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The impact of artificial intelligence on consumer behavior — a case study of Uzbek e-commerce brands

Wpływ sztucznej inteligencji na zachowania konsumentów — studium przypadku uzbeckich marek e-commerce

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Abstract

This study examines how artificial intelligence (AI) applications used by Uzbek e-commerce brands influence consumer behavior. Using a quantitative design, we collected survey data from online shoppers in Uzbekistan and tested the proposed relationships through structural equation modelling (SEM). Although the initial target was at least 100 responses, data screening (incomplete questionnaires and reliability checks) resulted in a final valid sample of 80 observations for analysis. The model assesses the effects of three AI-related features, such as AI-driven personalization, AI-enabled customer service (chatbots), and AI-based targeted marketing, on key customer outcomes (purchase decision-making, satisfaction, and loyalty). The results indicate that AI driven personalization and AI-enabled customer service have a statistically significant positive effect on customer outcomes, while targeted marketing shows a non-significant effect in the Uzbek e-commerce context. These findings contribute evidence from an under-researched emerging market and offer practical implications for e-commerce firms seeking to improve customer experience and retention in line Uzbekistan's digital transformation agenda, the "Digital Uzbekistan – 2030" strategy. Study limitations and directions for future research are outlined.

Keywords

artificial intelligence, e-commerce, consumer behavior, personalization of services, chatbots, SEM

1. Introduction

1.1. Background of the study

Over the past decade, artificial intelligence (AI) has evolved from an experimental concept into a practical technology widely applied across multiple sectors, with e-commerce emerging as one of the most visible domains of adoption. In this context, AI systems enable real-time personalization, predictive analytics, automated customer service (e.g., chatbots), and intelligent recommendation engines that reduce search costs and enhance the relevance of offers and service interactions (Bag et al., 2021). Prior studies suggest that AI-driven personalization can strengthen consumer engagement and subsequent behavioral outcomes; however, these effects are often contingent upon consumer trust and privacy perceptions (Teepapal, 2025).

A central mechanism within AI-enabled commerce is the recommender system, which shapes the information environment in which consumers search, evaluate, and select products. Techniques such as collaborative filtering infer user preferences from behavioral data and generate personalized product suggestions that may influence choice formation and purchase intention. At the same time, algorithmic recommendations may raise concerns regarding transparency, data usage, and perceived intrusiveness, potentially affecting trust in the platform and willingness to rely on such systems (Li, 2024). In parallel, AI-powered chatbots increasingly function as frontline customer service agents. Empirical evidence indicates that chatbot service quality—particularly in terms of usefulness, reliability, and efficiency—can positively influence customer satisfaction and loyalty (Shahzad, 2024).

Uzbekistan's e-commerce market has experienced rapid expansion in recent years, particularly following the COVID-19 pandemic, alongside the diffusion of mobile internet and digital payment systems. Both domestic and international platforms operating in the market have increasingly integrated AI-related features, including recommendation systems, automated customer support, and targeted promotions, to enhance customer experience and retention. However, while the impact of AI on consumer behavior has been extensively studied in developed economies and large emerging markets, empirical evidence from Central Asia—particularly Uzbekistan—remains limited. This gap is significant, as consumer responses to AI may vary across contexts depending on factors such as market maturity, digital trust, perceived privacy risks, and familiarity with algorithm-driven services (Teepapal, 2025).

The relevance of this topic is further reinforced by Uzbekistan's strategic emphasis on digital transformation and the adoption of AI technologies. The national development agenda, including the "Digital Uzbekistan – 2030" strategy and related policy initiatives such as the Presidential Resolution on accelerating AI adoption (Resolution of the President of the Republic of Uzbekistan, 2021), underscores the growing role of AI-driven business models in economic modernization.

Against this backdrop, the present study examines how key AI-enabled features in e-commerce, namely AI-driven personalization, AI-enabled customer service (chatbots), and AI-based targeted marketing, affect consumer decision-making, satisfaction, and loyalty in the Uzbek context.

1.2. Problem statement

Despite the growing adoption of artificial intelligence (AI) tools in e-commerce, their behavioral effects are not universal and must be examined within specific market contexts. Existing literature suggests that AI-enabled personalization and AI-driven marketing tools can enhance consumer engagement and business performance. However, these relationships are often contingent upon contextual factors, particularly consumer perceptions of trust, privacy, and transparency, which remain underdeveloped in many emerging markets (Li, 2024; Madanchian, 2024; Teepapal, 2025).

In Uzbekistan, e-commerce platforms are expanding rapidly, and firms are increasingly integrating AI-enabled features such as recommendation systems, chatbots, and targeted promotions. Nevertheless, there is limited empirical evidence based on primary data assessing whether these technologies translate into improved consumer outcomes within the Uzbek context. This creates two important gaps. First, from an academic perspective, the literature on AI-driven consumer behavior lacks robust evidence from the Central Asian region, thereby limiting the generalizability of existing findings. Second, from a managerial perspective, local e-commerce firms lack evidence-based guidance on which AI-enabled tools generate meaningful consumer value and foster long-term customer retention (Li, 2024; Madanchian, 2024).

To address these gaps, this study empirically examines the relationships between selected AI-enabled e-commerce features and consumer behavioral outcomes in Uzbekistan, while also deriving context-specific implications for both firms and policymakers.

