(Araştırma)

BEYOND TECHNOLOGY ACCEPTANCE: UNDERSTANDING HOW CONSUMPTION VALUES DRIVE AI ADOPTION IN RETAIL [1]

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ABSTRACT

Artificial intelligence (AI) is becoming increasingly integrated into retail environments; yet, little is known about how consumers with no prior AI shopping experience develop their attitudes and intentions toward such technologies. This study aims to investigate how functional, emotional, social, epistemic, and conditional values influence consumers' attitudes toward AI-assisted retail and how these attitudes shape their intention to use AI. Focusing specifically on consumers who have never used AI during their shopping process, the study aims to capture attitude formation at the early stage of AI adoption, where evaluations are not yet shaped by direct usage experience. To achieve this, consumers with no prior experience in AI shopping were introduced to AI-based retail scenarios and then completed a structured questionnaire. Structural Equation Modeling (SEM) was employed to examine both the measurement and structural models. The findings suggest that epistemic, functional, and conditional values enhance positive attitudes toward AI, whereas emotional and social values diminish them. Attitude, in turn, plays a central role in shaping consumers' intention to adopt AI in retail settings. The study extends the application of the Theory of Consumption Values to AI adoption, highlighting the distinct mechanisms through which inexperienced users form their evaluations. Practical implications are offered for designing AI-based retail experiences that enhance trust, curiosity, and situational value for consumers.

Keywords: Consumption Value Theory, Artificial Intelligence, AI, Intention to Use, Retailing

[1] The compliance of this study with ethical standards was approved by the Ethics Committee of Tekirdağ Namık Kemal University with the decision dated 06.02.2025 and numbered T2025-2391.

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TEKNOLOJİ KABULÜNÜN ÖTESİNDE: TÜKETİM DEĞERLERİNİN PERAKENDEDE YAPAY ZEKÂ BENİMSENMESİNE ETKİSİNİ ANLAMAK

ÖZ

Yapay zekâ (YZ) perakende deneyimlerine giderek daha fazla entegre edilmektedir; ancak YZ ile hiç alışveriş yapmamış tüketicilerin bu teknolojiyi benimsemeye yönelik tutum ve niyetlerini nasıl oluşturdukları yeterince bilinmemektedir. Bu çalışmanın amacı, fonksiyonel, duygusal, sosyal, epistemik ve durumsal değerlerin tüketicilerin YZ destekli alışverişe yönelik tutumları üzerindeki etkilerini ve bu tutumların YZ kullanma niyetini nasıl şekillendirdiğini incelemektir. Bu kapsamda, YZ ile daha önce alışveriş yapmamış tüketicilere YZ tabanlı alışveriş senaryoları tanıtılmış ve ardından yapılandırılmış bir anket uygulanmıştır. Ölçüm ve yapısal modelleri test etmek üzere Yapısal Eşitlik Modellemesi (YEM) kullanılmıştır. Bulgular, epistemik, fonksiyonel ve durumsal değerlerin tutumu güçlendirdiğini; duygusal ve sosyal değerlerin ise tutumu zayıflattığını göstermektedir. Tutumun YZ kullanma niyetinin oluşumunda merkezi bir rol oynadığı belirlenmiştir. Çalışma, Tüketim Değerleri Teorisi'nin YZ benimseme literatüründeki kullanımını genişletmekte ve deneyimsiz kullanıcıların değerlendirme süreçlerini açıklayan özgün bir bakış açısı sunmaktadır. Bulgular, perakendeciler için tüketicide güven, merak ve durumsal fayda yaratan YZ tabanlı deneyimlerin tasarlanmasına yönelik pratik öneriler sunmaktadır.

Anahtar Kelimeler: Tüketim Değerleri Teorisi, Yapay Zekâ, YZ, Kullanma Niyeti, Perakendecilik

1. Introduction

AI has become one of the most transformative forces shaping contemporary marketing and retailing. In retail settings, AI-assisted shopping typically involves applications such as chatbots providing real-time customer support, intelligent recommendation systems personalizing product suggestions, virtual or smart mirrors enhancing in-store experiences, and AI-based virtual assistants guiding purchase decisions. Businesses are increasingly utilizing AI to analyze customer data, personalize communication, optimize pricing strategies, and enhance the overall shopping experience (Mehta et al., 2022; Lee & Chen, 2022). In retailing, AI applications—such as intelligent recommendation systems, chatbots, and service robots—enable faster and more personalized interactions between consumers and brands. As AI becomes more embedded in the retail environment, understanding how consumers perceive and intend to use AI-based shopping tools has become a critical issue in marketing research (Bhagat et al., 2023).

Extant research on AI-enabled services and smart technologies has predominantly relied on technology acceptance frameworks, particularly the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). Prior studies examining augmented reality tools, AI-based media software, autonomous vehicles, chatbots, and service robots have largely focused on cognitive determinants such as perceived usefulness, perceived ease of use, performance expectancy, and facilitating conditions to explain consumers' intention to adopt AI technologies (e.g., Pantano et al., 2017; Park et al., 2021; Foroughi et al., 2023; Arık & Zeren, 2023; Jiang et al., 2023; Bilici & İnam, 2024; Özkaynar, 2024). While these models have generated valuable insights into cognitive evaluations of technology use, they also make an implicit assumption. They assume that users already have prior experience or enough familiarity with the technology being assessed.

