these effects may differ between both psychological (self-efficacy) and demographic (gender) differences. To achieve this aim, the following objectives were pursued in the research:

- To observe the impact of perceived advertising value on customers' purchase intentions in the context of AI-generated ads.
- To analyze consumer attitudes' mediating role toward AI-generated ads in the relationship between perceived ad value and customers' purchase intention.
- To examine the moderate effect of gender on the relationship between perceived ad value, attitude toward AI-generated ads, and purchase intentions.
- To examine self-efficacy' moderating effect on the relationship between perceived ad value, attitude toward AI-generated ads, and purchase intentions.
- To examine the proposed conceptual model from an empirical perspective.
- To provide actionable insights for practitioners on designing more effective and personalized AI-generated ad strategies tailored to consumers' psychological readiness and gender-based differences.

## 1.3 Research Questions

As AI-driven advertising becomes more prevalent, understanding the psychological and demographic factors that shape consumer responses has become increasingly important. While perceived advertising value and attitudes are known as an influence on purchase decisions, the strength of these relationships depends on consumers' self-efficacy and gender differences. Therefore, this research aims to address the following research questions:

- What is the effect of perceived advertising value on customers' purchase intentions in the context of AI-generated advertising?
- What is the mediating impact of consumers' attitudes towards AI-generated advertisements on the relationship between perceived ad value and purchase intention?
- Does gender moderate the relationship among perceived ad value, consumers' attitudes and purchase intentions in the context of toward AI-generated ads?
- Does self-efficacy moderate the relationships among perceived advertising value, attitudes toward AI-based advertisements, and purchase intentions?

# 2 LITERATURE REVIEW

Technological and digital advancement provide opportunities to companies in their marketing operations such as the ability to communicate directly with consumers through customized advertisements (Hassan et al., 2013). It also provides advertising with potential for growth and diversity (Van Tuan et al., 2023). With these technological developments, changes have been observed in the needs and expectations of consumers and in their consumption patterns. Talih Akkaya et al. (2017) stated that consumers have shifted from a passive mode to a more participatory mode with new communication ways. Therefore, a change in consumer behavior is inevitable. When companies develop solutions and take action to respond to constantly changing consumer demands, they can differentiate themselves from their competitors and sustain their presence in the market. Therefore, it is significant to understand consumer behavior and the factors that persuade them to purchase (Talih Akkaya et al., 2017).

Businesses should carry out their advertising strategies with a more careful and critical perspective since competition is intense in the business world. They should develop efficient marketing strategies by using their advertising budgets effectively. In this way, they can create effective advertisements while avoiding unnecessary costs that may arise (Disastra et al., 2019). To run their business and ensure continuity, company managers must be able to establish long-term relationships using components that benefit their business (Hassan et al., 2013). Since companies allocate large advertising budgets to market their products/services to consumers, they want to receive positive feedback from their advertisements that will directly lead consumers to make a purchase (Aktan et al., 2016). It can be said that consumers tend to perceive advertisements as annoying and unpleasant, and therefore mostly avoid advertisements. Disastra et al. (2019) argued that the success of advertisements is related to their preference by consumers. Ads that are preferred and successful help to create brand awareness and lead to the participation and purchasing behavior of consumers. Also, Van Tuan et al. (2023) mentioned that according to a study by Microsoft, an individual's attention span decreased by 4 seconds compared to previous years and decreased to 8 seconds in 2000. Therefore, it is crucial to ability to produce content which can attract the attention of consumers and increase their interaction with the company.

## 2.1 Marketing and Artificial Intelligence

The rapid transformation of digital markets has forced companies to seek smarter, faster, and more adaptive tools to understand and influence consumers. In this context, Artificial Intelligence (AI) has emerged as one of the most innovative forces in marketing, fundamentally changing how value is created and delivered (Hicham et al., 2023). AI provides significant opportunities for various industries by enabling systems that can act and think like humans. Also, it is defined as a technological system's ability to copy human intelligence in learning, reasoning, and decision-making actions (Haleem et al., 2022; Marinchak et al., 2018). Adoption of AI into marketing has grown rapidly due to the rise in data availability, computational capabilities, and algorithmic sophistication. Beyond its role as a technological advancement for companies, AI also represents a strategic shift in marketing operations due to enhancement in accuracy, speed and effectiveness in the process of decision-making (Stone et al., 2020).

AI plays a pioneering role in strategic decision-making by being deeply integrated into the customer journey and shaping real-time brand-consumer interactions (Mariani et al., 2022). With ongoing technological advancements, AI continues to attract growing interest from marketers. Modern marketing strategies increasingly rely on AI to optimize pricing, identify high potential customer segments, select most efficient communication channels, and adapt business models to proactively respond to changing consumer behavior (Stone et al., 2020). AI supports human decision-makers in evaluating alternatives and making data-driven strategic decisions instead of replacing them (Shrestha et al., 2019). Companies capable of successfully integrating AI into their marketing operations gain a competitive advantage in a challenging and uncertain environment.

In marketing, AI-based applications are both diverse and rapidly evolving, driven by advanced technologies. *Machine learning* enables to assess big consumer data and continuously improve performance through automated learning processes (Haleem et al., 2022). *Natural language* processing helps interpret unstructured data from sources such as customer reviews and feedback on social media (Mariani et al., 2021), while *computer vision* enhances in-store experiences through facial recognition and sentiment detection (Haleem et al., 2022). AI-based chatbots and assistants offer instant customer support, whereas recommender systems personalize offerings based on consumer preferences (Mariani et al., 2021). These technologies not only automate marketing functions but also enhance their intelligence and responsiveness to individual consumer needs. All those applications help marketers in segmentation, customized messaging, dynamic pricing and predictive analytics (Boddu et al., 2022). For instance, AI can detect consumers most likely to churn and help marketers target them with specific retention campaigns. Smart technologies such as facial recognition and geolocation-based messaging create seamless experiences both online and offline (Haleem et al., 2022). AI also provides marketers with analyzing competitors' campaigns and detect market trends earlier than traditional methods would allow. Despite these advantages, there are still concerns about data privacy, lack of transparency limit, and algorithmic bias its adoption in marketing (Mariani et al., 2021). The success of AI depends considerably on high-quality data and the organizational capacity to integrate AI strategically and ethically (Stone et al., 2020).

Considering the rapid and extensive influence of AI on marketing decision-making, its influence is more notable in advertising, where advanced personalization and automated predictions play a key role in consumer attitudes and choices. The following section explores how AI reshaped advertising strategies and created value in the digital communication environment.

## 2.2 Advertising and Artificial Intelligence

Since late 2022, AI technologies like ChatGPT, Google Bard, and Bing AI have gained rapid popularity and reshaped the advertising landscape with widespread adoption among both individuals and organizations (Bove, 2023). Usage of artificial intelligence in advertising not only means to automate advertising tasks but also a powerful driver of efficiency and personalization. In 2022, global AI-driven advertising expenditure reached $370 billion, and it is projected to rise to $1.3 trillion by 2032 (Statista, 2023). Supporting this trend, McKinsey (2024) predicts that AI could enriches annually up to $4.4 trillion to the global economy. Guided by these opportunities, major technology companies including Scope AI, Meta, Veritone, Alphabet, and Adobe have been investing AI to provide faster, safer, and more cost-effective advertising solutions (PR Newswire, 2024).

Ford et al. (2023) performed an analysis to evaluate the current academic landscape surrounding AI in advertising. Their review identified four dominant thematic areas: (1) programmatic advertising and automation, (2) ad planning and engagement, (3) advertising effectiveness, and (4) ethical concerns. Programmatic advertising involves the automated purchase and placement of ads using AI algorithms for real-time targeting. Ad planning and engagement refer to AI's role in understanding consumer behavior and delivering interactive experiences. Studies on advertising effectiveness highlight improvements in personalization, targeting accuracy, and campaign performance. In contrast, ethical debates highlight potential risks about data privacy, algorithmic bias, and manipulation potential.

A particularly advanced application of AI in advertising is the creation of AI-generated (synthetic) advertising. These are developed using technologies like generative adversarial networks (GANs) and deepfakes, which produce highly realistic yet artificial content (Campbell et al., 2022). These tools allow brands to customize ad elements such as age, gender, or background based on consumer profiles and campaign objectives (Floridi, 2021; Kietzmann et al., 2020). Compared with traditional ad production methods, AI-generated ads offer faster turnaround, lower costs, and enhanced creative flexibility (Antipov et al., 2017). The central goal of these practices is hyper-personalization: delivering highly tailored messages that reflect user preferences, locations, and behaviors to strengthen engagement (Campbell et al., 2022; Schelenz et al., 2020). Evidence shows that personalized ads can significantly increase attention, message relevance, and purchase intention (Aguirre et al., 2015; Mukherjee et al., 2018).

Certain benefits that AI offers to advertisers include being able to easily analyze large amounts of data, increasing the level of personalization of ads to consumers, and contributing to the optimization of brand-consumer interaction. The benefits of AI have attracted attention and been tried by global companies such as Lexus and Coca-Cola. Moreover, AI will be increasingly used in many steps of advertising in the coming years (Sands et al., 2025). Lexus, a Japanese car producer firm, has used AI to write the script for the commercial they released for the launch of the Lexus ES executive sedan. The AI was trained on industry-wide luxury car commercials to write a short storyline that appears to have been written by a human. The advertisement that was directed by an Oscar-winning director is considered the first example of AI being used in advertising (Lexus Europe, 2018; Wu et al., 2024).

**Figure 2.2.1 Lexus AI-Commercial**

In the Coca-Cola Masterpiece commercial, ChatGPT and DALL-E used AI tools to design a commercial where the Coca-Cola bottle changes shape as it moves through the artwork. This commercial, which was called innovative and was acclaimed by critics, used steady diffusion of AI technology to produce photorealistic images. (School of Marketing, 2024; Marr, 2024). Later, Coca-Cola released three short ads created by artificial intelligence for its Christmas-themed campaigns. Unlike the Masterpiece ad, many criticized the company's ads as creepy, disturbing, annoying and even losing the Christmas magic. Some consumers noted that the animals and objects in the ad looked strange (Horvath, 2024; Placido, 2024b).

**Figure 2.2.2 Coca-Cola Christmas AI Ad**


Toys”R”Us has released a commercial produced by OpenAI’s video creation tool Sora, featuring the company’s founder and the brand’s mascot. In the commercial, the company’s founder has a dream involving toys as a child, which inspires him to start the company. Many critics have expressed excitement about the integration of AI into modern advertising. However, the commercial has been called off-putting and irritating since the toy figures are complex and the human characters are not visually consistent with each other (Placido, 2024a).

**Figure 2.2.3 Toys”R”Us AI Ad**

However, growing concerns remain regarding authenticity, transparency, privacy, and consumer trust, calling for ethical guidelines in the development and proliferation of AI-generated advertising (Martin & Murphy, 2017; Plangger & Watson, 2015). Sands et al. (2025) said that skepticism and concerns about AI generally arise from brands' lack of confidence in how they use AI. To prevent this skepticism from overshadowing the benefits of AI and building trust, it is important for brands to overcome consumer concerns. Also, examining how consumers react when they notice the contribution of AI in advertisements will be beneficial to better gain insightfulness about the impact of AI on consumer behavior and determine better advertising practices by taking advantage of the benefits of AI (Wu et al., 2024).

## 2.3 Advertising Value

In today's highly saturated media environment, consumers constantly evaluate whether advertisements contribute meaningfully to their decision-making process. This assessment reflects the perceived value of an advertisement, which represents its overall usefulness and relevance from the consumer's perspective (Zha et al., 2015). Since consumers interpret advertising value based on how effectively the message supports their needs and interests, their purchasing decisions may be influenced accordingly (Karamchandani et al., 2021). When ads provide valuable and relevant information, consumers probably evaluate the ad favorably, leading to increased purchase intentions and more positive attitudes toward the promoted brand (Martins et al., 2019). Ducoffe (1995) introduced Ad Value as a foundational framework to comprehend how advertising value influences attitudes toward advertisements (Martins et al., 2019; Karamchandani et al., 2021). According to this model, advertising value is a subjective measure of the benefits that consumers believe they gain from advertising. Ducoffe identified three core factors of ad value: informativeness, entertainment, and irritation. Following, credibility (Brackett & Carr, 2001) and incentives (Kim & Han, 2014) were added to further strengthen the model (Martins et al., 2019).

According to Ducoffe's Ad Value Model, the *informativeness* of an advertisement is strongly associated with its perceived advertising value (Ducoffe, 1995; Martins et al., 2019). Consumers often seek advertisements that can efficiently deliver product-related insights and specifications, enabling them to make informed purchasing decisions (Tsang, Ho, & Liang, 2004; Kim et al., 2010). Similarly, the *credibility* of an advertisement can influence the perception of trust that consumers have towards a company or product/service (Martins et al., 2019). Credibility in advertising refers to how likely consumers found an advertisement as truthful, believable, and trustworthy (MacKenzie & Lutz, 1989; Pavlou & Stewart, 2000; Zha et al., 2015). When consumers perceive AI-generated ads as trustworthy and reliable, they tend to evaluate the ad and the brand favorably (Brackett & Carr, 2001; Xu, 2007). *Entertainment* value is a considerable source of creating positive advertising value since it gives signals such as aesthetic pleasure, relaxation, escape and distraction to consumers (Ducoffe, 1995; McQuail, 2010; Martins et al., 2019). Entertainment plays a central role in influencing consumers' positive attitudes about advertisements and, by extension, toward brand (Mitchell & Olson, 1981; Yang & Smith, 2009; Disastra et al., 2019). Prior studies consistently demonstrate that when advertisements are perceived as entertaining, consumers tend to form positive attitudes about the ads themselves (Zha et al., 2015; Gaber, 2019), as well as exhibit greater brand loyalty and purchase intention (Stern & Zaichowsky, 1991; Ling et al., 2010). Conversely, *irritation* is defined as the degree to which an ad provokes annoyance, discomfort, or frustration in consumers (Ducoffe, 1995; Aaker & Bruzzone, 1985). Irritating elements are negatively related with the perceived advertising value (Tsang et al., 2004; Yang et al., 2013; Aktan et al., 2016; Martins et al., 2019). When advertisements contain irritating elements such as insults, offensive elements or even restricting the freedoms of consumers, the advertisement is not welcomed by consumers and the value of the advertisement negatively affected (Ducoffe, 1995). On the other hand, *incentives* in advertising refer to the financial or non-financial benefits offered to consumers in exchange for their engagement with promotional content. These can include discounts, coupons, gifts, or other tangible rewards (Varnali et al., 2012). Research has shown that such incentives significantly shape consumer attitudes by strengthening the perceived value of advertisements (Tsang et al., 2004; Kim & Han, 2014; Martins et al., 2019).

