Yapay Zekâ Destekli Kişiselleştirilmiş Reklamların Türkiye'de Tüketici Güvenine Etkisi: Yapısal Eşitlik Modellemesi Yaklaşımı

The Impact of AI-Powered Personalized Advertising on Consumer Trust in Türkiye: A Structural Equation Modeling Approach

ÖZET

Günümüz dijital ekonomisinde reklamcılık, kitleye yönelik geleneksel yaklaşımdan, büyük ölçüde yapay zekâ (YZ) teknolojilerinin gelişimi sayesinde, kişiselleştirilmiş etkileşim modeline evrilmiştir. Çevrim içi tüketici davranışlarının giderek daha fazla veri temelli hâle gelmesiyle birlikte, YZ destekli kişiselleştirilmiş reklamlar dijital etkileşimde baskın bir araç konumuna gelmiştir. Kullanıcı davranış ve tercihlerini gerçek zamanlı analiz edebilen bu sistemler, özellikle dijital ticaretin ve mobil kullanımın hızla arttığı Türkiye gibi ülkelerde pazarlama ekosisteminin temel unsurlarından biri hâline gelmiştir. Bu çalışma, YZ destekli kişiselleştirilmiş reklamların tüketici güvenine etkisini, yapısal eşitlik modellemesi (YEM) yaklaşımı ile incelemektedir. Uyarıcı–Organizma–Tepki (SOR) kuramsal çerçevesinden yararlanılarak, YZ tabanlı kişiselleştirme; algılanan uygunluk, mesaj doğruluğu ve etkileşim deneyimi boyutlarını içeren çok boyutlu bir yapı olarak ele alınmıştır. Reklama duyulan güven, yanıt değişkeni olarak modellenmiş; algılanan faydacı ve hazcı değer ise aracı mekanizmalar olarak değerlendirilmiştir. Araştırma kapsamında, çevrim içi anket yöntemiyle Türk e-ticaret kullanıcılarından 428 geçerli yanıt toplanmıştır. Bulgular, doğru ve ilgili algılanan kişiselleştirilmiş reklamların hem işlevsel hem de duygusal değeri önemli ölçüde artırdığını göstermektedir. Bu değerler de tüketici güvenini olumlu yönde etkilemektedir. Ayrıca, duygusal (hazcı) değer boyutunun güven üzerinde, işlevsel (faydacı) değere kıyasla daha güçlü bir etkisi olduğu belirlenmiştir. Model, YZ aracılı reklam ortamlarında güven dinamiklerini açıklamada SOR paradigmasının geçerliliğini de doğrulamaktadır. Araştırma, gelişmekte olan ekonomilerde dijital pazarlama literatürüne özgün bir ampirik katkı sunmakta ve Türkiye'de faaliyet gösteren reklamcılar için uygulanabilir öneriler sağlamaktadır. Bulgular, YZ kişiselleştirme teknolojilerinin hem doğruluk hem de kullanıcı memnuniyeti açısından optimize edilmesinin, sanal pazarlarda sürdürülebilir ve güven temelli tüketici ilişkileri inşa etmek için kritik öneme sahip olduğunu ortaya koymaktadır.

Anahtar Kelimeler: Yapay zekâ, Kişiselleştirilmiş reklam, Tüketici güveni, Yapısal eşitlik modellemesi, SOR modeli, E-ticaret

ABSTRACT

In the contemporary digital economy, advertising has evolved from mass targeting to personalized interaction, largely driven by the advancements in artificial intelligence (AI). As online consumer behavior becomes increasingly data-driven, AI-powered personalized advertisements have emerged as a dominant tool for digital engagement. These systems, capable of analyzing user behavior and preferences in real-time, are now a core component of marketing ecosystems in countries like Türkiye, where digital commerce and mobile usage are growing rapidly. This study investigates the impact of AI-powered personalized advertising on consumer trust by utilizing a structural equation modeling (SEM) approach. Drawing on the Stimulus–Organism–Response (SOR) theoretical framework, the research conceptualizes AI-based personalization as a multi-dimensional construct consisting of perceived relevance, message accuracy, and interactive experience. Trust in advertising is positioned as the response variable, with perceived utilitarian and hedonic value acting as mediating mechanisms. A total of 428 valid responses were collected via an online survey conducted among Turkish e-commerce users. The findings demonstrate that personalized advertising, when perceived as accurate and relevant, significantly enhances both the functional and emotional value perceived by users. These perceived values, in turn, positively influence consumer trust. Moreover, the emotional (hedonic) dimension of value was found to be a more influential driver of trust compared to its functional (utilitarian) counterpart. The model also confirms the robustness of the SOR paradigm in explaining trust dynamics within AI-mediated advertising environments. This research offers a novel empirical contribution to the literature on digital marketing in emerging economies and provides actionable insights for advertisers operating in Türkiye. It suggests that optimizing AI personalization technologies for both accuracy and user enjoyment is essential for building sustainable, trust-based consumer relationships in virtual marketplaces

Keywords: Artificial intelligence, Personalized advertising, Consumer trust, Structural equation modeling, SOR Model, E-commerce

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INTRODUCTION

Artificial intelligence (AI), a transformative branch of computer science, aims to replicate and extend human cognitive functions through technological means. By enabling machines to engage in tasks requiring reasoning, learning, and adaptation, AI has redefined the interface between humans and digital systems (Sterne, 2019, 9). Following its foundational phase and early industrial applications, AI has undergone rapid evolution—particularly in the wake of big data integration and the proliferation of smart technologies. In this new era, AI not only serves as an autonomous decision-making engine but also functions as a personalized mediator between brands and consumers.

