KMANPUB | AI and Tech in Behavioral and Social Sciences Vol. 4 No. 4 (2026): 1-13

Article history:
Received 10 March 2026
Revised 01 June 2026
Accepted 08 June 2026
Initial Publication 19 June 2026
Final Publication 01 October 2026

Designing a Model of Factors Affecting Online Sales in AI Tool-Based Online Retail Stores

Morteza. Samami[1], Younos. Vakil Alroaia[2*], Hasan. Vahedi[1], Seyed Hossein. Hosseini[3]

1. Department of Management, Sha.C., Islamic Azad University, Shahrood, Iran
2. Department of Management, Mash.C., Islamic Azad University, Mahdishahr, Iran
3. Department of Management, Sha.c, Islamic Azad University, Shahrood, Iran

*** Corresponding author email address:** y.vakil@iau.ac.ir

Article Info

Article type:
Original Research

How to cite this article:
Samami, M., Vakil Alroaia, Y., Vahedi, H., & Hosseini, S. H. (2026). Designing a Model of Factors Affecting Online Sales in AI Tool-Based Online Retail Stores. *AI and Tech in Behavioral and Social Sciences, 4*(4), 1-13.
https://doi.org/10.61838/kman.aitech.5604

ABSTRACT

Artificial intelligence (AI) has become a major technological driver of online retailing and can influence sales through data-driven, automated, and personalized decision-support tools. The present study aimed to develop a localized model of factors affecting online sales in AI tool-based online retail stores. The research was conducted using a mixed-methods qualitative-quantitative approach with an exploratory sequential mixed-methods design. In the qualitative phase, thematic analysis based on the King and Horrocks approach was used to identify the dimensions and components of the conceptual model. Qualitative data were collected through semi-structured interviews with 15 experts in e-commerce, artificial intelligence, and digital marketing, selected through purposive and snowball sampling. Data collection and analysis continued until thematic saturation was achieved. In the quantitative phase, a survey method was used to empirically test the extracted model. The statistical population consisted of consumers of online retail stores in Iran who had prior experience with AI-enabled online shopping. A stratified sampling strategy was used, and the sample size was determined as 384 respondents based on Cochran's formula. Data were gathered through a researcher-made questionnaire and analyzed by structural equation modeling using the partial least squares approach (PLS-SEM). The qualitative findings showed that data-driven analysis, specialized human capital, and intelligent capabilities such as personalization and prediction emerged as core themes in explaining AI-enabled online sales, and that their effects are realized through interaction with organizational and cultural factors. By presenting a comprehensive localized conceptual framework, the qualitative phase strengthens the theoretical contribution of the study by identifying and integrating contextual factors, intelligent mechanisms, and outcomes of AI-enabled online sales. The quantitative results statistically supported the relationships among the model constructs and the significance of the principal paths. These results demonstrate the critical role of data-driven decision-making and intelligent capabilities in improving customer experience, trust, and online sales performance. By testing an integrated structural model, the findings also advance the empirical contribution of the study through the quantitative validation of an AI-enabled online sales model and the provision of actionable evidence for managerial decision-making.

Keywords: *Online sales; online retail stores; artificial intelligence; AI tools*

1. Introduction

In recent decades, the rapid development of online stores and the expansion of e-commerce have transformed the traditional structure of retailing globally and in Iran. Online sales, understood as commercial transactions conducted through the internet, have become a core pillar of the digital economy (Toutian & Ali-Atashi, 2024). The

COVID-19 pandemic, digital infrastructure transformation, and the increasing penetration of smartphones have fundamentally changed consumer purchase behavior and have made business-model innovation a competitive necessity (E Commerce Development Center, 2024; Nagy & Hajdú, 2021). International estimates suggest that by 2026 more than 24% of global retail sales will occur online, while in Iran the value of e-commerce transactions in 2023/2024 reached 2.3 quadrillion tomans (E Commerce Development Center, 2024; Statista, 2025). Online stores, through models such as business-to-consumer (B2C) and consumer-to-consumer (C2C) commerce, have responded to the needs of different groups of consumers and have increased their flexibility in the face of technological change (Shirmohammadi & Bostanmanesh, 2022).

Within this transformation, AI has played a decisive role in redefining the online shopping experience. Intelligent recommender systems, chatbots, machine-learning algorithms, behavioral-data analysis, and content personalization facilitate purchase decisions and, by increasing interaction and conversion rates, improve the competitiveness of online stores (Bawack et al., 2022; Dixit et al., 2025; Haleem et al., 2022; Wu et al., 2020). AI not only makes the shopping experience more efficient and targeted, but also uses individual-level data to provide users with personalized products and content (Chen & Prentice, 2025; Madanchian, 2024). Recent studies identify trust in AI technology, hedonic motivation, online shopping habits, personal innovativeness, perceived risk, and expected customer value as important variables affecting the acceptance of AI tools (Dixit et al., 2025; Nagy & Hajdú, 2021; Zhang et al., 2019). These factors are especially important among younger Iranian consumers, for whom online shopping has become part of everyday life.

Despite these developments, online sales industries at global and national levels still face several challenges. Globally, concerns about data security, privacy, algorithmic bias, and the transparency of intelligent decision-making can reduce users' willingness to use AI-based services (Gantumur, 2025; Zhang et al., 2019). Examples of data misuse or opaque automated decisions have contributed to the erosion of consumer trust and have made the policy environment more complex (Dixit et al., 2025; Wu et al., 2020). In Iran, these challenges have additional dimensions: weak data infrastructure, shortage of AI specialists, lack of localized recommender systems, cultural distance in trust toward technology, and legal gaps are among the key barriers to effective intelligent commerce (Iranian Virtual Businesses, 2023).

Although several studies have examined the application of AI in online sales, fewer studies have designed a comprehensive localized mixed model that simultaneously accounts for technological, organizational, behavioral, and environmental dimensions. Previous research has often relied on models such as the technology acceptance model (TAM) and the unified theory of acceptance and use of technology 2 (UTAUT2), which mainly focus on individual behavior or technology acceptance (Dixit et al., 2025; Papastamoulou & Antonopoulos, 2025). However, realistic analysis of online store performance requires models that also account for organizational strategy, digital maturity, and environmental factors. In Iran, many existing studies have used descriptive or single-factor approaches and have considered only one dimension, such as technology or customer behavior, while overlooking the complex interaction among humans, technology, and organizational structure.