According to Van Tuan et al. (2023) research on the purchase intention of Generation Z towards video advertising, they found that ad value has a direct favorable interaction with reliability, informativeness and incentives, whereas it is directly and negatively affected by irritation. Also, Karamchandani et al. (2021) employed a study in India to measure the influence of smartphone advertisements on consumers' purchasing behaviors for hygiene products in the Covid pandemic era and found that credibility, informativeness, and entertainment factors positively affected the perceived advertising value. Aktan et al. (2016) conducted a survey on Marmara University students to understand the attitudes of Internet users towards web advertisements. According to Aktan et al. (2016), it is critical for advertising value that ads are informative, credible and contain interesting features, since these elements affect attitudes of consumers positively towards the brand. Given that consumers' evaluations of advertising value play a critical role in shaping consumer reactions, the next section focuses on attitudes toward AI-based advertisements, mediator effect between advertising value and purchase intention.

## 2.4 Attitude Towards AI-Based Advertisement

Attitude is one of the crucial components used to examine behavioral intention and actual behavior in studies conducted on consumers. It is generally defined by subjective terms and general judgments that consumers favorable or unfavorable evaluation toward a product, service or behavior (Ahmed et al., 2020). For instance, consumers who generally have positive attitudes towards protecting the environment and green consumption are generally purchasing green products. Attitude can therefore be seen as a stored evaluation in memory that reflects consumers' psychological response toward a specific object (Ahmed et al; 2020). Supporting attitude's role in behaviors, a study found that attitudes significantly affect purchase intentions about organic food among Chinese students based on the TPB (Ahmed et al; 2020).

In advertising contexts, attitudes directly predict how consumers respond to and interact with brands. Aktan et al. (2016) emphasize that attitudes direct the behaviors of individuals and are the last stage before behavior. It can be said that consumers who have positive attitudes about the brand are generally purchasing from the brand. Therefore, it is significant for companies to examine consumer attitudes and the determinants that affect these attitudes.

The concept of advertising attitude can be described as the reaction that consumers give to the advertisement by evaluating it as useful or useless after being affected by various factors of the advertisement (Disastra et al., 2019). In addition, some researchers define the concept of advertising attitude as positive or negative evaluation of consumers about the advertisement according to the emotional state they feel towards that advertisement after seeing it (Disastra et al., 2019; Lee et al., 2017). Attitude towards ads is one of the main predictors about effectiveness of advertising that enables predictions about consumer behavior (Ting & de Run, 2015). According to the online survey performed by Zha et al. (2015) in China to understand consumers' attitudes and trust about web advertising, it was observed that reliability, perceived entertainment and informativeness contribute to shaping consumer attitudes.

Studies on advertising attitudes in the literature cover areas such as consumers' attitudes towards advertised product, consumers' attitudes about the brand, and consumers' purchasing interest. The message of an advertisement is one of the means of communication between the brand and the consumer (Disastra et al., 2019). The positive or negative reactions of the consumers after receiving the message of the advertisement, in line with the emotional and cognitive reactions, also express the attitude (Zha et al., 2015). When individuals have a positive attitude towards a product/service, they can be easily persuaded to perform buying behavior. Marketers try to strengthen the positive attitudes of consumers and to turn the negative attitudes of consumers into positive ones through advertisements (Talih Akkaya et al., 2017).

Given the role of attitudes as a psychological gateway from exposure to behavioral intention, this thesis conceptualizes attitude toward AI-based advertisements as a key mediator explaining how perceived advertising value translates into consumer purchase intention.

## 2.5 Purchase Intention

Purchase intention can be described as an indicator of individuals' tendency and possibility to purchase a product/service (Martins et al., 2019). It is considered as a powerful predictor of real behavior, since the more favorable a consumer's intentions, the higher the likelihood of a real purchase (Akkaya et al., 2017). Purchase intention provides a valuable insight into consumers' preferences, allowing marketers to predict potential market demand and evaluate the effectiveness of promotional activities. When consumers have positive intentions toward a brand or its offerings, this can often lead to supportive behaviors such as repeat purchase and recommendation to others (Martins et al., 2019).

Several studies emphasize the role of advertising value in shaping purchase intention. Martins et al. (2019) examined smartphone advertisements by integrating flow theory with Ducoffe's web advertising model. Their findings showed that irritation unfavorably influenced perceived advertising value, whereas informativeness, entertainment, and credibility enhanced it. Importantly, advertising value was observed to favorably influence purchase intention, demonstrating that valuable ads can help convert consumer interest into purchasing behavior. Similarly, Lee et al. (2017) found that advertising elements such as informativeness and entertainment contribute in a positive direction to advertising value unlike irritation. Their findings further confirmed that higher perceived advertising value enriches advertising attitudes, which in turn strengthens purchase intention. These results supported that purchase intention is an outcome shaped through cognitive and affective evaluations of promotional content.

Overall, prior research highlights that purchase intention arises when consumers perceive advertisements as beneficial and trustworthy and develop favorable attitudes in response (Van Tuan et al., 2023; Karamchandani et al., 2021). Therefore, in this thesis, purchase intention serves as the primary dependent variable, explaining how perceptions and attitudes toward AI-based advertisements ultimately translate into consumer behavior. Building on this foundation, the next section examines how self-efficacy, an important individual factor, may condition consumer responses in the context of AI advertising.

## 2.6 Self-Efficacy

Self-efficacy that is based on Bandura's social cognitive theory can be referred as individuals' beliefs about their ability to perform the necessary actions to achieve a desired outcome for a specific goal, rather than their actual skills (Bandura, 1986, 1997, 2012; Schunk, 1991). Self-efficacy is not a general concept for every behavior; that is, an individual can be highly effective at technology-related tasks while feeling less competent in interpersonal situations. (Bucy & Tao, 2007). In this sense, technology-related self-efficacy such as computers, internet, mobile, or technological self-efficacy, captures confidence in using technological systems effectively (Compeau & Higgins, 1999; Eastin & LaRose, 2006; Kraus et al., 2021; Lee & Hsieh, 2009).

Self-efficacy is one of the primary drivers of motivation and even behavior, as it can influence activity selection, effort, and persistence (Bandura, 1986, 1997; Pekkala & Van

Zoonen, 2022). Individuals who perceive themselves as capable in a given domain are more likely to engage in related tasks, while those who expect failure tend to avoid them. This pattern has been documented across multiple contexts, including technology use, internet use, sites of social networking, and social media (Qaisar et al., 2021; Hocevar et al., 2014; Eastin & LaRose, 2006; Compeau & Higgins, 1999). In social media settings, self-efficacy has been defined as confidence in producing and consuming content, finding information, and successfully performing social media–related tasks (Hocevar et al., 2014). Self-efficacy develops through prior experience, observing others, feedback, and emotional states (Chen & Gao, 2022; Hocevar et al., 2014; Bandura, 1997).

In technology and AI-related research, self-efficacy emerges as one of the main antecedents of technology usage and adoption (Bartsch et al., 2012; Latikka et al., 2019; Shao et al., 2024). Studies integrating self-efficacy and the Technology Acceptance Model (TAM) show that higher technological or AI self-efficacy enhances perceived ease of use, perceived usefulness, and attitudes toward AI, which in turn strengthen adoption intentions (Alharbi & Drew, 2018; Hong, 2022; Msry Herzallah & Makaldy, 2024; Wang et al., 2021). In educational settings, technological self-efficacy has been observed to fully or partially mediate the relationships between attitudes toward AI and AI adoption intentions, highlighting its importance in shaping AI acceptance (Msry Herzallah & Makaldy, 2024). Similar findings are seen in healthcare and care robots; self-efficacy increases trust in AI and thus the intention to use AI-based services (Latikka et al., 2019; Rahman et al., 2016; Lin et al., 2025).

Self-efficacy is also closely linked with attitudes toward AI and automated systems. Studies demonstrated that technology self-efficacy positively correlates with AI acceptance and negatively correlates with fear of AI (Montag et al., 2023). Individuals with higher technology self-efficacy are more likely to trust automated systems more, hold more positive attitudes toward AI, and experience less anxiety when interacting with such technologies (Kraus et al., 2021; Hsu & Lin, 2023; Rajapakse et al., 2024). In augmented reality advertising environments, technological self-efficacy was found to influence users' perceptions of new advertising formats, with users with high self-efficacy being more likely to transfer their evaluations of advertising content into brand attitudes (Hopp & Gangadharbatla, 2016). In the mobile context, Lee and Hsieh (2009) found that mobile self-efficacy significantly affects attitudes toward mobile advertising.

Beyond its role as an antecedent, self-efficacy has increasingly been conceptualized as a moderator. Prior studies suggest that self-efficacy can shape how individuals process messages, engage with interactive technologies, and respond to persuasive content (Bucy & Tao, 2007; Tremayne & Dunwoody, 2001; Wang & Wu, 2008; Lo et al., 2013). In social media branding, Bozkurt et al. (2023) demonstrated that self-efficacy about social media moderates in a positive direction the relationship between perceived social media agility and purchases of individuals. Customers high in social media self-efficacy are better able to notice and admire agile brand behaviors on social platforms and consequently are more willing to buy from those brands. This indicates that individuals' confidence in their own skills can strengthen or weaken the impact of perceived value or capability cues on behavioral outcomes.

## 2.7 Gender

Gender has been widely studied as one of the determinants of technology acceptance and behavioral intention (Bem, 1981) and has been integrated into major acceptance models such as the Technology Acceptance and the Theory of Planned Behavior (Venkatesh & Morris, 2000; Venkatesh et al., 2003). Previous studies suggest that gender differences shape how individuals evaluate and adopt technologies. Men generally tend to focus on performance outcomes and usefulness, when women are affected by perceived ease of using the technology and social norms (Hoffmann, 1972; Hofstede et al., 2010; Venkatesh & Morris, 2000; Tarhini et al., 2014). Women also show higher anxiety about technology with low self-efficacy, which affects their behavioral decisions and rely on external opinions (Schumacher & Morahan-Martin, 2001; Venkatesh & Morris, 2000; Huang et al., 2013).

In AI-specific contexts, recent consumer research confirms gender-based differences. Men tend to show higher familiarity with and more positive attitudes toward AI technologies, stronger expectations regarding long-term AI benefits, and greater acceptance of AI-enabled systems (Field, 2023; Grassini & Ree, 2023; Schepman & Rodway, 2023; Araujo et al., 2020; Kiper & Liang, 2025). For example, Kiper and Liang (2025) conducted eye-tracking research, their findings revealed that male consumers exhibited more favorable responses to AI-generated fashion advertisements, whereas women reacted more positively to traditional non-AI ads. These results highlighted that AI-driven advertising content may require gender-specific design strategies. On the contrary, women frequently tend to demonstrate stronger ethical and privacy concerns toward AI systems. Women often prioritize fairness, transparency, and reduced intrusion into personal information compared to men (Rahman et al., 2024; Jang et al., 2022; Mohamed & Ahmad, 2012; Hoy & Milne, 2010; Bartel Sheehan, 1999). They are more sensitive to potential digital discrimination and negative social consequences, likely due to historically gendered inequalities and risk perceptions (Van Berkel et al., 2021; Grgić-Hlača et al., 2022; Dineen et al., 2004). Female users prioritize fairness even if it compromises algorithmic accuracy (Jang et al., 2022).

Gender also moderates consumer readiness to adopt AI technologies, particularly in service and retail environments. While positive prior experiences with AI tend to increase adoption likelihood for both genders, perceived technological risks significantly hinder women more than men (Kolar et al., 2024). Furthermore, self-assessment of capability, which is defined as a form of perceived behavioral control, drives more strongly the AI adoption intention among men (Kolar et al., 2024; Tarhini et al., 2014). In the domain of

AI-powered voice technologies, male consumers also show higher willingness to adopt such systems compared to females (Choudhary et al., 2024).

Overall, the existing literature demonstrated that male consumers are more motivated by technological efficiency and usefulness, whereas female consumers respond more strongly to social, ethical, and privacy-related stimuli. As AI-generated advertising blends persuasive communication with advanced technology, gender-specific cognitive and emotional processes are expected to significantly shape the formation of attitudes and purchase intentions. Therefore, gender is included as a moderating construct in this research to better interpret differences in consumer responses to AI-generated advertisements.

# 3 THEORETICAL FRAMEWORK

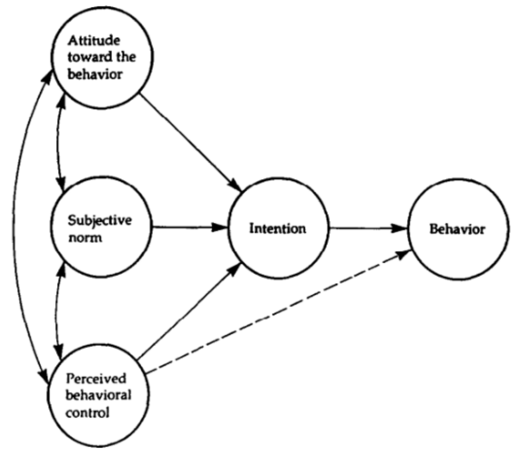
As the role of AI in advertising gains importance, researchers employ multiple theoretical frameworks such as Technology Acceptance Model (TAM), Heuristic-Systematic Model (HSM), and Signaling Theory to understand consumer reactions to AI-enabled technologies (Dwivedi et al., 2021; Gursoy et al., 2019). These theories mainly concentrate on technology adoption, perceived usefulness, and trust toward intelligent systems. However, in the concept of advertising, consumers' behavioral intentions toward advertised brands require not only an evaluation of the technology itself, but also how the advertisement is perceived in terms of value and persuasion effectiveness. For this reason, this research integrated two widely recognized and complementary theoretical perspectives: the Theory of Planned Behavior (TPB) and the Advertising Value. TPB provides a basis for interpreting how consumers’ attitudes toward AI-generated advertisements drive behavioral intentions such as purchase decisions. Additionally, the Advertising Value Model explains how consumers evaluate the value of advertising content. By combining these two frameworks, this study provides a more nuanced understanding of how perceived ad value influences attitude formation and ultimately drives purchase intentions in AI-enabled advertising environments. Together, these theories allow a stronger and more holistic examination of behavioral formation in AI-generated advertising environments.

