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Article

The Impact of AI on Marketing Offer Personalization and Customer Satisfaction: The Mediating Role of Perceived Value and the Moderating Factor of Privacy Concern

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Abstract

This paper examines the effect of AI-driven marketing where it offers personalization on customer satisfaction, where the mediating variable is perceived value and the moderating variable is the privacy concern. The study is based on the Perceived Value Theory and Privacy Calculus Theory. It follows the quantitative approach with the use of survey data of 307 e-commerce customers. The partial least squares structural equation modeling (PLS-SEM) was used to test the proposed research model. The results show that the personalization provided by AI has a strong direct and indirect positive impact on customer satisfaction via perceived value, which supports the mediating role of value perceptions. Perceived value was found to be one of the major explanatory mechanisms that would turn the benefits of personalization into an outcome of satisfaction. Contrastingly, the privacy concern did not directly affect customer satisfaction or moderate the relationship between personalization and customer satisfaction, which indicates that perceived benefits are more important in this regard than privacy concerns. These findings underscore the primary importance of value creation as part of AI-based personalization plans. In practice, the study suggests that companies should focus on value-adding personalization procedures and be responsible in data management to be able to keep customers satisfied in AI-powered digital contexts.

Keywords: Privacy concern, Customer satisfaction, Perceived value, AI-powered offer personalization, Spain.

1. Introduction

The fast proliferation of artificial intelligence (AI) technologies has significantly transformed the modern ways of marketing, especially in the sphere of the offer personalization. The use of advanced algorithms can now provide companies with the ability to process large amounts of behavioral and preference data in real time and optimize marketing offers with previously unseen levels of precision and contextuality (Davenport & Ronanki, 2018; Huang & Rust, 2018; Wedel & Kannan, 2016). This personalization transformation has been commonly positioned as a strategic reaction to more and more heterogeneous consumer demands and rising competition in the digital space (Huang & Rust, 2021; Singh et al., 2019; Timimi et al., 2025). In this regard, personalization is no longer a marginal strategy but a core process by which companies are trying to improve customer satisfaction, interaction, and long-term relationships (Ahmed et al., 2025; Hardcastle et al., 2025; Hollebeek et al., 2024).

The general idea in extant marketing literature is that personalities offers enhance customer experiences by making them feel more relevant, less overloaded with information, and easier to make a decision (Bleier & Eisenbeiss, 2015; Belanche et al., 2019; Zahra et al., 2023). Empirical research proves that AI-based personalization may have a positive effect on satisfaction and loyalty by matching the offerings to personal needs and preferences (Singh & Singh, 2024; Ahmed et al., 2025; Khan et al., 2022). Nonetheless, a significant part of this literature takes a rather result-focused approach and tends to focus on direct implications without providing much knowledge about the psychological processes by which personalization is converted into satisfaction. Consequently, the theoretical foundations of the value perceptions that consumers develop in reaction to AI-driven personalization have not been adequately theorized and empirically validated (Tam, 2004; Sweeney & Soutar, 2001; Zeithaml, 1988).

Perceived Value Theory offers an effective conceptual framework to overcome this limitation by assuming that the assessments of value created by consumers can be seen as the result of a trade-off between perceived benefits and perceived sacrifices (Zeithaml, 1988; Sweeney & Soutar, 2001; Tam, 2004). In previous studies, it is always demonstrated that perceived value is at the center of determining satisfaction, loyalty, and behavioral intentions in digital and service environments (Alkufahy et al., 2023; Chang et al., 2009; Ilyas et al., 2021). Personalized offers can also increase functional, emotional, and epistemic value in e-marketing contexts, particularly by increasing efficiency, enjoyment, and relevance (Hsin Chang & Wang, 2011; Alkufahy et al., 2023; Islam & Rahman, 2016). However, the empirical research on AI-based personalization frequently considers the perceived value as the secondary or control variable, instead of a fundamental mediating construct that defines how the personalization efforts can be converted into customer satisfaction (Tam, 2004; Chang et al., 2009; Alkufahy et al., 2023).

Meanwhile, the rise in using consumer data to support AI-driven personalization has exacerbated the issues of privacy, data ownership, and surveillance (Martin & Murphy, 2017; France et al., 2021; Martin et al., 2017). According to Privacy Calculus Theory, consumers are rational in their decision-making as they consider the perceived advantages of personalization and the perceived danger of exposing data (Chellappa & Sin, 2005; Fortes & Rita, 2016; Joinson et al., 2010). Although personalization has the potential to enhance perceived value, enhanced privacy issues might diminish or even reverse the beneficial impact of personalization on satisfaction by reducing trust and provoking psychological anxiety (Aimeur et al., 2016;

Bleier & Eisenbeiss, 2015; Martin et al., 2017). The empirical evidence on the moderating role of privacy concern, however, is scattered and even conflicting, and the moderating role of privacy in the context of AI-driven personalization is not given much attention (Chellappa & Sin, 2005; Fortes & Rita, 2016; Gursoy et al., 2019).

Importantly, although the literature on AI in marketing is increasing, there are still some gaps. To begin with, the empirical models that would consider the results of personalization, the underlying value perceptions, and the privacy-related boundary conditions simultaneously are lacking (Huang & Rust, 2021; Hollebeek et al., 2024; Timimi et al., 2025). Second, the body of empirical research on the topic in the European digital markets, especially in Spain, is limited, although the region has stringent data protection laws and a high level of digital platforms penetration, which could condition the increasing importance of privacy issues in the process of personalization (Martin & Murphy, 2017; Perrigot et al., 2020; France et al., 2021). Third, structural equation modeling has rarely been used in previous research to measure both mediation and moderation in the context of AI-driven personalization, which restricts theoretical accuracy and explanatory richness (Hair, 2014; Henseler et al., 2015; Kline, 2023).

Although there is an increasing literature on AI-based personalization in marketing, there are still some critical gaps. First, existing literature has conducted a significant amount of research on the results of personalization based on direct-effect models but has not paid much attention to the mechanisms that underlie the process of how personalization is converted into customer satisfaction. In particular, the mediating role of perceived value has not been sufficiently explored within integrated frameworks. Second, the moderating effect of privacy concern is inconclusive and under-investigated, particularly in AI-based situations where the use of data is intensive. Third, the European markets, especially in Spain, do not have empirical evidence, as data protection laws are strict, and the digital adoption is high, which could influence consumer reactions in a different way. Lastly, the concurrent analysis of mediation and moderation effects with structural equation modeling has been underutilized in this line of research and limits the explanatory capability of current models.