This assumption limits the explanatory power of traditional technology acceptance models in contexts where consumers have no direct experience with AI-assisted shopping. In such early-stage adoption contexts, consumers are unable to rely on usage-based performance evaluations and instead form attitudes based on broader value-oriented judgments, including curiosity, perceived novelty, situational benefits, emotional comfort, or social meaning (Tanrikulu, 2021; Bahoo et al., 2024). Building on prior studies, research has generated important insights into the cognitive antecedents of AI adoption; however, it has devoted limited attention to these broader consumption values—particularly emotional, social, epistemic, and conditional factors—that may shape consumer attitudes and intentions in AI-driven retail environments. This gap is especially pronounced for AI-inexperienced consumers, for whom value-based evaluations substitute for direct experiential knowledge.

To address these limitations, the present study employs the CVT (Sheth et al., 1991) to provide a more comprehensive understanding of how consumers evaluate and decide to utilize AI in retail contexts. CVT suggests that consumer decisions are shaped by multiple independent yet complementary value dimensions: functional, emotional, social, epistemic, and conditional. Unlike TAM and UTAUT, which primarily emphasize cognitive efficiency and performance-related beliefs, CVT integrates affective, social, and situational motivations that are particularly salient when consumers encounter unfamiliar or emerging technologies. Prior research has demonstrated the applicability of CVT across diverse consumption and technology-related contexts, including mobile applications, service robots, digital platforms, and immersive technologies (Hur et al., 2012; Wang et al., 2013; Chakraborty et al., 2025). However, empirical applications of CVT to AI-assisted retailing—especially among consumers with no prior AI shopping experience—remain scarce.

Building on this theoretical perspective, the primary purpose of the present study is to examine how functional, emotional, social, epistemic, and conditional values influence consumers' attitudes toward AI-assisted retail applications and how these attitudes subsequently shape their intention to use AI. By focusing exclusively on consumers who have never used AI during their shopping process, the study captures attitude formation under conditions of experiential uncertainty and early-stage technology diffusion.

This study adds three main contributions to the literature. First, it extends CVT to AI-assisted retailing and shows its value for AI-inexperienced consumers, complementing other acceptance models. Second, the study offers new evidence of an asymmetric value structure. Here, functional, epistemic, and conditional values boost positive attitudes toward AI. In contrast, emotional and social values have a negative effect at the early stage, challenging the idea that these always aid adoption. Third, by specifically studying AI-inexperienced consumers, this research reveals how value-based judgments replace experience-based ones. It offers practical insights for retailers designing AI-enabled shopping experiences in the early stages of use.

2. Literature Review

Extant research on AI adoption has predominantly emphasized cognitive and performance-based determinants, often treating emotional responses as secondary facilitators of acceptance. However, emerging evidence suggests that emotional value does not universally enhance positive attitudes toward AI-based services, particularly among consumers with no prior experience with these services. In early-stage adoption contexts, AI systems may evoke feelings of discomfort, unease, or emotional distance, as they are frequently perceived as lacking empathy, warmth, and human sensitivity. Longoni et al. (2019) demonstrate that consumers may resist AI-driven solutions—even when they outperform human alternatives—because AI is perceived as less capable of understanding individual circumstances, thereby reducing emotional reassurance. Similarly, research on algorithm aversion indicates that consumers exhibit lower acceptance of algorithms in tasks perceived as subjective or human-centered, as such systems can generate affective discomfort and threaten individuals' sense of autonomy and identity (Dietvorst et al., 2015; Castelo et al., 2019). These findings suggest that emotional value can function as a psychological cost rather than a benefit, weakening favorable attitudes toward AI-assisted shopping when consumers lack direct experience and emotional trust in the technology.

Beyond emotional reactions, social value may also operate as a constraining rather than facilitating factor in AI-assisted retailing, particularly at the early stage of diffusion. While social influence is typically conceptualized as a positive driver within TAM and UTAUT, AI-mediated consumption may introduce social and relational concerns that undermine perceived social benefits. Mende et al. (2019) show that interactions with nonhuman service agents can reduce perceived social warmth and elicit compensatory responses, as consumers seek to reaffirm their social identity and human distinctiveness. In addition, when AI-assisted shopping has not yet achieved normative acceptance, consumers may anticipate limited social approval—or even social risk—from relying on AI during the purchasing process. Individual differences in anthropomorphism further indicate that when consumers do not attribute humanlike social agency to AI, social bonding and social signaling mechanisms fail to materialize (Waytz et al., 2010). Accordingly, social value may not enhance adoption intentions in early-stage AI contexts; instead, it may suppress positive attitudes when AI use is perceived as socially impersonal or misaligned with prevailing norms.

Taken together, this stream of research highlights that emotional and social values may exert asymmetric or even negative effects on attitudes toward AI, particularly among consumers inexperienced with AI, thereby reinforcing the need for a multidimensional value-based framework, such as the CVT.

2.1. Consumption Value Theory

CVT, or the Theory of Consumption Values, assesses how consumers perceive value when purchasing a product or service (Bahoo et al., 2024). The theory confessed by Sheth et al. (1991) explains consumer behavior by addressing the question of why a consumer chooses (or chooses not) to purchase a product, product category, or brand, based on the perspective of perceived value. The theory is founded on three core propositions (Tanrikulu, 2021):

- Consumer choice is influenced by multiple consumption values: functional value (FV), social value (SV), emotional value (EMV), conditional value (CV), and epistemic value (EV).
- These values contribute differently depending on the specific choice situation,
- The values operate independently of one another.