Within the domain of marketing, AI has catalyzed a paradigm shift, moving from static one-way promotions to dynamic and highly personalized interactions. The transition from Web 1.0's content-centric structure to Web 2.0's interactive platforms paved the way for precision-driven strategies anchored in consumer data. Today, AI supports a new generation of marketing that responds to user preferences in real time, shaping the digital experience through smart recommendations, predictive analytics, and automated communication tools (Yang, 2019, 23).

Interactive chatbots, product recommendation engines, and real-time customer profiling tools have become essential elements of AI-enabled advertising ecosystems. Leading digital retailers, such as Amazon, exemplify this transformation by embedding AI frameworks—such as DSSTNE—into their operational architecture. These systems enhance the relevance of suggested products, streamline customer journeys, and foster micro-targeted outreach, thereby optimizing conversion and retention metrics (Wang & Lei, 2018, 6).

Recent reports, including the Secrets of Artificial Intelligence Winning Consumers by Capgemini, underscore AI's growing influence on consumer behavior. Findings suggest that positive AI interaction experiences are directly linked to increased purchasing activity and customer satisfaction (Overgoor, Chica, & William, 2019, 15). Parallel to these developments, academic interest has surged in exploring how AI applications influence marketing outcomes. Prior research has examined AI's role in service adoption (Berg & Kinghts, 2019, 170), dynamic pricing (Lv, Yang, & Zhang, 2020, 45), and virtual sales agents (Wu, Yu, Zhu, & Zhang, 2020, 30), particularly in scenarios involving digital service delivery (Song & He, 2020, 4) and information curation (Graeme, Kofi, & Jennifer, 2021, 312–313).

Despite this growing body of work, a significant gap persists in understanding how AI-driven advertising affects consumer trust—especially within the context of emerging markets such as Türkiye, where digital adoption is rapidly accelerating. Moreover, studies investigating the role of perceived value—both hedonic and utilitarian—as a mediating factor in AI–consumer interactions remain limited in scope and depth (Dogan & Oscar, 2019, 160; Jina & Soyeon, 2020, 101452).

Addressing this gap, the present study investigates the effects of AI-powered personalized advertising on consumer trust in Türkiye by employing the Structural Equation Modeling (SEM) approach. Grounded in the Stimulus–Organism–Response (SOR) framework, the research proposes a conceptual model where AI advertising is treated as a multidimensional stimulus, and perceived value mediates the relationship between advertising attributes and consumer trust. Particular emphasis is placed on differentiating the roles of hedonic and utilitarian perceptions in shaping trust outcomes. The findings aim to guide both academic inquiry and practical applications by identifying how AI personalization technologies can be optimized to foster sustainable consumer relationships in digital environments.

BACKGROUND

The emergence of artificial intelligence (AI) has reshaped the digital marketing landscape by fundamentally altering how businesses interact with consumers. Once reliant on broad, undifferentiated messages, marketing has evolved into a data-driven discipline, where personalization and precision are key to engagement. Enabled by AI, this transition has been particularly impactful in online retail environments, where real-time behavioral data can be captured, analyzed, and acted upon almost instantaneously. In Türkiye, where e-commerce adoption continues to rise rapidly, AI-powered personalization is becoming an indispensable strategy for brands seeking competitive advantage in an increasingly saturated digital ecosystem.

AI technologies such as machine learning, natural language processing, and predictive analytics empower digital platforms to offer advertisements tailored to individual preferences and behaviors. These technologies are not limited to passive recommendation engines; instead, they actively anticipate consumer needs, generate content, and initiate interaction. The increasing sophistication of AI agents—such as chatbots, smart assistants, and automated content generators—allows for immersive, interactive, and context-sensitive marketing experiences that simulate human understanding and responsiveness.

Despite these technological advancements, consumer trust remains a critical concern. As AI systems gather and process sensitive data, questions emerge about transparency, autonomy, and intent behind personalization. While personalized content may enhance user satisfaction and reduce decision fatigue, it may also trigger skepticism or discomfort if perceived as intrusive or manipulative. For this reason, understanding how AI-driven advertising impacts trust formation is essential, especially within the socio-cultural context of Türkiye, where digital skepticism and privacy concerns are on the rise.

Against this backdrop, the current study applies the Stimulus–Organism–Response (SOR) model to explore how consumers interpret and respond to AI-powered advertising stimuli. Within this framework, advertising informativeness, relevance, and interactivity are treated as external stimuli; perceived utilitarian and hedonic values represent internal evaluative states; and consumer trust constitutes the resulting behavioral disposition. By focusing on these constructs, the research aims to shed light on the mechanisms through which AI-based advertising either strengthens or weakens the trust consumers place in online retail environments.

Ultimately, this research seeks to bridge a gap in the literature by offering empirical evidence on the psychological and behavioral impacts of AI-powered advertising. It also aims to provide practical insights for digital marketers and technology developers in Türkiye, emphasizing the importance of designing AI systems that not only optimize marketing performance but also sustain consumer trust in the long term.