To address these gaps, the current research explores how AI-based offer personalization affects customer satisfaction, specifically exploring the mediating and moderating role of perceived value and the moderating effect of privacy concern. Based on the Perceived Value Theory and Privacy Calculus Theory and applying a quantitative methodology with the use of structural equation modeling (SEM) analysis, this study seeks to help to better understand the mechanism of AI-based personalization and under what conditions it leads to customer satisfaction. The study aims to answer the following questions: How does AI-based offer personalization affect customer satisfaction? What is the mediating effect of perceived value? What impact does privacy concern have on the intensity of the effect of personalization on satisfaction? These questions are investigated by focusing on the consumers in Spain who have recently interacted with AI-based offer personalization. Answering these questions, the research contributes to theoretical progress and practical solutions to the problem of the marketer who has to enter the world of opportunities and threats of AI-driven personalization in data-sensitive online space.

2. Literature Review

2.1 AI-Driven Personalization in Marketing

The development of AI has radically changed the concept of marketing personalization, as it does not rely on rules when dividing the market into segments, but rather on adapting and creating offers based on the data (Davenport & Ronanki, 2018; Wedel & Kannan, 2016; Huang & Rust, 2021). Initial theories of personalization focused on the technological acceptance and usefulness, and they relied on earlier studies in information systems that connected perceived usefulness to user adoption (Davis, 1989; Belanche et al., 2019). More recent research builds on this point of view by showing that personalization based on AI improves customer engagement and relationship outcomes by providing contextually appropriate and timely offers at digital touchpoints (Ahmed et al., 2025; Hardcastle et al., 2025; Hollebeek et al., 2024).

This advancement notwithstanding, the literature shows that there is much heterogeneity in the reported outcomes. Although in some studies AI-based personalization has a positive impact on satisfaction and loyalty (Singh & Singh, 2024; Zahra et al., 2023), other researchers warn that the beneficial effect of using algorithms can be mitigated by their lack of transparency and perceived intrusion (Bleier & Eisenbeiss, 2015; Gursoy et al., 2019). This contradiction implies that the results of personalization cannot be explained by the direct effects only, and it is necessary to analyze the intervening psychological processes.

2.2 Perceived Value as an Explanatory Mechanism

The Perceived Value Theory provides a highly developed theory of the explanation of the conversion of marketing stimuli into evaluative and behavioral responses. Basing itself on the means-end approach, perceived value is the general evaluation of benefits against sacrifices by consumers (Zeithaml, 1988; Sweeney & Soutar, 2001). Empirical studies always place perceived value as one of the antecedents of customer satisfaction in service and digital settings (Tam, 2004; Chang et al., 2009; Ilyas et al., 2021).

In e-marketing contexts, perceived value has been found to mediate the relationships between service attributes and satisfaction or loyalty, which supports the key explanatory role of perceived value (Alkufahy et al., 2023; Hsin Chang & Wang, 2011; Khan et al., 2022). Nevertheless, research that explicitly incorporates the perceived value in the models of AI-driven personalization is scarce. Though personalization is believed to add value in terms of functionality and emotions, as it increases relevance and efficiency, the assumption is not always explicit but tested empirically (Ahmed et al., 2025; Singh & Singh, 2024; Zahra et al., 2023). Therefore, the mediating effect of perceived value on the personalization-satisfaction relationship has not been studied in depth, especially in digital environments that are highly dependent on AI.

2.3 Privacy Concern and the Personalization Privacy Trade-Off

In line with the progress in the field of personalization, the issue of data privacy has become a burning boundary condition that determines how consumers will react to AI-driven marketing activities. Privacy Calculus Theory assumes that consumers make a trade-off between the benefits of personalization and the perceived privacy threats (Chellappa & Sin, 2005; Fortes & Rita, 2016). Initial studies revealed that personalization may lead to a rise in perceived usefulness and at the same time raise the issue of privacy, which creates a structural conflict in digital marketing approaches (Chellappa & Sin, 2005; Joinson et al., 2010).

The later research focuses on the importance of trust and transparency in reducing the anxieties caused by privacy. The alterations in the presentation of the privacy policy and data practices play a significant role in the user trust and disclosure behaviors (Aimeur et al., 2016; Martin & Murphy, 2017). In addition to that, the issue of privacy has been indicated to have negative impacts on satisfaction and firm performance in case it is perceived to be too high or unwarranted (Martin et al., 2017; France et al., 2021). Nevertheless, in spite of these observations, empirical studies seldom simulate privacy concern as a moderator that preconditions the efficiency of AI-based personalization, even in satisfaction-oriented models (Bleier & Eisenbeiss, 2015; Gursoy et al., 2019).

3. Theoretical Framework and Hypotheses Development

3.1 Theoretical Framework

The current research is based on Perceived Value Theory and Privacy Calculus Theory, which jointly offer a holistic perspective of explaining how consumers react to AI-based marketing when it comes to offering personalization. The conceptualization of the Perceived Value Theory is that the value is the total evaluation of the utility of an offering by a consumer through a comparison of the perceived benefits and the perceived costs (Zeithaml, 1988; Sweeney & Soutar, 2001). In digital and service-related settings, it is always the perceived value that is found to be a key factor in customer satisfaction and after-consumption judgments (Tam, 2004; Chang et al., 2009). Since AI-based personalization is expected to raise the relevance, convenience, and efficiency, it is theoretically placed to augment the perceived value of consumers by intensifying functional and experiential advantages (Huang & Rust, 2018; Ahmed et al., 2025).

In support of this view, Privacy Calculus Theory describes the way in which consumers consider personalization practices by balancing the perceived benefits with the perceived privacy risks of data collection and use (Chellappa & Sin, 2005; Fortes & Rita, 2016). The issue of privacy in AI-driven settings where personalization is largely dependent on behavioral and preference information can potentially change the evaluative processes of consumers, potentially undermining positive attitudes towards personalization (Martin & Murphy, 2017; Martin et al., 2017). A combination of these two theories can support a more subtle framework where the AI-based personalization affects customer satisfaction in both direct and indirect ways via perceived value and privacy concern serves as a contextual boundary condition.

3.2 Hypotheses Development

Personalization based on AI allows companies to provide extremely customized offers that are as close to personal needs of consumers as possible, which increases the perceived relevance and quality of the marketing interaction (Davenport & Ronanki, 2018; Huang & Rust, 2021). Previous studies indicate that customized AI-based customer experiences have a positive impact on the overall customer experience and satisfaction because they decrease the search effort and enhance the perceived responsiveness (Hardcastle et al., 2025; Zahra et al., 2023). Furthermore, it has been empirically demonstrated that AI-based personalization enhances relational performance by creating the feeling of recognition and appreciation (Ahmed et al., 2025; Singh & Singh, 2024). On these grounds, it can be assumed that there will be a positive correlation between AI-driven offer personalization and customer satisfaction.