Marketing is crucial in creating, nurturing, and enhancing customer relationships by delivering superior customer value. As a marketing theory, CVT provides essential insights into consumer behavior. Over time, CVT has become a dominant framework for researchers examining consumer decision-making processes (Bahoo et al., 2024). Sheth et al. (1991) stated that the theory of consumption values can be utilized to analyze and explain consumer preferences across diverse product categories.

Several studies have leveraged the CVT to examine diverse consumer behaviors across contexts. For instance, Ray et al. (2021) explored the behavioral intentions related to e-learning services using user-generated content from social media platforms and merchandise websites, employing the CVT framework. Huriah et al. (2022) investigated the factors influencing the adoption of halal cosmetics through CVT, while Peng and Chen (2019) analyzed determinants affecting consumers' repurchase intentions for luxury hotels. Xiao and Kim (2009) investigated the changing value system of consumers, Chakraborty et al. (2025) applied CVT to understand consumers' intentions to use the Metaverse, Aravindan et al. (2023) and Gonçalves et al. (2016) examined green purchasing behaviors, Biswas (2017) examined sustainable consumption through the same theoretical lens. Additionally, Kaur et al. (2018) studied consumer intentions to continue engaging with social media brand communities based on CVT, and Phau et al. (2014) and Jamrozy and Lawonk (2017) explored consumers' tourism purchase intentions within the CVT framework. Hur et al. (2012) examined the effect of consumption values on the intention to buy at-home robots, and Wang et al. (2013) examined the theory of consumption values of consumers of mobile apps. However, very limited research has applied CVT to consumers who have no prior experience with AI-based shopping. Most technology adoption studies rely on models such as TAM or UTAUT, which focus primarily on cognitive evaluations (e.g., perceived usefulness, perceived ease of use) and therefore overlook affective, social, and situational motivations. By contrast, CVT provides a more holistic explanatory framework that can account for how inexperienced consumers form attitudes toward AI through multiple value-based mechanisms. This gap in the literature presents a clear opportunity to apply CVT to AI adoption in retail. The current study leverages this theoretical advantage by employing CVT to investigate how consumers who have never shopped using AI form their attitudes and usage intentions. Because inexperienced consumers lack direct performance-based evaluations, their perceptions of AI rely more heavily on affective (EMV), epistemic (EV), and situational (CV) judgments. Thus, CVT offers strong explanatory power by capturing how curiosity, perceived novelty, contextual benefits, or emotional comfort shape early-stage attitude formation and, ultimately, intention to use AI in retail environments.

Consumption values, defined as consumers' perceived importance of specific product or service attributes, serve multiple key functions in consumer behavior. They justify purchasing decisions, stimulate interest and desire for products or services, and encourage acceptance, patronage, or the actual act of purchasing. These values play an essential role in shaping consumer preferences by aligning product attributes with the needs and motivations of individuals, thereby enhancing their likelihood of engaging with and acquiring goods or services (Xiao & Kim, 2009).

FVs typically pertain to the practical or operational features of the service platform, such as a website or application (Ray et al., 2021). FV refers to a product's physical attributes and usage performance, encompassing aspects such as variety, durability, comfort, reliability, safety, and cost-effectiveness (Aravindan et al., 2023). Wang et al. (2013) stated that FV affects the IU significantly. The current study aimed to examine the FV of AI-used shopping, such as speed, performance, ease of shopping, and better prices, because inexperienced users rely on rational cues to build initial trust; FV is expected to have a positive effect on attitude. The hypothesis generated for this purpose is

H_1: Functional value impacts attitudes towards using AI.

EMV refers to the satisfaction or affection evoked by using a product, stemming from the emotions or feelings it inspires (Aravindan et al., 2023). According to his research, Van der Heijden (2004) found that perceived enjoyment is a strong determinant of IU. The current study tries to understand which emotions affect AI usage when shopping.

H_2: Emotional value impacts attitudes towards using AI.

Sheth et al. (1991) stated that SV refers to the benefits individuals gain from acceptance and recognition within various social groups after purchasing products or services. Recognizing SV is crucial because it helps explain why consumers may feel societal pressure to use specific products or services (Jamrozy & Lawonk, 2017). Wang et al. (2013) found that SV has effects on consumers' IU. The current study aims to address the utility derived from association with AI usage at shopping.

H_3: Social value impacts attitudes towards using AI.

Sheth et al. (1991) examined EV as the advantage gained from products and services that spark curiosity, introduce novelty, or fulfill the pursuit of knowledge. Hur et al. (2012) and Wang et al. (2013) analyzed the effect of EVs on consumers' intentions. In the present study, EV addresses the value generated by gaining information from AI usage when shopping.

H_4: Epistemic value impacts attitudes towards using AI.

CV refers to the benefits individuals receive in specific circumstances, such as discounts, special offers, or other situational incentives (Ray et al., 2021). In consumer research, knowledge is recognized as a key factor that influences every stage of the decision-making process (Gonçalves et al., 2016). Hur et al. (2012) analyzed the effect of CV on home robot buying. The current study used CV to understand consumer intention in different shopping cases.

H_5: Conditional value impacts attitudes towards using AI.