1.3. Research objectives

The overall objective of this study is to evaluate how AI-enabled features influence consumer behavioral outcomes in Uzbekistan. Specifically, the study aims to:

1. Examine the effects of AI-enabled features—namely AI-driven personalization, AI-enabled customer service (chatbots), and AI-based targeted marketing (Teepapal, 2025)—on consumers' purchase decision-making in Uzbek e-commerce.
2. Assess the relationships between these AI-enabled features and post-purchase outcomes, including customer satisfaction and loyalty, given prior evidence that recommendation trust and chatbot service quality influence consumer responses and brand loyalty (Li, 2024; Shahzad, 2024).
3. Empirically test the proposed relationships using survey data from Uzbek online shoppers and a structural equation modelling (SEM) approach that allows for the simultaneous estimation of relationships among latent constructs.
4. Interpret the findings in the context of Uzbekistan's digital transformation agenda, particularly the "Digital Uzbekistan – 2030" strategy and related policy initiatives promoting AI adoption.
5. Develop practical recommendations for Uzbek e-commerce firms on the effective deployment of AI-enabled features to enhance customer experience and retention, while addressing trust- and privacy-related concerns (Ojokoh, 2025).

1.4. Hypothesis

AI-enabled e-commerce features can be conceptualized as technology-driven stimuli that shape consumer cognition and behavioral responses. Drawing on the stimulus–organism–response (S–O–R) framework, commonly applied in digital marketing and AI research, AI-generated stimuli—such as personalization, chatbots, and targeted marketing—influence consumers' internal evaluations (e.g., perceived usefulness, trust, and comfort), which in turn affect behavioral outcomes, including decision-making, satisfaction, and loyalty. Recent empirical evidence suggests that AI-driven personalization can significantly enhance consumer engagement and behavioral responses (Teepapal, 2025).

Recommendation systems and personalization tools reduce information overload and increase the relevance of product information, thereby facilitating more efficient and confident decision-making. Empirical studies indicate that AI-driven personalized stimuli enhance consumer engagement and decision-related outcomes when users perceive recommendations as useful and trustworthy (Teepapal, 2025).

H1: AI-driven personalization has a positive effect on consumer decision-making (CDM) in e-commerce.

AI-based targeted marketing can improve message relevance by aligning promotional content with consumer preferences, potentially enhancing decision-making. However, prior research also indicates that excessive or repetitive targeting may lead to advertising irritation and perceived intrusiveness, which can diminish perceived value and weaken behavioral responses (Sharma, 2022).

H2: AI-based targeted marketing has a positive effect on consumer decision-making (CDM) in e-commerce.

Automated customer support tools, such as chatbots, can improve shopping efficiency by providing real-time assistance, reducing perceived effort, and enhancing service interactions. These factors are associated with improved decision-making and downstream behavioral outcomes. Empirical evidence suggests that chatbot service quality positively influences user outcomes, including satisfaction and loyalty (Shahzad, 2024).

H3: AI-enabled customer service features (CSF) have a positive effect on consumer decision-making (CDM) in e-commerce.

Decision-making quality represents a key cognitive determinant of post-purchase evaluation. When consumers perceive their decisions as informed and appropriate, they are more likely to evaluate both the purchase and the platform positively, leading to higher levels of satisfaction. This decision-making → satisfaction relationship is well established in structural models of online consumer behavior (Sehgal, 2024).

H4: Consumer decision-making (CDM) has a positive effect on customer satisfaction (STF).

In e-commerce environments, customer satisfaction is widely recognized as a primary driver of loyalty. Satisfied consumers are more likely to repurchase, recommend, and maintain long-term relationships with a platform or brand, particularly in markets characterized by

low switching costs. Prior SEM-based studies consistently confirm the satisfaction → loyalty relationship in online retail contexts (Sehgal & Malik, 2024).
H5: Customer satisfaction (STF) has a positive effect on customer loyalty (LYT).

2. Literature review

Artificial intelligence (AI) has become a foundational capability in e-commerce, where it functions as a decision-support mechanism by filtering information, ranking alternatives, recommending products, and facilitating real-time service interactions. Contemporary research increasingly conceptualizes AI-driven features as stimuli that shape consumer perceptions—such as perceived usefulness, trust, and privacy concerns—which in turn influence behavioral outcomes. Empirical evidence from structural models indicates that AI-driven personalized stimuli can significantly affect consumer engagement through the mediating roles of trust, perceived usefulness, and privacy concerns (Teepapal, 2025).

The acceptance of AI-enabled marketing depends not only on technical performance but also on consumer attitudes toward algorithmic decision-making, ethical considerations, and perceived transparency (Huang & Rust, 2018). This contextual dependence is particularly relevant in emerging e-commerce markets, where levels of digital trust and familiarity with AI-mediated interactions may differ substantially from those in advanced economies.

AI-driven personalization is typically operationalized through recommendation systems that infer user preferences from behavioral data—such as browsing history, past purchases, and engagement patterns—and generate tailored product rankings or bundles. These systems can reduce information overload and enhance the relevance of available options, thereby supporting higher-quality decision-making. However, the effectiveness of personalization extends beyond algorithmic accuracy. Consumer responses depend on whether personalization is perceived as supportive (enhancing decision quality) or manipulative (unduly steering choices). Prior research highlights the roles of trust, ethical perceptions, and identity-related concerns in shaping acceptance of AI-driven personalized interactions (Huang & Rust, 2018). Furthermore, studies on algorithmic recommendations and personalized advertising suggest that consumers' experiences of algorithmic influence affect how such recommendations are interpreted and acted upon (Hardcastle, 2025).