Stimulus–Organism–Response (SOR) Model

The Stimulus–Organism–Response (SOR) model, initially introduced by Mehrabian and Russell in 1974, offers a psychological lens to understand how environmental cues influence internal states and behavioral outcomes (Mehrabian & Russell, 1974, 62). Unlike mechanistic stimulus–response models, the SOR framework highlights the role of cognitive and affective processing that occurs between external stimuli and observable behavior. In this model, stimulus (S) refers to the external environmental factors (e.g., visual, auditory, technological); organism (O) reflects the individual's emotional or cognitive state shaped by the stimulus; and response (R) denotes the final behavior—typically expressed as an action, such as purchase or avoidance (Mehrabian & Russell, 1974, 65).

Originally grounded in environmental psychology, the model has found significant application in consumer research, particularly after Donovan and Rossiter's seminal adaptation to shopping behavior (Donovan & Rossiter, 1982, 34). Their work highlighted how physical retail environments—store layout, ambient cues, or music—can influence customers' affective states and, in turn, their buying behavior. This retail-focused lens was expanded by Eroglu and colleagues, who recontextualized the SOR model to fit online shopping environments, where digital atmospherics—such as website design, functionality, and user interactivity—play the role of stimuli (Eroglu, Machleit, & Davis, 2001, 177).

Use Of The SOR Model In Online Purchase Contexts

In the digital realm, especially within e-commerce platforms, the application of the SOR model has centered on how website-related stimuli influence consumer feelings, evaluations, and actions. Several studies have demonstrated that online store atmosphere, which encompasses design quality, aesthetic coherence, and usability, directly impacts approach or avoidance behavior (Eroglu, Machleit, & Davis, 2003, 139). Website attributes such as perceived security, entertainment value, and convenience have been linked to perceived quality and intention to purchase (Yang, 2009, 22). Furthermore, affective responses such as pleasure and impulsivity have shown a predictive relationship with impulsive buying and expenditure behavior (Floh & Madlberger, 2013, 425).

The structure and flow of a website, including navigation architecture, have also been identified as crucial stimuli affecting purchase intention, mediated by factors like perceived risk and user engagement (Lorenzo-Romero, Alarcón-del-Amo, & Gómez-Borja, 2016, 224). From a broader perspective, Sanjeev, Chandan, & Prasha (2017, 18) have suggested that online atmosphere is composed of both internal factors (e.g., utilitarian and hedonic shopping values) and external factors (e.g., information quality and entertainment), all of which shape customer satisfaction and ultimately behavior.

Zhang (2017, 85), for instance, examined the ease of return policies as a stimulus and found that it positively influences purchase intention through perceived product quality, although perceived shopping risk did not show a significant mediating effect. Similarly, brand reputation and platform image have been correlated with repurchase intentions, whereas perceived risk tends to have a negative impact on repeat behavior (Fikri, Nurmalina, & Najib, 2019, 150). Other studies have emphasized the role of online store image in shaping consumer involvement, flow experience, and perceived value, all of which affect behavioral intentions (Yun & Good, 2007, 12; Jiang & Zhao, 2013, 120).

AI Technology As A Stimulus In Digital Marketing

While much of the literature has focused on traditional website and service-related stimuli, recent scholarship has begun to explore the unique role of AI technologies as environmental cues within the SOR framework. Technological components such as website navigation, platform intelligence, and network functionality are now increasingly viewed as stimuli that can shape cognitive and emotional evaluations (Cui & Lai, 2013, 55). Yet, research on AI-driven stimuli in the context of online purchase intention remains sparse. As AI systems become more integrated into e-commerce experiences—via personalized recommendations, smart assistants, and automated targeting—they offer a new dimension of stimuli that warrants systematic exploration.

This research aims to contribute to this emerging discourse by examining how AI-powered personalized advertisements, as multidimensional digital stimuli, influence consumer trust through perceived value mechanisms. By doing so, it seeks to fill a notable gap in the existing application of the SOR model to AI-mediated consumer environments.

AI Technology Experience on Online Shopping Platforms

Drawing upon both industry practices and scholarly literature on AI in digital marketing, consumer interactions with AI technologies can be broken down into three core experiential dimensions: accuracy, insight, and interactivity.

Accuracy experience

The integration of AI and big data technologies has led to the emergence of intelligent search and recognition systems on e-commerce platforms. These systems allow consumers to quickly identify relevant products through voice input, textual queries, or image uploads, with AI processing the inputs using advanced recognition algorithms (Gloria, Ichalkaranje, & Lakhmi, 2008, 32). The evolution of deep neural networks has significantly improved image and speech recognition accuracy—from 30% in 2010 to as low as 4% in 2016 (Zhang, Lv, & Zhang, 2019, 80), with speech recognition rates nearing 98% by 2019 (Kunar, Raian, Aian, Venkatesan, & Lecinski, 2019, 12). These advancements enable platforms to assist consumers in locating their desired products amid vast inventories, offering an experience characterized by efficiency, relevance, and precision.