2.2. Consumers' Attitude Towards Intention to Use AI in The Purchasing Process

In this study, since examining the IU AI among consumers who have not previously used it, the influence of ATT on this behavioral change has also been analyzed. The connection between ATT and intention has been widely explored in various studies, with research findings highlighting that the intention to adopt technology-based products is strongly influenced by ATT toward their use (Jiang et al., 2023). ATT reflects the user's system evaluation, while BI indicates the extent to which the user plans to engage with or utilize the system (Pantano et al., 2017). Businesses' use of AI has significantly enhanced the customer experience, fostering greater trust and intent among consumers toward specific products and services (Bhagat et al., 2023). Customers' virtual experiences play a critical role in shaping their purchase intentions, with research consistently demonstrating that a positive virtual experience significantly enhances the likelihood of purchase. Customers' virtual experiences play a critical role in shaping their purchase intentions, with research consistently demonstrating that a positive virtual experience significantly enhances the likelihood of purchase (Özkaynar, 2024; Arık & Zeren, 2023). Thus, ATT serves as the core mediator that integrates functional, emotional, social, epistemic, and conditional evaluations into a behavioral response. The present study aims to examine how consumers' use of AI influences their attitudes toward it. The value–attitude–intention chain constitutes the conceptual foundation of the research and offers the theoretical rationale for the proposed hypotheses, which are operationalized in the research model presented in Figure 1.

H_6: For consumers inexperienced with AI shopping, their attitude toward AI impacts their IU AI.

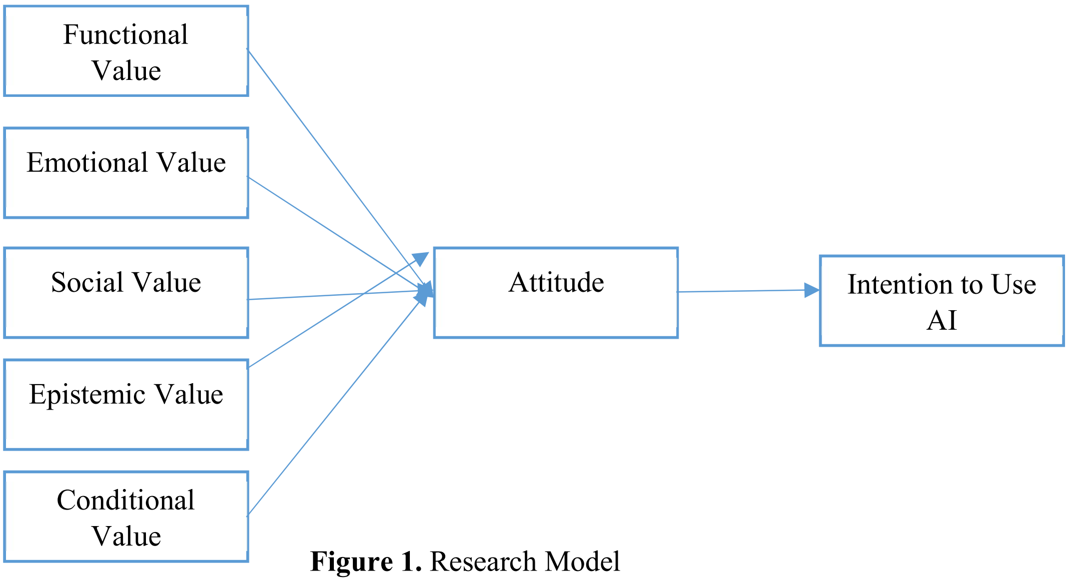

Figure 1. Research Model

3. Methodology

A questionnaire based on existing literature was developed to collect empirical data. To target consumers without prior experience with AI shopping, the survey began with a filter question: "Have you ever used any artificial intelligence (AI) application during your shopping experience?" Only those answering "No" proceeded with the questionnaire. At the start of the survey, respondents received an explanation and a short video link on how AI is used in shopping, helping them understand AI-assisted shopping before answering the questions. The video was short and descriptive in nature and presented common AI-assisted shopping applications without persuasive or evaluative content. It was intended solely to ensure an understanding of AI-assisted shopping among AI-inexperienced individuals. The survey comprised five-point Likert-type closed-ended items, ranging from 1 (strongly disagree) to 5 (strongly agree). It also included demographic questions, such as age, household income, and gender. The measurement scales were adapted from previous studies: consumption value scales from Farha et al. (2024), ATT from Yoo et al. (2018), and IU from Hwang and Choe (2019) (See Appendix). Initially written in English, the scales were translated into Turkish and then back-translated into English to ensure semantic consistency following established cross-cultural translation procedures (Brislin, 1970; Sousa & Rojjanasrirat, 2011).

Before launching the study, a panel of experts, including academics and private sector professionals, reviewed the questionnaire to confirm its clarity and relevance. A pilot study was conducted following this review, and the findings were evaluated against the relevant literature to confirm the questionnaire's validity and reliability.

Data collection was conducted in February via an online survey administered to Turkish consumers, using a purposive nonprobability sampling technique, yielding 201 valid responses. The sample size is consistent with prior AI and consumer behavior studies employing Structural Equation Modeling (SEM), which have demonstrated that medium-sized samples are methodologically adequate when model complexity, factor loadings, and measurement reliability are acceptable. For example, Yuan et al. (2023) validated their structural model using 210 responses, while Guerra-Tamez et al. (2024) employed a sample of 224 participants in a multi-sector AI adoption study. In addition, following the guidelines of Hair et al. (2021), the sample size exceeds the minimum recommended threshold for SEM given the number of constructs, indicators, and the satisfactory reliability and validity of the measurement model, thereby supporting the adequacy of the sample for hypothesis testing.