This theoretical and practical gap has limited the design of a localized success model for AI-enabled online sales. If this gap continues, it may reduce customer loyalty, increase dependence on foreign platforms, waste organizational resources, and deepen the digital divide between Iran and more digitally advanced economies (E Commerce Development Center, 2024; Iranian Virtual Businesses, 2023; Vakil Alroaia & Nazari Ghazvini, 2022). Therefore, the present study seeks to develop a comprehensive localized model of factors affecting online sales in AI tool-based online retail stores. By emphasizing the three-way interaction among technology, human agency, and organization, the model may provide a strategic framework for the intelligent development of e-commerce in Iran and for improving customer satisfaction, loyalty, and sustainability of the national digital ecosystem (Bawack et al., 2022; Harandi & Ebrahimi, 2024). Therefore, the main research question is: *How can a model of factors affecting online sales in AI tool-based online retail stores be designed, explained, and localized?*

2. Literature Review

In recent years, AI has increasingly influenced digital marketing. Domestic studies have examined its effects on consumer behavior and business performance from different angles. Nasrabadi et al. (2025) showed that targeted use of AI tools can improve the quality of the purchase experience by providing personalized recommendations and more efficient responses (Nasrabadi et al., 2025). Pashaei et al. (2025) designed a qualitative AI-based model for improving the online purchase process of sports products and highlighted personalization, security, and intelligent interactions as key determinants of customer satisfaction (Pashaei et al., 2025). Salehi-Nasab (2025), using grounded theory, identified factors affecting the use of AI in sports-goods marketing and proposed strategies for improving business performance (Salehi-Nasab, 2025). Farjami et al. (2025) used bibliometric analysis to examine the growth and evolution of AI in digital marketing among small and medium-sized enterprises, identifying four major thematic clusters that suggest a movement from infrastructural issues toward strategic and functional concerns (Farjami et al., 2025).

Other studies have emphasized both the opportunities and risks of AI. Esmailzadeh-Ashini and Asadollahi Dehkordi (2025), using a mixed-methods approach, examined negative consequences of AI in digital marketing and identified privacy violations, reduced human interaction, and high implementation costs as major challenges (Esmailzadeh-Ashini & Asadollahi Dehkordi, 2025). Safinia and Ghavami (2024) showed that the integration of the Internet of Things and AI can enable real-time data collection and analysis, prediction of emotional behavior, and identification of impulse-purchase stimuli (Safinia & Ghavami, 2024). Mirfazli et al. (2024) showed in the insurance industry that AI, through improved advertising targeting, content personalization, decision automation, and advertising cost optimization, can increase marketing effectiveness and sales performance (Mirfazli et al., 2024). Fekrat and Jaberi (2024) demonstrated that AI-based marketing can strengthen sales and exports of Iranian sports goods through big-data analysis, digital marketing development, content-marketing strategies, and neuromarketing (Fekrat & Jaberi, 2024).

Domestic studies also show that AI is not merely an efficiency tool but a transformational approach to redesigning decision-making models, customer-interaction strategies, and data-management structures in online sales. Zarei et al. (2024) found that AI reshapes branding, customer-behavior analysis, and customer-relationship management in international marketing (Zarei et al., 2024). Dabestani Ghomsari et al. (2024) reported that big-data analysis and machine-learning algorithms improve advertising targeting, customer acquisition and retention, and conversion rates (Dabestani Ghomsari et al., 2024). Harandi and Ebrahimi (2024), through meta-synthesis, proposed a three-level framework of mechanical, thinking, and feeling AI in banking marketing (Harandi & Ebrahimi, 2024). Najafi et al. (2024) showed that integrating AI into marketing policy redesigns market strategies, increases decision agility, and improves customer-behavior analysis (Najafi et al., 2024).

Further domestic research has addressed implementation conditions. Bashkooh-Ajirloo and Mohammadkhani (2023), using a mixed approach and grounded theory, proposed a structural model for implementing B2B digital marketing with an emphasis on AI-based customer relationship management (Bashkooh-Ajirloo & Mohammadkhani, 2023). Jafari and Haji-Babaei (2023), drawing on TAM, identified trust, perceived usefulness, ease of use, and positive attitude as the main drivers of AI acceptance in online shopping (Jafari & Haji-Babaei, 2023). Kazemi Saraskanrood and Safari (2023), through a systematic review of 140 papers, proposed a five-stage AI-based marketing process that includes mechanical, thinking, and feeling AI (Kazemi Saraskanrood & Safari, 2023). Shirmohammadi and Bostanmanesh (2022) found that ease of use, perceived usefulness, perceived enjoyment, and technological readiness positively affect purchase intention in smart stores during the COVID-19 period (Shirmohammadi & Bostanmanesh, 2022). Yazdanparast et al. (2022) classified forty AI applications in online marketing and identified personalized advertising and sentiment analysis as among the most important applications (Yazdanparast et al., 2022).

International research similarly confirms the transformational role of AI in online purchasing and online sales. Gantumur (2025) found that chatbots, personalized recommender systems, and user-identification technologies can align the purchase journey with individual customer characteristics and increase interaction, decision ease, and purchase intention, although privacy and cybersecurity remain major trust-related concerns (Gantumur, 2025). Dixit et al. (2025), using UTAUT2, showed that trust in AI systems, habit, and hedonic motivation are strong predictors of behavioral intention and use behavior in online shopping (Dixit et al., 2025). Papastamoulou and Antonopoulos (2025) compared AI practices across leading e-commerce platforms and highlighted applications in customer service, logistics, personalization, security, and supply-chain management (Papastamoulou & Antonopoulos, 2025). Gao and Liang (2025) showed that AI-powered virtual try-on technology can increase young consumers' impulsive purchase intention through perceived functional and hedonic value and immersion, with brand trust acting as a moderator (Gao & Liang, 2025).

International reviews also emphasize predictive analytics, conversational AI, and customer perceptions. Bawack et al. (2022) and Haleem et al. (2022) reported that AI applications in e-commerce and marketing improve targeting, personalization, customer engagement, and decision support when supported by appropriate data quality and governance (Bawack et al., 2022; Haleem et al., 2022). Riandhi et al. (2025) concluded that customer attitudes and perceptions, especially trust and privacy concerns, play an important role in the acceptance of AI-oriented technologies (Riandhi et al., 2025). Chen and Prentice (2025) proposed a conceptual framework for AI and customer experience, showing that AI improves the customer journey through personalization, need prediction, and interaction facilitation (Chen & Prentice, 2025). Aljarboa (2024) identified dynamic capabilities, entrepreneurial orientation, and customer-centric systems as key determinants of AI adoption in e-commerce SMEs (Aljarboa, 2024). Madanchian (2024) concluded that AI-driven marketing tools, including chatbots and personalization systems, positively affect customer acquisition, conversion rate, and overall sales performance (Madanchian, 2024).