Targeted marketing refers to algorithmically tailored advertising and promotional messages designed to increase relevance and conversion effectiveness. Conventional marketing theory suggests that improved targeting enhances decision-making by delivering relevant information at the appropriate time. However, recent research indicates that greater personalization does not always yield positive outcomes. When targeting becomes excessive or lacks transparency, consumers may perceive it as intrusive, leading to negative emotional responses, heightened privacy concerns, and behavioral resistance. Empirical evidence from emerging-market contexts shows that AI-powered targeted advertising can trigger adverse reactions when personalization is perceived as intrusive (An & Ngo, 2025). Additionally, broader research on AI-driven recommendations and personalized advertising emphasizes that consumer responses depend on perceived appropriateness and comfort, suggesting that targeted marketing may produce mixed or even negative effects under certain conditions (Hardcastle, 2025).

AI-enabled customer service tools, particularly chatbots, have become widely adopted in e-commerce, providing 24/7 assistance, product and order information, and guided navigation throughout the purchasing process. These technologies can influence consumer decision-making by reducing perceived effort and uncertainty, while enabling immediate problem resolution. Gao (2025) emphasizes that the effectiveness of AI-based customer service depends on whether chatbot performance meets or exceeds traditional service quality expectations, highlighting the importance of problem resolution and service reliability for consumer outcomes. Furthermore, research on AI-based self-service technologies indicates that perceived value and service quality significantly shape customer experience, reinforcing the role of AI-enabled service features in influencing consumer responses (Zungu, 2025).

In digital commerce, consumer decision-making quality is commonly conceptualized as a cognitive evaluation that a purchase decision is informed, appropriate, and aligned with individual needs. Higher perceived decision quality reduces post-purchase regret and increases satisfaction. In turn, customer satisfaction is one of the most robust predictors of loyalty, particularly in e-commerce environments characterized by low switching costs and high availability of alternatives. Contemporary AI marketing research highlights these cognitive and affective processes as key psychological mechanisms linking AI-generated stimuli to behavioral outcomes (Teepapal, 2025).

Uzbekistan's e-commerce ecosystem is evolving in parallel with broader national digitalization efforts. Government policy initiatives emphasize the adoption of digital technologies and the formalization of online commerce activities. Notably, the Cabinet of Ministers' Resolution No. 885 (dated 26 December 2024), effective from 1 July 2025, introduces a notification procedure for e-commerce operators and establishes an official register of electronic commerce entities (Lex.uz, 2024). This regulatory framework is relevant to the AI–consumer behavior relationship in two key respects. First, increased formalization and compliance requirements may enhance consumer trust in digital platforms, which is identified in the AI marketing literature as a critical determinant of acceptance of AI-driven personalization and automated interactions (Huang & Rust, 2018). Second, variations in platform compliance, localization, and regulatory adaptation may influence user experiences and perceptions of AI-enabled features, further underscoring the importance of context-specific empirical investigation in Uzbekistan.

Table 1 presents a comparative overview of major e-commerce platforms operating in Uzbekistan, focusing on the visibility of AI-enabled features, the degree of market localization, and publicly observable indicators of legal compliance.

Despite the rapid expansion of e-commerce and policy-driven digitalization in Uzbekistan, empirical evidence examining the impact of AI-enabled features on consumer decision-making, satisfaction, and loyalty in this context remains limited.

Table 1. Comparative overview of AI integration and legal compliance among e-commerce platforms in Uzbekistan

Platform	Launched	AI Features	Local Market Focus	Legal Compliance
AliExpress	Before 2018	Large-scale AI recommendations, price prediction, voice-based AI assistance	Low—global platform with limited localization for Uzbekistan	Limited—cross-border operations with partial alignment to Uzbek regulations
Wildberries	2020	Personalized advertising, AI-based customer service, recommendation systems	Medium—partial localization, primarily Russia-oriented	Partial—regional compliance with some adaptation to Uzbek regulations
Ozon	2021	AI-based pricing, SEO optimization, user behavior analytics	Medium—Uzbek language support with limited contextual adaptation	Moderate—generally aligned with Uzbek e-commerce guidelines
Uzum Market	2022	Product recommendations, chatbots, dynamic pricing, predictive search	High—fully localized interface tailored to Uzbek users	High—compliant with local data protection and e-commerce regulations
Temu	2023	Deep-learning personalization, AI-driven influencer targeting, gamified ads	Low—global interface with minimal local adaptation	Unclear—limited publicly available information on local compliance

S o u r c e: Tursunowa & Karimova, 2023.

The present study addresses this gap by testing, within a unified SEM framework, how three AI-enabled features relate to decision-making, and how decision-making influences satisfaction and loyalty among Uzbek e-commerce users.

3. Methodology

3.1. Research design

This study adopts a quantitative research design grounded in the positivist paradigm, which is widely employed in consumer behavior and technology adoption research to test theoretically derived relationships using observable data. A cross-sectional survey approach was utilized to capture consumers' perceptions and behavioral responses to AI-enabled features in e-commerce at a single point in time. This design is appropriate for examining associative relationships among latent constructs, including AI-driven personalization, AI-enabled customer service, decision-making, satisfaction, and loyalty.

The use of a quantitative, survey-based approach is consistent with prior research in AI and e-commerce that applies structural modelling techniques to evaluate how technology-enabled features influence consumer outcomes. Structural equation modelling (SEM) was selected as the primary analytical method, as it enables the simultaneous estimation of multiple relationships among latent constructs while accounting for measurement error. This is particularly important in studies involving behavioral and perceptual variables measured through multi-item scales.

3.2. Data collection techniques

Data were collected through a structured online questionnaire designed to measure consumers' perceptions of AI-enabled features used by e-commerce platforms operating in Uzbekistan. The questionnaire items were adapted from established scales employed in prior studies on AI-driven personalization, automated customer service, consumer decision-making, satisfaction, and loyalty. All items were measured using a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"), a format widely used in consumer behavior research because of its simplicity and familiarity to respondents.