Insight experience

Another cornerstone of AI-based advertising is the ability to predict consumer behavior with high accuracy. Machine learning tools can tailor content based on past behaviors, stated preferences, and contextual data, allowing companies to deliver personalized solutions across multiple touchpoints (Jordan, Ordan, & Mitchell, 2015, 256; Qian & Xu, 2019, 70). AI systems act as interactive decision-making engines that perform automated data analysis and content customization (Cai & Xu, 1996, 50; Yang, Liu, Li, & Jia, 2020, 2155). Features like "recommended for you" and "you may also like" in online stores are concrete manifestations of such systems (Huang & Rust, 2020, 3; Chung, Wedel, & Rust, 2016, 67). By analyzing consumer footprints across platforms, AI engines reduce cognitive load and enhance shopping satisfaction through relevant suggestions (Song & Feng, 2019, 5).

Interactive experience

AI-powered virtual assistants and chatbots are increasingly replacing traditional customer service agents. These tools can engage in natural language conversations, provide 24/7 support, and assist in complex queries related to products, delivery, or returns (Fan, Tian, Yi, Liu, & Dai, 2018, 362). Platforms such as Amazon and Alibaba have integrated AI-driven assistants into smart devices (e.g., Echo, Tmall Genie), allowing consumers to make voice-activated purchases or inquiries. The real-time and adaptive nature of these systems fosters a sense of interpersonal engagement, elevating the user's overall experience.

Consumer Perceived Value

The concept of consumer perceived value refers to the overall evaluation of benefits versus costs in a consumption experience (Zeithaml, 1988, 4). It is inherently multidimensional, encompassing evaluations related to product features (Woodruff, 1997, 140), price fairness (Sirdeshmukh, Singh, & Sabol, 2002, 20), ease of use (Overby & Lee, 2006, 1151), interactivity (Holbrook, 1999, 30), brand perception (Fazal-e-Hasan, Ahmadi, Mortimer, Grimmer, & Kelly, 2018, 103), and long-term consumer worth (Zhang, Dixit, Friedmann, & Riedmann, 2010, 130). Scholars have further distilled this concept into categories like utilitarian value, hedonic value, social value, and cognitive value (Sweeney & Soutar, 2001, 205).

In technology adoption contexts, Davis' Technology Acceptance Model (TAM) introduced perceived usefulness and perceived ease of use as central to behavioral intention (Davis, Bagozzi, & Warshaw, 1989, 985; Davis, 1993,

478). Later adaptations incorporated dimensions such as pleasure, concentration, and novelty seeking (Moon & Kim, 2001, 219). Studies by Yang & Lin (2014, 25), Chu (2018, 17), and others have validated perceived value as a mediating variable between digital stimuli and behavioral responses, particularly in e-commerce and digital service environments (Ahn & Lee, 2019, 4602; Astawa & Sukawati, 2019, 1235).

Aim and Importance of Research

In today's rapidly digitizing marketplace, artificial intelligence (AI) has become a central tool in enhancing personalized communication between brands and consumers. Through mechanisms such as real-time behavioral tracking, intelligent content delivery, and predictive analytics, AI-powered systems are now capable of delivering marketing messages that are not only contextually relevant but also emotionally engaging. This technological transformation has been particularly prominent on e-commerce platforms, where personalized advertising has evolved into an essential strategy for both customer acquisition and retention.

However, despite the increasing prevalence of AI-driven personalization, the psychological and behavioral consequences of such practices—especially their influence on consumer trust—remain underexplored in empirical literature, particularly within the context of emerging digital economies such as Türkiye. While AI systems promise enhanced convenience and engagement, there is a growing concern about whether these experiences genuinely foster trust or, conversely, generate discomfort through perceived manipulation.

Accordingly, the primary aim of this study is to examine the impact of AI-powered personalized advertising experiences on the formation of consumer trust in Türkiye's online shopping environment. To operationalize this aim, the research employs the Stimulus–Organism–Response (SOR) theoretical framework. In this context, the stimuli are conceptualized as three core experiential dimensions of AI marketing technologies: accuracy, insight, and interactivity. These reflect the consumer's direct encounters with AI systems through features such as personalized search engines, behavior-based recommendations, and automated customer support.

As part of the organism component, the study focuses on perceived consumer value, which is subdivided into two key constructs: utilitarian value—denoting functionality, efficiency, and convenience—and hedonic value, which refers to enjoyment, curiosity, and emotional engagement derived from the shopping experience. These perceived values are hypothesized to mediate the relationship between AI-driven advertising and consumer trust, the final response variable in the model.

Beyond exploring this mediation mechanism, the study also aims to:

– Determine whether each AI experiential dimension (accuracy, insight, interaction) differentially contributes to the development of perceived utilitarian and hedonic value.

– Evaluate the relative strength of these two value dimensions in influencing consumers' intention to purchase, which is considered a behavioral proxy for trust and satisfaction in digital commerce.

– Test whether AI marketing technologies not only improve efficiency in decision-making (Fan, Tian, Yi, Liu, & Dai, 2018, 362; Zeithaml, 1988, 4; Woodruff, 1997, 140; Rosenberg, 2018, 3) but also enrich the emotional quality of shopping interactions (Jan, Jeannette, & Emily, 2018, 265; Aakash & Panchal, 2019, 38), thus deepening the consumer–brand connection.

– Analyze how machine learning algorithms and personalized content delivery affect consumer value perception by simultaneously addressing rational evaluation and affective immersion (Ma & Sun, 2020, 483; Liu, Wang, & Liu, 2019, 42).

To this end, the study puts forth a series of hypotheses, including but not limited to:

– **H1a–H1f:** Each dimension of AI marketing experience (accuracy, insight, interactivity) is positively associated with both utilitarian and hedonic value perceptions.