Recent applied literature provides a more detailed picture of AI in sales optimization. Pereira et al. (2022) showed that customer models can support AI-based decision making in online retail supply chains (Pereira et al., 2022). Madanchian (2024) emphasized that customer-data analysis, conversational engagement, and recommender systems can transform purchase experience, satisfaction, loyalty, and conversion (Madanchian, 2024). Alkudah and Almomani (2024) found that recommender systems, conversational tools, and smart analytics engines personalize the online shopping experience and increase purchase probability and user satisfaction, while highlighting data accuracy and privacy concerns (Alkudah & Almomani, 2024). Bawack et al. (2022) and Haleem et al. (2022) likewise emphasized AI applications in personalization, marketing decision-making, and sentiment analysis, while noting the growing importance of ethics and algorithmic transparency (Bawack et al., 2022; Haleem et al., 2022).

Overall, the domestic and international literature shows that AI is a driving force in e-commerce and online sales. AI tools such as recommender systems, intelligent chatbots, and big-data analytics increase trust, personalize purchase experience, and support intelligent sales decisions. At the same time, ethical issues, privacy protection, data quality, and algorithmic transparency remain fundamental conditions for sustainable implementation. Thus, an effective model of AI-enabled online sales must integrate technological, behavioral, organizational, and ethical dimensions in a single explanatory framework.

3. Methods and Materials

This study was conducted to design and test a model of factors affecting online sales in AI tool-based online retail stores. It used a mixed qualitative-quantitative approach with an exploratory sequential mixed-methods design. In the first stage, thematic analysis based on King and Horrocks (2010) was used to identify the dimensions, components, and main indicators of the conceptual model. Qualitative data were collected through semi-structured interviews with experts in e-commerce, artificial intelligence, and digital marketing (King & Horrocks, 2010). Initial coding, theme clustering, and construction of thematic networks were then used to extract basic, organizing, and overarching themes, which formed the basis of the initial conceptual model.

Qualitative sampling was non-probability purposive and snowball sampling. This approach was used to reach participants with the richest information and the highest practical or research experience related to the topic. Consistent with Patton (2002), purposive sampling in qualitative research enables concentration on information-rich cases, and snowball sampling facilitates access to specialized expert networks (Patton, 2002). The qualitative population consisted of three groups: senior managers of online stores, experts in sales-technology start-ups, and university faculty members in AI and digital marketing. Selection criteria included effective managerial or executive experience, practical experience in applying AI tools to online sales, participation in innovative digital projects, or credible research experience in the relevant field.

Thematic saturation was reached after 12 initial interviews and the absence of new themes in three consecutive interviews; ultimately, 15 semi-structured interviews formed the basis of the conceptual modeling. In the second phase, the extracted model was empirically tested using a quantitative survey. The statistical population consisted of consumers of active online retail stores across

AITBSS E-ISSN: 3041-9433

Iran who had at least one online purchase experience from reputable Iranian stores during the previous two years and had encountered AI tools such as recommender systems, chatbots, or personalized advertisements during the purchase process.

A stratified sampling strategy was used to reflect diversity in consumer behavior and levels of interaction with smart technologies. Stratification was based on age, geographic location, online purchase experience, and level of interaction with AI tools; participants were then recruited within each stratum according to the predefined sampling plan. Because the size of the target population was large and not precisely known, the sample size was calculated using Cochran's formula (1963), with a 95% confidence level and a 0.05 margin of error. The final sample consisted of 384 respondents. Quantitative data were collected through a researcher-made questionnaire administered both online and in person. Questionnaire items were developed based on the components extracted from thematic analysis.

PLS-SEM was used to analyze the data and test the proposed model, using SmartPLS software. This method was selected because of the exploratory nature of the study, the complexity of the conceptual model, the presence of multidimensional constructs, and the absence of a strict normality requirement. First, the measurement model was assessed through reliability and validity indices. Then, the structural model was evaluated through path coefficients, explained variance, predictive power, and model-fit indicators.

4. Findings and Results

Qualitative data were collected through semi-structured interviews with 15 experts. Interviews continued until thematic saturation was achieved, meaning that sampling proceeded until responses became repetitive and no new data emerged. After transcribing the interviews and completing them with field notes taken during the interview sessions, the researcher repeatedly reviewed the interview texts and identified independent ideas as basic themes. These basic themes were then abstracted into organizing and overarching themes, and a thematic network was drawn. Thematic networks show relationships among themes in a non-linear manner; they are analytical tools rather than the analysis itself. After developing a satisfactory thematic network, the researcher returned to the original texts and interpreted them with the aid of the network.

To strengthen qualitative trustworthiness, coding was reviewed by an independent second coder, and inter-coder agreement was assessed. Cohen's kappa coefficient was 0.75, indicating acceptable agreement. In addition, the extracted themes were reviewed by three academic experts to support content validity and interpretive credibility.

In the thematic analysis process, 121 initial codes were extracted from expert responses. To avoid excessive length in the main manuscript, Table 1 summarizes the final thematic structure by core theme and representative basic themes; the complete coding matrix can be provided as supplementary material.

Table 1

Summary of Final Research Themes

No.	Core theme	Representative basic themes
1	Specialized human capital and professional expertise	Data-driven activity background; R&D and technology-management roles; market-data analysis; online-sales management; start-up experience; computer-science and UX expertise; digital-sales consulting; smart product management
2	Data analysis and data-driven decision-making based on AI tools	Customer and transaction-data analysis; conversion of data into insight; managerial decision support; technical-business KPIs; real-time decision-making; BI integration; organizational analytical maturity; automation of sales processes
3	Personalization and recommender systems based on AI tools	Sales personalization; improved targeting accuracy; customer clustering; AI-based dynamic pricing; campaign personalization; recommendation based on purchase history and browsing behavior
4	Prediction and predictive intelligence based on AI tools	Prediction of purchase behavior, churn, dissatisfaction, campaign return, and offer effectiveness; use of machine learning; sales-scenario analysis; predictive view of future sales
5	User experience and customer experience (UX/CX)	Interaction-data analysis; user-search data; chatbot use; purchase-decision simplification; reduced purchase friction; customer textual-feedback and sentiment analysis; smart customer-journey design; real-time intelligent interaction
6	Human role and trust in AI use	Human role in analysis; privacy concerns; data and algorithm transparency; user sense of control; social acceptance of AI; human-machine hybrid model; ethics-oriented AI use
7	Data and infrastructure challenges of AI tools	Fragmented and siloed data; weak system integration; data-quality problems; local API use; system-connectivity limitations; data-integration challenges; data-security concerns