H1: *AI-powered offer personalization positively impacts customer satisfaction.*

In the lens of the perceived value, personalization is a value-adding process that elevates the utility that consumers gain out of marketing propositions. AI-driven personalization can be used to increase both functional and experiential aspects of value by increasing relevance, timeliness, and fit (Zeithaml, 1988; Sweeney & Soutar, 2001). According to the studies within the digital marketing setting, personalized interactions enhance the perceived value by maximizing the benefit-sacrifice trade-off, especially in information-saturated settings (Chang et al., 2009; Alkufahy et al., 2023). The latest studies of AI-centered research also confirm that the value perceptions can be enhanced through the means of the efficiency and quality of decisions made by the algorithms (Ahmed et al., 2025; Singh & Singh, 2024). In this regard, the hypothesis is as follows:

H2: *AI-powered offer personalization positively impacts perceived value.*

The perceived value and customer satisfaction relationship is not new in the marketing literature. Perceived value is a cognitive appraisal that comes before the affective reactions like satisfaction (Tam, 2004; Chang et al., 2009). Empirical data indicate that the greater the perceived value, the more satisfaction will be achieved in online, service, and e-marketing environments (Ilyas et al., 2021; Alkufahy et al., 2023). Perceived value will become even more salient in influencing the satisfaction judgments in AI-based settings where consumers evaluate both technological and relational advantages (Huang & Rust, 2018; Zahra et al., 2023). In this way, the hypothesis below is created:

H3: *Perceived value positively impacts customer satisfaction.*

Based on the Perceived Value Theory, the perceived value is supposed to mediate the relationship between AI-powered personalization and customer satisfaction. Personalization is also effective in increasing value perceptions by adding value benefits like relevance and convenience, which subsequently leads to satisfaction (Zeithaml, 1988; Tam, 2004). The mediating effect of perceived value between digital marketing practices and satisfaction and loyalty outcomes is supported by the previous empirical studies (Chang et al., 2009; Alkufahy et al., 2023). Nevertheless, this mediating process has been given little focus in AI-based personalization settings, especially in integrated models. In this regard, this research hypothesizes the following:

H4: *Perceived value mediates the relationship between AI-powered offer personalization and customer satisfaction.*

Although personalization might be a value-adding and satisfying factor, the Privacy Calculus Theory posits that consumers can shift their personalized offer assessments based on the issue of privacy. The perceived risk due to heightened privacy concern may reduce the positive impact of personalization (Chellappa & Sin, 2005; Fortes & Rita, 2016). It has been shown that the privacy-related concerns have a negative impact on trust, satisfaction, and acceptance of data-driven marketing practices (Aimieu et al., 2016; Martin et al., 2017). Privacy concern is expected to mediate the personalization-satisfaction relationship in an AI-powered setting, where data usage is more widespread and less transparent, by undermining the positive effect of the former. Thus, the ultimate hypothesis is as follows:

H5: *Privacy concern moderates the relationship between AI-powered offer personalization and customer satisfaction.*

Based on a literature review and hypothesis development, Figure 1 represents the conceptual model for this study.

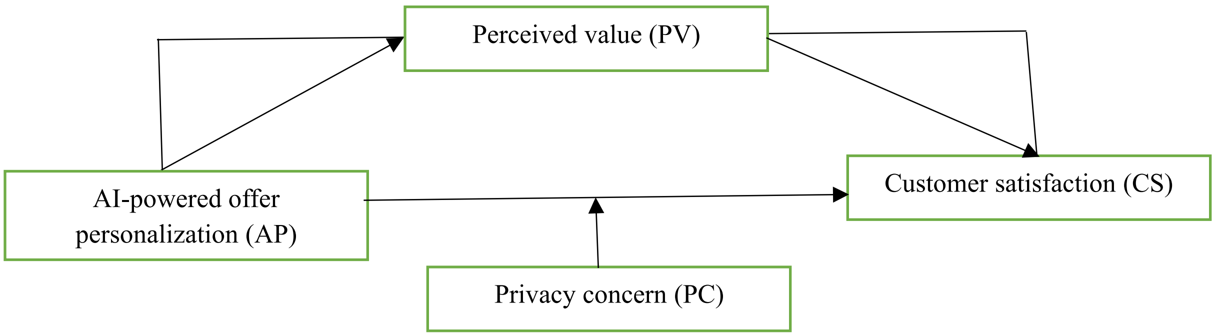

Figure 1: Conceptual model

4. Methodology

4.1 Research Design

This study adopted a quantitative research design to investigate the relationships between AI-powered offer personalization, perceived value, customer satisfaction, and privacy concern in an empirical manner. A cross-sectional survey was used because it is suitable to measure the assessments of AI-based personalization experiences of consumers at a particular time and to test theoretically based causal relationships (Hair, 2014; Kline, 2023). The main method of analysis is SEM because it is the most suitable method to evaluate direct, mediating, and moderating relationships at once and in a complex theoretical framework (Kline, 1998; Hair, 2014). Following the previous studies on AI and digital marketing, SEM allows strong validation of both measurement and structural models, which guarantee conceptual rigor and explanatory depth (Henseler et al., 2015; Zahra et al., 2023).

4.2 Population and Sample

The sample of this research included consumers in Spain that actively used digital platforms and were exposed to personalized marketing offers using AI, such as e-commerce platforms, food delivery apps, digital subscriptions, and targeted advertising on social media. This group was deemed especially topical in the context of the prevailing popularity of data-driven marketing technologies and the increased sensitivity of consumers to the topic of data privacy in the European digital markets (Martin & Murphy, 2017; France et al., 2021). To guarantee the relevance of respondents and the quality of their assessments, only those people who had obtained AI-generated personalized offers or recommendations in the last three months were invited. This inclusion criterion was used to guarantee recent and cognitively available experiences of AI-powered personalization, which reduces recall bias and provides a higher degree of response reliability (Gursoy et al., 2019; Hardcastle et al., 2025).

The data collection was conducted in the form of an online survey which was sent to 400 potential respondents who passed the screening criteria. The total amount of usable questionnaires sent back was 307, and it is estimated that the response rate was about 76.8%, which is reasonable and can be compared to response rates cited in previous surveys on digital marketing and AI-related topics (Hair, 2014; Singh &

Singh, 2024). The obtained sample size was above the minimum levels suggested by SEM, which guaranteed sufficient statistical power to estimate both mediation and moderation effects (Hair, 2014; Kline, 2023). In this regard, the final sample was considered adequate to conduct potent SEM analysis and hypothesis testing.