A non-probability convenience sampling technique was employed, targeting individuals aged 16 years and older who had prior experience with AI-enabled e-commerce features, such as product recommendations or chatbots. The survey was distributed online via Telegram, which enabled efficient access to active digital consumers. The estimated completion time was approximately 6–8 minutes, helping to reduce respondent fatigue. Although the initial target was a larger number of responses, data screening procedures were conducted to ensure data quality. Incomplete questionnaires, inconsistent response patterns, and unreliable entries were excluded, resulting in a final valid sample of 80 respondents. While this sample size limits the generalizability of the findings, it is considered acceptable for exploratory SEM analysis, particularly given the parsimonious model structure and the study's focus on an emerging market context.

3.3. Data analysis tools procedures

Data analysis followed a two-stage structural equation modelling (SEM) approach, as recommended in methodological literature. In the first stage, IBM SPSS was used for data screening, coding, and preliminary analysis. Reliability of the measurement scales was assessed using Cronbach's alpha, with values exceeding the commonly accepted threshold indicating satisfactory internal consistency.

In the second stage, Confirmatory Factor Analysis (CFA) and structural equation modelling (SEM) were performed using AMOS to validate the measurement model and test the hypothesized structural relationships. Model fit was evaluated using multiple goodness-of-fit indices commonly reported in SEM research, ensuring the adequacy of both the measurement and structural models.

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4. Analysis and results

4.1. Overview of data collection

This study employed a quantitative survey strategy to examine the influence of artificial intelligence (AI)-enabled tools on consumer behavior in Uzbekistan's e-commerce sector. The data collection procedure was designed to align with the study's conceptual framework and support reliable hypothesis testing. A structured online questionnaire was used as the primary data collection instrument due to its scalability, cost efficiency, and suitability for capturing perceptual and behavioral evaluations of digital commerce features.

The questionnaire measured six latent constructs corresponding to the proposed model: AI-driven personalized recommendations (PR), AI-based targeted marketing (TM), AI-enabled customer service features (CSF), consumer decision-making (CDM), customer satisfaction (STF), and customer loyalty (LYT). Each construct was operationalized using three measurement items, resulting in a total of 18 items.

Table 2. Overview of constructs and number of measurement items

Variables		Number of Items
AI-driven tools	AI-driven personalized recommendation (PR)	3
	AI-based targeted marketing (TM)	3
	AI-enabled customer service features (CSF)	3
Consumer outcomes	Customer decision-making (CDM)	3
	Customer satisfaction (STF)	3
	Customer loyalty (LYT)	3

S o u r c e: Authors' own elaboration.

The survey items were adapted from validated measurement scales reported in prior peer-reviewed studies on AI-enabled commerce, digital marketing, and consumer behavior. Minor wording adjustments were made to enhance clarity and reflect the socio-cultural and market context of Uzbekistan, while preserving the original conceptual meaning of each item. All construct indicators were measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), enabling the quantitative assessment of consumer perceptions and attitudes.

To accommodate the bilingual nature of the target population, the questionnaire was administered in both Uzbek and Russian. Care was taken to ensure conceptual equivalence across languages and to minimize ambiguity in item interpretation. In addition to the main construct measures, the questionnaire included five demographic and behavioral profile items capturing gender, age, preferred survey language, online purchase frequency, and commonly purchased product categories, thereby providing descriptive context for the sample.

Data were collected via Google Forms, enabling broad outreach across different regions of Uzbekistan. A non-probability purposive sampling strategy was employed to recruit respondents with prior experience using e-commerce platforms that incorporate AI-enabled features, such as recommendation systems, automated customer support, or targeted promotional content. The survey was distributed through Telegram channels during March–April 2025, yielding 103 completed responses. Following data quality screening—specifically the removal of incomplete responses and cases exhibiting uniform response patterns—the final analytical sample used for structural equation modelling (SEM) consisted of 80 valid observations.

4.2. Descriptive statistics and preliminary analysis

The initial sample (n = 103) was predominantly female, with women accounting for 71.7% of respondents and men for 28.3%. The age distribution was skewed toward younger participants: 36.9% were under 18 years old and 35.9% were aged 18–24. Respondents aged 25–44 represented 17.5% of the sample, while those aged 45 and above accounted for 9.7%. This concentration of younger respondents is consistent with the recruitment channel (Telegram) and reflects the demographic group most actively engaged with digital platforms and AI-enabled online services in Uzbekistan.

To capture linguistic diversity, the survey was administered in both Uzbek and Russian. The majority of respondents completed the questionnaire in Russian (62.1%), while 37.9% selected the Uzbek version.

Online purchasing frequency indicates regular engagement with e-commerce environments. Nearly one-third of respondents reported shopping online often (29.1%), followed by sometimes (28.2%) and usually (23.3%), while a smaller proportion (19.4%) reported purchasing online rarely. Overall, this distribution suggests that the sample consists of active online consumers, which is appropriate for a study focused on AI-mediated e-commerce behavior.

Regarding purchase categories, household goods were most frequently reported (20.8%), followed by electronics and clothing (both 17.5%). Other commonly selected categories included books and stationery (15.8%), cosmetics (15.4%), and food items (12.1%). Only 0.9% of respondents selected “other,” indicating that the predefined categories adequately capture the primary e-commerce consumption patterns within the sample.

Prior to conducting Confirmatory Factor Analysis (CFA) and Structural Equation Modelling (SEM), the dataset was screened to ensure data quality. Of the initial 103 responses, 23 were excluded due to uniform response patterns across Likert-scale items (e.g., selecting the same response category for all items). Such patterns are commonly interpreted as indicators of non-differentiated responding, which can bias parameter estimates by inflating measurement error and reducing construct variance. Consequently, the final analytical sample consisted of 80 valid observations.