AITBSS E-ISSN: 3041-9433

8	Organizational and cultural challenges of AI tools	Cultural resistance to data-driven decision-making; unrealistic expectations from tools; employee training needs; resistance to AI and chatbots; organizational knowledge gaps; gradual deployment; technical-marketing collaboration; senior-management support; data-driven leadership
9	Sales performance outcomes	Customer lifetime value; conversion-rate increase; average order value; customer retention and loyalty; customer satisfaction; revenue sustainability; AI-based competitive advantage; digital brand differentiation; marketing-cost reduction
10	Operational and logistics applications	Market-demand forecasting; inventory optimization; intelligent order scheduling; seasonal demand analysis; supply-chain coordination; delivery-delay reduction; improved delivery-time accuracy; sales-logistics data connection

The results of the thematic analysis (Table 1) show that the factors affecting online sales in AI tool-based online retail stores constitute a multidimensional and dynamic phenomenon that depends on the simultaneous interaction of human, technological, data-driven, and organizational factors. The extracted themes begin with the specialized human-capital and professional-expertise dimensions and then move toward the central role of data analysis and AI-based data-driven decision-making in sales, marketing, customer experience, and logistics operations. Expert backgrounds, including data-driven experience, managerial and technical roles, and experience in technology, digital sales, customer experience, and AI, provide the context for analytical thinking and organizational acceptance of AI tools.

The findings indicate that data analysis and decision-making based on AI tools form the core of the phenomenon. The use of behavioral, transactional, and market data; conversion of data into actionable insights; application of analytical effectiveness indicators; and connection of business-intelligence systems to operational processes enable more accurate, faster, and smarter decisions in competitive online sales environments. In this regard, organizational analytical maturity and the institutionalization of a data-driven decision culture are decisive conditions for AI effectiveness.

Sales personalization and AI-based recommender systems were identified as one of the most important practical applications of AI in online stores. Customer clustering, improved targeting, personalized prices, discounts, content, and offers based on behavior and purchase history can increase interaction, improve purchase experience, and strengthen campaign effectiveness. Predictive intelligence also plays an important role in sales foresight. Machine-learning algorithms can predict purchase behavior, churn, dissatisfaction, campaign returns, and offer effectiveness, thereby transforming online sales from a reactive activity into a predictive intelligent process.

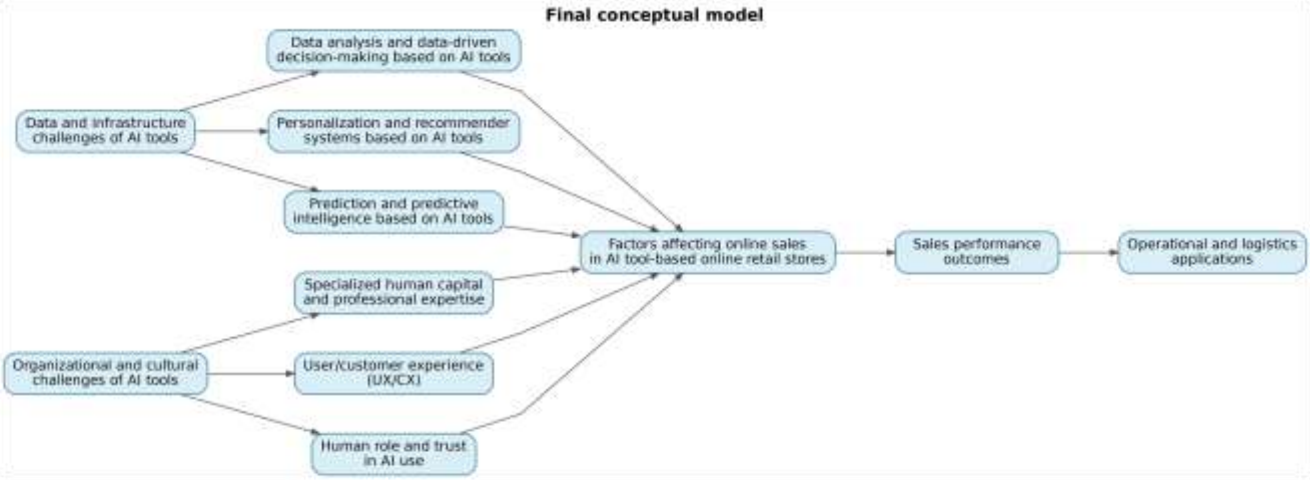
UX/CX was also identified as a central source of competitive advantage in AI-enabled online stores. Analysis of interaction data, user search behavior, textual feedback, and customer sentiment, together with chatbots and intelligent customer-journey design, reduces friction in the purchase process, simplifies decision-making, and creates an integrated personalized experience. At the same time, the findings emphasize the role of humans, trust, and ethical considerations. Privacy, algorithmic transparency, user control, and social acceptance show that AI effectiveness depends not only on technical capability but also on how humans interact with these technologies.

The findings also reveal data, infrastructure, organizational, and cultural challenges. Data fragmentation, weak system integration, data-quality problems, security concerns, employee resistance, and organizational knowledge gaps can limit the realization of AI-enabled smart sales. Conversely, senior management support, data-driven leadership, continuous employee training, and collaboration between technical and marketing teams help overcome these barriers. The main performance and operational outcomes include increased conversion rate, higher customer lifetime value, customer loyalty and satisfaction, lower marketing costs, revenue sustainability, AI-based competitive advantage, demand forecasting, inventory optimization, and supply-chain coordination.

AITBSS
E-ISSN: 3041-9433

Figure 1

Final Research Model



Composite reliability. Construct reliability is usually assessed using Cronbach's alpha, but in PLS-SEM a more appropriate and modern criterion, composite reliability (CR), is also used. Composite reliability estimates reliability based on the actual correlations among indicators rather than assuming equal loadings, as is the case in Cronbach's alpha. Therefore, both indices are generally reported in PLS-SEM. CR values above 0.70 indicate acceptable internal consistency. For higher-order constructs, CR should be computed manually when necessary using the standard formula based on factor loadings (λ) and error variances (δ): $CR = (\Sigma\lambda_i)^2 / [(\Sigma\lambda_i)^2 + \Sigma\delta_i]$.