4.3 Data Collection Instruments

A structured, self-administered questionnaire was used to collect the data. The questionnaire was created to assess the study constructs in the framework of AI-powered marketing personalization. The measurement scales of all variables were five-item operationalizations, which align with the principles of quantitative marketing research and studies based on SEM to provide sufficient levels of construct coverage and reliability (Hair, 2014; Henseler et al., 2015). The items measuring AI-powered provided personalization reflected the perceptions of relevance, customization, and responsiveness of personalized marketing offers among respondents and were based on the previous studies of AI-powered personalization and customer experience in online settings (Bleier & Eisenbeiss, 2015; Ahmed et al., 2025; Hardcastle et al., 2025). The value of perceptions was assessed based on five items, which included the global benefit-sacrifice assessment by the consumers, which is based on Perceived Value Theory and is generally tested in service and e-marketing settings (Zeithaml, 1988; Sweeney & Soutar, 2001; Tam, 2004).

The satisfaction of customers was measured with five items representing the net evaluative judgments of respondents with AI-personalized marketing offers and digital interactions based on the familiar measures of satisfaction in electronic and AI-enhanced service environments (Chang et al., 2009; Alkufahy et al., 2023; Zahra et al., 2023). The concept of privacy concern was assessed with five items that indicated apprehensions of consumers about personal data collection, use, and control in the context of personalized marketing, as per the previous research on the concept of privacy calculus and digital privacy behavior (Chellappa & Sin, 2005; Fortes & Rita, 2016; Martin et al., 2017). Each questionnaire item was measured on a Likert-type scale where the respondents could respond to the question by giving their degree of agreement with the statement. This was a suitable measurement method to capture latent constructs and made it compatible with SEM with SmartPLS or AMOS (Hair, 2014; Kline, 2023).

All measurement items were based on the well-established scales in the previous literature to guarantee content validity and measurement reliability. In particular, the AI-powered items (AP1–AP5) were based on the past research on AI-based personalization and online customer experience (Bleier & Eisenbeiss, 2015; Ahmed et al., 2025; Hardcastle et al., 2025). The customer satisfaction items (CS2–CS4) were based on pre-existing scales of customer satisfaction in digital and e-service environments (Chang et al., 2009; Alkufahy et al., 2023; Zahra et al., 2023). Perceived value items (PV1, PV3, PV5) were based on the Perceived Value Theory literature, especially on the validated scales of the service and e-marketing studies (Zeithaml, 1988; Sweeney & Soutar, 2001; Tam, 2004). Lastly, the items of privacy concerns (PC1, PC4, PC5) were based on previous research on privacy calculus and privacy concerns of consumers in online contexts (Chellappa & Sin, 2005; Fortes & Rita, 2016; Martin et al., 2017). Everything was rephrased slightly to make it fit in the context of AI-driven personalization without losing the original conceptual meaning.

5. Data Analysis and Result

5.1 Descriptive Analysis

5.1.1 Demographic Profile

Table 1 shows the demographics of the respondents that were used in this study. The sample is comprised of 307 participants. The gender distribution is rather balanced, with females comprising 52.8 percent of the participants and males making 47.2 percent. In terms of age, the sample is majorly constituted of economically active and digitally active consumers, with most of them falling within the age bracket of 18–44 (77.9%). In particular, the age group of 18–24 years represents 28.3% of the sample, 35–44 years (25.4%), and 25–34 years (24.1%). The given age distribution is not an exception as the previous studies have suggested that younger and middle-aged consumers tend to use AI-powered digital platforms and personalized online services more frequently (Gursoy et al., 2019; Huang & Rust, 2021).

Table 1: Demographic profile of the respondents

Question	Answer	Frequency	Percent	Cumulative Percent
Gender	Male	145	47.2	47.2
	Female	162	52.8	100.0
	Total	307	100.0	
Age group	18–24 years	87	28.3	28.3
	25–34 years	74	24.1	52.4
	35–44 years	78	25.4	77.9
	45–54 years	51	16.6	94.5
	55 years and above	17	5.5	100.0
	Total	307	100.0	
Educational level	High school or below	42	13.7	13.7
	Diploma	93	30.3	44.0
	Bachelor's degree	105	34.2	78.2
	Postgraduate degree (Master's or PhD)	67	21.8	100.0
	Total	307	100.0	
Monthly income level	Low	58	18.9	18.9
	Medium	130	42.3	61.2
	High	119	38.8	100.0
	Total	307	100.0	
Online shopping frequency (last 3 months)	1–2 times	51	16.6	16.6
	3–5 times	96	31.3	47.9
	6–10 times	87	28.3	76.2
	More than 10 times	73	23.8	100.0
	Total	307	100.0	
Primary online platform used	E-commerce websites/apps	138	45.0	45.0
	Food delivery applications	46	15.0	59.9
	Subscription-based digital platforms	70	22.8	82.7
	Social media platforms	53	17.3	100.0
	Total	307	100.0	

The respondents are relatively well educated with 56.0 percent of them having a bachelor's degree and 21.8 percent having postgraduate degrees. The profile indicates that the sample is in the right position to measure AI-powered personalization practices because higher educational levels are usually linked to a higher level of familiarity with online technologies and decision-making processes (Belanche et al., 2019; Singh & Singh, 2024). Moreover, most of the respondents have medium to high monthly income levels (81.1 percent) which is consistent with the high rate of online shopping recorded in the sample. It is worth noting that 83.4% of the participants have purchased online products at least three times in the past three months, which means that they have received exposure to personalized digital marketing offers significantly. E-commerce platforms become the most common one (45.0%), then subscription-based digital platforms (22.8%), and social media platforms (17.3%). This distribution represents the modern trends of digital consumption, as AI-based personalization is most common in online shopping and platform-based contexts (Davenport & Ronanki, 2018; Wedel & Kannan, 2016).

5.1.2 Descriptive Statistics for Variables

Table 2 provides the descriptive statistics of the key variables of the study, namely, AI-powered offer personalization (AP), perceived value (PV), customer satisfaction (CS), and privacy concern (PC). The average scores show that the perceptions of AP (M = 3.406) and PV (M = 3.476) are moderate and relatively high, which can be interpreted to mean that the respondents tend to think that AI-driven personalized offers are applicable and useful. The PC also shows a moderate level of mean score (M = 3.418), indicating a certain level of awareness and sensitivity to the issue of data privacy in AI-enabled marketing settings. CS, in turn, has a relatively lower mean value (M = 2.826), which means that the AP and the PV are rated well, yet the overall satisfaction level is average. This trend can be explained by the fact that personalization benefits are not necessarily directly linked to high satisfaction levels, as previous research indicates that PC can be relevant in this context (Bleier & Eisenbeiss, 2015; Martin & Murphy, 2017; Huang & Rust, 2021).