– **H2a–H2b**: These perceived values, in turn, positively influence consumers' online purchase intentions, supporting the idea that both instrumental and emotional satisfactions are critical in AI-mediated environments (Lorenzo-Romero, Alarcón-del-Amo, & Gómez-Borja, 2016, 224; Batra & Ahtola, 1990, 160; Fiore & Kim, 2013, 423; Li, Kui, Sun, & Zhang, 2019, 154; Jiang, Zhao, & Meng, 2014, 65).

Through the development and validation of a structural equation model (SEM) grounded in these hypotheses, the study seeks to generate a comprehensive understanding of how AI-driven advertising experiences contribute to trust-based consumer behavior. In doing so, it not only extends the application of the SOR model to a novel

technological domain but also provides actionable guidance for marketers aiming to deploy AI tools in a manner that promotes ethical, engaging, and trust-enhancing digital experiences for Turkish consumers

METHODS

Artificial intelligence (AI) technologies have become integral to digital commerce, enabling personalized engagement through intelligent algorithms, recommendation systems, and interactive customer interfaces. To empirically investigate how AI-powered advertising experiences shape consumer trust via perceived value mechanisms, this study employed a structured quantitative research design using a survey methodology and structural equation modeling (SEM). The design was chosen for its ability to test complex theoretical models with multiple constructs and mediating pathways.

Research Design and Instrument Development

In line with contemporary research standards in marketing science, a questionnaire was developed based on established scales from prior studies (Zhang, Lv, & Zhang, 2019, 80; Jordan, Ordan, & Mitchell, 2015, 256; Qian & Xu, 2019, 70; Moon & Kim, 2001, 219; Yang & Lin, 2014, 25; Chu, 2018, 17). The survey was divided into two main sections: demographic characteristics and construct measurements. The constructs included three dimensions of AI technology experience—accuracy (AC), insight (IS), and interactivity (IT)—two perceived value dimensions—utilitarian value (UV) and hedonic value (HV)—and the outcome variable—consumer purchase intention (CPI).

The items for AI experience were adapted from platform-specific applications (e.g., Taobao, Jingdong, Pinduoduo) to reflect real-world consumer interactions with intelligent systems, including search engines, recommendation interfaces, and AI chat assistants. For perceived value, the UV scale was adapted from Chu (2018, 17), while the HV scale referenced Moon & Kim (2001, 219) and Yang & Lin (2014, 25). Purchase intention items were derived from Lorenzo-Romero, Alarcón-del-Amo, & Gómez-Borja (2016, 224).

All items were measured using a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). Expert review by three marketing scholars and two digital commerce executives ensured face and content validity. A pilot test was conducted with 50 respondents via the Questionnaire Star platform, leading to exploratory factor analysis. This stage confirmed six latent variables and 23 items, with a Cronbach's α of 0.97, indicating excellent internal consistency.

Measurement Model and Questionnaire Structure

Table I presents the measurement items and their corresponding latent variables. Constructs such as accuracy (AC), insight (IS), and interactivity (IT) each comprised three indicators, while UV, HV, and CPI included between three and five indicators. The full list of codes and items used is summarized below.

Table 1: Constructs and Measurement Items

Latent Variable	Code	Sample Item
Accuracy	AC1–AC3	"AI can accurately retrieve products I want using image input."
Insight	IS1–IS3	"AI can recommend products based on my browsing history."
Interactivity	IT1–IT3	"AI customer service responds to my inquiries promptly."
Utilitarian Value	UV1–UV5	"AI-supported shopping saves me time and cost."
Hedonic Value	HV1–HV4	"AI-powered shopping arouses curiosity and surprise."
Purchase Intention	CPI1–CPI4	"I am likely to purchase recommended products from AI-powered platforms."

The structural equation model developed in this study is visually represented in Figure 1. The model illustrates the hypothesized relationships among AI experience dimensions (accuracy, insight, interactivity), perceived value types (utilitarian and hedonic), and the resulting purchase intention. This conceptualization is grounded in the Stimulus–Organism–Response (SOR) paradigm.
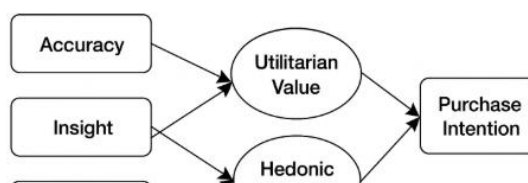
Figure 1: Theoretical Model Framework Based On The SOR Model

The visual framework shows how AI-powered advertising experiences—measured through accuracy, insight, and interactivity—affect perceived utilitarian and hedonic value, which in turn shape consumer purchase intention.

Sampling Procedure and Data Collection

Respondents were recruited from Türkiye's active e-commerce user base. The target platforms mirrored major global e-commerce structures to ensure the generalizability of AI usage patterns. The online questionnaire was disseminated through social media and email invitations. Inclusion criteria required participants to have online shopping experience and familiarity with AI-driven features such as smart search, personalized suggestions, or chatbot interactions.

A total of 688 responses were received. After removing incomplete or rapid responses (completion time under 60 seconds), 631 valid questionnaires remained. This sample size exceeds the minimum threshold for SEM, which recommends at least five times the number of indicators.