Table 2

Composite Reliability Values of Research Variables

Core themes	Composite reliability (CR)	Cronbach's alpha (α)	Status
Specialized human capital and professional expertise	0.942	0.928	Confirmed
Data analysis and data-driven decision-making based on AI tools	0.955	0.946	Confirmed
Personalization and recommender systems based on AI tools	0.961	0.953	Confirmed
Prediction and predictive intelligence based on AI tools	0.958	0.949	Confirmed
User experience and customer experience (UX/CX)	0.947	0.936	Confirmed
Human role and trust in AI use	0.934	0.921	Confirmed
Data and infrastructure challenges of AI tools	0.929	0.914	Confirmed
Organizational and cultural challenges of AI tools	0.936	0.922	Confirmed
Sales performance outcomes	0.963	0.956	Confirmed
Operational and logistics applications	0.951	0.941	Confirmed

As shown in Table 2, the CR and Cronbach's alpha values for all core themes are above the 0.70 threshold, indicating desirable reliability of the constructs in the measurement model. These results show that the indicators defined for each core theme have adequate internal consistency and that the measurement instrument has sufficient stability for structural-model analysis.

Convergent validity. Convergent validity is an important criterion for assessing the fit of measurement models in PLS-SEM and is examined using average variance

AITBSS E-ISSN: 3041-9433

extracted (AVE). AVE indicates the average shared variance between a construct and its indicators. According to Fornell and Larcker (1981), AVE values above 0.50 indicate acceptable convergent validity. In this study, the AVE values of all variables were above 0.50 and were within the acceptable range.

Table 3

Convergent Validity Indices of the Constructs

Core themes	AVE	Composite reliability (CR)	Convergent validity status
Specialized human capital and professional expertise	0.762	0.942	Confirmed
Data analysis and data-driven decision-making based on AI tools	0.801	0.955	Confirmed
Personalization and recommender systems based on AI tools	0.824	0.961	Confirmed
Prediction and predictive intelligence based on AI tools	0.809	0.958	Confirmed
User experience and customer experience (UX/CX)	0.771	0.947	Confirmed
Human role and trust in AI use	0.748	0.934	Confirmed
Data and infrastructure challenges of AI tools	0.721	0.929	Confirmed
Organizational and cultural challenges of AI tools	0.735	0.936	Confirmed
Sales performance outcomes	0.832	0.963	Confirmed
Operational and logistics applications	0.787	0.951	Confirmed

Based on Table 3, AVE values for all core themes exceed 0.50, confirming convergent validity in the measurement model. Moreover, CR values for all constructs exceed 0.70, indicating appropriate reliability and internal coherence of the indicators.

Discriminant validity. To ensure conceptual distinction among the model constructs, discriminant validity was assessed using the Fornell–Larcker matrix. The main rule is that the square root of AVE (√AVE) for each construct should be greater than the correlations of that construct with all other constructs.

Table 4

Discriminant Validity Based on the Fornell–Larcker Matrix

Constructs	SHC	DDM	PER	FOR	UXCX	HT	DCH	OCH	SPO	OPL
Specialized human capital and professional expertise (SHC)	0.872									
Data analysis and data-driven decision-making (DDM)	0.641	0.895								
Personalization and recommender systems (PER)	0.598	0.712	0.908							
Prediction and predictive intelligence (FOR)	0.567	0.689	0.746	0.899						
User/customer experience (UXCX)	0.624	0.671	0.709	0.683	0.878					
Human role and trust (HT)	0.655	0.634	0.612	0.598	0.742	0.865				

E-ISSN: 3041-9433

Data and infrastructure challenges (DCH)	0.511	0.566	0.583	0.552	0.601	0.617	0.849			
Organizational and cultural challenges (OCH)	0.537	0.591	0.603	0.578	0.621	0.648	0.709	0.857		
Sales performance outcomes (SPO)	0.613	0.746	0.778	0.752	0.715	0.642	0.588	0.617	0.912	
Operational and logistics applications (OPL)	0.589	0.703	0.734	0.719	0.694	0.623	0.571	0.598	0.781	0.887

As shown in Table 4, the square root of AVE for each core theme on the diagonal of the matrix is greater than the correlations between that construct and other constructs. Therefore, discriminant validity is established according to the Fornell–Larcker criterion, and the measurement model has sufficient validity for structural analysis.

To evaluate the proposed model within the PLS-SEM framework, several indicators were examined at three levels: measurement-model quality, structural-model explanatory power, and overall model fit. In the structural component, R^2, communality, and redundancy were considered. SRMR was reported as the main overall model-fit criterion, while d_ULS, d_G, and NFI were treated as supplementary indices. GoF was not retained as a primary validation criterion because contemporary PLS-SEM reporting gives greater priority to measurement reliability, discriminant validity, SRMR, R^2, predictive relevance, and bootstrapped path coefficients (Hair et al., 2022). Predictive-relevance indices were not interpreted because the original SmartPLS blindfolding or PLSpredict output was not available for independent verification. The results are summarized in Table 5.

Table 5

Summary of Model-Fit Criteria in the PLS Approach

Section	Criterion	Desired range	Study result	Status
Structural model fit	R^2	> 0.67 = strong	0.67 to 0.76	Strong fit
Structural model fit	Communality	Higher is better	0.72 to 0.83	Desirable
Structural model fit	Redundancy	Higher value = more desirable	0.52 to 0.63	Desirable
Overall model fit	SRMR	< 0.08	0.052 (saturated) / 0.056 (estimated)	Desirable
Overall model fit	d_ULS	Reported as supplementary residual-based information	1.214 / 1.186	Acceptable
Overall model fit	d_G	Reported as supplementary residual-based information	0.628 / 0.642	Desirable
Overall model fit	NFI	> 0.90	0.93 / 0.91	Desirable

The model-fit results indicate acceptable overall fit based primarily on SRMR and supportive structural indices. Because verified predictive-relevance output was not available in the submitted materials, predictive relevance is not interpreted in the present report.

After evaluating the measurement, structural, and overall models, the standardized path coefficients and t-values were examined. A t-value greater than 1.96 or less than -1.96 indicates significance at the 95% confidence level. Figure 2 presents the standardized path coefficients, and Figure 3 presents the t-values for the relationships among the main and core factors.