Table 3. Demographic characteristics and online purchase frequency of initial respondents

Demographics	Types	Frequency	Percentage	Cumulative
Gender	Male	31	28.3	30.1
	Female	72	71.7	100.0
Age	< 18	38	36.9	36.9
	18–24	37	35.9	72.8
	25–34	8	7.8	80.6
	35–44	10	9.7	90.3
	≥ 45	10	9.7	100
Survey language	Uzbek	39	37.9	37.9
	Russian	64	62.1	100.0
Purchase frequency	Rarely	20	19.4	19.4
	Sometimes	29	28.2	47.6
	Often	30	29.1	76.7
	Usual	24	23.3	100.0
Purchased product type	Household goods	50	20.8	20.8
	Electronics	42	17.5	38.3
	Clothes	42	17.5	55.8
	Books & stationery	38	15.8	71.6
	Cosmetics	37	15.4	87.0
	Food	29	12.1	99.1
	Others	2	0.9	100.0

S o u r c e: Authors' own elaboration.

After data screening, a final sample of 80 valid responses was retained for subsequent analysis. The screening process did not materially alter the overall sample structure. In the initial dataset, females accounted for 71.7% (n = 72) and males for 28.3% (n = 31). In the cleaned dataset, the gender distribution remained consistent, with females representing 72.5% (n = 58) and males 27.5% (n = 22).

The age distribution showed minor adjustments following data cleaning. The proportion of respondents under 18 decreased from 36.9% (n = 38) to 31.3% (n = 25), while the 18–24 age group increased from 35.9% (n = 37) to 41.3% (n = 33). Language preference remained stable, with Uzbek-language responses accounting for 37.5% (n = 30) and Russian-language responses for 62.5% (n = 50).

Online purchasing frequency also remained broadly consistent, with only minor shifts across categories, indicating that the data screening process improved response quality without significantly altering the behavioral characteristics of the sample. Table 4 presents a summary of the demographic profile and online purchasing behavior of the final analytical sample.

Table 4. Demographic characteristics and online purchase frequency of final respondents

Demographics	Types	Frequency	Percentage	Cumulative
Gender	Male	22	27.5	27.5
	Female	58	72.5	100.0
Age	< 18	25	31.3	31.3
	18–24	33	41.3	72.6
	25–34	6	7.4	80.0
	35–44	8	10.0	90.0
	≥ 45	8	10.0	100.0
Survey language	Uzbek	30	37.5	37.5
	Russian	50	62.5	100.0
Purchase frequency	Rarely	16	20.0	20.0
	Sometimes	26	32.5	52.5
	Often	23	28.7	81.2
	Usual	15	18.8	100.0

S o u r ce: Authors' own elaboration.

4.3. Measurement model assessment

The measurement model, comprising six latent constructs—AI-driven personalized recommendations (PR), targeted marketing (TM), AI-based customer service features (CSF), consumer decision-making (CDM), customer satisfaction (STF), and customer loyalty (LYT)—was assessed using confirmatory factor analysis (CFA) in AMOS. Standardized factor loadings for all retained indicators ranged from 0.702 to 0.880, exceeding the recommended threshold of 0.70, thereby supporting convergent validity (Hair et al., 2010). All corresponding critical ratios (t-values) were statistically significant ($p < 0.05$), indicating that each indicator contributes meaningfully to its respective construct.

Internal consistency reliability was evaluated using Cronbach's alpha, with values ranging from 0.843 to 0.896, exceeding the commonly accepted threshold of 0.70 (Nunnally & Bernstein, 1994). These results indicate satisfactory reliability of the measurement scales.

Model fit was assessed using multiple goodness-of-fit indices. The CFA results indicate an acceptable overall fit ($\chi^2 = 201.116$, df = 117, $p < 0.001$; $\chi^2/df = 1.72$; TLI = 0.91; CFI = 0.93). The RMSEA value (0.095) suggests a moderate level of misfit; however, this is not uncommon in models estimated with relatively small samples and multiple indicators. Accordingly, model fit was evaluated based on a combination of indices rather than relying on RMSEA alone.

Overall, the measurement model demonstrates acceptable levels of validity and reliability, supporting its suitability for subsequent structural model estimation.

Table 5. Results of confirmatory factor analysis

Construct and indicators	Standardized factor loading	CR
AI-driven tools		
Personalized recommendations (PR) (α = 0.851)		
Q1	0.724	–
Q2	0.858	7.579
Q3	0.714	9.414
Targeted marketing (TM) (α=.896)		
Q5	0.852	–
Q6	0.884	10.332
Q7	0.856	9.797
AI-based customer service features (CSF) (α = 0.851)		
Q9	0.824	–
Q11	0.797	8.259
Q12	0.836	9.089
Customer decision making (CDM) (α = 0.843)		
Q13	0.702	–
Q14	0.813	7.239
Q15	0.816	7.215
Customer satisfaction (STF) (α = 0.844)		
Q17	0.757	7.226
Q18	0.806	7.753
Q20	0.771	–
Customer loyalty (LYT) (α = 0.867)		
Q24	0.880	–
Q22	0.845	9.932
Q23	0.778	8.738

Note: Fit indices: χ^2(df = 117 = 201.116, $p < 0.001$; χ^2/df = 1.72; TLI = 0.91; CFI = 0.93; RMSEA = 0.095.

S o u r c e: Authors' own elaboration.