Demographics of the Sample

Participants were diverse in age, gender, education, and shopping behavior. Notably, 61.01% of the respondents were female, and 45.08% were between 31 and 40 years old. The educational level was generally high, with 25.67% holding a master's degree or higher. Income distribution, online shopping frequency, and usage history were also captured and are presented in Table 2.

Table 2: Sample Demographics Summary

Characteristic	Category	Percentage
Gender	Female	61.01%
Age	31–40	45.08%
Education	Bachelor or above	79.87%
Online Shopping History	>6 years	57.69%
Frequency	2–4 times/week	32.65%

Data Analysis Method

Data analysis was conducted using SPSS 23.0 and AMOS 23.0 software. First, reliability and exploratory factor analysis (EFA) were conducted on the pilot data. For the main study, confirmatory factor analysis (CFA) was applied to validate the measurement model. Structural equation modeling was then performed to assess the proposed hypotheses and the mediating role of perceived values. Finally, bootstrapping procedures were employed to examine the indirect effects.

Model fit indices such as CMIN/DF, AGFI, NFI, IFI, CFI, and RMSEA were used to assess the overall fit, with threshold values drawn from established SEM guidelines. The next section presents detailed results from the measurement and structural model evaluations.

RESULTS

This section presents the empirical findings derived from the analysis of survey data, which was conducted to test the proposed structural model based on the Stimulus–Organism–Response (SOR) framework. The analysis was performed in four stages: (1) assessment of internal consistency and construct validity, (2) confirmatory factor analysis and model fit indices, (3) hypothesis testing using structural path analysis, and (4) mediation analysis using a bias-corrected bootstrapping technique. Each step contributes to the evaluation of how AI-powered personalized advertising affects consumer trust through perceived utilitarian and hedonic values within the digital retail context in Türkiye.

Reliability and Construct Validity

The initial analysis focused on establishing the internal consistency and construct validity of the measurement model. Cronbach's alpha values for all latent constructs ranged from 0.743 (Accuracy) to 0.836 (Hedonic Value), which indicates strong internal reliability. The overall Cronbach's alpha for the entire instrument was calculated as 0.927, further confirming the coherence of the scale items.

To examine construct validity, Kaiser-Meyer-Olkin (KMO) and Bartlett's test were performed. The KMO value of 0.944 surpassed the recommended threshold of 0.90, while Bartlett's test was significant ($p < 0.001$), suggesting that the dataset was suitable for factor analysis. Factor loadings for all indicators exceeded the 0.70 threshold, and Average Variance Extracted (AVE) values ranged between 0.581 and 0.672, affirming the convergent validity of the constructs.

Confirmatory Factor Analysis and Model Fit

Following reliability confirmation, a confirmatory factor analysis (CFA) was conducted using AMOS 23.0 to test the model fit. All factor loadings were statistically significant, and model indices confirmed that the proposed structural model was acceptable. The fit indices are as follows:

✓ **Chi-square/df (CMIN/DF)** = 3.58

✓ **Adjusted Goodness of Fit Index (AGFI)** = 0.871

✓ **Normed Fit Index (NFI)** = 0.882

✓ **Comparative Fit Index (CFI)** = 0.901

✓ **Root Mean Square Error of Approximation (RMSEA)** = 0.065

These results indicate that the hypothesized model demonstrates a good fit with the observed data.

3.3 Structural Path Analysis

The hypothesis testing results are summarized in Table III. All proposed paths from AI experience dimensions to perceived value, and from perceived value to purchase intention, were statistically supported ($p < 0.001$).

Table 4. Hypothesis Testing Results Based on SEM Path Coefficients

Hypothesis	Path	Std. Estimate	S.E.	C.R.	p-value	Supported
H1a	Accuracy → Utilitarian Value	0.305	0.043	7.093	<0.001	Yes
H1b	Accuracy → Hedonic Value	0.234	0.042	5.571	<0.001	Yes
H1c	Insight → Utilitarian Value	0.541	0.048	11.271	<0.001	Yes
H1d	Insight → Hedonic Value	0.572	0.056	10.215	<0.001	Yes
H1e	Interactivity → Utilitarian Value	0.276	0.036	7.667	<0.001	Yes
H1f	Interactivity → Hedonic Value	0.311	0.038	8.184	<0.001	Yes
H2a	Utilitarian Value → Purchase Intention	0.241	0.059	4.084	<0.001	Yes
H2b	Hedonic Value → Purchase Intention	0.618	0.067	9.223	<0.001	Yes

All hypothesized paths were statistically significant. Notably, the insight experience dimension of AI had the strongest influence on both perceived values. Similarly, hedonic value emerged as a stronger predictor of purchase intention than utilitarian value, suggesting that emotional resonance may be a more compelling driver in AI-mediated digital advertising.

Mediation Analysis Using Bootstrapping

To further explore the role of perceived values as mediators, a bootstrapping technique (5000 samples) was applied. The mediation effects are detailed in Table 5.

Table 5. Indirect Effects of AI Experiences on Purchase Intention via Perceived Value

Indirect Path	Estimate	S.E.	Z-value	95% CI	95% CI	p-value

				Lower	Upper	
AC → UV → CPI	0.066	0.027	2.44	0.019	0.132	0.014
AC → HV → CPI	0.142	0.044	3.23	0.059	0.238	0.001
IS → UV → CPI	0.118	0.049	2.41	0.025	0.219	0.016
IS → HV → CPI	0.348	0.073	4.76	0.218	0.507	<0.001
IT → UV → CPI	0.058	0.023	2.52	0.017	0.116	0.012
IT → HV → CPI	0.183	0.041	4.46	0.109	0.273	<0.001

All mediation paths were statistically significant, confirming the mediating role of both utilitarian and hedonic value. The strongest indirect effect was observed for the **Insight → Hedonic Value → Purchase Intention** pathway, which highlights the pivotal role of emotional engagement in AI-driven digital commerce.