To assess and mitigate the potential impact of common method variance (CMV), several procedural remedies were implemented. At the beginning of the survey, respondents were informed that participation was voluntary, responses would remain anonymous and confidential, and the data would be used solely for academic research purposes. The use of validated measurement scales, expert review, and pilot testing further helped reduce evaluation apprehension and social desirability bias. In addition, including a filter question ensured that only consumers with no prior AI shopping experience participated in the study, thereby reducing systematic response bias.

Prior to the distribution of the survey, ethical approval was obtained from the Scientific Research and Publication Ethics Committee for Social and Human Sciences at Tekirdağ Namık Kemal University (Meeting No: T2025-2391). This approval ensured that the study complied with institutional ethical standards, and data collection was conducted accordingly.

4. Findings

4.1. Sample Characteristics

Demographic characteristics of the participants are in age distribution; 16.3% of the respondents were between 18 and 27, while the majority, 55.4%, were in the 28-43 age range. Participants aged 44-59 comprised 22.8% of the sample, whereas those aged 60 and above constituted 5.4%. Regarding household income, 3.3% of the participants reported an income of 0-17,500 TL, while 31.5% had an income between 17,501-50,000 TL. The most significant portion, 34.8%, fell within the 50,001-100,000 TL income bracket. Participants earning between 100,001 and 150,000 TL made up 19.6% of the total, whereas those with an income exceeding 150,000 TL accounted for 10.9%. For the gender distribution, 60.9% of the respondents were women, while men comprised 39.1% of the sample.

Table 1. Explanatory Factor Analysis and Reliability Analysis

Factors*	Loadings	KMO	X²	df	p	α
FV1	0.923					
FV2	0.925					
FV3	0.943					
FV4	0.897	0.910	803.694	21	0.000	0.966
FV5	0.935					
FV6	0.879					
FV7	0.868					
CV1	0.892					
CV2	0.909	0.851	299.172	6	0.000	0.932
CV3	0.919					
CV4	0.928					
EV1	0.889					
EV2	0.929	0.749	406.729	6	0.000	0.940
EV3	0.940					
EV4	0.924					
EMV1	0.879					
EMV2	0.872					
EMV3	0.905					
EMV4	0.937	0.918	848.208	28	0.000	0.963
EMV5	0.899					
EMV6	0.946					
EMV7	0.842					
EMV8	0.872					
SV1	0.918					
SV2	0.944					
SV3	0.921	0.898	620.636	15	0.000	0.955
SV4	0.942					
SV5	0.849					
SV6	0.844					
ATT1	0.960					
ATT2	0.962	0.736	267.227	3	0.000	0.939
ATT3	0.912					
IU1	0.960					
IU2	0.962	0.734	265.483	3	0.000	0.939
IU3	0.911					

* FV: Functional value, CV: Conditional Value, EV: Epistemic Value, EMV: Emotional Value, SV: Social Value, A: Attitude, IU: Intention to Use

4.2. Measurement Model Evaluation

Before testing the hypothesized relationships, the measurement model's adequacy was assessed. The Kaiser–Meyer–Olkin (KMO) values for all scales exceeded the recommended threshold of 0.50, confirming the suitability of the sample for factor analysis. Bartlett's test of sphericity was statistically significant ($p < 0.05$), indicating sufficient inter-item correlations.

Exploratory Factor Analysis (EFA) results demonstrated that the measurement scales were appropriate for further analysis (Durmuş et al., 2016). All items exhibited factor loadings above 0.50; therefore, no item removal was required. The detailed EFA and reliability results are presented in Table 1.

The results presented in the table indicate a strong structure concerning factor analysis and reliability assessment. Firstly, the factor loadings range from 0.842 to 0.962, suggesting that all variables are highly representative of their respective factors. The KMO test results strongly support the adequacy of the sample size for conducting factor analysis. Additionally, the chi-square test (X^2), along with degrees of freedom (df) and p-values, confirms the significance of all factor configurations. All p-values in the table are at the 0.000 level, indicating that the factors significantly explain the total variance of the independent variables, thereby further validating the overall model fit. Cronbach's Alpha (α) values, which measure the reliability of the scales, range from 0.932 to 0.966, demonstrating high reliability across all scales. Overall, the table results confirm that the factors are strongly represented, the data suitability is sufficient, and the scales exhibit high reliability. This provides a solid foundation for understanding and explaining the relationships between the variables in the model.

Tabachnick and Fidell (2013) state that a skewness and kurtosis coefficient within the range of -1.5 to +1.5 indicates a normal distribution. A review of the normal distribution test results confirms that the skewness and kurtosis values fall within this range, aligning with the expectations outlined in the literature for normal distribution. The skewness values for the variables are as follows: IU (-0.647), FV (-1.010), CV (-1.191), EV (-1.319), EMV (-0.720), SV (-0.213), and ATT (-0.711). The kurtosis values are IU (-0.117), FV (0.397), CV (1.052), EV (1.565), EMV (0.023), SV (-0.764), and ATT (-0.124). These findings confirm that the dataset adheres to the assumptions of normality. Overall, the normality test results indicate that the dataset is suitable for subsequent statistical analyses, including SEM and hypothesis testing. These results support the appropriateness of applying SEM to the data, contributing to the methodological soundness of the study.