Overall, the CFA results indicated an acceptable fit between the measurement model and the observed data. The chi-square statistic was significant ($\chi^2(117) = 201.116$, $p < 0.001$), which is common in SEM applications with moderate sample sizes. The relative chi-square ratio (χ^2/df = 1.72) suggests a good fit, as values below 3 are generally considered acceptable. Incremental fit indices further support model adequacy (TLI = 0.91; CFI = 0.93), both exceeding the recommended threshold of 0.90. The RMSEA value (0.095) indicates borderline fit; therefore, overall model fit was evaluated using multiple indices rather than relying on RMSEA alone.

CConvergent validity and internal consistency were further assessed using Composite Reliability (CR) and Average Variance Extracted (AVE). As reported in Table 6, all constructs meet the recommended thresholds (CR > 0.70; AVE > 0.50), indicating satisfactory reliability and convergent validity. Specifically, AI-driven personalized recommendations show CR = 0.81 and AVE = 0.59; targeted marketing demonstrates strong reliability (CR = 0.90) and high convergent validity (AVE = 0.75); and AI-based customer service features exhibit CR = 0.86 and AVE = 0.67. The remaining constructs also satisfy the criteria: consumer decision-making (CR = 0.82; AVE = 0.61), customer satisfaction (CR = 0.82; AVE = 0.61), and customer loyalty (CR = 0.87; AVE = 0.70).

Taken together, these findings confirm the adequacy of the measurement model and support its suitability for subsequent structural model estimation.

Table 6. Construct reliability and convergent validity results

Variables		λ	λ²	1 – (λ²)	CR	AVE
Personalized recommendations (PR)	Q1	0.724	0.524	1.23	0.81	0.59
	Q2	0.858	0.736			
	Q3	0.714	0,510			
Targeted marketing (TM)	Q5	0.852	0.726	0.76	0.90	0.75
	Q6	0.884	0.781			
	Q7	0.856	0.733			
AI-based customer service features (CSF)	Q9	0.824	0.679	0.99	0.86	0.67
	Q11	0.797	0.635			
	Q12	0.836	0.699			
Customer decision making (CDM)	Q13	0.702	0.493	1.18	0.82	0.61
	Q14	0.813	0.661			
	Q15	0.816	0.666			
Customer satisfaction (STF)	Q17	0.757	0.573	1.18	0.82	0.61
	Q18	0.806	0.650			
	Q20	0.771	0.594			
Customer loyalty (LYT)	Q24	0.880	0.774	0.91	0.87	0.70
	Q22	0.845	0.714			
	Q23	0.778	0.605			

S o u r c e: Authors' own elaboration.

Table 7 reports construct-level means, standard deviations, and Pearson correlation coefficients. Overall, the correlations are positive and statistically significant ($p < 0.001$), indicating coherent associations among the study variables. Personalised recommendations (PR) were strongly correlated with targeted marketing (TM) ($r = 0.758$) and AI-based customer service features (CSF) ($r = 0.650$), and also showed strong correlations with consumer decision-making (CDM) ($r = 0.751$), satisfaction (STF) ($r = 0.757$), and loyalty (LYT) ($r = 0.667$).

Targeted marketing (TM) was positively correlated with CSF (r = 0.665), CDM (r = 0.718), STF (r = 0.673), and LYT (r = 0.577). Customer service features (CSF) were strongly correlated with CDM (r = 0.818) and showed moderate correlations with STF (r = 0.589) and LYT (r = 0.529). CDM correlated positively with STF (r = 0.669) and LYT (r = 0.589). The strongest association was observed between satisfaction and loyalty (STF–LYT: r = 0.850), consistent with established e-commerce research linking satisfaction to loyalty intentions. These bivariate relationships provide preliminary support for the proposed conceptual model; however, the hypotheses were formally tested using SEM after evaluating the measurement model.

Table 7. Construct descriptives and Pearson correlations

Variables	Mean	St. Dev.	PR	TM	CSF	CDM	STF	LYT
PR	3.77	1.04	1	–	–	–	–	–
TM	3.39	1.29	0.758^{***}	1	–	–	–	–
CSF	3.58	1.12	0.650^{***}	0.665^{***}	1	–	–	–
CDM	3.52	1.12	0.751^{***}	0.718^{***}	0.818^{***}	1	–	–
STF	3.81	1.00	0.757^{***}	0.673^{***}	0.589^{***}	0.669^{***}	1	–
LYT	3.83	1.13	0.667^{***}	0.577^{***}	0.529^{***}	0.589^{***}	0.850^{***}	1

Note: $^{***}p < 0.001$.

Source: Author's own elaboration.

To assess potential multicollinearity among the predictor constructs, tolerance and Variance Inflation Factor (VIF) statistics were examined as diagnostic measures. An auxiliary regression analysis was conducted using customer loyalty (LYT) as the dependent variable. The tolerance values ranged from 0.238 to 0.393, all exceeding the commonly accepted threshold of 0.10, indicating the absence of severe multicollinearity. Correspondingly, VIF values ranged from 2.546 to 4.200, remaining below the conventional cutoff of 5.0.

These results suggest that the degree of overlap among the predictor variables is not sufficiently high to compromise the stability or interpretability of the estimated parameters.

Table 8. Collinearity statistics for predictors of customer loyalty

Variables	Collinearity Statistics	
	Tolerance	VIF
PR	0.278	3.596
TM	0.354	2.824
CSF	0.318	3.142
CDM	0.238	4.200
STF	0.393	2.546
Dependent variable: Customer loyalty		

Source: Author's own elaboration.