Figure 2

Research Model in Standardized Coefficient Mode

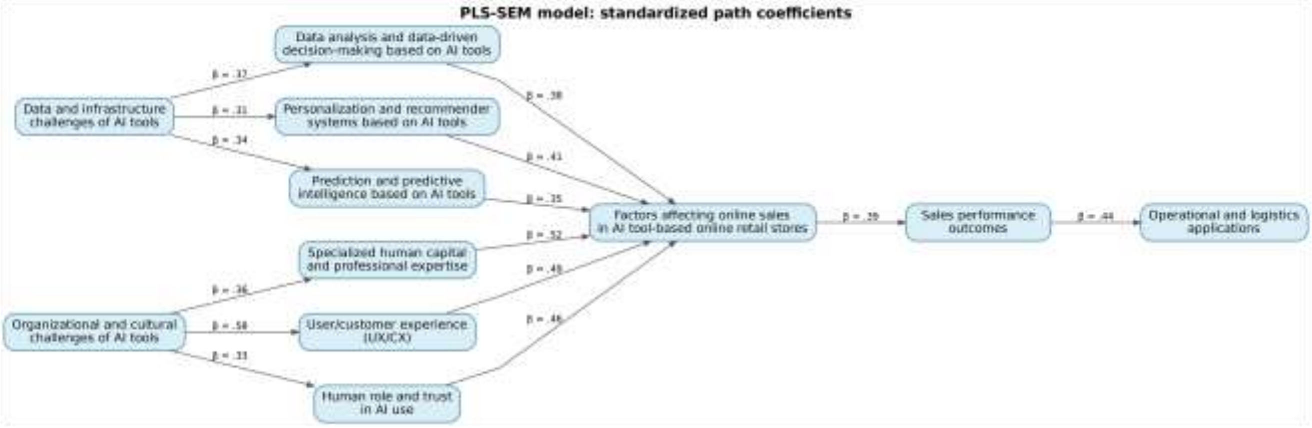


Figure 3

Research Model in t-Value Mode

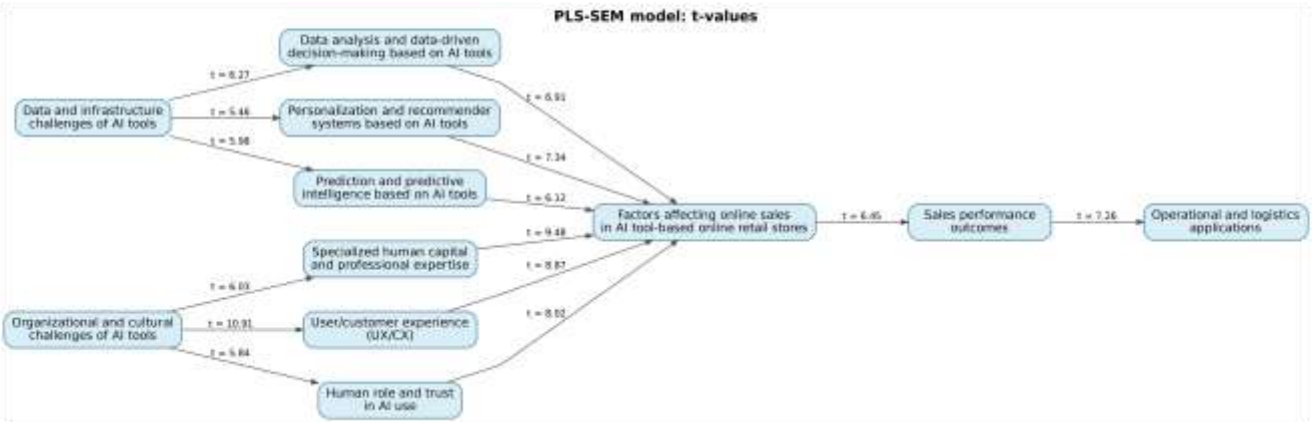


Table 6

Results of Structural Model Hypothesis Testing (PLS-SEM)

No.	Hypothesized path	Path coefficient (β)	t	p	Result
H1	Data analysis and data-driven decision-making based on AI tools → factors affecting online sales	0.38	6.91	< 0.001	Confirmed
H2	Personalization and recommender systems based on AI tools → factors affecting online sales	0.41	7.34	< 0.001	Confirmed
H3	Prediction and predictive intelligence based on AI tools → factors affecting online sales	0.35	6.12	< 0.001	Confirmed
H4	Specialized human capital and professional expertise → factors affecting online sales	0.52	9.48	< 0.001	Confirmed
H5	User experience and customer experience (UX/CX) → factors affecting online sales	0.49	8.87	< 0.001	Confirmed
H6	Human role and trust in AI use → factors affecting online sales	0.46	8.02	< 0.001	Confirmed
H7	Factors affecting online sales → sales performance outcomes	0.39	6.45	< 0.001	Confirmed
H8	Sales performance outcomes → operational and logistics applications	0.44	7.26	< 0.001	Confirmed
H9	Organizational and cultural challenges → specialized human capital and professional expertise	0.36	6.03	< 0.001	Confirmed
H10	Organizational and cultural challenges → user/customer experience (UX/CX)	0.58	10.91	< 0.001	Confirmed
H11	Organizational and cultural challenges → human role and trust	0.33	5.84	< 0.001	Confirmed
H12	Data and infrastructure challenges → data analysis and data-driven decision-making	0.37	6.27	< 0.001	Confirmed
H13	Data and infrastructure challenges → personalization and recommender systems	0.31	5.46	< 0.001	Confirmed
H14	Data and infrastructure challenges → prediction and predictive intelligence	0.34	5.98	< 0.001	Confirmed

Considering the research topic and the results of hypothesis testing, the findings can be explained as follows. The proposed model has acceptable explanatory support, as all 14 hypothesized paths were statistically significant at $p < 0.001$. This indicates that the defined relationships among the technological, human, organizational, and outcome-related dimensions of AI-enabled online sales are statistically supported within the proposed model.

At the level of factors affecting online sales, the findings show that human and experience-oriented components have the strongest effects. Specialized human capital and professional expertise had the highest path coefficient (β = 0.52), indicating that the success of AI tools in online stores depends strongly on expertise, knowledge, and professional experience in designing, implementing, and interpreting the outputs of these technologies. UX/CX followed with a high coefficient (β = 0.49), demonstrating the importance of intelligent, user-friendly, and personalized customer interactions in the online environment. Human role and trust (β = 0.46) also had a significant effect, emphasizing algorithmic transparency, data privacy, and the continued importance of the human element in intelligent interactions.

Technological components also had positive and significant effects on online sales: personalization and recommender systems (β = 0.41), data analysis and data-driven decision-making (β = 0.38), and prediction and predictive intelligence (β = 0.35). These findings indicate that successful online sales result from combining advanced data analysis with AI tools capable of predicting customer behavior and presenting personalized offers.