Table 2: Descriptive statistics of the study variables

Descriptive	N	Mean	SD	Skewness	Std. Error	Kurtosis	Std. Error
AP	307	3.406	0.4362	-0.218	0.241	-0.103	0.478
PV	307	3.476	0.3385	0.096	0.241	-1.171	0.478
CS	307	2.826	0.3286	-0.268	0.241	-0.458	0.478
PC	307	3.418	0.4998	0.308	0.241	-0.328	0.478
Valid N (list-wise)	307						

In terms of data dispersion and distributional properties, the values of standard deviations vary between 0.3286 and 0.4998, which are reasonable variability of constructs without a high level of homogeneity or dispersion. The skewness values are quite within the suggested ±1 range, and the kurtosis values are also within acceptable limits, indicating that all the variables have approximately normal distributions. These findings prove that the data can be further analyzed with structural equation modeling as it is appropriate to conduct a multivariate analysis (Hair, 2014; Kline, 2023). In addition, the lack of extreme skewness or kurtosis contributes to the strength of the estimation of measurements and structural models. In general, the descriptive statistics represent realistic response patterns that are typical of the survey-based research concerning AI-driven personalization and digital consumer behavior, which is why they offer a solid basis of further hypothesis testing (Gursoy et al., 2019; Hollebeek et al., 2024).

5.2 Measurement Model Assessment

To test the structural relationships, the measurement model was evaluated to determine the reliability and validity of the constructs before testing the structural relationships. Table 3 has indicated that the reliability of the indicators was tested in terms of outer loadings, Cronbach alpha, and composite reliability. All reflective indicators are above the prescribed level of factor loading of 0.70, which implies the satisfactory level of indicator reliability (Hair, 2014). The alpha values are between 0.732 and 0.835, whereas the composite reliability values (rho_C) are all greater than 0.80, which proves a strong internal consistency. Though the Cronbach alpha with CS and PV are somewhat lower than the traditional 0.70 threshold, this is deemed as acceptable in partial least squares structural equation modeling (PLS-SEM) when the composite reliability values are satisfactory as composite reliability offers a better estimate of internal consistency in variance-based SEM models (Hair, 2014; Kline, 2023).

Average variance extracted (AVE) was also used to measure convergent validity. According to Table 3, the constructs have an AVE of above 0.50, which is the recommended minimum, meaning that every construct accounts for over half of the variance of its indicators (Hair, 2014). In particular, AVE values vary between 0.545 in the case of AI-powered personalization and 0.748 in the case of PC, which is a good indication of convergent validity across the measurement model. These findings indicate that the indicators in each construct have a large percentage of shared variance, which indicates the suitability of the construct operationalization in the AI-based personalization and online consumer behavior (Zeithaml, 1988; Sweeney & Soutar, 2001).

Table 3: Construct reliability and convergent validity

Indicator	Factor	Cronbach's Alpha	CR (rho_A)	CR (rho_C)	AVE
AP1	0.75	0.792	0.793	0.857	0.545
AP2	0.746				
AP3	0.731				
AP4	0.732				
AP5	0.731				
CS2	0.75	0.732	0.732	0.803	0.577
CS3	0.808				
CS4	0.719				
PC1	0.869	0.835	0.869	0.899	0.748
PC4	0.827				
PC5	0.896				
PV1	0.799	0.769	0.767	0.819	0.602
PV3	0.757				
PV5	0.77				
PC × AP	1				

The Fornell-Larcker criterion was used to determine the discriminant validity, and the results are shown in Table 4. The square root of the AVE of each construct is larger than the correlations of the construct with all other constructs, which meets the Fornell–Larcker requirement of discriminant validity (Fornell & Larcker, 1981; Henseler et al., 2015). Even though there are moderate correlations between some of the constructs, especially between AI-driven personalization and customer satisfaction, the correlations are lower than the corresponding square roots of AVE, and it can be concluded that the constructs cover different conceptual areas. The theoretical explanation of this finding is that the relationship between personalization practices and satisfaction outcomes in digital marketing situations is close but conceptually separate (Bleier & Eisenbeiss, 2015; Huang & Rust, 2021).

Table 4: Fornell–Larcker criterion

Construct	AP	CS	PC	PV
AP	**0.74**			
CS	0.64	**0.76**		
PC	-0.21	-0.26	**0.87**	
PV	0.41	0.54	-0.14	**0.78**

Lastly, the presence of collinearity between indicators was checked with the help of variance inflation factor (VIF) values to make sure that there is no multicollinearity and possible common method bias. Table 5 indicates that the VIF values are significantly lower than the conservative level of 3.3, with the highest value of 2.371. The fact that these values are not negative means that there is no threat of multicollinearity and that the estimates of the parameters are consistent and valid (Hair, 2014). The low values of VIF also indicate that the common method bias will not interfere with measurement results, which reinforces the belief in the strength of the measurement model and its applicability to the further analysis of the structural model (Kline, 2023; Gursoy et al., 2019).

Table 5: Collinearity statistics (VIF)

Indicator	VIF	Indicator	VIF	Indicator	VIF
AP1	1.595	**CS2**	1.275	**PC5**	2.371
AP2	1.579	**CS3**	1.399	**PV1**	1.369
AP3	1.473	**CS4**	1.182	**PV3**	1.232
AP4	1.558	**PC1**	1.694	**PV5**	1.345
AP5	1.428	**PC4**	2.118	**PC × AP**	1

5.3 Structural Model Assessment

The structural model represented in Figure 2 has standardized path coefficients and coefficients of determination (R^2). The findings suggest that AP has a very strong direct impact on CS but also positively affects the PV. In its turn, PV demonstrates a strong positive influence on CS, which explains its primary explanatory role in the model. The R^2 values indicate that the model explains 52.3 percent of the variation in CS and 16.5 percent of the variation in PV, which is moderate to high explanatory power of consumer behavior studies in the digital and AI-enabled marketing setting (Hair, 2014; Kline, 2023).

The bootstrapping results are provided in Figure 3 to determine whether the hypothesized relationships are statistically significant or not. Direct relationships between AP and CS and PV and the direct relationship between the PV and CS are statistically significant, which proves the strength of the proposed relationships. The results are consistent with the Perceived Value Theory that states that the satisfaction judgments of consumers are formed as a result of value-based cognitive appraisals based on the marketing stimuli (Zeithaml, 1988; Sweeney & Soutar, 2001; Tam, 2004). Conversely, the moderating role of the PC in the personalization-satisfaction relationship is not significant, which indicates that the perceived benefits can be stronger than privacy-related issues in the context of AI-driven e-commerce (Bleier & Eisenbeiss, 2015; Martin & Murphy, 2017).