## 3.1 Theory of Planned Behavior

Theory of Planned Behavior (TPB), like The Theory of Reasoned Action (TRA), is a theory used to explain likelihood of a certain behavior occurring. TPB, that draws attention to individual motivational factors and theoretical structures, is an extended version of the TRA (Ajzen, 1991; Montaño and Kasprzyk, 2008). TRA and TPB that can largely explain behavioral intention have been used in studies to explain various behaviors such as smoking, green eating, using seat belts, purchasing behavior through the internet and more (Montaño and Kasprzyk, 2008; George, 2004). The TPB, which is used by psychologists to predict behavioral intentions, is one of the comprehensive models used to elucidate a person's behavior towards a specific concept. The theory, which is used in various fields, has also been used in studies examining environmental actions such as understanding consumers' intentions towards concepts such as purchasing organic food, recycling behavior, voluntariness to pay for a parking spot and protecting the environment (Ahmed et al., 2020; Xu et al., 2019). George (2004) indicated that although this theory is used in certain studies in literature, it is not limited to specific behavior and beliefs about that behavior. In other words, it is not used only in studies of specific behavior; the behavior to be investigated and the intention towards that behavior are determined by the researchers.

Both TRA and TPB theories argue that intention is the best predictor of whether a behavior will occur and include a causal chain model that connects intentions to behaviors. TPB comprise a component of perceived behavioral control over performance, unlike TRA, in addition to attitudes and social normative perceptions (Montaño and Kasprzyk, 2008). TPB argued that the measures of behavioral intentions are attitudes toward the behavior, social norms toward the behavior, and perceived behavioral control (Ajzen, 1991).

**Figure 3.1.1 The Theory of Planned Behavior**




***Notes:*** *1) Reference: Ajzen (1991)*

Attitude is related to the individual's opinions of the outcomes of performing the behavior. When an individual considers that performing a behavior would produce positive results, they will have a favorable attitude toward the behavior. In contrast, individuals perform a negative attitude when they know that they will encounter negative results as a result of the behavior (Montaño and Kasprzyk, 2008).

In addition, individuals' social norms and normative beliefs also affect their beliefs about performing a behavior (Montaño and Kasprzyk, 2008). The social pressure we are subjected to by the important people in our lives and the people around us represent subjective norms (Xu et al., 2019). Whether an individual internally approves or disapproves of performing a behavior affects whether they perform the behavior. When individuals think that they should perform the behavior and approve of it, they have a positive private norm toward the behavior. On the contrary, when they think that they should not implement the behavior, they have a negative private norm (Montaño and Kasprzyk, 2008).

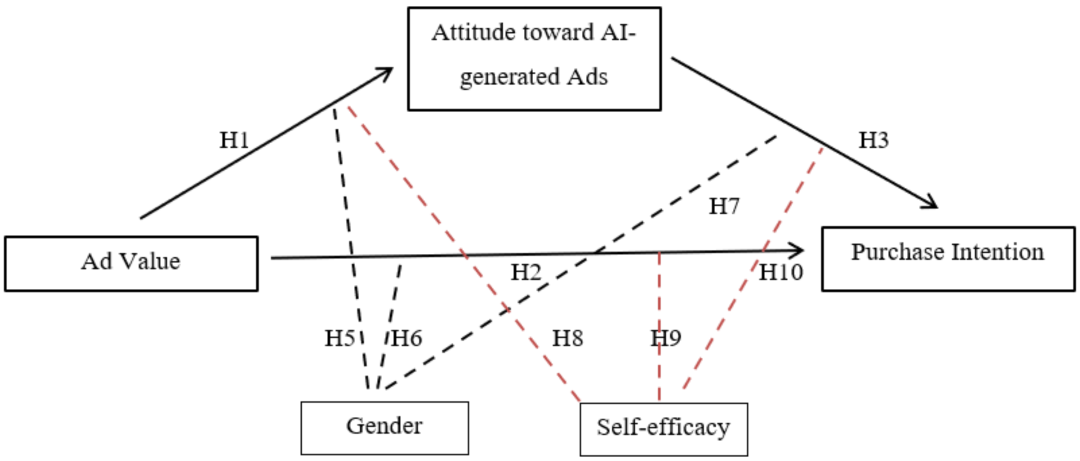
While TRA can explain situations in which individuals have control over behavior, TBP also considers perceived behavioral control to explain also situations in which control is diminished. Individuals' perception of the ease with which they can perform a behavior may be a predictor of whether they will perform the behavior (Montaño and Kasprzyk, 2008). It can also be called the judgment of individuals regarding their ability to perform a behavior (Ahmed et al., 2020). When individuals who intend to perform a behavior are compared, it can be said that individuals who are confident in their abilities are tend to perform the behavior and be successful (George, 2004).

## 3.2 Hypothesis Development

In this study, conceptual framework is grounded in the TPB and the Advertising Value Model. Within this framework, purchase intention serves as a proxy for future consumer behavior, whereas actual behavior typically reflects past purchasing patterns. Given that data in such studies are gathered at a single point in time, including both intention and actual behavior in the same model may introduce conceptual redundancy and temporal inconsistency (George, 2004). Accordingly, this research focuses on purchase intention to assess whether consumers’ intentions to purchase a product are influenced after exposure to an advertisement generated by artificial intelligence (AI).

The model includes ten hypotheses, and these hypotheses are formulated based on the core constructs of the TPB and the Advertising Value model, supported by relevant literature and aligned with the research questions.

**Figure 3.2.1 Theoretical Model**




The concept of advertising value, created by Ducoffe (1996), serves as a fundamental framework to understand how consumers evaluate advertisements and develop attitudes toward them. According to Ducoffe’s model advertising value is shaped by key perceptual dimensions (informativeness, entertainment, and irritation) which collectively influence consumer attitudes toward advertising. Subsequent research has expanded the model to include credibility (Choi & Rifon, 2002) and inventiveness as additional contributors to perceived ad value, particularly in digital contexts. Advertising value represents a consumer’s holistic assessment of an ad's utility and relevance and is often associated with both cognitive and affective evaluations (Brown & Stayman, 1992; Tsang et al., 2004). In the context of AI-generated advertising, these evaluative dimensions become even more salient as consumers form attitudes not only toward the product or brand, but also toward the technological medium itself. Therefore, this study hypothesizes that higher perceived advertising value positively influences consumers’ attitudes toward AI-generated advertisements. Furthermore, it indicates that ad value has a significant impact on consumer purchase intention.

Attitude toward advertising reflects consumers' overall evaluation of an ad, including emotional and cognitive reactions that influence consumers' behaviors (Mitchell & Olson, 1981; Lee et al., 2012). A substantial body of research has demonstrated that positive attitudes toward advertisements are strongly associated with increased purchase intentions (Kim et al., 2009; Goldsmith et al., 2000). When consumers perceive an ad, especially one generated by AI, as appealing, credible, or valuable, they are more likely to consider the advertised product or service favorably (Ducoffe, 1995; Trivedi, 2020). This affective response is a vital factor in the decision-making process, in line with the TPB, which suggests that attitudes significantly shape intentions (Ajzen, 2002). Given that AI-based advertising introduces novel content formats and delivery methods, a favorable attitude toward such ads is expected to enhance consumers' likelihood of purchase. Therefore, this study hypothesizes a positive relationship between consumers' attitudes toward AI-based advertisements and their purchase intentions. Therefore:

**H1:** Perceived ad value has a significant effect on consumers' attitudes toward AI-based advertisements.

**H2:** Perceived ad value has a significant effect on consumers' purchase intention about products or services that are placed on AI-generated advertisements.

**H3:** Positive consumers' attitudes toward AI-based advertisements positively influence their purchase intention.

**H4:** Consumer attitudes towards AI-generated advertisements have a mediating role in the relationship between perceived advertising value and customers' purchase intention.

Gender has long been recognized as a critical variable in shaping consumer behavior, influencing how individuals process advertising stimuli and make purchase decisions (Bem, 1981; Meyers-Levy & Maheswaran, 1991; Putrevu, 2004). Research has consistently shown that males and females differ in their attitudes toward advertisements, online shopping behavior, and digital engagement (Kempf et al., 1997; Wolin & Korgaonkar, 2003). These variations are often explained through gender schema theory and social role theory, which suggest that men are typically more goal-oriented and heuristic in their decision-making, while women tend to be more relational and detail-focused (Putrevu, 2004; Lim et al., 2021). In online contexts, men are often driven by utilitarian motives, whereas women seek emotional resonance and community (Muscanell & Guadagno, 2012). As AI-generated advertisements become increasingly prominent, these gender-specific processing tendencies may influence how attitudes toward such ads translate into purchase intentions. Therefore, this study hypothesizes following:

**H5:** Gender moderates the relationship between perceived ad value and consumers' attitudes toward AI-based advertisements.

**H6:** Gender moderates the relationship between perceived ad value and consumers' purchase intention toward AI-based advertisements.

**H7:** Gender moderates the relationship between consumers' attitudes toward AI-based advertisements and their purchase intention.

Drawing on Bandura's Social Cognitive Theory, self-efficacy is defined as an individual's belief about their capability to plan and undertake actions by handling situations effectively. Applied to AI-based advertising, this research defines self-efficacy as consumers' perceived capability to understand, assess, and effectively interact with AI-generated advertisements in digital environments. Existing research demonstrates that people with higher technology-related self-efficacy tend to engage more deeply with digital content, feel a greater sense of control during interactions, and experience reduced uncertainty (Bozkurt et al., 2023; Hopp & Gangadharbatla, 2016).

Accordingly, consumers with higher levels of self-efficacy are likely to engage more thoroughly with AI-generated advertising. Higher levels of self-efficacy allow them to better recognize and appreciate key value components such as informativeness, credibility, entertainment, and incentive-based benefits. This deeper level of engagement enhances more favorable attitudes when the advertisement is perceived as valuable. In contrast, consumers with lower self-efficacy may struggle to interpret or feel comfortable with AI-driven content. Lower levels of self-efficacy make them less responsive to perceived value, resulting in skepticism or psychological discomfort when exposed to AI-based persuasive communication.

Self-efficacy is therefore integrated into this study as a boundary condition that shapes how strongly perceived advertising value influences consumers' attitudes toward AI-generated advertisements. Moreover, since attitudes constitute a central determinant of purchase intention under the Theory of Planned Behavior, self-efficacy is also expected to condition the link between attitudes and behavioral intention. When consumers feel competent in digital environments, they are more likely to act upon their favorable attitudes and translate them into purchase intentions. Conversely, those with low self-efficacy may remain hesitant to engage in purchase behavior despite holding positive attitudes. Therefore, this study hypothesizes following:

**H8:** Self-efficacy moderates the relationship between perceived ad value and consumers' attitudes toward AI-based advertisements.

**H9:** Self-efficacy moderates the relationship between perceived ad value and consumers' purchase intention toward AI-based advertisements.

**H10:** Self-efficacy moderates the relationship between consumers' attitudes toward AI-based advertisements and their purchase intention.

# 4 METHODOLOGY

This section outlines the methodological procedures adopted in this research by aiming to examine the relationships proposed in the conceptual model integrating the TPB Behavior and the Advertising Value in the context of AI-generated advertising. Quantitative research design was employed to empirically test the direct, mediating, and moderating effects among perceived advertising value, attitude toward AI-based advertisements, purchase intention, self-efficacy, and gender. The survey procedure in this thesis followed key stages outlined by Blair et al. (2013), including survey design, pilot testing, questionnaire revision, sampling, data collection, and data analysis. Accordingly, the methodology section explains development of the survey design, procedures for pilot testing, and the data collection process. Then, the statistical techniques used in data analysis include measurement assessment, structural model evaluation, mediation and moderation testing, and bootstrapping methods. Together, these steps ensure the reliability, validity, and robustness of the empirical findings.

## 4.1 Survey Design

To develop the survey instrument, extensive literature review was performed to understand measurement items aligned with the study's hypotheses. Based on this review, established scales from prior empirical studies were adapted to operationalize the constructs included in the theoretical framework. The constructs of advertising value, attitude, purchase intention, and self-efficacy that are abstract psychological constructs in nature, therefore they were operationalized using multi-item scales rather than single-item measures. As noted by Bergkvist & Rossiter (2007), multi-item measures enhance reliability and provide richer information by allowing assessment of internal consistency and inter-item correlations. Perceived advertising value was measured with three items adapted from studies by Ducoffe (1995), Lee et al. (2017), Martins et al. (2019), Chetioui et al. (2021), and Fayyaz et al. (2023). The attitude scale was assessed with eight items that are adapted from Zha et al. (2015), Shaouf ate al. (2016), Lee et al. (2017), and Chetioui et al. (2021). The seven scale items for Purchase Intention are adapted from Kim et al. (2013), Kim & Han (2014), Yadav & Pathak (2017), Lee et al. (2017), Chetioui et al. (2019; 2021), and Jayasing et al. (2025). Finally, self-efficacy is evaluated with four scale items adapted from studies by Bozkurt et al. (2023), and Falebita & Kok (2024). All scale items, their definitions and sources are summarized in Table 4.1.1

**Table 4.1.1. Measurement Items (Part 1 of 2)**

| Constructs | Definition | Measurement Items |
|---|---|---|
| **Advertising Value (AD)** | Advertising value is defined as the consumer's cognitive and effective evaluation of an advertisement. | - I feel that AI-generated ads are useful.<br>- I feel that AI-generated ads are valuable.<br>- I feel that AI-generated ads are important.<br>**References:**<br>(Ducoffe, 1995; Lee et al., 2017; Martins et al., 2019; Chetioui et al., 2021; Fayyaz et al., 2023) |
| **Attitude (A)** | Attitude toward an ad is defined as consumers' overall emotional and cognitive evaluation of an advertisement. | - I think AI-generated ads are: Persuasive.<br>- I like AI-generated ads in terms of their visuals, content, and style of presentation.<br>- I think AI-generated ads are: Satisfying.<br>- I think AI-generated ads are: Recommendable.<br>- I do believe that AI-generated ads present interesting content.<br>- Overall, I like AI-generated advertisements.<br>- Overall, my attitude toward AI-generated ads is very favorable.<br>- Overall, I consider AI-generated ads a good advertising channel.<br>**References:**<br>(Zha et al., 2015; Shaouf ate al., 2016; Lee et al., 2017; Chetioui et al., 2021) |

**Table 4.1.1. Measurement Items (Part 2 of 2 – Continued from Page 43)**

| Constructs | Definition | Measurement Items |
|---|---|---|
| **Purchase Intention (PI)** | Purchase intention can be described as an indicator of individuals' tendency and possibility to purchase a product or service. | - I would consider purchasing products/services that feature on AI-Generated ads.<br><br>- I intend to purchase products or services featured in AI-generated ads.<br><br>- I can recommend the products or services featured in AI-generated ads to others based on my own experiences and the knowledge I have acquired.<br><br>- I am willing to purchase products or services featured in AI-generated ads.<br><br>- I am more likely to purchase products or services featured in AI-generated ads.<br><br>- My decisions to purchase products or services featured in AI-generated ads are influenced by these ads.<br><br>- I think there is value in purchasing products or services featured in AI-generated advertisements.<br>**References:**<br>(Kim et al., 2013; Kim & Han, 2014; Yadav & Pathak, 2017; Lee et al., 2017; Chetioui et al., 2019; Chetioui et al., 2021; Jayasing et al., 2025) |
| **Self-efficacy (SE)** | Self-efficacy is defined as individuals' beliefs about their capabilities to coordinate and implement actions required to accomplish desired outcomes. | - I believe that I am fully competent in using AI tools.<br><br>- I am confident in my ability to effectively use AI tools.<br><br>- I perceive the use of AI tools as being within my capabilities.<br><br>- I feel that I possess the necessary knowledge and skills to utilize AI tools.<br>**References:**<br>(Bozkurt et al., 2023; Falebita & Kok, 2024) |

As part of the study, participants were first asked to watch a short commercial created by a real brand using artificial intelligence (AI) and respond to survey questions. The commercial was created by a real brand, Heinz Ketchup Canada, using artificial intelligence (AI). The video features visual content generated by the DALL·E 2 AI tool and was officially released on YouTube. This commercial is considered one of the first AI-powered commercials released by a real company, making it a valuable and relevant sample for this research. Although the ad video was publicly available on YouTube, it was downloaded using the open-source Python library yt-dlp to minimize privacy and data security risks (such as account tracking, cookies, or viewing history). Participants accessed the ad video through a secure OneDrive link during the survey.