Table 2. Results of Common Method Bias of Variables

		IU	FV	CV	EV	EMV	SV	A
IU	Pearson Correlation	1	.879**	.814**	.722**	.829**	.625**	.878**
	Sig. (2-tailed)		.000	.000	.000	.000	.000	.000
FV	Pearson Correlation	.879**	1	.934**	.796**	.854**	.680**	.882**
	Sig. (2-tailed)	.000		.000	.000	.000	.000	.000
CV	Pearson Correlation	.814**	.934**	1	.809**	.860**	.691**	.863**
	Sig. (2-tailed)	.000	.000		.000	.000	.000	.000
EV	Pearson Correlation	.722**	.796**	.809**	1	.752**	.567**	.728**
	Sig. (2-tailed)	.000	.000	.000		.000	.000	.000
EMV	Pearson Correlation	.829**	.854**	.860**	.752**	1	.844**	.902**
	Sig. (2-tailed)	.000	.000	.000	.000		.000	.000
SV	Pearson Correlation	.625**	.680**	.691**	.567**	.844**	1	.765**
	Sig. (2-tailed)	.000	.000	.000	.000	.000		.000
ATT	Pearson Correlation	.878**	.882**	.863**	.728**	.902**	.765**	1
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	

**. Correlation is significant at the 0.01 level (2-tailed).

4.3. Assessment of Common Method Variance

Before testing the research hypotheses, the potential for common method variance (CMV) among variables was assessed. A correlation analysis was conducted to evaluate this variance.

According to Bagozzi et al. (1991) and Tehseen et al. (2017), the absence of common method variance is indicated when the correlation coefficient between variables does not exceed 0.90. The results of the correlation analysis show that all correlations in the table are significant at the $p < 0.01$ level. This supports the validity of the relationships between variables despite the presence of CMV presented in Table 2.

After establishing the adequacy of the measurement model and confirming that common method variance was not a critical concern, the structural model was subsequently examined to test the hypothesized relationships among the constructs.

4.4. Structural Model and Hypothesis Testing

A Confirmatory Factor Analysis (CFA) was conducted to assess the reliability and accuracy of our measures. All item scores were strong (above .70 and statistically significant), showing good reliability. Overall model fit was acceptable to excellent (Hair et al., 2021; Kline, 2023): $\chi^2/df = 2.88$, CFI = 0.969, TLI = 0.966, SRMR = 0.049, RMSEA = 0.110. Although RMSEA was slightly above the ideal cutoff of 0.08, this value is considered acceptable for moderately sized samples because RMSEA can be sensitive to sample size, often producing higher values in such cases (Marsh, Hau, & Wen, 2004).

The reliability and validity indicators are summarized in Table 3. All Average Variance Extracted (AVE) scores were over 0.50, and Composite Reliability (CR) scores were above 0.70, confirming that items measured the same thing. Discriminant validity was shown using the Fornell–Larcker method, where each measure's AVE square root was higher than its shared scores with other measures (Fornell & Larcker, 1981).

Table 3. Measurement Model and Reliability Indicators

Construct	Items	Std. Loadings	AVE	CR	Cronbach's α
FV	7	.90–.96	.873	.94	.94
EV	4	.94–.97	.916	.96	.95
SV	6	.83–.95	.842	.93	.94
CV	4	.90–.92	.827	.91	.92
EMV	8	.86–.95	.849	.95	.95
ATT	3	.87–.95	.855	.94	.94
IU	3	.92–.99	.913	.95	.96

All standardized loadings are significant at $p < .001$. AVE $\geq .50$ and CR $\geq .70$ indicate adequate convergent validity (Hair et al., 2021; Fornell & Larcker, 1981).

After confirming the adequacy of the measurement model, the structural model was examined to test the hypothesized relationships among the constructs. This stage of the analysis aimed to assess the extent to which consumption values predict consumers' attitudes toward AI-assisted shopping and, subsequently, their behavioral intentions. The hypothesized model was analyzed using SEM, which enables the simultaneous estimation of multiple dependent relationships and provides an overall assessment of model fit and explanatory power.

The model demonstrated excellent fit indices ($\chi^2/df = 2.88$, CFI = 0.969, TLI = 0.966, SRMR = 0.049, RMSEA = 0.110), all of which fall within the recommended thresholds (Hair et al., 2021; Kline, 2023). All hypothesized paths were statistically significant and in the expected directions (see Table 4). Specifically, FV, CV, and EV had strong positive effects on ATT, whereas EMV and SV were significantly but negatively associated with attitude. This result implies that consumers with higher emotional or social orientations may perceive AI-driven shopping as less personal or authentic. In turn, ATT strongly and positively predicted IU (β = .935, $p < .001$). Overall, the model explained 86.2% of the variance in ATT and 77.1% in IU, indicating high explanatory power and strong model validity (Kline, 2023).