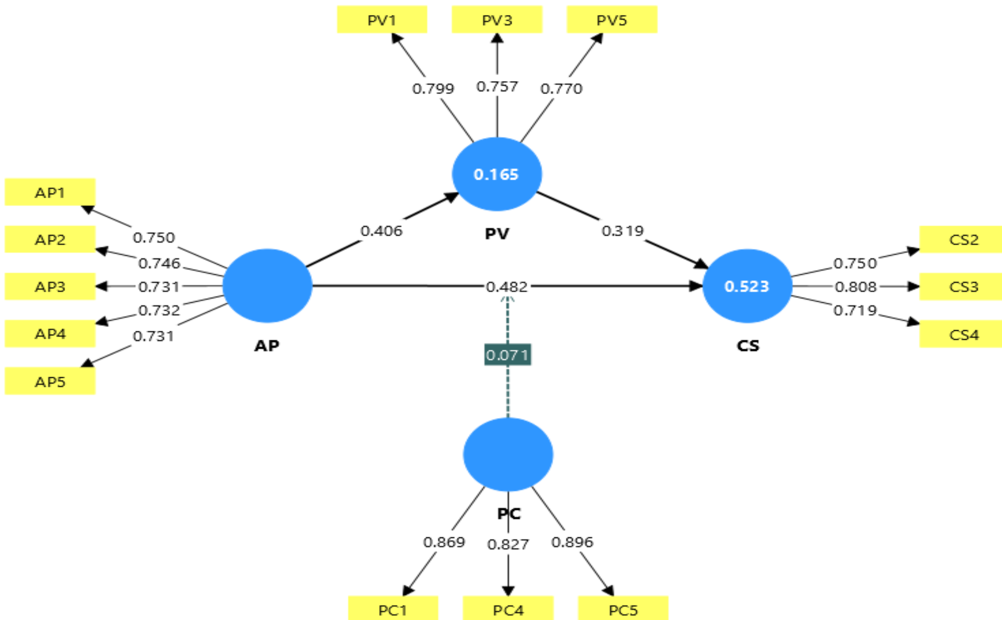

Figure 2: Structural model with path coefficients and R² values

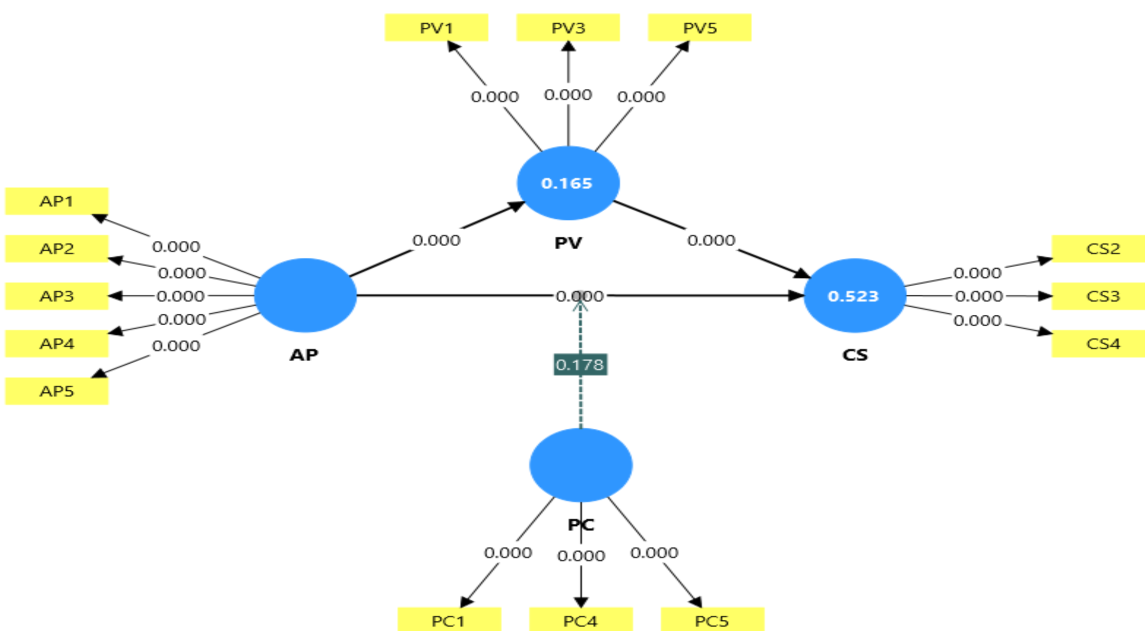

Figure 3: Structural model with bootstrapping results (p-values)

Table 6 indicates the model fit statistics of the saturated and the estimated model. The standardized root mean square residual (SRMR) of 0.088 shows that there is an acceptable fit of the model in the framework of the PLS-SEM, where the values below 0.10 are typically regarded as being satisfactory (Hair, 2014). Both models have similar and constant values of the d_ULS and d_G indices indicating that there is no significant misspecification. The normed fit index (NFI) value is lower than the traditional values applied to the covariance-based SEM, but it is understood descriptively in PLS-SEM and does not affect the sufficiency of the structural model (Henseler et al., 2015; Kline, 2023).

Table 6: Model fit indices

Fit Index	Saturated Model	Estimated Model
SRMR	0.088	0.088
d_ULS	0.817	0.822
d_G	0.274	0.274
Chi-square	162.857	162.06
NFI	0.674	0.675

5.4 Path Coefficients

The results of the structural model and hypothesis testing are provided in Table 7 as the standardized path coefficients, t-values, and the level of significance. The results are very empirically strong to support the hypothesized direct and indirect relationships between study variables. In particular, personalization enabled by AI positively and significantly impacts CS ($\beta = 0.482$, $p = 0.000$), which confirms H1. This outcome means that individually tailored offers created with the help of AI technologies can positively impact the evaluative judgments of customers by making the marketing interactions more relevant, efficient, and responsive. The result aligns with the previous literature that indicated that AP reinforced customer experiences and satisfaction in both digital and service environments (Ahmed et al., 2025; Hardcastle et al., 2025; Zahra et al., 2023).