To measure the study constructs, a five-point Likert scale ("Strongly Disagree, Disagree, Not Sure, Agree, Strongly Agree") was employed. Quality of translation is crucial for ensuring participants properly understand and avoid misinterpreting the questions, and ensuring survey reliability (Coskun Benlidayi & Gupta, 2024). Therefore, the question items were adapted linguistically and contextually to ensure clarity and conceptual equivalence. For analysis and reporting purposes, the survey questions were also back translated into English.

## 4.2 Pilot Testing

Pilot testing is a critical component of survey-based research, as it helps ensure the clarity, reliability, and validity of the measurement instrument before distributing it to a larger sample. In this study, a pilot survey was conducted as a preliminary quantitative step to evaluate the suitability of the questionnaire items adapted from prior literature and to identify any issues related to wording, comprehension, length, or technical implementation. Conducting a pilot helps detect potential ambiguities, reduce measurement error, and improve overall response quality, ultimately strengthening the robustness of the final data collection process (Bryman & Bell., 2011; Saunders et al., 2007).

For the pilot phase, data was collected from 95 participants. Their responses and written feedback were analyzed to assess item clarity, internal consistency, and the time required to complete the survey. Based on these insights, several revisions were made to improve linguistic clarity, contextual relevance, and scale functionality. Items that appeared ambiguous or showed weak preliminary reliability were refined to ensure conceptual equivalence and measurement accuracy.

After these modifications, 3 items measured perceived advertising value, 8 items assessed consumer attitudes toward AI-generated advertisements, and 7 items captured consumer purchase intentions. Additionally, demographic questions cover participants' age, gender, and education level. This structured approach ensured that all constructs within the conceptual model were measured comprehensively and reliably, providing a strong basis for the subsequent data analysis.

## 4.3 Data Collection

Data were gathered through an online, self-administered survey developed to empirically test the proposed research model and hypotheses. Prior to data collection, the study protocol, consent form and questionnaire were reviewed and approved by the Abdullah Gül University Social Sciences Research Ethics Committee (Approval Date: 30.06.2025). All participants were informed about research aim, their rights, and the voluntary nature of their contribution, and provided informed consent before accessing the questionnaire.

A non-probability convenience sampling strategy was employed, which is commonly used in behavioral research when the target population is broad and geographically dispersed. Eligible participants included adults between the ages of 18 and 65 who regularly use digital media platforms and were able to view and evaluate online advertisements.

Data collection took place via Google Forms. The survey link was shared through controlled dissemination channels, specifically WhatsApp and LinkedIn, to prevent uncontrolled public access. To minimize the risk of unauthorized or unintended participation (e.g., minor or automated responses), the link was not posted in public groups, open forums, or social networking platforms. Instead, it was selectively distributed through personal networks and professional contacts to ensure respondent validity and data quality.

Participants first viewed an AI-generated brand commercial embedded as a secure OneDrive link and subsequently completed the questionnaire. No personally identifiable information (PII) was collected, ensuring complete anonymity and compliance with ethical standards. Responses were gathered between August and September 2025.

## 4.4 Data Analysis

In the first stage, Preliminary Analysis and Data Screening were carried out using IBM SPSS Statistics 25. After data collection, all responses were examined for completeness, response patterns, and attention-check accuracy. A total of 361 survey responses (excluding the pilot test) were initially obtained. During screening, 81 respondents who failed the control question and 2 participants who provided uniform responses across all items were removed from the dataset. As a result, 278 valid responses were retained for further analyses. Missing data, outliers, and normality assumptions were evaluated, and descriptive statistics were computed to characterize the demographic distribution and overall structure of the dataset. This step ensured that the final sample was suitable for psychometric evaluation and subsequent hypothesis testing.

In the second stage, Pretest Reliability and Exploratory Factor Analysis (EFA) were conducted to verify the robustness and adequacy of the measurement instruments. The pilot survey with 95 participants provided initial reliability indicators for each construct, and items with unclear wording or low contribution to scale reliability were revised prior to the final survey launch. After the main data screening, EFA was performed on the full dataset (N = 278) using SPSS to examine factor structure of perceived advertising value, attitude, purchase intention, and self-efficacy. Reliability analyses using Cronbach's alpha confirmed that all constructs exhibited strong internal consistency, while factor loadings demonstrated that items loaded appropriately onto their respective dimensions. These results validated the suitability of the measurement scales for confirmatory and structural analyses.

In the final stage, Measurement Model Assessment and Hypothesis Testing were conducted using a combination of SPSS and Python to rigorously test the proposed theoretical framework. While SPSS contributed to the evaluation of convergent and discriminant validity, the main confirmatory analysis, mediation tests, moderation models, and structural path estimations were performed in Python. Python libraries were used to implement regression-based mediation, moderation, interaction modeling, and bootstrapping procedures, allowing for precise estimation of indirect and conditional effects. While various software programs exist for using the SEM model, many are limited to basic SEM functions and are not free and open source. In contrast, Python is a popular open-source programming language and includes the *semopy* library, which can be easily integrated and implemented into research processes (Igolkina & Meshcheryakov, 2020). The structural model assessed the relationships among perceived advertising value, attitudes, purchase intentions, gender, and self-efficacy. This integrated analytical approach, SPSS for foundational psychometric verification and Python for advanced structural modeling ensured methodological rigor and enhanced the reliability of the hypothesis-testing process. Table 4.4.1 summarized the data analysis steps.

**Table 4.4.1 Stages of Data Analysis**

| Stage | Software | Purpose |
|---|---|---|
| Data screening & Descriptive statistics | SPSS | Cleaning, normality, demographics |
| Pretest & reliability | SPSS | Cronbach's alpha, item purification |
| Exploratory Factor Analysis | SPSS | Factor structure, validity check |
| Measurement validity | SPSS & Python | Loadings, AVE, CR, discriminant validity |
| Hypothesis testing | Python | Direct, indirect, conditional effects |
| Mediation & moderation | Python | Bootstrapping, interaction modeling |
| Structural model (path analysis) | Python | Full estimation of proposed model |

# 5 RESULTS

Data analysis began with preliminary data analysis that is a quantitative analysis method and an examination of participants' demographic profiles. Descriptive statistics were then introduced. After these stages, reliability assessment was conducted, and the results of the exploratory factor analysis (EFA) were reported. Subsequently, confirmatory factor analysis (CFA) and structural model testing, was applied to validate research models and to test hypothesized relationships.

## 5.1 Preliminary Data Analysis

This section presents the preliminary data analysis obtained by examining the main data. Conducting preliminary data analysis after obtaining primary data from survey responses is a critical step in the analysis in quantitative research. Preliminary analysis can be defined as a series of analyses performed before moving on to subsequent main data analyses, such as correlation, regression, and statistical tests. If the analyzed dataset contains erroneous or misleading values, the conclusions drawn can also be misleading. Therefore, preliminary data analysis is vital to ensure the validity of the main analyses conducted in the research (Hair et al., 2019; Mat Roni & Djajadikerta, 2021). The preliminary data analysis consists of subsections such as missing values, outliers (Skewness and Kurtosis), and normality.

### *5.1.1 Missing Value*

Quantitative data analysis first involves data entry and scanning by aiming to data scanning to obtain error-free data. IBM SPSS Statistics 25 and the programming language Python were used to complete these steps and conduct data analysis. In preliminary data analysis, the two most obvious problems that can be found in raw data are missing values and outliers. If participants drop out of the survey before completing the questions or leave a question unanswered, this results in missing values. These missing values can be re-imputed with certain methods or removed entirely from the survey responses (Mat Roni & Djajadikerta, 2021). During data scanning, the steps of checking for errors in the data, identifying existing errors, and correcting them were followed. These data scanning steps were followed in pilot study and main data analysis.

The survey included a control question to determine whether participants had actually read the questions, and the responses of participants who answered incorrectly were deleted. In addition, the responses of participants who answered the same on every question were also removed from the survey data. No missing values were found since this incomplete and unsatisfactory data were removed from the survey during data entry.

### *5.1.2 Outliers*

Another problem that can be found in raw data is outliers, which can be defined as data that is very far away or different from the main cluster in a data set (Hair et al., 2019; Mat Roni & Djajadikerta, 2021). Outlier values can cause problems such as distorting or misrepresenting the results, thus leading to inaccurate interpretations of interactions between variables (Tabachnick and Fidell, 2014; Leys et al., 2019). Therefore, it can be said that it is significant to examine outliers in the data set before analysis. Outliers found in the data can be limited to minimum/maximum values, or responses with these values can be removed from the dataset (Mat Roni & Djajadikerta, 2021).

The main variables in the study were measured with a 5-point Likert scale. Likert scales are numerical descriptors where participants select the number, they feel appropriate to express their level of agreement with a given statement or question (Dawes, 2008). In this study, participants responded to questions on a limited scale, running from 1 (Strongly Disagree) to 5 (Strongly Agree). It can be said that Likert scales restrict responses to a specific range, making them ordinal and limited in nature. On a Likert scale, a participant's selection of 1 or 5 could be considered an extreme value. However, it can be supported that these values are part of the scale and do not fall outside the scale limits, so they are not considered statistical outliers. In the study, demographic data on age, gender, and education level were collected by having participants select specific categories. For example, participants indicated their gender by selecting the options: Female, Male, or Prefer not to say. A category being lower than the others is not considered an outlier because the response was selected from among the defined categories. Therefore, it can be said that outlier problems do not arise in this type of data. In summary, the question types and dataset structure used along with the data cleaning steps implemented in this study minimized the presence of traditional statistical outliers, and there are no outliers.

### *5.1.3 Normality*

Descriptive statistics were used to examine the distribution of the data which means determining whether it exhibits a normal distribution. Testing for normality is important because the distribution of the data can affect the reliability of the inferences and outputs. While perfect normality is rarely observed, data can be skewed and kurtosis in general. Understanding skewness and kurtosis values (the distribution of data) through normality tests is significant for conducting appropriate analytical tests (Kamath et al., 2025). Zero skewness and kurtosis values represent that the distribution of the data has perfect normality (Tabachnick and Fidell, 2014; Hatem et al., 2022). According to Hair et al. (2019), the most acceptable ranges for these values are ±2.58.

Table 5.1.3.1 shows the skewness and kurtosis values, all of which are within acceptable limits. In other words, all scales are close to a normal distribution and are suitable for parametric analyses such as correlation, regression, structural equation modeling, and so on.

**Table 5.1.3.1 Scores of Skewness and Kurtosis**

| Variable | N | Mean | Std Deviation | Skewness | Kurtosis |
|---|---|---|---|---|---|
| Ad Value | 278 | 9.37 | 3.167 | -0.157 | -0.508 |
| Purchase Intention | 278 | 20.65 | 7.133 | -0.056 | -0.659 |
| Attitude | 278 | 27.12 | 8.016 | -0.380 | -0.560 |
| Self-efficacy | 278 | 11.95 | 4.475 | -0.104 | -0.777 |

## 5.2 Demographic Profile

In this section, descriptive statistics were analyzed to describe the survey structures. Survey data were collected from 361 participants in Türkiye between August and September 2025. During the transfer of the data to the analysis programs, 83 incomplete and inconsistent surveys were excluded. Therefore, in the analysis section of the research, 278 responses were analyzed, and various inferences were drawn. The literature has not yet presented a directly suitable formula for determining sample size in SEM-based studies, which is frustrating for researchers (Westland, 2010). While there is no single sample size requirement in literature, there are generally accepted minimum threshold recommendations. It is thought that a larger sample size is required for SEM compared to other multivariate approaches. Sample size is important for generalizing to the population, but achieving large samples can be time-consuming and costly (Hair et al., 2019). A minimum sample size of 100 (Hair et al., 2019) or 200 (Kline,2023) is recommended for testing relationships between variables. The table below shows the frequency and percentage values regarding the socio-demographic characteristics of the participants in detail.

**Table 5.2.1 Demographic Profile of Survey Respondent (n = 278)**

| Measure | Item | Frequency | Percentage (%) |
|---|---|---|---|
| Gender | Female | 189 | 68 |
| | Male | 84 | 30.2 |
| | Prefer not to say | 5 | 1.8 |
| Age | 18-24 | 46 | 16.6 |
| | 25-34 | 150 | 54 |
| | 35-44 | 46 | 16.6 |
| | 45-54 | 29 | 10.4 |
| | 55-64 | 7 | 2.5 |
| Education | Primary School | 3 | 1.1 |
| | High School | 30 | 10.8 |
| | Undergraduate | 183 | 65.8 |
| | Postgraduate | 62 | 22.3 |

As shown in Table 5.2.1, 68% of the participants are female, 30.2% are male, and 1.8% choose Prefer not to say their gender. The majority of the participants in the study were female. It can be said that the distribution of participants by gender is imbalanced.