Table 4. Structural Model and Hypothesis Testing

Hypothesis	Path	β	SE	z	p	Results
H1	FV → ATT	.410	.055	7.397	< .001	Supported
H2	EMV→ ATT	−.148	.067	−2.211	.027	Not Supported
H3	SV → ATT	−.107	.041	−2.641	.008	Not Supported
H4	EV → ATT	.544	.051	10.679	< .001	Supported
H5	CV → ATT	.281	.104	2.702	.007	Supported
H6	ATT → IU	.935	.011	82.099	< .001	Supported

5. Discussion and Conclusion

5.1. Theoretical Implications

The increasing role of AI in retail has led researchers to examine consumers' ATT and behaviors towards AI. In this context, studies evaluating the impact of AI on purchase intention from the perspective of consumption values have gained importance. Understanding the ATT and IU of consumers who have not yet shopped with AI is important in encouraging the adoption of AI-based technologies in retail environments. The current study investigates the impact of AI on purchase intention in terms of consumption values. It examines the factors that affect their ATT towards AI and their usage through an empirical study conducted with consumers who have not yet shopped using AI. The SEM results provide evidence suggesting that different consumption values shape consumers' attitudes toward AI-assisted retail.

The key finding is that FV has a significant positive effect on ATT, indicating that consumers in retail prioritize the utilitarian benefits of AI. AI that simplifies tasks, improves efficiency, and offers practical solutions receives favorable evaluations. In cultures where technology adoption is developing, such as Turkey, consumers prioritize concrete functionality and cognitive evaluation over emotional or symbolic cues. Thus, AI is seen not as an emotional companion but as a tool that delivers efficiency, control, and predictability, reducing uncertainty in unfamiliar digital environments. These results indicate that perceived usefulness and performance expectancy significantly influence technology acceptance, aligning with previous research (Chakraborty et al., 2024; Jamrozy & Lawonk, 2017; Hur et al., 2012; Wang et al., 2013). Consumers' trust in new technologies increases when systems are reliable and save time, especially where AI experience is limited (Lee & Chen, 2022). Thus, H_1 is supported: AI adoption in retail relies on trust in functional reliability and cognitive assessment, compensating for the lack of prior experience. Accordingly, these findings should be understood as context-specific and not readily generalizable to other cultural settings without further empirical validation.

In contrast, EMV shows a negative association with ATT, suggesting that emotionally oriented evaluations may not foster favorable perceptions of AI-assisted shopping in this context. One possible interpretation is that AI-based retail applications may be perceived as impersonal or emotionally distant, particularly when compared with human-centered service encounters. This interpretation should be viewed as context-specific, as prior research has shown that emotional value can positively influence adoption in hedonic or entertainment-oriented technologies (Huriah et al., 2022; Chakraborty et al., 2025). In task-oriented retail settings, however, emotional value may function as a psychological cost rather than a benefit. Cultural explanations, such as the importance of human warmth and relational interaction in certain societies, are also relevant. Thus, H_2 is rejected, highlighting that emotional value may constrain AI adoption under specific contextual conditions.

The significant but negative relationship between SV and ATT implies that consumers who value social recognition and peer approval may view AI shopping as socially undesirable. This occurs because AI-assisted consumption has not yet become a normatively approved or prestigious behavior in the current cultural and technological context. In the early stages of diffusion, when reference groups and role models do not endorse a new technology, its social signaling capacity remains weak or even counterproductive. This explanation is consistent with the CVT's premise that social value arises only when product use conveys symbolic status or conformity (Sheth et al., 1991). In the absence of such social signaling mechanisms, social considerations may suppress rather than enhance positive attitudes toward AI. Accordingly, H_3 is rejected, indicating that social value does not uniformly promote AI adoption in emerging technological contexts.

The strong positive impact of EV on ATT indicates that curiosity, learning desire, and innovation-seeking significantly shape favorable perceptions of AI-assisted retail. This occurs because AI is perceived as a novel and knowledge-enhancing technology that satisfies consumers' cognitive motivations for exploration and discovery. In a market where direct AI experience is limited, exposure to new scenarios sparks interest and a willingness to learn, resulting in more positive attitudes. These findings align with earlier studies, which have shown that epistemic value predicts technology adoption when consumers perceive novelty and informational enrichment (Hur et al., 2012; Chakraborty et al., 2025). Sheth et al. (1991) also describe epistemic value as a cognitive motivator that drives consumers toward innovative consumption choices. In early adoption contexts, epistemic motivations may partially substitute for hands-on experience, encouraging consumers to explore AI-based services despite limited familiarity. Therefore, H_4 is supported, suggesting that in early AI adoption contexts, epistemic motives compensate for experiential limitations and enhance the acceptance of AI.

The significant positive effect of CV on ATT reveals that situational advantages—such as time efficiency, discounts, and convenience — under specific conditions play an essential role in forming favorable evaluations of AI. This occurs because consumers are more likely to adopt unfamiliar technologies when immediate contextual benefits reduce perceived risk and uncertainty. AI tools that offer flexibility and problem-solving in dynamic circumstances, therefore, strengthen positive perceptions. This outcome aligns with prior research identifying conditional value as a context-dependent driver. It encourages technology adoption when it enhances decision efficiency (Ray et al., 2021; Gonçalves et al., 2016). In markets where economic sensitivity is high and digital trust is still emerging, consumers often evaluate innovation based on its short-term utility rather than its long-term symbolic meaning. Thus, H5 is supported. Situational utility and contextual convenience motivate positive attitudes toward AI, reflecting pragmatic adoption behavior in transitional technology environments.