Table 7: Structural model results and hypotheses testing

Hypothesis	Relationship	β (Path Coefficient)	STDEV	T-value	P-value	Decision
H1	AP to CS	0.482	0.081	5.969	0.000	Supported
H2	AP to PV	0.406	0.080	5.076	0.000	Supported
H3	PV to CS	0.319	0.081	3.929	0.000	Supported
H4	AP to PV to CS (Indirect Effect)	0.130	0.045	2.892	0.004	Supported (Partial Mediation)
H5a	PC to CS	−0.102	0.063	1.608	0.108	Not Supported
H5b	PC × AP to CS	0.071	0.053	1.346	0.178	Not Supported

The findings also indicate that AP also affects the PV ($\beta = 0.406$, $p = 0.000$), thereby proving H2. This implies that personalization improves the benefit-sacrifice judgments of consumers by increasing the functional and experience value dimensions, including convenience, relevance, and decision efficiency. This result, as per the Perceived Value Theory, proves the hypothesis that AP is a value-creating process but not a technological functionality (Zeithaml, 1988; Sweeney & Soutar, 2001; Ahmed et al., 2025). Furthermore, the PV is observed to influence CS (H3) significantly and positively ($\beta = 0.319$, $p = 0.000$), which confirms H3 and confirms the already established notion that in digital marketing and e-marketing, value perceptions are the antecedents of satisfaction judgments (Tam, 2004; Chang et al., 2009; Alkufahy et al., 2023).

As far as the mediating role of PV is concerned, the indirect impact of AP on CS via PV is statistically significant (β = 0.130, p = 0.004), which supports H4. Since the direct route between personalization and satisfaction is still important, the mediation is partly mediation. This finding underscores the importance of PV as an important explanatory construct upon which AP is converted into satisfaction outcomes. The result expands the existing literature by empirically proving the mediational role of PV in an integrated AP system, which has been under-researched in the literature (Chang et al., 2009; Alkufahy et al., 2023; Huang & Rust, 2021).

Contrastingly, the findings do not uphold the hypothesized effects of PC. The direct impact of privacy issue on CS is also negative but not statistically significant (β = -0.102, p = 0.108), which rejects H5a. Also, the interaction effect of AP and PC on CS is not significant (β = 0.071, p = 0.178), which led to the rejection of H5b. These results indicate that privacy issues in the considered setting do not significantly reduce the beneficial outcomes of AP on satisfaction. This finding can be compared to the recent evidence that shows that when personalization is associated with the obvious value benefits, consumers can accept privacy risks, especially in well-known and regularly used online platforms (Bleier & Eisenbeiss, 2015; Martin & Murphy, 2017; Huang & Rust, 2021). According to Privacy Calculus, the perceived advantages of personalization seem to dominate perceived privacy disadvantages in the determination of satisfaction ratings in this context (Chellappa & Sin, 2005; Fortes & Rita, 2016).

5.5 Structural Model Assessment

The explanatory power and effect sizes of the structural model are reported in Table 8. Coefficient of determination (R^2) shows that the model is able to account for 52.0 percent of the variation in CS and 17.0 percent of the variation in PV, which is moderate to high explanatory power in terms of consumer behavior and digital marketing research (Hair, 2014; Kline, 2023). The adjusted R^2 values are nearly the same as the R^2 estimates implying that the model is stable and robust. Analysis of effect sizes (f^2) indicates that AP has a huge impact on CS, which underlines its pivotal role in determining the level of satisfaction. The PV is associated with a medium effect on CS, which proves it is an important explanatory mechanism. Conversely, PC and the interaction term between PC and personalization have small effect sizes, meaning that they have little practical impact on the outcomes of satisfaction in the context under study. The AP indicates a medium effect size on the PV, which further supports its importance as a key driver of value perceptions. On the whole, these findings indicate that the structural model has sufficient predictive relevance and explanatory power, which justifies its appropriateness in testing hypotheses and making theory-based interpretations (Hair, 2014; Huang & Rust, 2021).

Table 8: Explained variance (R^2) and effect sizes (f^2) of the structural model

Endogenous Construct	R^2	Adjusted R^2	Predictor	f^2	Effect Size
Customer Satisfaction (CS)	0.52	0.503	AI Personalization (AP)	0.393	Large
			Perceived Value (PV)	0.177	Medium
			Privacy Concern (PC)	0.021	Small
			PC × AP	0.013	Small
Perceived Value (PV)	0.17	0.156	AI Personalization (AP)	0.197	Medium

6. Discussion

The current research aimed to investigate the effect of AI-powered marketing that provides personalization on CS with a specific focus on the mediating impact of PV and the moderating impact of PC. Altogether, the results have a strong empirical basis of the key role of AP in determining CS, and at the same time, they have some valuable insights into the cognitive processes and boundary conditions underlining consumer reactions in AI-based marketing settings.

First, the findings indicate that there is a strong and significant direct correlation between AP and CS. The result is consistent with the previous studies indicating that AP can improve customer experiences, making it more relevant, less information-saturated, and more efficient to make a decision (Ahmed et al., 2025; Hardcastle et al., 2025; Zahra et al., 2023). Theoretically, the findings support the idea that personalization has ceased to be a fringe marketing strategy but a central element of the experiential quality in the digital setting (Huang & Rust, 2021; Hollebeek et al., 2024). Similarly to previous research, AP seems to contribute to satisfaction, as it makes customers feel acknowledged and understood, which enhances evaluative marketing-related judgments (Singh & Singh, 2024; Belanche et al., 2019). This direct effect is very strong, which is why AP is strategically important in competitive e-commerce settings.

In addition to direct effects, the results are very compelling towards the explanatory power of PV in the personalization-satisfaction relationship. Personalization with AI was identified to greatly increase the PV, and the PV positively affects the CS. This trend is entirely in line with the Perceived Value Theory which assumes that satisfaction is achieved when the consumers make cognitive judgments regarding the ratio of the perceived benefits and the perceived sacrifices (Zeithaml, 1988; Sweeney & Soutar, 2001; Tam, 2004). AI-enabled personalized offers seem to enhance both functional and experience value by enhancing relevance, convenience, and accuracy of decisions, which enhances value judgments by consumers (Chang et al., 2009; Alkufahy et al., 2023). The results are a contribution to existing literature by empirically showing that PV is not just a result of personalization, but a key psychological process in which AP is converted into satisfaction (Ilyas et al., 2021; Ahmed et al., 2025).

Notably, the mediation analysis shows that the PV mediates the relationship between AP and CS to some degree. This implies that although personalization has a direct positive satisfaction effect, a significant part of its impact is indirect, via value perceptions. This finding is theoretically significant, as it fills an important gap in the literature that has tended to focus on direct personalization results without providing sufficient explanation of how consumers cognitively process personalized experiences (Tam, 2004; Chang et al., 2009; Alkufahy et al., 2023). The PV is positioned as a mediating construct, which is why the study can be considered a contribution to a more sophisticated perspective on the effectiveness of AP and the answer to the recent demand in integrative models that would capture both experiential and cognitive processes (Huang & Rust, 2021; Timimi et al., 2025; Hollebeek et al., 2024).