Also, while 54% of the participants are between the ages of 25-34, only 2.5% are between the ages of 55-64. The majority of participants were young adults. In addition, participants were divided into four categories: primary school, high school, undergraduate and postgraduate. As shown in Table 4.2, the majority of the participants (65.8%) have undergraduate degrees. 22.3% have a postgraduate degree, 10.8% have a high school degree and only 1.1% have a primary school degree. It can be said that most of the survey participants had a higher education level.

## 5.3 Descriptive Statistics

A five-point Likert scale that ranges from strongly disagree (1) to strongly agree (5) was used for measurement in this study. Descriptive statistics for all observed variables are presented in Table 5.3.1. The mean values for the Advertising Value items ranged from 3.09 to 3.19. For Purchase Intention, the mean values ranged from 2.70 to 3.19, and for Attitude items, the mean values ranged from 3.10 to 3.69. Finally, the Self-efficacy items ranged from 2.83 to 3.08. Based on the item mean scores, it can be said that participants generally reported moderate scores across all constructs. Standard deviations range from 1.10 to 1.27. This indicates a reasonable degree of variability in responses across items, without excessive clustering or dispersion. Overall, the data is well distributed and suitable for further parametric analysis.

**Table 5.3.1 Descriptive Statistics of Survey Measurements**

| Variable | Measures | Mean | Std. Deviation |
|---|---|---|---|
| Ad Value | ADV1 | 3.19 | 1.10 |
| | ADV2 | 3.10 | 1.13 |
| | ADV3 | 3.09 | 1.14 |
| Purchase Intention | P1 | 3.19 | 1.13 |
| | P2 | 3.05 | 1.11 |
| | P3 | 2.97 | 1.18 |
| | P4 | 2.90 | 1.16 |
| | P5 | 2.81 | 1.14 |
| | P6 | 3.03 | 1.18 |
| | P7 | 2.70 | 1.16 |
| Attitude | A1 | 3.19 | 1.17 |
| | A2 | 3.68 | 1.12 |
| | A3 | 3.33 | 1.18 |
| | A4 | 3.10 | 1.20 |
| | A5 | 3.69 | 1.13 |
| | A6 | 3.53 | 1.19 |
| | A7 | 3.22 | 1.13 |
| | A8 | 3.37 | 1.14 |
| Self-efficacy | SE1 | 2.83 | 1.24 |
| | SE2 | 3.08 | 1.27 |
| | SE3 | 3.03 | 1.19 |
| | SE4 | 3.02 | 1.20 |

## 5.4 Reliability Assessment

Reliability assesses the consistency of a measurement across repeated applications. Also, internal consistency is referred to the consistency among variables within an aggregate measure. The logic of internal consistency is that if the indicators are highly correlated, all indicators of the scale accurately measure the same construct (Hair et al., 2019).

Cronbach's alpha was examined to check the internal consistency of the measures. Cronbach's alpha is the most commonly used reliability coefficient, which assesses the consistency of the whole scale. While Cronbach's alpha can be as low as .60 for exploratory research, the accepted lower limit is .70 (Hair et al., 2019). A Cronbach's alpha value of 0.90 and above indicates excellent reliability, 0.80-0.89 indicates good reliability, 0.70-0.79 indicates acceptable reliability, 0.60-0.69 indicates questionable reliability, and ≤0.60 indicates poor reliability (Ahmad et al., 2024). The number of items on a scale can influence Cronbach's alpha, meaning that scales with a large number of items tend to yield a higher value. Therefore, researchers should be careful when examining Cronbach's alpha (Hair et al., 2019).

**Table 5.4.1 Reliability Statistics (Cronbach's Alpha)**

| Construct | Items | Cronbach's Alpha | Type |
|---|---|---|---|
| Ad Value | 3 | 0.932 | Excellent Reliability |
| Purchase Intention | 7 | 0.953 | Excellent Reliability |
| Attitude | 8 | 0.951 | Excellent Reliability |
| Self-efficacy | 4 | 0.930 | Excellent Reliability |

According to Table 5.4.1, Cronbach's Alpha for advertising value was found to be 0.932. Although the variable was measured with 3 items, the consistency was excellent. In other words, it can be said that the items strongly measure the same construct. Cronbach's Alpha for the purchase intention was calculated as .953. This value may indicate that the items for this variable, measured with 7 items, are very similar to each other. However, it is a ratio generally accepted and considered reliable in the social sciences. The Cronbach's Alpha value for the attitude variable measured with 8 items was found to be .951. The scale can be said to be homogeneous and excellent. Lastly, the self-efficacy variable was measured with 4 items, and Cronbach's Alpha was calculated as

.930. This high value can be attributed to the consistency of the items and indicates high reliability. In short, Cronbach's alpha values for all scales range from 0.93 to 0.95. These values indicate excellent internal consistency. A very high alpha (>0.95) can sometimes be associated with item duplication. However, this can be considered natural and acceptable since the scales have 7–8 items.

## 5.5 Kaiser-Meyer-Olkin (KMO) and Bartlett's Test

The Kaiser-Meyer-Olkin (KMO) and Bartlett Test of Sphericity are two useful tests used to examine the suitability of data for analysis before factor analysis. The KMO test examines whether the data is adequate for the sample. The KMO value ranges from 0-1, with values above 0.6 being considered acceptable for factor analysis. When the value falls below this threshold, factor analysis fails to account for most of the variability in the data. Therefore, analysis can yield ineffective results. On the other hand, the Bartlett Test of Sphericity examines the relationships(correlation) between the variables used in the study. When the p-value is less than 0.05, the data is suitable for analysis. In other words, correlations between the data are suitable for analysis (Hinton, 2004; Hair et al., 2019).

**Table 5.5.1 KMO and Bartlett's Test**

| | | |
|---|---|---|
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy | | ,956 |
| Bartlett's Test of Sphericity | Approx. Chi-Square | 6491,346 |
| | df | 231 |
| | Sig. | ,000 |

There is a high level of sampling adequacy, since the KMO value (0.956) is above 0.90. In other words, the data set is highly suitable for factor analysis. According to Bartlett's Test of Sphericity, there is a significant correlation between the variables, meaning that factor analysis can be performed. In short, the KMO is very high, and the Bartlett test is significant. There are significant relationships between the scale items, and the sample size is sufficient. In other words, the dataset is suitable for Exploratory Factor Analysis (EFA) or Confirmatory Factor Analysis (CFA).

## 5.6 Exploratory Factor Analysis (EFA)

EFA is employed to understand the interrelationships of numerous variables and interpret them in terms of common factors (Watkins, 2018; Hair et al., 2019). In this study, EFA was conducted using IBM SPSS Statistics 25 before confirmatory factor analysis (CFA). Results are shown in Table 5.6.1. The measurement scales for the constructs (advertising value, purchase intention, attitude, and self-efficacy) were adapted from reliable scales in the existing literature for this research.

The Principal Axis Factoring (PAF) method and the Promax (oblique) rotation method, which allows for correlation between factors, were used when applying EFA. Attitude1 and Attitude4 were deleted because they were below 0.5 and cross-loadings. Consequently, Attitude is measured with 6 items. Furthermore, other factor loadings are strong, the distribution is clear, and the rotation is stable. The scale structure conforms to the expected theoretical model. Therefore, it can be said that the EFA results provide a solid basis for proceeding to confirmatory factor analysis (CFA).

**Table 5.6.1 EFA Result Table**

| Pattern Matrix | | | | |
|---|---|---|---|---|
| | Factor | | | |
| | 1 | 2 | 3 | 4 |
| AdValue1 | | | | ,535 |
| AdValue2 | | | | ,817 |
| AdValue3 | | | | ,659 |
| Purchase1 | ,786 | | | |
| Purchase2 | ,883 | | | |
| Purchase3 | ,879 | | | |
| Purchase4 | ,993 | | | |
| Purchase5 | ,906 | | | |
| Purchase6 | ,828 | | | |
| Purchase7 | ,694 | | | |
| Attitude1 | ,514 | | | |
| Attitude2 | | ,917 | | |
| Attitude3 | | ,808 | | |
| Attitude4 | ,412 | ,454 | | |
| Attitude5 | | ,941 | | |
| Attitude6 | | ,894 | | |
| Attitude7 | | ,604 | | |
| Attitude8 | | ,542 | | |
| SE1 | | | ,801 | |
| SE2 | | | ,917 | |
| SE3 | | | ,921 | |
| SE4 | | | ,868 | |

## 5.7 Internal Consistency Reliability Test

Following the EFA, reliability testing was performed separately for the final factors, and Cronbach's alpha values were examined. The results shown in Table 5.7.1 indicated that Cronbach's alpha values for all constructs provided excellent reliability.

**Table 5.7.1 Cronbach's Alpha for Each Construct**

| Construct | Items | Cronbach's Alpha | Type |
|---|---|---|---|
| Ad Value | 3 | 0.932 | Excellent Reliability |
| Purchase Intention | 7 | 0.953 | Excellent Reliability |
| Attitude | 6 | 0.940 | Excellent Reliability |
| Self-efficacy | 4 | 0.930 | Excellent Reliability |

## 5.8 Confirmatory Factor Analysis

Initially, confirmatory factor analysis was conducted for four variables (Advertising Value, Purchase Intention, Attitude, and Self-Efficacy) consisting of 22 items. CFA is an analysis that helps test how well the measured variables in the established model reflect the latent construct. In other words, it is an analysis method for measuring how well the variables and factors in a predetermined measurement theory fit reality. With CFA, researchers can evaluate the contribution of the scale items and the concept, while also making inferences about the reliability of the scale. When CFA fit results and construct validity tests are evaluated together, the quality of the established theoretical measurement model can be evaluated (Hair et al., 2019).

### *5.8.1 The goodness of fit indices*

To test the validity of CFA and conduct it, Goodness of Fit Indices and Construct Validity were examined. The seven goodness-of-fit indices mentioned by Hair et al. (2019) were examined for their compliance with the recommended criterion ranges. The findings are shown in Table 5.8.1.1.

- List of checked fit indices;
- Chi-square ($\chi 2$) to the degree of freedom (Df)
- Goodness of fit index (GFI)
- Adjusted goodness of fit index (AGFI)
- Incremental fit index (IFI)
- Tucker-Lewis index (TLI)
- Comparative fit index (CFI)
- Root mean square error of approximation (RMSEA)

**Table 5.8.1.1 The Goodness of Fit Indices for Initial CFA**

| Model Fit Indices | Default Model | Recommended Criteria |
|---|---|---|
| $\chi 2$/df | 2.80 | 1:3 |
| GFI | 0.915 | ≥ 0.90 |
| AGFI | 0.904 | ≥ 0.80 |
| IFI | 0.944 | ≥ 0.90 |
| TLI | 0.936 | ≥ 0.90 |
| CFI | 0.944 | ≥ 0.90 |
| RMSEA | 0.081 | <.80 |

Analyzing the results it revealed that the model had good fit indices. However, the RMSEA of 0.081 is borderline, meaning some parts of the model may not fit the data well.

The EFA results indicated that some items fell outside the value range and loaded on more than one factor, and removal was considered. Based on the CFA analysis results conducted without removing these items, it was determined that some items needed improvement. Therefore, model fit was improved by deleting items Attitude1 and Attitude4. The CFA values obtained after removing these items are shown in Table 5.8.1.2 below.

**Table 5.8.1.2 The goodness of fit indices for the Model**

| Model Fit Indices | Default Model | Recommended Criteria |
|---|---|---|
| $\chi 2/df$ | 2.62 | 1:3 |
| GFI | 0.928 | ≥ 0.90 |
| AGFI | 0.917 | ≥ 0.80 |
| IFI | 0.954 | ≥ 0.90 |
| TLI | 0.947 | ≥ 0.90 |
| CFI | 0.954 | ≥ 0.90 |
| RMSEA | 0.077 | <.80 |

When the values were examined, it was observed that all model fit indices improved when Attitude1 and Attitude4 were removed. The RMSEA decreased, while the CFI and TLI increased. While the RMSEA was still within limits, the remaining values were very good. This can be interpreted as indicating that these two items compromised the overall fit of the model, and their removal made the model more consistent and explanatory. It can be said that the model now exhibits a better fit, both theoretically and statistically.

### *5.8.2 Construct Validity Assessment*

Assessing the construct validity of a proposed measurement theory is one of the primary goals of CFA and SEM. Construct validity is the expression of the extent to which a set of measured items accurately measures the theoretical construct they are designed to measure (Hair et al., 2019). The two widely accepted subtypes of validity are convergent and discriminant validity. Convergent validity refers to the maximum variance between indicators measuring the same construct with different methods, that is, the degree of correlation between the measurements. Factor loadings, composite reliability (CR), average variance extracted (AVE), and critical ratio (t-value) are examined to measure convergent validity. Values higher than 1.96 for critical ratios and higher than 0.50 for factor loadings are considered acceptable (Hair et al., 2019; Cheung et al., 2023). Table 5.8.2.1 below shows the factor loading, CR and AVE values of the items for the variables.

**Table 5.8.2.1 Convergent Validity**

| Factor | CR | AVE |
|---|---|---|
| Ad Value | 0.911 | 0.774 |
| Purchase Intention | 0.917 | 0.611 |
| Attitude | 0.898 | 0.594 |
| Self-efficacy | 0.897 | 0.684 |

For Ad Value, CR (0.911) and AVE (0.774) represent a very high reliability and variance ratio. It can be said that the items in this factor measure the concept consistently and robustly. The CR (0.917) and AVE (0.611) values indicate excellent reliability for Purchase Intention. Which means that the items represent the construct well and convergent validity has been achieved. Additionally, the CR (0.898) and AVE (0.594) values for Attitude indicate high CR and AVE above the 0.50 threshold. These values are acceptable, and convergent validity exists. Lastly, the CR (0.897) and AVE (0.684) values indicate both good reliability and explained variance for Self-Efficacy. Shortly, it was observed that the factors in the model were consistent with their items, and the measurement model was statistically strong and valid in this respect when the results were examined. Therefore, it can be said that Convergent Validity was achieved for all constructs.

On the other hand, discriminant validity measures the extent to which a variable differs from other variables, and the extent to which two conceptually similar concepts are actually different. Each square root of the Average Variance Extracted (AVE) is expected to be higher than the other correlation coefficient (Hair et al., 2019). Table 5.8.2.2 shows the discriminant validity results.