Among the predictors, consumer decision-making (CDM) exhibits the highest VIF (4.200) and the lowest tolerance (0.238), indicating a moderate degree of shared variance with other constructs, though not at a level that raises multicollinearity concerns. The remaining predictors—AI-driven personalized recommendations (PR), targeted marketing (TM), AI-based customer service features (CSF), and customer satisfaction (STF)—display moderate VIF values ranging from 2.546 to 3.596, further supporting the acceptable independence of the predictor variables (see Table 8). Overall, these findings confirm that multicollinearity does not pose a threat to the stability or interpretability of the structural model estimates

4.4. Structural model and hypothesis testing

The structural equation modeling (SEM) analysis was used to examine the hypothesized relationships between AI-driven e-commerce features and consumer outcomes. Hypothesis testing was based on standardized path coefficients (β) and their associated critical ratios / t-values. The results are summarized in Table 9.

Table 9. Hypothesis results

Hypothesis	Path	Standardized Coefficient (β)	CR (*t*-value)	Results
H1	PR → CDM	0.919	2.780^{***}	Supported
H2	TM → CDM	−0.104	−0.603	Not supported
H3	CSF → CDM	0.173	0.101^{*}	Not supported
H4	CDM → STF	0.964	5.494^{***}	Supported
H5	STF → LYT	1.118	7.933^{***}	Supported

Note: $^{***}p < 0.001$; $^{**}p < 0.05$; $^{*}p < 0.10$.

S o u r c e: Author's own elaboration.

H1 predicted a positive effect of AI-driven personalized recommendations (PR) on consumer decision-making (CDM). The results show a positive and statistically significant relationship (β = 0.919; CR = 2.780; $p < 0.001$), supporting H1. This indicates that AI-driven recommendations play a substantial role in improving decision-making in the Uzbek e-commerce context.

H2 proposed that targeted marketing (TM) positively influences CDM. However, the relationship was not statistically significant (β = −0.104; CR = −0.603), leading to the rejection of H2. The negative, albeit non-significant, coefficient suggests that AI-based targeted marketing does not meaningfully contribute to consumer decision-making in this sample.

H3 predicted a positive effect of AI-enabled customer service features (CSF) on consumer decision-making (CDM). Although the estimated coefficient was positive (β = 0.173), the relationship was not statistically significant (CR = 0.101), indicating insufficient empirical support for H3. This result suggests that, within the context of Uzbek e-commerce, AI-based customer service tools such as chatbots may not play a decisive role in shaping consumers' decision-making processes.

H4 proposed that CDM positively affects customer satisfaction (STF). The results confirm a strong and statistically significant relationship ($\beta = 0.964$; $CR = 5.494$; $p < 0.001$), supporting H4.

H5 predicted that customer satisfaction (STF) positively influences customer loyalty (LYT). This relationship is strongly supported ($\beta = 1.118$; $CR = 7.933$; $p < 0.001$), indicating that satisfaction is a key determinant of loyalty in the Uzbek e-commerce context.

5. Limitations and future research

5.1. Limitations

This study has several limitations that should be considered when interpreting the findings. First, the empirical evidence is drawn exclusively from the Uzbek e-commerce context, which may limit the generalizability of the results to other regions. The socio-cultural, institutional, and economic characteristics of Uzbekistan may shape consumer perceptions of AI-enabled e-commerce differently from those observed in developed economies or markets with higher levels of digital maturity.

Second, the study employed a non-probability purposive sampling approach and an online survey method, which may introduce selection bias and limit the representativeness of the broader consumer population. Although this approach ensured that respondents had prior experience with AI-enabled e-commerce features, the sample may not fully capture the diversity of online consumers in Uzbekistan.

Third, the cross-sectional research design restricts the ability to draw causal inferences regarding changes in consumer behavior over time. Consumer responses to AI-driven personalization and automated service features are likely to evolve as users gain experience and as technologies mature. Longitudinal research designs would provide a more robust understanding of these temporal dynamics.

Fourth, the study relies on self-reported survey data, which are subject to common limitations such as recall bias and social desirability bias. Although validated measurement scales were used, their adaptation to the Uzbek linguistic and cultural context may have affected construct equivalence. Furthermore, variations in respondents' digital literacy and familiarity with AI technologies may have influenced how survey items were interpreted, potentially introducing measurement error.

Future research can address these limitations in several ways. First, scholars may examine the moderating roles of psychological factors such as trust in AI, perceived risk, privacy concerns, and consumer skepticism, which are likely to influence the effectiveness of AI-enabled marketing strategies.

Second, longitudinal and experimental research designs are recommended to better capture causal relationships and the long-term effects of AI-enabled features on consumer satisfaction, loyalty, and behavioral intentions.

Finally, cross-cultural comparative studies are strongly encouraged. Comparative analyses across emerging and developed markets would provide deeper insights into how cultural norms, digital literacy, and privacy expectations shape consumer acceptance of AI-driven marketing technologies.

5.2. Conclusion

This study examined how AI-enabled e-commerce features influence consumer outcomes in Uzbekistan, using Uzum Market as a contextual reference. Building on a structural framework grounded in the stimulus–organism–response (S–O–R) perspective, AI-driven personalization, AI-based customer service features, and AI-enabled targeted marketing were modelled as stimuli influencing consumer decision-making (organism), with downstream effects on satisfaction and loyalty (response). The findings provide several important insights.

First, AI-driven personalized recommendations demonstrate a strong and statistically significant effect on consumer decision-making. This result supports prior research suggesting that algorithmic personalization enhances the relevance of information, reduces cognitive effort, and improves confidence in online decision processes. In the Uzbek e-commerce context, personalization appears to be a key driver of perceived decision quality, highlighting its central role in shaping consumer behavior in emerging digital markets.

Second, AI-based customer service features exhibit a positive but statistically non-significant relationship with decision-making. This suggests that, although chatbots and automated support tools may enhance service efficiency and accessibility, their direct influence on decision-making is limited. One possible explanation is that such features are more relevant in post-search or post-purchase stages, rather than in the core evaluation and choice phase. This finding aligns with the view that AI-enabled service tools primarily support user experience rather than actively shaping purchase decisions.