Contrary to the expectations based on Privacy Calculus Theory, PC did not have significant direct impact on CS, and it did not have significant moderating effect between AP and CS. Although the PC had a negative coefficient, the effect was not statistically significant, which suggests that privacy-related concerns did not significantly reduce the results of satisfaction in the studied situation. This result, however, is opposite to previous research that highlighted the harmful effect of privacy issues on trust and satisfaction (Martin & Murphy, 2017; Martin et al., 2017; Aimeur et al., 2016), but it is consistent with more recent data that postulates that consumers can accept privacy risks when they perceive their benefits as salient and immediate (Bleier & Eisenbeiss, 2015; Fortes & Rita, 2016; Huang & Rust, 2021). In terms of Privacy Calculus, it means that the perceived advantages of AP exceed perceived privacy costs, especially on familiar and regularly used digital platforms where consumers have acquired adaptive coping strategies (Chellappa & Sin, 2005; Joinson et al., 2010; Gursoy et al., 2019).

A combination of these findings has significant theoretical implications. The combination of Perceived Value Theory and Privacy Calculus Theory in one structural framework shows that value-based cognitive judgments are more decisive than privacy-related issues in the determination of satisfaction reactions to AP. This combined view builds upon the existing body of literature by demonstrating that privacy issues are less of a veto and more of a situational factor in satisfaction-based models, at least in fully grown e-commerce systems. In addition, the findings also highlight the significance of studying the mediation and moderation effect concurrently in order to model the complexity of consumer reactions in an AI-facilitated marketing setting (Hair, 2014; Henseler et al., 2015; Kline, 2023).

7. Theoretical and Practical Implications

7.1 Theoretical Implications

This paper contributes to the body of research on AP and consumer behavior in a number of significant ways. First, the results are applicable to the current theoretical framework because by incorporating both Perceived Value Theory and Privacy Calculus Theory into the framework of a single structure, the results show that the concept of PV can serve as a key explanatory variable connecting AP to CS. Although the previous researchers tended to focus on the effects of personalization separately, the current findings empirically prove that value-based cognitive assessments are decisive factors in the conversion of AI-based marketing stimuli into satisfaction outcomes (Zeithaml, 1988; Sweeney & Soutar, 2001; Tam, 2004). Furthermore, the partial mediation effect shows that personalization has a direct and indirect impact on satisfaction, which adds to the theoretical knowledge on the joint operation of the experiential and cognitive pathways under AI-supported service settings (Chang et al., 2009; Alkufahy et al., 2023; Huang & Rust, 2021). Lastly, the insignificant moderating effect of privacy concern indicates that Privacy Calculus Theory can be context-sensitive especially in the mature e-commerce environment where perceived benefits exceed perceived risks. This result not only narrows down the current body of knowledge by suggesting that the effect of privacy concerns on the outcome of personalization is not always negative, but also, in some circumstances, it is a side effect (Chellappa & Sin, 2005; Martin & Murphy, 2017; Hollebeek et al., 2024).

7.2 Practical Implications

As a manager, the results provide concrete and practical information to companies that use AP strategies. Since personalization, in particular, has a high direct impact on CS, managers ought to focus on investing in AI systems that would increase the relevance, accuracy, and timeliness of marketing offers. More to the point, the mediating effect of PV implies that the personalization efforts must be clearly aimed at increasing the value perceptions of customers, i.e., by prioritizing convenience, transparency, and tangible benefits, as opposed to focusing on technological sophistication (Zeithaml, 1988; Wedel & Kannan, 2016; Ahmed et al., 2025). Also, the lack of a notable moderating role of the privacy concern means that although the protection of privacy is a crucial factor, companies should not overestimate its adverse influence on satisfaction. Rather, companies need to strike a middle ground and explicitly articulate the value creation but still be responsible in their data usage, thus strengthening trust without compromising the effectiveness of personalization (Bleier & Eisenbeiss, 2015; Martin et al., 2017; Huang & Rust, 2021). All in all, AI-driven personalization can be used as a strategic tool by managers working in e-commerce and digital platforms to enhance satisfaction, but as long as value delivery is at the center of their personalization strategies.

8. Limitations and Future Research

This research has its contributions, but it is limited in several ways, which leaves the future research open. First, cross-sectional survey data limits the possibility to make a causal conclusion about the dynamic impacts of AI-powered personalization in the long run. The longitudinal or experimental designs might be used in the future to understand how the perceptions of value, satisfaction, and privacy of customers change over time when subjected to further exposure to AI-driven personalization (Kline, 2023; Hair, 2014; Aimeur et al., 2016). Second, the research targets e-commerce consumers in a particular digital environment, which can restrict the extrapolation of the results to other areas or cultural environments. The proposed model might be tested in various service industries or geographical areas to investigate the possible contextual differences in privacy sensitivity and value perceptions in the future (Fortes & Rita, 2016; Gursoy et al., 2019; Timimi et al., 2025). Lastly, although the privacy concern was studied as a moderating factor, other boundary conditions (e.g., trust, data transparency, or perceived control) can be studied in the future to build a more detailed picture of how consumers balance the advantages of personalization and privacy risks in AI-enabled settings (Joinson et al., 2010; Martin & Murphy, 2017; Khan et al., 2024).

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Appendix A: Measurement Items

#	Items	Strongly agree	Agree	Neutral	Disagree	Strongly disagree
AP	**AI-Powered Offer Personalization**					
AP1	The personalized offers I receive are relevant to my needs.					
AP2	The offers I receive are tailored to my personal preferences.					
AP3	AI-based recommendations match my interests well.					
AP4	Personalized offers make it easier for me to find what I need.					
AP5	The system responds effectively to my preferences and behavior.					
CS	**Customer Satisfaction**					
CS2	I am satisfied with my experience with AI-personalized offers.					
CS3	The personalized offers meet my expectations.					
CS4	Overall, I am pleased with AI-based personalized marketing offers.					
PV	**Perceived Value**					
PV1	AI-personalized offers provide good value for me.					
PV3	The benefits of personalized offers outweigh any costs or effort.					
PV5	Overall, I consider AI-based personalized offers valuable.					
PC	**Privacy Concern**					
PC1	I am concerned about how my personal data is collected.					
PC4	I worry about how my personal information is used by companies.					
PC5	I feel that my privacy may be at risk when receiving personalized offers.					