In the outcome section, the factors affecting online sales had a direct effect on sales performance outcomes (β = 0.39). This means that effective use of AI tools not only increases sales, conversion rates, and customer satisfaction, but also improves key sales-performance indicators. Sales performance outcomes also had a significant association with operational and logistics applications (β = 0.44), indicating that smart-sales mechanisms are connected not only with marketing and customer interaction but also with operations, supply chains, and intelligent logistics.

The analysis of challenges revealed that organizational and cultural challenges had the strongest effect on UX/CX (β = 0.58). This indicates that organizational resistance, traditional culture, lack of innovation acceptance, and weak digital orientation can directly affect online customer experience. These challenges also affected specialized human capital and professional expertise (β = 0.36) and human role and trust (β = 0.33), emphasizing the importance of cultural and structural readiness for effective AI adoption. Data and infrastructure challenges significantly affected all technological components, with the strongest effect on data analysis and data-driven decision-making (β = 0.37), followed by prediction and predictive intelligence (β = 0.34), and personalization and recommender systems (β = 0.31). These results show that without appropriate data infrastructure, data quality, system integration, and information security, the advanced capabilities of AI in online sales cannot be fully realized.

5. Discussion and Conclusion

The present study aimed to explain the factors affecting the use of AI in online sales and its consequences by proposing a conceptual model based on data-driven analysis and expert perspectives. The model was tested using PLS-SEM. The findings show that data analysis and data-driven decision-making constitute the central core of the model and play a fundamental role in activating intelligent capabilities in online sales. This result is consistent with research emphasizing the role of big data, machine-learning algorithms, and advanced analytics in improving marketing and sales decisions.

Specialized human capital and professional expertise were identified as an important contextual factor for the successful implementation of AI-based technologies. Without specialized human capital, even advanced technological infrastructures may fail to produce desirable outcomes. The results also showed that personalization and recommender systems, as well as prediction and predictive intelligence, were significant components of the broader AI-enabled online sales model. Therefore, the main value of AI in online sales lies not merely in the technology itself but in the intelligent use of technology to understand customer behavior more accurately and respond to individual needs more precisely.

UX/CX and customer trust were identified as central experience- and trust-related components that support the explanation of sales performance and operational-logistics efficiency. At the same time, data, infrastructure, organizational, and cultural challenges represent serious barriers to the deployment of AI in online sales. These barriers can influence the direction and strength of the effects among the main constructs. Therefore, success in using AI requires simultaneous attention to technical, human, and organizational dimensions.

E-ISSN: 3041-9433

From a theoretical perspective, this study contributes to the literature by proposing an integrated model that simultaneously accounts for contextual factors, intelligent mechanisms, and performance outcomes. From an applied perspective, the findings can guide managers and decision-makers in designing data-driven strategies, investing in AI infrastructure, and developing specialized human resources.

6. Limitations and Future Research

This study is limited by its cross-sectional design, reliance on self-reported survey responses, and focus on consumers of Iranian online retail stores. Therefore, causal interpretation should be avoided and the generalizability of the model should be tested in other industries, countries, and organizational contexts. Future studies should report full item-level measurement information, bootstrapping settings, HTMT ratios, and PLSpredict or blindfolding outputs, and should examine potential moderating variables such as organization size, digital maturity, market type, and consumer AI literacy.

For managers, the findings indicate that technological development alone is insufficient. Organizations should build a data-driven culture, train employees, integrate technical and marketing teams, strengthen customer trust, and ensure transparency and privacy protection. In this way, the benefits of AI in online sales can be achieved more sustainably and effectively.

Authors' Contributions

All authors contributed to the study conception and design, data interpretation, manuscript preparation, and critical revision. All authors reviewed and approved the final version of the manuscript.

Declaration

AI-based language assistance was used only for translation, English-language editing, and formatting support. The authors remain fully responsible for the scientific content, accuracy of data, interpretation of results, reference accuracy, and final approval of the manuscript.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

Acknowledgments

We would like to express our gratitude to all individuals helped us to do the project.

Declaration of Interest

The authors report no conflict of interest.

Funding

According to the authors, this article has no financial support.

Ethics Considerations

The study involved expert interviews and consumer survey responses. Participation was voluntary, and participants were informed about the purpose of the study, the confidentiality of responses, and their right to withdraw from participation. No personally identifiable information is reported in the manuscript. Interview and questionnaire data were used only for research purposes and were stored securely. No formal ethical approval code is reported in the submitted materials; therefore, this manuscript does not claim institutional ethics approval.

References

Aljarboa, S. (2024). Factors influencing the adoption of artificial intelligence in e-commerce by small and medium-sized enterprises. *International Journal of Information Management Data Insights*, *4*(2), 100285. https://doi.org/10.1016/j.jjimei.2024.100285

Alkudah, N. M., & Almomani, T. O. (2024). The integration of artificial intelligence techniques in e-commerce: Enhancing online shopping experience and personalization. *Global Journal of Economics and Business*, *14*(6), 640-658. https://doi.org/10.31559/GJEB2024.14.6.8

Bashkooh-Ajirloo, M., & Mohammadkhani, R. (2023). Designing a model for implementing business-to-business digital marketing with an emphasis on AI-based customer relationship management. *Modern Marketing Research*, *13*(3), 133-158.

Bawack, R. E., Wamba, S. F., Carillo, K. D. A., & Akter, S. (2022). Artificial intelligence in e-commerce: A bibliometric study and literature review. *Electronic Markets*, *32*(1), 297-338. https://doi.org/10.1007/s12525-022-00537-z

Chen, Y., & Prentice, C. (2025). Integrating artificial intelligence and customer experience. *Australasian Marketing Journal*, *33*(2), 141-153. https://doi.org/10.1177/14413582241252904

Dabestani Ghomsari, E., Zibaei, E., & Dabestani Ghomsari, M. (2024). Examining the role of artificial intelligence in digital marketing strategies. Proceedings of the 10th International Conference on Science, Engineering, Technology, and Technology-Based Businesses,

Dixit, R. S., Choudhary, S. L., & Govil, N. (2025). Analyzing the impact of artificial intelligence on the online purchase decision-making process through the lens of the UTAUT 2 model. *Discover Computing*, *28*, 88. https://doi.org/10.1007/s10791-025-09575-5