The exceptionally strong positive relationship between ATT and IU demonstrates that consumers' overall evaluation of AI directly and powerfully determines their behavioral intentions. This occurs because ATT serves as the cognitive filter that integrates all value-based judgments—functional, epistemic, emotional, social, and conditional—into a single behavioral outcome. When consumers perceive AI as useful, informative, and contextually beneficial, they develop a stable intention to adopt it. This result aligns fully with both the CVT and classical technology acceptance models (TAM, UTAUT). In these models, ATT mediates the link between beliefs and behavioral intentions (Pantano et al., 2017; Jiang et al., 2023). Similar patterns were observed in chatbot and service-robot adoption studies (Pham et al., 2024; Bilici & İnam, 2024), where positive ATT fully mediated usage intentions. Accordingly, H_6 is supported. This confirms that strengthening positive cognitive and affective appraisals of AI remains the most effective way to encourage consumer adoption.

The findings collectively reveal a dual-value mechanism in AI adoption: cognitive–utilitarian values (FV, EV, CV) foster acceptance, while affective–social values (EMV, SV) hinder it. This asymmetry reflects differences in consumer culture and technology experience. In contexts where AI adoption is still emerging, consumers prioritize efficiency, knowledge, and contextual utility over emotional enjoyment or social recognition. Similar patterns have been identified in cross-cultural technology research, where rational and epistemic motives dominate the early stages of adoption, while emotional and social gratifications gain relevance as users accumulate experience (Tanrikulu, 2021; Mehmood et al., 2024).

5.2. Managerial Implications

The findings of this study offer several managerial implications that are directly grounded in the observed relationships between consumption values and attitudes toward AI-assisted retail.

First, FV drives adoption; consumers use AI when it clearly improves shopping efficiency, reliability, and simplicity. Managers should design function-focused systems. Use fast recommendation algorithms, transparent decision logic, and intuitive interfaces to save consumers' time and effort. Maintain stable and reliable performance to establish functional trust, a key driver of AI adoption in emerging markets.

Second, the positive role of epistemic and conditional values indicates that consumers appreciate AI when it facilitates learning, offers novelty, or provides situational convenience. Retailers can use this by promoting discovery-oriented engagement. For example, let users explore “smart try-on,” virtual assistance, or personalized tips that inspire curiosity. Time-sensitive incentives or AI-specific promotions can also boost perceived benefits. This strategy aligns with consumers' pragmatic expectations in developing technology ecosystems, where immediate value is paramount.

Third, the negative effects of emotional and social values show barriers tied to perceived impersonality and a lack of human connection in AI-assisted shopping. To address these barriers, retailers should focus on emotional design and anthropomorphism to make AI interactions feel more relatable and human-like by incorporating warmer tones of voice, empathy-based responses, and personalized communication. Such design strategies can transform emotionally distant interactions into more engaging experiences. In addition, retailers may enhance the social legitimacy of AI-assisted shopping by integrating AI tools with human support, emphasizing endorsements from trusted brands, and positioning AI use as a mainstream, socially accepted practice rather than a purely technological choice. Social recognition mechanisms—such as shareable experiences, gamified feedback, and community-based engagement—may further strengthen social value as AI becomes more normalized in retail settings.

Overall, these findings imply that AI adoption strategies should be tailored to the early-stage adoption context, where cognitive and situational benefits outweigh emotional enjoyment and social signaling. Aligning AI design and communication strategies with these value priorities can enhance consumer acceptance and sustained use. In general, managers should use a two-phase strategy. First, at early stages of AI diffusion, focus on functional reliability and epistemic curiosity to attract consumers. Second, as familiarity grows, slowly add emotional engagement and social signaling features to support long-term acceptance and loyalty.

5.3. Limitations and Directions for Future Research

Although this study contributes to understanding AI adoption through the lens of consumption values, several opportunities remain for future research.

First, the current sample consisted solely of Turkish consumers with limited experience in AI. Future studies should replicate this model in various cultural and technological contexts to investigate how consumer culture influences the relative strength of value dimensions. Comparative cross-national studies (e.g., between emerging and developed markets) could reveal how cultural orientation, individualism, and uncertainty avoidance shape the balance between emotional and functional motives.

Second, future research could focus on specific AI technologies, such as chatbots, service robots, or virtual mirrors, to examine whether value perceptions vary by interaction type. Each AI tool may elicit different combinations of functional, epistemic, and emotional responses, offering richer insights into the dynamics between consumers and AI. Third, while this study relied on hypothetical shopping scenarios, future research could employ experimental or longitudinal designs to measure how repeated exposure and real experience alter the weight of each consumption value. It is plausible that as users gain familiarity, social and emotional values may gradually turn from inhibitors to enablers of AI adoption.

Finally, integrating CVT with complementary frameworks such as the Technology Readiness Index or Trust-based Acceptance Models could advance theoretical depth by explaining not only what drives AI acceptance but also how readiness, trust, and risk perception interact with underlying consumption values.

Despite its contributions, this study has several limitations that should be acknowledged. The sample consisted solely of Turkish consumers with no prior experience of AI-assisted shopping, which may limit the generalizability of the findings to other cultural or technological contexts. As cultural dimensions were not directly measured, any cultural interpretations should be considered context-specific rather than universal. In addition, the data were collected using a cross-sectional, self-reported survey design, which limits causal inference and raises the possibility of CMV, despite the procedural remedies applied. Although procedural remedies were implemented, CMV was assessed using correlational diagnostics; therefore, more advanced techniques (e.g., marker variables or longitudinal designs) could be employed in future research to further address potential method bias.

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