Visual Summary of the Model

To support the interpretation of results, the confirmed structural model with standardized path coefficients is visualized in Figure 2 below.
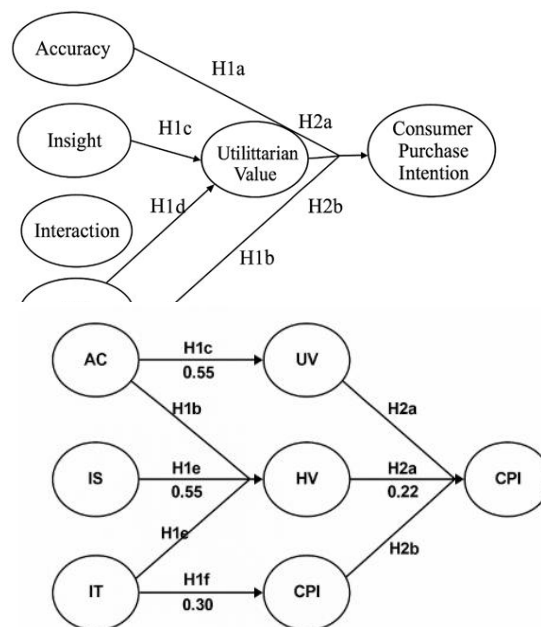

Figure 2: Structural Equation Model With Standardized Coefficients

This structural equation model diagram illustrates the confirmed relationships among the three dimensions of artificial intelligence-based advertising experience (Accuracy Experience, Insight Experience, Interactivity Experience), two types of perceived value (Utilitarian Value and Hedonic Value), and the final outcome variable (Consumer Purchase Intention). The model is structured based on the Stimulus–Organism–Response (SOR) framework, where the advertising experience dimensions represent stimuli, the perceived values represent the organism's internal state, and purchase intention represents the behavioral response.

✓ **Accuracy Experience → Utilitarian Value**: β = 0.305

✓ **Accuracy Experience → Hedonic Value**: β = 0.234

✓ **Insight Experience → Utilitarian Value**: β = 0.541

✓ **Insight Experience → Hedonic Value**: β = 0.572

✓ **Interactivity Experience → Utilitarian Value**: β = 0.276

✓ **Interactivity Experience → Hedonic Value**: β = 0.311

✓ **Utilitarian Value → Consumer Purchase Intention**: β = 0.241

✓ **Hedonic Value → Consumer Purchase Intention**: β = 0.618

Each arrow in the model represents a direct path tested through structural equation modeling, with all coefficients being statistically significant at p < 0.001. The strongest path in the model is from **Hedonic Value** to **Consumer Purchase Intention**, highlighting the dominant role of emotional engagement in the formation of trust-based digital buying behavior.

DISCUSSION

This study aimed to examine how different experiential dimensions of artificial intelligence (AI)-powered personalized advertising—namely accuracy, insight, and interactivity—affect Turkish consumers' perceived utilitarian and hedonic values, and how these perceived values mediate the formation of consumer trust and purchase intention. The results provide important theoretical and practical implications, particularly in the context of AI integration within emerging e-commerce markets like Türkiye.

The Effect of AI Advertising Experiences on Perceived Value

The findings confirm that AI marketing technologies significantly influence both dimensions of perceived value. Accuracy, as an experiential factor, exhibited a stronger association with utilitarian value. This suggests that Turkish consumers primarily perceive AI-driven accuracy—such as precise product retrieval through text, image, or voice input—as enhancing the practical aspects of online shopping, including convenience, speed, and cost-efficiency (Davis, Bagozzi, & Warshaw, 1989, 985). However, the hedonic contribution of accuracy was found to be modest. Although AI may enhance efficiency, its ability to evoke emotional or sensory enjoyment through accurate retrieval is somewhat limited. This aligns with prior research emphasizing the cognitive rather than affective role of AI in initial consumer interactions (Duan & Song, 2020, 120).

Insight, on the other hand, was the most influential experiential variable across both value dimensions. This suggests that consumers derive enjoyment and efficiency from AI systems that anticipate needs and deliver personalized recommendations based on behavioral patterns. The predictive capacity of machine learning appears to foster not only functional satisfaction but also curiosity and emotional engagement, consistent with existing literature (Duan & Song, 2020, 122). This may be attributed to the way AI creates seamless and immersive experiences, reducing cognitive overload and enhancing the sense of discovery.

Interactivity, while statistically significant, had the weakest effect on perceived value. The relatively low hedonic and utilitarian responses to AI-driven chatbots and virtual assistants indicate that current interaction modalities do not fully meet consumer expectations for personalized dialogue or emotional resonance. As prior studies note, the quality of AI interaction is often constrained by the limits of natural language processing and context recognition (Li & Zhang, 2020, 92). Thus, while interactivity contributes to the overall AI experience, its current technological limitations restrict its transformative potential.