**Table 5.8.2.2 Discriminant Validity**

| | Ad Value | Purchase I. | Attitude | Self-efficacy |
|---|---|---|---|---|
| Ad Value | 1.000 | | | |
| Purchase I. | 0.899 | 1.000 | | |
| Attitude | 0.869 | 0.812 | 1.000 | |
| Self-efficacy | 0.379 | 0.389 | 0.379 | 1.000 |

A value of 0.899 was found for AdValue – PurchaseIntention. It can be said that these two constructs are highly similar conceptually because the value is right on the borderline. However, since it is below 0.90, discriminant validity is acceptable. A value of 0.869 for AdValue – Attitude demonstrates a similarly high correlation. However, since the value is still below 0.90, discriminant validity is achieved. Also, a value of 0.812 for PurchaseIntention – Attitude indicates a strong correlation, but acceptable, and discriminant validity is present. Lastly, Self-efficacy and the other constructs have values between 0.37 and 0.39. In other words, low correlations and excellent discriminant validity are achieved. After conducting EFA and CFA analyses and confirming their validity, the structural model testing phase was initiated to examine the hypotheses.

## 5.9 Structural Equation Modelling (SEM)

This statistical model is widely used to explain the direction and magnitude of hypothesized causal effects in quantitative studies examining the relationship between multiple variables (Hair et al., 2019; Kline,2023). According to Westland (2010), using SEM is useful in social sciences when many fundamental variables cannot be directly observed. To examine whether hypotheses H1, H2, and H3 were supported, a model was developed, and SEM analysis was conducted. The analyses examined both model fit indices and parameter estimates. Detailed Structural Equation Model Parameter Estimates Table is included in Table 1 in the Appendix. Analyzing the model fit indices, shown in Table 5.9.1 in the appendix, revealed that the SEM model generally fits the data well. The structural equation model was found to fit the data well ($\chi^2/df = 2.61$, CFI = .954, TLI = .947, RMSEA = .076). All hypothesized paths (H1–H3) were statistically significant and in the expected directions. In other words, the structural model (AdValue → Attitude → PurchaseIntention) established to examine hypotheses H1, H2, and H3, statistically supported.

**Table 5.9.1 Model Fit Indices**

| Model Fit Indices | Default Model | Recommended Criteria | Interpretation |
|---|---|---|---|
| $\chi 2/df$ | 2.61 | 1:3 | within the good fit range |
| GFI | 0.9274 | ≥ 0.90 | general fit is good |
| AGFI | 0.9169 | ≥ 0.80 | acceptable fit |
| IFI | 0.954 | ≥ 0.90 | incremental fit of the model is very good |
| TLI | 0.9470 | ≥ 0.90 | very good fit |
| CFI | 0.9537 | ≥ 0.90 | very good fit |
| RMSEA | 0.076 | <.80 | good fit |

Table 5.9.2 below shows the parameter values for the hypotheses. When the values are examined, all hypothesized paths are found to be statistically highly significant when the p-value is $< 0.001$. Furthermore, the β (impact coefficient) values are positive.

**Table 5.9.2 Path Coefficients and Parameter Estimates Table**

| H | Path | β (Estimate) | Std. Err | z-value | p-value | Interpretation |
|---|---|---|---|---|---|---|
| H1 | AdValue → Attitude | 0.823 | 0.0557 | 14.77 | 0.000 | Supported |
| H2 | AdValue → PurchaseIntention | 0.640 | 0.0747 | 8.56 | 0.000 | Supported |
| H3 | Attitude → PurchaseIntention | 0.276 | 0.0696 | 3.97 | 0.00007 | Supported |

H1's $\beta = 0.823$, $p < 0.001$ indicates that the perception of advertising value significantly and strongly influences consumer attitudes. So, attitudes toward AI ads increase as advertising value increases. H2's $\beta = 0.640$, $p < 0.001$ indicates that the perception of advertising value positively and significantly affects purchase intention. As advertising value increases, purchase intentions for products/services in AI ads increase. H3's $\beta = 0.276$, $p < 0.001$ indicates that attitude positively affects purchase intention. In other words, a positive attitude toward AI ads positively affects purchase intention. These results indicate that the structural model operates in the theoretically expected directions, and hypotheses H1, H2, and H3 are all strongly supported.

Additionally, H4 was analyzed using the Bootstrapping method in Python in the context of SEM to examine whether consumer attitude has a mediating role. Bootstrapping is a statistical method that uses randomly replacing samples from an observed set to simulate the dataset to draw inferences about a sample. This method, typically used for datasets with non-normal distributions and small sample sizes, allows for the measurement of the reliability and accuracy of sample-related assumptions (Egbert & Plonsky, 2020). The results are shown in Table 5.9.3. According to the indirect effect coefficient (0.2548), an increase in perceived ad value positively increases attitudes toward AI ads, indirectly increasing purchase intentions. Consumers' attitudes towards artificial intelligence advertisements have a significant mediating role in the relationship between perceived advertising value and purchase intention, that is, H4 is supported.

**Table 5.9.3 Bootstrapping Analysis Table**

| H | Path | Estimate (a * b) | Bootstrap SE | z-value | p-value | 95% Confidence Interval (CI) | Interpretation |
|---|---|---|---|---|---|---|---|
| H4 | Ad Value → Attitude → Purchase Intention | 0.2548 | 0.0451 | 5.66 | < 0.001 | [0.1665, 0.3431] | Supported |

### *5.9.1 Moderating Role of Gender*

To measure the moderating role of gender, multi-group analysis is employed which is a common method used to compare groups and examine whether there are statistically significant differences between them. Differences between structural paths across multiple groups can be examined using various techniques within multi-group analysis (Cheah et al., 2023). Multi-group SEM analysis was performed to test hypotheses H5, H6, and H7. In the study, participants were given three options to indicate their gender: "Female, Male, and Prefer not to say". The "Prefer not to say" group represented a very small percentage of the responses. To perform statistical analyses, each group must have enough participants. This group was excluded to avoid distorting the model's fit indices and to increase statistical reliability of the results. When examining the model fit indices (in Table 5.9.1.1), the overall model fit in the female group is good. In other words, the model statistically fits the data quite well for the female participants. In contrast, the model fits well in the male group, but the GFI and RMSEA values are slightly lower than in females. This is due to the lower response diversity or sample size in the male group.

**Table 5.9.1.1 Table of Fit Indices by Gender**

| Model Fit Indices | Women's Group | Men's Group | Recommended Criteria | Interpretation |
|---|---|---|---|---|
| χ2/df | 2.33 | 1.76 | ≤ 3 (good) ≤ 5 (acceptable) | both groups show good compatibility |
| GFI | 0.906 | 0.856 | ≥ 0.90 good ≥ 0.85 acceptable | good fit in women and acceptable fit in men |
| AGFI | 0.893 | 0.836 | ≥ 0.85 acceptable | good in women, borderline in men |
| IFI | 0.944 | 0.932 | ≥ 0.90 good fit | both groups are well adjusted |
| TLI | 0.936 | 0.922 | ≥ 0.90 good fit | both groups are well matched, with women being slightly higher |
| CFI | 0.944 | 0.932 | ≥ 0.90 good ≥ 0.95 excellent | both are in good harmony |
| RMSEA | 0.084 | 0.095 | ≤ 0.08 good ≤ 0.10 acceptable | the women group is borderline good, the male group is acceptable |

Table 5.9.1.2 shows the Path Coefficients and Parameter Estimates by Gender. When examining the β values for H4, β=.85 for women and β=.79 for men are similar, meaning the difference is not statistically significant (p=.615). This can be interpreted as "gender does not moderate the effect of perceived ad value on attitude." In other words, gender does not moderate the relationship between perceived ad value and attitude. When β values were analyzed to examine H5, this effect was significantly stronger for men (β=.89) than for women (β=.54), and the difference was significant (p=.040). In other words, gender moderates purchase intention. In fact, the perceived value of an ad has a

stronger effect on purchase intention for men than for women. When β values were analyzed to examine H6, it was significant in women (β=.35), weak in men (β=.05), and the difference was marginal (p=.051). In other words, advertising attitudes have a slightly stronger effect on purchase intention in women than in men. However, the difference is statistically marginal, so the hypothesis can be said to be partially supported.

**Table 5.9.1.2 Path Coefficients and Parameter Estimates Table by Gender**

| H | Path | Kadın (β) | Erkek (β) | p-value | Result | Interpretation |
|---|---|---|---|---|---|---|
| H5 | Attitude ~ AdValue | 0.846 | 0.788 | 0.615 | no difference | Not supported |
| H6 | PurchaseIntention ~ AdValue | 0.541 | 0.886 | 0.040 | the difference is significant | Supported |
| H7 | PurchaseIntention ~ Attitude | 0.352 | 0.046 | 0.051 | borderline significant | Partially supported |

### *5.9.2 Moderating Role of Self-Efficacy*

In this part, an interaction SEM analysis was conducted to test whether self-efficacy moderates the relationship between individuals' perceptions of AI-generated advertising value, their attitudes toward these ads, and their purchase intentions. According to Table 5.9.2.1, Ad Value significantly and strongly increases individuals' attitudes toward AI-based ads. $\beta = 0.874$ indicates the magnitude of this effect, which is a relatively high coefficient. $z = 14.97$ and $p < 0.001$ indicate that this effect is highly statistically significant. In other words, individuals' positive attitudes toward ads significantly increase as Ad Value increases. Also, individuals' self-efficacy has a positive and significant effect on their attitudes toward AI-based ads ($\beta = 0.145$, $p < 0.001$). This suggests that as individuals' self-efficacy increases, they develop more positive attitudes toward AI-supported ads. The relationship in the third row of the table shows that the Self-efficacy variable weakens the relationship between Perceived Ad Value and Attitude. As ad value increases, attitudes generally increase (this was already positive and significant, $\beta = 0.874$). However, as Self-efficacy increases, the strength of this positive effect decreases. In other words, the Self-efficacy variable significantly negatively affects the relationship between perceived ad value and attitude ($\beta = -0.024$, $p < 0.001$). This suggests that as individuals' self-efficacy levels increase, the positive effect of perceived ad value on attitude weakens.

**Table 5.9.2.1 Interaction SEM Analysis Main Pathways and Interaction Effects**

| Relationship | β (Estimate) | z | p | Interpretation |
|---|---|---|---|---|
| Attitude ~ AdValue | 0.874 | 14.97 | <0.001 | AdValue → Attitude is strong and meaningful (+) |
| Attitude ~ SelfEfficacy | 0.145 | 3.51 | <0.001 | The direct effect of Self-efficacy on Attitude is significant (+) |
| Attitude ~ AdValue × SelfEfficacy (AdValue_SE) | -0.024 | -3.57 | <0.001 | The interaction is significant — there is moderation (negative) |
| PurchaseIntention ~ AdValue | 0.341 | 4.51 | <0.001 | AdValue → PurchaseIntention significant (+) |
| PurchaseIntention ~ Attitude | 0.471 | 6.43 | <0.001 | Attitude → Purchase Intention significant (+) |
| PurchaseIntention ~ SelfEfficacy | -0.013 | -0.36 | 0.721 | The direct effect of Self-Efficacy on Purchase Intention is insignificant |
| PurchaseIntention ~ AdValue × SelfEfficacy (AdValue_SE) | 0.069 | 4.64 | <0.001 | Significant moderation (positive direction) |
| PurchaseIntention ~ Attitude × SelfEfficacy (Attitude_SE) | -0.046 | -3.24 | 0.001 | Significant moderation (negative direction) |

The fourth row of the table shows that Perceived Ad Value has a positive and significant effect on consumers' purchase intention (β = 0.341, $p < 0.001$). This result indicates that the more valuable consumers perceive the ad, the greater their inclination to purchase the product promoted by that ad. According to the fifth row, consumers' attitudes toward AI-based ads have a positive and significant effect on purchase intentions (β = 0.471, $p < 0.001$). This means that individuals who develop a positive attitude toward the ad are more willing to purchase the product promoted by the ad. Looking at the sixth row, the direct effect of Self-efficacy on purchase intention is not significant (β = -0.013, p = 0.721). This shows that individuals' self-efficacy levels do not directly affect their purchase intentions. According to the seventh row, self-efficacy significantly strengthens the relationship between perceived ad value and purchase intention (β = 0.069, $p < 0.001$), indicating that individuals with high self-efficacy tend to have higher purchase intentions when they find the ad valuable in AI-based ads. In the last row, self-efficacy was found to significantly weaken the relationship between attitude and purchase intention (β = -0.046, p = 0.001). This indicates that the effect of attitude on purchase intention is weaker in individuals with high self-efficacy levels.

**Table 5.9.2.2 Path Coefficients and Parameter Estimates Table by Self-efficacy**

| H | Path | Interpretation | |
|---|---|---|---|
| H8 | Attitude ~ AdValue × Self-Efficacy | Self-efficacy moderates the relationship between **AdValue → Attitude (-)** | Supported |
| H9 | PurchaseIntention ~ AdValue × Self-Efficacy | Self-efficacy moderates the relationship between **AdValue → PurchaseIntention (+)** | Supported |
| H10 | PurchaseIntention ~ Attitude × Self-Efficacy | Self-efficacy moderates the relationship between **Attitude → PurchaseIntention (-)** | Supported |

According to Table 5.9.2.2, self-efficacy significantly moderates the effect of perceived ad value on attitude in a negative direction. As self-efficacy increases, the positive impact of perceived ad value on attitude decreases. Also, self-efficacy significantly moderates the effect of perceived ad value on purchase intention in a positive direction. The positive effect of ad value on purchase intention becomes stronger for consumers with higher self-efficacy. Lastly, self-efficacy significantly moderates the effect of attitude on purchase intention in a negative direction. The influence of attitude on purchase intention weakens as self-efficacy increases.

# 6 DISCUSSION AND CONCLUSION

This section presents discussion and conclusions of the research. Results of the survey data and hypothesis testing are evaluated in relation to existing literature, followed by theoretical contributions and managerial implications. Finally, the limitations and recommendations for future work are discussed.

Artificial intelligence increasingly shapes marketing activities of organizations, particularly in advertising, where personalization, automation, and predictive analytics change consumer and brand interactions. Existing literature focuses on efficiency, performance, and brand-level outcomes of AI applications. There are limited studies which investigate how AI-generated advertisements influence consumer behavior directly. To fulfil this gap, the present thesis examined effects of AI-generated advertisements on consumer attitudes and purchase intentions. Additionally, moderating roles of gender and self-efficacy were assessed to understand how individual-level differences shape responses to AI-driven advertising.

To analyze these relationships, a new theoretical model integrating the Theory of Planned Behavior (TPB) and the Advertising Value was suggested. An online survey was performed that starts with watching a real AI-generated commercial (Heinz Ketchup Canada) before completing the survey. Following a pilot test (n = 95), the final dataset consisted of 278 valid responses collected in August and September 2025. Reliability, validity, and hypothesis testing were conducted using IBM SPSS Statistics 25 and Python-based SEM procedures. Table 6 summarizes the hypothesis analysis.