AITBSS
E-ISSN: 3041-9433

E Commerce Development Center. (2024). *Annual report on e-commerce in Iran*. Ministry of Industry, Mine and Trade.
Esmailzadeh-Ashini, M. T., & Asadollahi Dehkordi, E. (2025). Examining the negative consequences of using artificial intelligence in digital marketing. *Advertising and Sales Management*, *6*(2), 1-16.
Farjami, M., Feyz, D., Khademi, M., & Sharafi, V. (2025). Bibliometric analysis of the application of artificial intelligence in digital marketing in small and medium-sized enterprises: Past, present, and future. *Management Research in Iran*.
Fekrat, E., & Jaberi, A. (2024). Phenomenology of the role of artificial intelligence marketing in increasing sales and exports of Iranian sports goods. *Sport Marketing Studies*, *5*(2), 1-15. https://gsmsmr.uok.ac.ir/article_63167_en.html?lang=fa
Gantumur, K. (2025). The impact of artificial intelligence on online shopping. *European Scientific Journal*, *21*(4), 1-13. https://doi.org/10.19044/esj.2025.v21n4p1
Gao, Y., & Liang, J. (2025). The impact of AI-powered try-on technology on online consumers' impulsive buying intention: The moderating role of brand trust. *Sustainability*, *17*(7), 2789. https://doi.org/10.3390/su17072789
Haleem, A., Javaid, M., Qadri, M. A., Singh, R. P., & Suman, R. (2022). Artificial intelligence (AI) applications for marketing: A literature-based study. *International Journal of Intelligent Networks*, *3*, 119-132. https://doi.org/10.1016/j.ijin.2022.08.005
Harandi, A., & Ebrahimi, A. (2024). Identifying factors affecting artificial intelligence in banking-industry marketing using a meta-synthesis approach. *Media Management Reviews*, *3*(3), 311-340.
Iranian Virtual Businesses, U. (2023). *Annual report on Iranian virtual businesses*.
Jafari, M., & Haji-Babaei, H. (2023). Examining factors affecting customers' acceptance of artificial intelligence in online purchases. Proceedings of the Sixth International Conference on New Developments in Management, Economics, and Accounting, Tehran.
Kazemi Saraskanrood, Z., & Safari, M. (2023). Designing an AI-based marketing process model: Application of the systematic review strategy. *Business Reviews*, *21*(123), 109-126.
King, N., & Horrocks, C. (2010). *Interviews in qualitative research*. Sage. https://www.torrossa.com/gs/resourceProxy?an=5019272&publisher=FZ7200
Madanchian, M. (2024). The impact of artificial intelligence marketing on e-commerce sales. *Systems*, *12*(10), 429. https://doi.org/10.3390/systems12100429
Mirfazli, S. M., Taghizadeh Fashkcheh, H., Mohammadpour Khabazi, N., & Gharibi, H. (2024). The effect of customer experience with artificial intelligence on electronic customer satisfaction, customer trust, and online purchase intention in the insurance industry. *New Approaches in Management and Marketing*, *3*(4), 1-21.
Nagy, S., & Hajdú, N. (2021). Consumer acceptance of the use of artificial intelligence in online shopping: Evidence from Hungary. *Amfiteatru Economic*, *23*(56), 155-173. https://doi.org/10.24818/EA/2021/56/155
Najafi, A., Noormohammad Nasrabadi, G., & Mohammadzadeh, S. (2024). The role of artificial intelligence in marketing policies and market management. *Standard and Quality Management*, *14*(1), 1-19.
Nasrabadi, G., Amiri, S., & Mohammadifar, Y. (2025). Examining the effect of artificial intelligence on customer satisfaction in purchasing consumer goods. *Modern Marketing Research*, *15*(1), 87-120.
Papastamoulou, P., & Antonopoulos, N. (2025). Artificial intelligence in e-commerce: A comparative analysis of best practices across leading platforms. *Systems*, *13*(9), 746. https://doi.org/10.3390/systems13090746
Pashaei, S., Abdovi, F., & Al-Azzawi, H. A. H. (2025). Designing an artificial intelligence model for improving the online purchase process of sports products. *Smart Strategic Management*, *4*(2), 135-168.
Patton, M. Q. (2002). *Qualitative research and evaluation methods* (3rd ed.). Sage. https://aulasvirtuales.files.wordpress.com/2014/02/qualitative-research-evaluation-methods-by-michael-patton.pdf
Pereira, A. M., Moura, J. A. B., Costa, E. D. B., Vieira, T., Landim, A. R. D. B., Bazaki, E., & Wanick, V. (2022). Customer models for artificial intelligence-based decision support in fashion online retail supply chains. *Decision Support Systems*, *158*, 113795. https://doi.org/10.1016/j.dss.2022.113795
Riandhi, A. N., Arviansyah, M. R., & Sondari, M. C. (2025). AI and consumer behavior: Trends, technologies, and future directions from a Scopus-based systematic review. *Cogent Business & Management*, *12*(1). https://doi.org/10.1080/23311975.2025.2544984
Safinia, A. M., & Ghavami, M. (2024). Examining the use of the Internet of Things in analyzing consumer behavior in emotional purchases using artificial intelligence. *Smart Marketing Management*, *5*(1), 105-129.
Salehi-Nasab, M. (2025). *Designing a conceptual model of factors affecting the application of artificial intelligence in sports-goods marketing* Behavioral Sciences Campus].
Shirmohammadi, Y., & Bostanmanesh, A. (2022). Designing a model of customer purchasing from smart stores during the COVID-19 period with an emphasis on artificial intelligence. *Smart Business Management Studies*, *11*(40), 233-263.
Statista. (2025). *Retail e-commerce sales worldwide*. Statista.
Toutian, S., & Ali-Atashi, E. (2024). Presenting a sustainable sales model with an emphasis on artificial intelligence in internet businesses. *Smart Marketing Management*, *5*(3), 90-111.
Vakil Alroaia, Y., & Nazari Ghazvini, S. (2022). Designing and explaining a model for creation and development of knowledge-based cooperative companies with a mixed qualitative-quantitative approach. *Journal of Applied Research on Industrial Engineering*, *9*(3), 291-311. https://doi.org/10.22105/jarie.2021.283145.1315
Wu, J., Yu, H., & Zhu, Y. Z. X. (2020). Impact of artificial intelligence recommendation on consumers' willingness to adopt. *Journal of Management Science*, *33*, 29-43.
Yazdanparast, S. M., Jamipour, M., & Jafari, S. M. B. (2022). Identifying and prioritizing applications of artificial intelligence in online marketing. *Business Management Explorations*, *14*(28), 103-137.
Zarei, G., Mohammadkhani, R., & Fathi, H. (2024). Examining and identifying the consequences of applying artificial intelligence in marketing. *Management Research in Iran*, *28*(2), 1-31.
Zhang, Y., Lv, W., & Zhang, J. (2019). Marketing research of AI: Prospect and challenges. *Journal of Management Science*, *32*, 75-86.

AITBSS
E-ISSN: 3041-9433