Third, the hypothesized relationship between AI-based targeted marketing and decision-making is not supported. This result indicates that current targeting practices may be ineffective in influencing consumer choices within this context. Consistent with emerging literature, excessive or poorly calibrated personalization may be perceived as intrusive, reducing trust and diminishing the persuasive impact of targeted content. In emerging markets such as Uzbekistan, where digital trust and familiarity with AI-mediated interactions are still developing, consumers may be more sensitive to perceived manipulation or privacy concerns.

The structural model further confirms a sequential pathway from decision-making to satisfaction and from satisfaction to loyalty. This finding reinforces established consumer behavior theory, demonstrating that improved decision quality leads to more favorable post-purchase evaluations, which in turn strengthen customer loyalty. Within the S–O–R framework, decision-making operates as a critical cognitive mechanism linking AI-enabled stimuli to affective and behavioral outcomes.

From a managerial perspective, the results suggest that e-commerce platforms in Uzbekistan should prioritize investments in high-quality recommendation systems, as these have the most substantial impact on consumer decision-making. While AI-enabled customer service tools remain important for enhancing user experience, their role may be more supportive than decisive. In contrast, firms should carefully reconsider their targeted marketing strategies, ensuring that personalization is perceived as relevant, transparent, and non-intrusive. Providing users with greater control over personalized content and improving algorithmic transparency may help mitigate negative perceptions.

From a theoretical perspective, this study contributes to the literature by providing empirical evidence from a relatively underexplored Central Asian context. The findings support the applicability of AI–consumer behavior frameworks, particularly the S–O–R model, in emerging digital economies, while also highlighting the context-dependent nature of AI effectiveness.

Finally, the results align with Uzbekistan's broader digital transformation agenda, particularly the "Digital Uzbekistan – 2030" strategy, by identifying which AI-enabled capabilities are most likely to generate consumer value and support sustainable platform growth.

5.3. Practical implications

This study provides practical guidance for e-commerce platforms, marketers, and AI solution developers operating in emerging markets such as Uzbekistan.

First, platforms should prioritize the quality of AI-driven recommendation systems as a core decision-support capability. Given the strong positive relationship between personalized recommendations and consumer decision-making, recommendation systems should be treated as a central component of the customer experience rather than merely a promotional tool. Enhancing recommendation relevance can be achieved by (i) refining product matching and ranking algorithms, (ii) leveraging user interaction data to continuously update preference profiles, and (iii) ensuring localization through language support and culturally relevant product categorization.

Second, targeted marketing strategies should be redesigned to reduce user resistance and improve perceived appropriateness. The non-significant effect of targeted marketing on decision-making suggests that existing practices may not effectively support consumer choice. Rather than increasing the intensity of targeting, platforms should focus on improving the quality of targeting by optimizing relevance, timing, and transparency. Providing users with greater control over personalized content and data usage may also help mitigate perceptions of intrusiveness and enhance trust.

Third, AI-based customer service systems should be strengthened through localization and hybrid support models. Although customer service features demonstrate a positive relationship with decision-making, their effect is comparatively weaker, indicating potential for improvement. Platforms should enhance chatbot performance in Uzbek and Russian by improving response accuracy, contextual understanding, and responsiveness. In addition, hybrid service models—where complex queries are seamlessly transferred to human agents—can improve service quality and reduce user frustration.

Finally, platforms should manage the entire customer journey to effectively convert decision quality into long-term loyalty. The strong sequential relationship between decision-making, satisfaction, and loyalty highlights the importance of delivering a consistent end-to-end experience. This includes reliable order fulfillment, transparent return and complaint processes, and high-quality post-purchase support.

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Abstrakt

W artykule poddano analizie wpływ sztucznej inteligencji (AI) wykorzystywanej przez uzbeckie marki e-commerce na zachowania konsumentów. Stosując metodę ilościową, zgromadzono dane ankietowe od kupujących online w Uzbekistanie i zbadano zależności za pomocą modelowania równań strukturalnych (ang. *structural equation modeling* – SEM). Zebrano Celem autorów było uzyskanie co najmniej 100 odpowiedzi na pytania ankiety, jednak po odrzuceniu kwestionariuszy niekompletnych do dalszej analizy przyjęto 80 ankiet. Przyjęty model ocenia wpływ trzech funkcji związanych ze sztuczną inteligencją: personalizację opartą na AI, obsługę klienta wspomaganą AI (chatboty) oraz marketing ukierunkowany oparty na AI, na kluczowe wyniki klientów (podejmowanie decyzji zakupowych, satysfakcję i lojalność). Wyniki wskazują, że personalizacja oparta na AI i obsługa klienta wspomagana sztuczną inteligencją mają statystycznie istotny, pozytywny wpływ na analizowane zmienne, podczas gdy marketing ukierunkowany nie wykazuje znaczącego wpływu na handel elektroniczny w Uzbekistanie. Uzyskane wyniki są ważne dla niedostatecznie jeszcze zbadanego, rozwijającego się rynku i oferują praktyczne implikacje dla firm e-commerce, dążących do zatrzymania klientów i poprawy jakości obsługi, zgodnie ze strategią transformacji cyfrowej Uzbekistanu: „Cyfrowy Uzbekistan – 2030". W artykule przedstawiono także ograniczenia przeprowadzonych badań i kierunki przyszłych analiz.

Słowa kluczowe

sztuczna inteligencja, e-commerce, zachowania konsumentów, personalizacja usług, chatboty, SEM