**Table 6.1 Hypothesis Analysis**

| | Hypothesis | Results |
|---|---|---|
| **H1** | Perceived ad value has considerable influence on consumers' attitudes toward AI-generated advertisements. | Supported |
| **H2** | Perceived ad value has considerable influence on consumers' purchase intention about products or services that are placed on AI-generated advertisements. | Supported |
| **H3** | Positive consumers' attitudes toward AI-generated advertisements positively influence their purchase intention. | Supported |
| **H4** | Attitudes of consumers towards AI-generated advertisements have a mediating role in perceived advertising value and customers' purchase intention relations. | Supported |
| **H5** | Gender moderates the relationship between perceived ad value and consumers' attitudes toward AI-based advertisements. | Not Supported |
| **H6** | Gender moderates the relationship between perceived ad value and consumers' purchase intention toward AI-based advertisements. | Supported |
| **H7** | Gender moderates the relationship between consumers' attitudes toward AI-based advertisements and their purchase intention. | Partially Supported |
| **H8** | Self-efficacy moderates the relationship between perceived ad value and consumers' attitudes toward AI-based advertisements. | Supported |
| **H9** | Self-efficacy moderates the relationship between perceived ad value and consumers' purchase intention toward AI-based advertisements. | Supported |
| **H10** | Self-efficacy moderates consumers' attitudes toward AI-based advertisements and their purchase intention relations. | Supported |

Advertising value can be briefly described as consumers' cognitive and affective evaluation of an advertisement in terms of its usefulness, informativeness, entertainment, relevance, and overall perceived value (Ducoffe, 1996; Brown & Stayman, 1992; Tsang et al., 2004). Researchers in the literature have argued that advertisements that are informative, credible, entertaining, non-irritating, and offer incentives positively impact advertising value (Martins et al., 2019; Aktan et al.,2016; Karamchandani et al.;2021; Van Tuan et al.;2023). Furthermore, when consumers perceive an advertisement as valuable, they may evolve positive attitudes, and their purchase intentions may be influenced accordingly (Karamchandani et al., 2021; Martins et al., 2019). Also, consumers can be more easily persuaded to purchase a product or service, when they have a positive attitude about it. So, consumers with a positive attitude are more likely to purchase it (Kim et al., 2009; Goldsmith et al., 2000; Aktan et al., 2016; Talih Akkaya et al., 2017; Ahmed et al; 2020). Coherent with the existing literature, the SEM results approved that perceived ad value significantly and positively affects both attitudes towards AI-generated ads (H1 supported) and purchase intentions (H2 supported). Similarly, attitudes towards AI-generated ads significantly predicted purchase intentions (H3 supported). Additionally, when examining the mediating role of consumers' attitudes toward AI-generated ads, it was found that it mediates perceived ad value and customers' purchase intentions relations (H4 supported).

Existing literature generally suggests that toward technological concepts such as artificial intelligence women tend to experience privacy and ethical concerns, while men tend to exhibit familiarity and more positive attitudes (Field, 2023; Grassini & Ree, 2023; Schepman & Rodway, 2023; Araujo et al., 2020; Kiper & Liang, 2025; Hoy & Milne, 2010; Mohamed & Ahmad, 2012; Bartel Sheehan, 1999; Rahman et al., 2024; Jang et al., 2022). H5, H6 and H7 were developed to examine the moderating effect of gender that can play a role in forming consumer behavior, on attitudes, advertising value and purchasing behavior towards artificial intelligence-generated ads. Multi-group SEM analysis was performed to test these hypotheses; it was reached that gender did not moderate the relationship between perceived ad value and attitude (H5 was not supported). The influence of ad value on purchase intention was found more intense for men. Men are more responsive to functional and performance-oriented gains reflected in ad value. Gender moderates relationship on ad value and purchase intention (H6 supported). The perceived value of an ad has stronger influence on purchase intention in men than in women. When the β value for H7 was examined, it was observed that advertising attitudes had a slightly stronger influence on purchase intention in women than in men. But the difference was statistically insignificant, the impact was not large enough to yield a full moderation effect (H7 partially supported).

Technological self-efficacy influences how individuals comprehend and interact with digital content and is consistently associated with stronger acceptance of AI technologies (Montag et al., 2023). Self-efficacy significantly moderates relationship between ad value and attitudes but interestingly in a negative way. As self-efficacy increases the influence of perceived value on attitude decreases. This may be because high self-efficacy significantly moderates the relationship between ad value and attitudes but interestingly in a negative way. As self-efficacy increases effect of perceived value on attitude decreases. It might be result of high-efficacy users evaluating AI-generated ads more critically and do not relying on simple surface level features when shaping their attitude (H8 supported). Self-efficacy strengthens the effect of advertising value on purchase intention. The positive effect of ad value on purchase intention becomes strengthened with higher self-efficacy (H9 supported). Finally, self-efficacy negatively significantly influences the effect of attitude on purchase intention. As self-efficacy increases, the effect of attitude on purchase intention decreases. High self-efficacy consumers appear less dependent on attitudes when shaping purchase intentions, while low self-efficacy relies more on affective evaluations (H10 supported). As can be seen from these results, although 2 relationships are negative and 1 positive, self-efficacy moderates consumers' attitudes, ad value, and purchase intentions toward AI-based ads.

## 6.1 Theoretical and Managerial Contributions

Artificial intelligence is rapidly gaining popularity in marketing, as in many other fields. However, while research in the field of AI is becoming widespread globally, research in Türkiye remains open to development. This research, which examines the influence of AI-generated advertising on consumer attitudes, purchase intentions, and advertising value through the moderating effects of gender and self-efficacy, aims to offer theoretical and managerial contributions. These contributions offer academics, marketers and practitioners and managers new insights into AI-based advertising and marketing and implications for strategic decision-making.

From the theoretical perspective, this research expands the emerging knowledge on AI in marketing by integrating two well-established models: Theory of Planned Behavior and the Advertising Value. By combining these theories, the study develops a comprehensive theoretical model that explains how consumers form attitudes and intentions towards AI-generated ads. It contributes to a profound comprehension of consumers' cognitive and emotional evaluation processes toward AI-enabled advertising. The results demonstrated that perceived advertising value significantly affects attitudes towards AI-generated ads and consumers' purchase intentions. Moreover, the study extends the literature by empirically validating the new model that includes moderating roles of self-efficacy and gender, highlighting that consumers' technological capabilities and demographic characteristics meaningfully shape their responses to AI-generated ads. These insights deepen the theoretical understanding of how individual differences influence digital persuasion processes.

Managerially, this study's results provide actionable implications for businesses adopting AI technologies in their advertising strategies. AI-generated content has become increasingly common; marketers should understand that not all consumers react to AI-generated content in the same way. The results highlight that women and men show different reactions to AI-generated ads, therefore gender sensitive advertisement campaign design may enhance the efficiency. Similarly, self-efficacy plays crucial role in forming how consumers evaluate and respond to AI contents. While consumers with high technology efficacy may engage more with AI-generated content, those with lower efficacy may need simple and clear messages. This might be considered in segmentation, message framing and designing AI-enhanced customer experiences. Designing adaptive communication strategies that align with consumers' confidence in interacting with AI technologies can increase ad engagement and encourage stronger brand-focused purchase intentions.

Overall, this research contributes to existing literature by enhancing theoretical models to a new technological context and offers practical implications for companies which are using AI-generated ads.

## 6.2 Limitations and Future Studies

This research has number of limitations that should be highlighted. First, this research relied on a single AI-generated ad created by Heinz Ketchup, which may limit results' generalizability. The future studies could include multiple brands, product categories or different types of AI-generated content.

Second, the data were gathered using a cross-sectional survey, which does not allow for strong causal inferences. Due to time limitations of a master’s thesis, experimental or longitudinal research designs could not be applied. Further studies are encouraged to use these designs to better examine causal effects.

Third, the research was conducted in Türkiye, but other countries may have different cultural norms and perceptions of technology. Therefore, generalizing the results to different cultural settings may not be accurate. Cross-cultural or comparative studies are recommended to gain valuable insights by determining how these relationships vary across different societies.

# 7 APPENDICIES

## 7.1 Appendix 1: Structural Equation Model Parameter Estimates Table

| | lval | op | rval | Estimate | Std. Err | z-value | p-value |
|---|---|---|---|---|---|---|---|
| 0 | Attitude | ~ | AdValue | 0.823089 | 0.055711 | 14.774159 | 0.0 |
| 1 | PurchaseIntention | ~ | AdValue | 0.639925 | 0.07474 | 8.562078 | 0.0 |
| 2 | PurchaseIntention | ~ | Attitude | 0.276489 | 0.069628 | 3.970964 | 0.000072 |
| 3 | AdValue1 | ~ | AdValue | 1.000000 | - | - | - |
| 4 | AdValue2 | ~ | AdValue | 1.079517 | 0.048029 | 22.476481 | 0.0 |
| 5 | AdValue3 | ~ | AdValue | 1.103304 | 0.04765 | 23.154254 | 0.0 |
| 6 | Attitude2 | ~ | Attitude | 1.000000 | - | - | - |
| 7 | Attitude3 | ~ | Attitude | 1.092430 | 0.055292 | 19.757544 | 0.0 |
| 8 | Attitude5 | ~ | Attitude | 1.001375 | 0.0543 | 18.4414 | 0.0 |
| 9 | Attitude6 | ~ | Attitude | 1.098765 | 0.055736 | 19.713869 | 0.0 |
| 10 | Attitude7 | ~ | Attitude | 0.998466 | 0.054995 | 18.155711 | 0.0 |
| 11 | Attitude8 | ~ | Attitude | 0.958012 | 0.057288 | 16.722852 | 0.0 |
| 12 | Purchase1 | ~ | PurchaseIntention | 1.000000 | - | - | - |
| 13 | Purchase2 | ~ | PurchaseIntention | 1.046409 | 0.050064 | 20.901445 | 0.0 |
| 14 | Purchase3 | ~ | PurchaseIntention | 1.082363 | 0.054435 | 19.883433 | 0.0 |
| 15 | Purchase4 | ~ | PurchaseIntention | 1.102973 | 0.051333 | 21.486777 | 0.0 |
| 16 | Purchase5 | ~ | PurchaseIntention | 1.058889 | 0.051483 | 20.567762 | 0.0 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 17 | Purchase6 | ~ | PurchaseIntention | 0.971427 | 0.058731 | 16.540367 | 0.0 |
| 18 | Purchase7 | ~ | PurchaseIntention | 0.966867 | 0.057466 | 16.825173 | 0.0 |
| 19 | SE1 | ~ | SelfEfficacy | 1.000000 | - | - | - |
| 20 | SE2 | ~ | SelfEfficacy | 1.136087 | 0.056856 | 19.981939 | 0.0 |
| 21 | SE3 | ~ | SelfEfficacy | 1.069781 | 0.053369 | 20.04516 | 0.0 |
| 22 | SE4 | ~ | SelfEfficacy | 0.977579 | 0.057127 | 17.11239 | 0.0 |
| 23 | AdValue | ~~ | AdValue | 0.920699 | 0.100588 | 9.153162 | 0.0 |
| 24 | Attitude | ~~ | Attitude | 0.292257 | 0.039032 | 7.487704 | 0.0 |
| 25 | PurchaseIntention | ~~ | PurchaseIntention | 0.210398 | 0.028178 | 7.46669 | 0.0 |
| 26 | SelfEfficacy | ~~ | SelfEfficacy | 1.063020 | 0.126465 | 8.405622 | 0.0 |
| 27 | SelfEfficacy | ~~ | AdValue | 0.388175 | 0.069761 | 5.564369 | 0.0 |
| 28 | AdValue1 | ~~ | AdValue1 | 0.281388 | 0.029351 | 9.58716 | 0.0 |
| 29 | AdValue2 | ~~ | AdValue2 | 0.208744 | 0.025284 | 8.255835 | 0.0 |
| 30 | AdValue3 | ~~ | AdValue3 | 0.180858 | 0.023962 | 7.54771 | 0.0 |
| 31 | Attitude2 | ~~ | Attitude2 | 0.345886 | 0.034228 | 10.105268 | 0.0 |
| 32 | Attitude3 | ~~ | Attitude3 | 0.308782 | 0.032397 | 9.53113 | 0.0 |
| 33 | Attitude5 | ~~ | Attitude5 | 0.352313 | 0.034773 | 10.131745 | 0.0 |
| 34 | Attitude6 | ~~ | Attitude6 | 0.315747 | 0.033044 | 9.555438 | 0.0 |
| 35 | Attitude7 | ~~ | Attitude7 | 0.372906 | 0.03644 | 10.233505 | 0.0 |
| 36 | Attitude8 | ~~ | Attitude8 | 0.464138 | 0.043613 | 10.642253 | 0.0 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 37 | Purchase1 | ~~ | Purchase1 | 0.355745 | 0.033496 | 10.620473 | 0.0 |
| 38 | Purchase2 | ~~ | Purchase2 | 0.224281 | 0.023009 | 9.747644 | 0.0 |
| 39 | Purchase3 | ~~ | Purchase3 | 0.310225 | 0.030371 | 10.214355 | 0.0 |
| 40 | Purchase4 | ~~ | Purchase4 | 0.211670 | 0.022558 | 9.383283 | 0.0 |
| 41 | Purchase5 | ~~ | Purchase5 | 0.250641 | 0.025266 | 9.920157 | 0.0 |
| 42 | Purchase6 | ~~ | Purchase6 | 0.513817 | 0.046591 | 11.028203 | 0.0 |
| 43 | Purchase7 | ~~ | Purchase7 | 0.480540 | 0.043754 | 10.982803 | 0.0 |
| 44 | SE1 | ~~ | SE1 | 0.475451 | 0.047096 | 10.095318 | 0.0 |
| 45 | SE2 | ~~ | SE2 | 0.244305 | 0.033416 | 7.310998 | 0.0 |
| 46 | SE3 | ~~ | SE3 | 0.210655 | 0.029276 | 7.195553 | 0.0 |
| 47 | SE4 | ~~ | SE4 | 0.433292 | 0.043289 | 10.009325 | 0.0 |