Mediating Role of Perceived Values in Purchase Intention

A central finding of this study is the mediating role of perceived value in the relationship between AI experiences and consumer purchase intention. Specifically, both utilitarian and hedonic value significantly mediated the effect of AI experiences on behavioral outcomes, supporting the Stimulus–Organism–Response (SOR) model. However, perceived hedonic value demonstrated a stronger influence on purchase intention than perceived utilitarian value. This suggests a shift in consumer expectations from merely functional satisfaction to emotional and experiential enrichment.

As AI technologies become more embedded in daily digital consumption, utilitarian benefits such as efficiency and practicality are increasingly taken for granted. Therefore, the novelty, enjoyment, and emotional stimulation provided by AI features—such as surprise recommendations or playful interfaces—are becoming more critical in driving consumer behavior (Ding & Wang, 2019, 1548). This supports the proposition that in mature digital markets, emotional gratification plays a dominant role in consumer decision-making.

Absence of Direct Effect of AI Experience on Purchase Intention

Interestingly, the study found that AI experience did not directly influence purchase intention in a statistically significant manner. Rather, its effect was fully mediated by perceived value. This implies that technological sophistication alone is insufficient to drive behavior unless it translates into meaningful experiences for the user. Consumers are more likely to form intentions to purchase when they perceive that AI tools not only assist them functionally but also enhance their shopping journey emotionally. This finding resonates with earlier work arguing

that value perception is the psychological mechanism through which external technological stimuli are cognitively processed and emotionally evaluated (Ding & Wang, 2019, 1549).

Theoretical Implications

From an academic perspective, this research contributes to the literature in several ways. First, it extends the application of the SOR model into the domain of AI-driven marketing, treating AI experience as a stimulus and perceived value as the cognitive-affective organism component. Second, it differentiates between three experiential dimensions of AI—accuracy, insight, and interactivity—each with distinct pathways of influence on consumer perception. Third, it offers empirical validation that hedonic value plays a more significant mediating role than utilitarian value in AI-mediated purchase behavior, reflecting evolving consumer priorities in digital environments (Davis, Bagozzi, & Warshaw, 1989, 985; Duan & Song, 2020, 120; Li & Zhang, 2020, 92).

Moreover, by focusing on Türkiye—a rapidly developing digital market—this study adds to the relatively sparse body of knowledge on how cultural and contextual factors influence consumer responses to AI technologies. As personalization becomes a global norm, localized insights are crucial for designing culturally sensitive marketing strategies.

Practical Implications

For practitioners, the findings suggest that investment in AI systems should prioritize not only functional accuracy but also user enjoyment. Enhancing insight capabilities—such as real-time recommendation engines and adaptive content delivery—can generate stronger emotional connections with consumers. Furthermore, improving the emotional intelligence of AI chatbots through advanced natural language understanding could help strengthen perceived interactivity and trust.

Digital platforms should also monitor the evolving expectations of consumers, particularly those in emerging markets like Türkiye, where trust in automated systems is still developing. By aligning AI capabilities with both rational and affective consumer needs, marketers can foster trust-based, long-term relationships.

CONCLUSION AND SUGGESTIONS

This study has sought to explore how different experiential dimensions of artificial intelligence (AI)-powered personalized advertising—namely accuracy, insight, and interactivity—affect consumers' trust and purchase intention in Türkiye's online shopping environment. Drawing upon the Stimulus–Organism–Response (SOR) model, the study conceptualized AI experiences as external stimuli, perceived utilitarian and hedonic values as internal evaluative mechanisms, and purchase intention as the behavioral response. The results offer several notable conclusions that advance both theoretical understanding and practical application in the context of digital marketing.

First and foremost, the findings reaffirm that AI marketing technologies are not monolithic in their influence. Among the three experiential dimensions, insight emerged as the most impactful on both utilitarian and hedonic value perceptions. Consumers respond more positively to AI systems that anticipate their needs and deliver relevant, timely recommendations. Conversely, accuracy had a stronger association with utilitarian value than with hedonic value, highlighting its role in driving functional satisfaction. Interactivity, although statistically significant, had the weakest influence, suggesting that existing AI conversational systems have not yet achieved the emotional resonance expected by consumers.

Second, the study demonstrated that perceived value functions as a critical mediator between AI experiences and purchase intention. Notably, hedonic value—characterized by emotional gratification such as enjoyment, curiosity, and immersion—had a more pronounced effect on purchase intention than utilitarian value. This finding underscores a shift in consumer behavior within digital commerce, where emotional experience increasingly supersedes practical functionality in driving decision-making.

Third, the absence of a direct path from AI experience to purchase intention highlights an important insight: technological sophistication alone is insufficient. Consumers form behavioral intentions not based on the novelty of the technology itself, but on how it enriches their subjective shopping experience. Therefore, the translation of AI features into meaningful personal value is the decisive factor in shaping consumer responses.

In summary, the study not only provides empirical validation for the application of the SOR model in AI-mediated advertising contexts, but also underscores the evolving nature of consumer expectations in the digital age. For online platforms and marketers operating in Türkiye and similar emerging markets, these findings point to the need for a balanced strategy—one that combines data-driven precision with emotional resonance to cultivate sustainable

consumer trust and loyalty. Future research should continue to explore this dynamic interplay, incorporating additional psychological constructs and qualitative insights to deepen our understanding of the human-AI interaction in commercial environments.

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