## 7.2 Appendix 2: SEM Results of the Moderating Effects of Self-efficacy

| | lval | op | rval | Estimate | Std. Err | z-value | p-value |
|---|---|---|---|---|---|---|---|
| 0 | Attitude | ~ | AdValue | 0.873740 | 0.058371 | 14.968774 | 0.0 |
| 1 | Attitude | ~ | SelfEfficacy | 0.145243 | 0.041347 | 3.512782 | 0.000443 |
| 2 | Attitude | ~ | AdValue_SE | -0.023929 | 0.006697 | -3.572871 | 0.000353 |
| 3 | PurchaseIntention | ~ | AdValue | 0.341063 | 0.07567 | 4.507269 | 0.000007 |
| 4 | PurchaseIntention | ~ | Attitude | 0.471333 | 0.073255 | 6.434124 | 0.0 |
| 5 | PurchaseIntention | ~ | SelfEfficacy | -0.012705 | 0.035511 | -0.357782 | 0.720507 |
| 6 | PurchaseIntention | ~ | AdValue_SE | 0.069116 | 0.014893 | 4.640931 | 0.000003 |
| 7 | PurchaseIntention | ~ | Attitude_SE | -0.046086 | 0.014212 | -3.242707 | 0.001184 |
| 8 | AdValue1 | ~ | AdValue | 1.000000 | - | - | - |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 9 | AdValue2 | ~ | AdValue | 1.080095 | 0.048105 | 22.452816 | 0.0 |
| 10 | AdValue3 | ~ | AdValue | 1.103845 | 0.047772 | 23.106721 | 0.0 |
| 11 | Attitude2 | ~ | Attitude | 1.000000 | - | - | - |
| 12 | Attitude3 | ~ | Attitude | 1.092754 | 0.049628 | 22.018913 | 0.0 |
| 13 | Attitude5 | ~ | Attitude | 1.001847 | 0.048753 | 20.549553 | 0.0 |
| 14 | Attitude6 | ~ | Attitude | 1.097155 | 0.050101 | 21.89908 | 0.0 |
| 15 | Attitude7 | ~ | Attitude | 0.998792 | 0.049381 | 20.226218 | 0.0 |
| 16 | Attitude8 | ~ | Attitude | 0.961325 | 0.051356 | 18.718817 | 0.0 |
| 17 | Purchase1 | ~ | PurchaseIntention | 1.000000 | - | - | - |
| 18 | Purchase2 | ~ | PurchaseIntention | 1.045730 | 0.052285 | 20.000623 | 0.0 |
| 19 | Purchase3 | ~ | PurchaseIntention | 1.081515 | 0.056858 | 19.021415 | 0.0 |
| 20 | Purchase4 | ~ | PurchaseIntention | 1.102304 | 0.053607 | 20.562532 | 0.0 |
| 21 | Purchase5 | ~ | PurchaseIntention | 1.058300 | 0.053761 | 19.685099 | 0.0 |
| 22 | Purchase6 | ~ | PurchaseIntention | 0.971389 | 0.061328 | 15.83912 | 0.0 |
| 23 | Purchase7 | ~ | PurchaseIntention | 0.966306 | 0.060024 | 16.098612 | 0.0 |
| 24 | SE1 | ~ | SelfEfficacy | 1.000000 | - | - | - |
| 25 | SE2 | ~ | SelfEfficacy | 1.135984 | 0.056857 | 19.979645 | 0.0 |
| 26 | SE3 | ~ | SelfEfficacy | 1.069944 | 0.053362 | 20.050684 | 0.0 |
| 27 | SE4 | ~ | SelfEfficacy | 0.978035 | 0.057123 | 17.121664 | 0.0 |
| 28 | AdValue | ~~ | AdValue | 0.921437 | 0.100715 | 9.148947 | 0.0 |
| 29 | AdValue | ~~ | SelfEfficacy | 0.375697 | 0.069657 | 5.393527 | 0.0 |
| 30 | Attitude | ~~ | Attitude | 0.281019 | 0.037362 | 7.521436 | 0.0 |
| 31 | PurchaseIntention | ~~ | PurchaseIntention | 0.214444 | 0.028242 | 7.593127 | 0.0 |
| 32 | SelfEfficacy | ~~ | SelfEfficacy | 1.062863 | 0.126454 | 8.405152 | 0.0 |
| 33 | AdValue1 | ~~ | AdValue1 | 0.281025 | 0.029624 | 9.48636 | 0.0 |
| 34 | AdValue2 | ~~ | AdValue2 | 0.207101 | 0.02573 | 8.049103 | 0.0 |
| 35 | AdValue3 | ~~ | AdValue3 | 0.179273 | 0.024524 | 7.309985 | 0.0 |
| 36 | Attitude2 | ~~ | Attitude2 | 0.346439 | 0.034064 | 10.170375 | 0.0 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 37 | Attitude3 | ~~ | Attitude3 | 0.309041 | 0.03214 | 9.615431 | 0.0 |
| 38 | Attitude5 | ~~ | Attitude5 | 0.352137 | 0.034554 | 10.190914 | 0.0 |
| 39 | Attitude6 | ~~ | Attitude6 | 0.319773 | 0.033062 | 9.671913 | 0.0 |
| 40 | Attitude7 | ~~ | Attitude7 | 0.372858 | 0.036235 | 10.29 | 0.0 |
| 41 | Attitude8 | ~~ | Attitude8 | 0.458879 | 0.043031 | 10.664029 | 0.0 |
| 42 | Purchase1 | ~~ | Purchase1 | 0.354729 | 0.033417 | 10.61511 | 0.0 |
| 43 | Purchase2 | ~~ | Purchase2 | 0.224547 | 0.023032 | 9.749321 | 0.0 |
| 44 | Purchase3 | ~~ | Purchase3 | 0.310779 | 0.030418 | 10.217031 | 0.0 |
| 45 | Purchase4 | ~~ | Purchase4 | 0.211873 | 0.022577 | 9.384511 | 0.0 |
| 46 | Purchase5 | ~~ | Purchase5 | 0.250697 | 0.025273 | 9.919525 | 0.0 |
| 47 | Purchase6 | ~~ | Purchase6 | 0.513141 | 0.046539 | 11.025966 | 0.0 |
| 48 | Purchase7 | ~~ | Purchase7 | 0.480731 | 0.043772 | 10.982709 | 0.0 |
| 49 | SE1 | ~~ | SE1 | 0.475681 | 0.047081 | 10.103426 | 0.0 |
| 50 | SE2 | ~~ | SE2 | 0.244819 | 0.033333 | 7.344683 | 0.0 |
| 51 | SE3 | ~~ | SE3 | 0.210509 | 0.029172 | 7.216125 | 0.0 |
| 52 | SE4 | ~~ | SE4 | 0.432719 | 0.043216 | 10.01283 | 0.0 |

## 7.3 Appendix 3: References of Advertisements

**Coca-Cola Masterpiece Advertisement:** Coca-Cola. (2023, March 6). *Coca-Cola® Masterpiece*. YouTube. https://www.youtube.com/watch?v=VGa1imApfdg

**Coca-Cola Christmas Advertisement:** Coca-Cola. (n.d.). *Coca-Cola | Holidays Are Coming*. YouTube. https://www.youtube.com/watch?v=Yy6fByUmPuE

**Lexus Advertisement:** YouTube. (2018, November 21). *A.I. World's First A.I. Created Ad Lexus ES AI Commercial Full Length Directors Cut*. YouTube. https://www.youtube.com/watch?v=FpCIeRMECPE

**Toys”R”Us Advertisement:** YouTube. (2024, June 25). *Toys R Us + OpenAi Sora | AI Commercial*. YouTube. https://www.youtube.com/watch?v=ah4kzfuc3wo

## 7.4 Appendix 4: References of Pictures

Chedraoui, K. (2025, November 28). *Coca-Cola’s AI holiday ad is everywhere. it’s a sign of a much bigger problem*. CNET. https://www.cnet.com/tech/services-and-software/the-worst-thing-about-coca-colas-holiday-ad-isnt-the-ai/

Feng, V. (2024, June 27). *Toys “R” US calls AI-made video successful despite criticism*. NBCNews.com. https://www.nbcnews.com/tech/internet/toys-r-us-ai-video-ad-controversy-explained-commercial-rcna159030

## 7.5 Appendix 5: AI-Generated Ad Survey

Değerli Katılımcı,

Bu araştırmanın amacı, yapay zeka tarafından geliştirilen reklamlarda algılanan reklam değerinin tüketici tutumları ve satın alma niyeti üzerindeki etkisini incelemek ve bu ilişkide cinsiyet ve öz-yeterliliğin düzenleyici rolünü değerlendirmektir. Anket sırasında kimliğinizi açığa çıkaracak hiçbir soru yer almamaktadır. Kişisel bilgileriniz ve verdiğiniz yanıtlar gizli tutulacak, toplanan veriler sadece bilimsel amaçlar için kullanılacak ve üçüncü taraflarla paylaşılmayacaktır. Anketimizde yapay zeka ile oluşturulmuş 1 dakikalık reklam filmi izledikten sonra, reklamla ilgili görüş ve düşüncelerinizi yansıtacak sorulara cevap vermeniz beklenmektedir. Anketi tamamlamanız tahmini olarak 5-8 dakika sürecektir. Soruların doğru ya da yanlış cevabı yoktur. Araştırmanın başarısı sorulara vereceğiniz içten ve samimi cevaplara bağlıdır. Katılımınız tamamen gönüllülüğe dayalıdır ve istediğiniz zaman anketi terk etme hakkınız vardır. Katkılarınızdan dolayı teşekkür ederiz.

Anketimizde yer alan yapay zeka ile oluşturulmuş "Heinz A.I. Ketchup" başlıklı reklam filmini izleyip anket devamında yer alan soruları düşünce ve görüşlerinize göre cevaplayınız. Lütfen soruları cevaplarken izlediğiniz 1 dakikalık bu reklam filmini göz önünde bulundurun.

"Heinz A.I. Ketchup" REKLAM FİLMİ


| | Kesinlikle Katılmıyorum | Katılmıyorum | Emin Değilim | Katılıyorum | Kesinlikle Katılıyorum |
|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 |
| Yapay zeka ile oluşturulmuş reklamlar:<br>Ürünler veya hizmetler hakkında zamanında bilgi sağlar | | | | | |
| Yapay zeka ile oluşturulmuş reklamlar:<br>Ürünler veya hizmetler hakkında faydalı bilgiler sunar. | | | | | |
| Yapay zeka ile oluşturulmuş reklamlar:<br>Bilgi edinmek için iyi bir kaynaktır. | | | | | |
| Yapay zeka ile oluşturulmuş reklamlar:<br>Güncel ürün veya hizmetler hakkında iyi bir bilgi kaynağıdır. | | | | | |
| Yapay zeka ile oluşturulmuş reklamların:<br>İkna edici olduğunu düşünüyorum. | | | | | |
| Yapay zeka ile oluşturulmuş reklamların:<br>İnandırıcı olduğunu düşünüyorum. | | | | | |

| | | | | | |
|---|---|---|---|---|---|
| Yapay zeka ile oluşturulmuş reklamların:<br>Güvenilir olduğunu düşünüyorum. | | | | | |
| Yapay zeka ile oluşturulmuş reklamların:<br>Ürün veya hizmet satın alırken iyi bir referans olduğunu düşünüyorum. | | | | | |
| Yapay zeka ile oluşturulmuş reklamların:<br>İlgi çekici olduğunu düşünüyorum. | | | | | |
| Yapay zeka ile oluşturulmuş reklamların:<br>Keyifli olduğunu düşünüyorum. | | | | | |
| Yapay zeka ile oluşturulmuş reklamların:<br>Eğlenceli olduğunu düşünüyorum. | | | | | |
| Yapay zeka ile oluşturulmuş reklamların:<br>Hoş bir izlenim bıraktığını düşünüyorum. | | | | | |
| Yapay zeka ile oluşturulmuş reklamların:<br>Rahatsız edici olmadığını düşünüyorum. | | | | | |
| Yapay zeka ile oluşturulmuş reklamların:<br>Can sıkıcı olmadığını düşünüyorum. | | | | | |
| Yapay zeka ile oluşturulmuş reklamların:<br>Müdahaleci olmadığını düşünüyorum. | | | | | |
| Yapay zeka ile oluşturulmuş reklamların:<br>Aldatıcı olmadığını düşünüyorum. | | | | | |
| Yapay zeka ile oluşturulmuş reklamların:<br>Kafa karıştırıcı olmadığını düşünüyorum. | | | | | |
| Bu soruda lütfen KESİNLİKLE KATILIYORUM seçeneğini işaretleyiniz | | | | | |
| Yapay zeka ile oluşturulmuş reklamlar:<br>Ödül verdiğinde beni memnun eder. | | | | | |
| Yapay zeka ile oluşturulmuş reklamlar:<br>Ödül verdiğinde bu reklamlara ulaşmak için harekete geçerim. | | | | | |

| | | | | | |
|---|---|---|---|---|---|
| Teşviklerden yararlanmak için yapay zeka reklamlarına yanıt veririm. | | | | | |
| Yapay zeka ile oluşturulmuş reklamların: Faydalı olduğunu düşünüyorum. | | | | | |
| Yapay zeka ile oluşturulmuş reklamların: Değerli olduğunu düşünüyorum. | | | | | |
| Yapay zeka ile oluşturulmuş reklamların: Önemli olduğunu düşünüyorum. | | | | | |
| Yapay zeka ile oluşturulmuş reklamlarda yer alan ürün veya hizmetleri: Satın almayı düşünebilirim. | | | | | |
| Yapay zeka ile oluşturulmuş reklamlarda yer alan ürün veya hizmetleri: Satın almaya niyetlenirim. | | | | | |
| Yapay zeka ile oluşturulmuş reklamlarda yer alan ürün veya hizmetleri: Başkalarına da tavsiye edebilirim. | | | | | |
| Yapay zeka ile oluşturulmuş reklamların: İkna edici olduğunu düşünüyorum. | | | | | |
| Yapay zeka ile oluşturulmuş reklamların: Hoşuma gittiğini düşünüyorum. | | | | | |
| Yapay zeka ile oluşturulmuş reklamların: Tatmin edici olduğunu düşünüyorum. | | | | | |
| Yapay zeka ile oluşturulmuş reklamların: Tavsiye edilebilir olduğunu düşünüyorum. | | | | | |
| Genel olarak, yapay zeka tarafından oluşturulan reklamları beğeniyorum. | | | | | |

| | |
|---|---|
| **Demografik Bilgileriniz** | |
| Cinsiyetiniz | ( ) Kadın |
| | ( ) Erkek |
| | ( ) Belirtmek İstemiyorum |

| | |
|---|---|
| Yaşınız | ( ) 18-24 |
| | ( ) 25-34 |
| | ( ) 35-44 |
| | ( ) 45-54 |
| | ( ) 55-64 |
| Eğitim Durumunuz | ( ) İlköğretim |
| | ( ) Lise |
| | ( ) Lisans |
| | ( ) Lisansüstü |

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