Future of Work and Digital Management Journal

Article type:
Original Research

Article history:
Received 09 April 2026
Revised 27 May 2026
Accepted 14 July 2026
Initial Publish 28 July 2026
Published online 01 May 2027

Explaining an Online Consumer Behavior Model in the Retail Industry: A Mixed-Methods Approach Based on Artificial Intelligence Tools

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How to cite this article:
Faridi, A., Mahmoudzadeh, M., & Budaghi Khajeh Nobar, H. (2027). Explaining an Online Consumer Behavior Model in the Retail Industry: A Mixed-Methods Approach Based on Artificial Intelligence Tools. *Future of Work and Digital Management Journal, 5*(3), 1-20. https://doi.org/10.61838/fwdmj.299

ABSTRACT

This study aimed to explain a comprehensive model of online consumer behavior in Iran's retail industry, with an emphasis on the role of artificial intelligence tools and local contextual considerations. The study was conducted using an exploratory mixed-methods design. In the qualitative phase, the main categories were extracted through grounded theory and semi-structured interviews with 15 experts in the retail industry. Subsequently, in the quantitative phase, a researcher-developed questionnaire was designed based on the qualitative findings and administered to 384 customers selected through convenience-based random sampling. The conceptual model was then tested. Quantitative data were analyzed using path analysis and structural equation modeling. The qualitative findings resulted in the identification of a paradigmatic model comprising causal conditions, including intelligent personalization and data-driven interaction; contextual conditions, including technological infrastructure, digital trust, and a culture of technology acceptance; and intervening conditions, including privacy concerns and economic constraints. In addition to confirming the significance of the proposed relationships, the quantitative findings demonstrated that "environmental readiness for e-commerce" played a key mediating role in transforming intelligent capabilities into an "intelligent purchasing process" and "perceived value." The analyses indicated that artificial intelligence exerted direct and significant effects on customer satisfaction and loyalty by improving the quality of the customer experience and simplifying the decision-making journey. The proposed model demonstrates that artificial intelligence in Iran's retail industry is not merely a technological tool but rather a strategic capability whose success depends on a dual approach integrating technology and ethics. Explaining consumer behavior in this complex environment requires strengthening trust-building infrastructure and algorithmic transparency alongside the development of data analytics capabilities. The findings provide retail managers with a roadmap for transitioning toward "knowledge-based intelligent retailing" to achieve sustainable competitive advantage.

Keywords: Artificial intelligence, online consumer behavior, intelligent retailing, exploratory mixed-methods design, grounded theory.

Introduction

The rapid expansion of digital technologies has fundamentally transformed the structure, logic, and competitive dynamics of the retail industry. Consumers are no longer passive recipients of standardized products and marketing messages; instead, they participate in highly interactive, data-intensive, and technology-mediated purchasing environments in which their preferences, searches, clicks, reviews, purchase histories, and post-purchase responses continuously generate behavioral data. Online retail platforms use these data to recognize consumption patterns, predict future demand, personalize recommendations, automate communication, and shape customers' decision-making processes. This transformation has made online consumer behavior one of the most strategically important fields in contemporary marketing and retail management. Understanding why consumers select a platform, how they evaluate algorithmically generated recommendations, what factors influence their trust, and how artificial intelligence affects their satisfaction and loyalty has become essential for retailers seeking sustainable competitive advantage in increasingly crowded digital markets. Artificial intelligence has therefore moved beyond its traditional role as an operational technology and has become a central mechanism through which retail organizations interpret customer behavior, design value propositions, and manage long-term customer relationships [1, 2].

Online consumer behavior refers to the set of cognitive, emotional, social, and behavioral processes through which individuals recognize needs, search for information, evaluate alternatives, make purchasing decisions, and assess consumption outcomes in digital environments. Although many foundational principles of consumer behavior remain relevant in online settings, the digital purchasing environment introduces distinctive characteristics, including reduced physical interaction, extensive information availability, algorithmic mediation, virtual product presentation, automated communication, and heightened uncertainty regarding privacy and security. In conventional retailing, consumers often rely on direct product inspection, face-to-face interaction, physical cues, and the reputation of the store. In online retailing, however, the purchasing process is influenced by platform design, information quality, recommendation systems, ratings, digital payment mechanisms, delivery reliability, and perceptions of data protection. These conditions create a complex behavioral environment in which technological convenience may coexist with mistrust, personalization may coexist with privacy concerns, and automated efficiency may coexist with uncertainty regarding the intentions and accountability of intelligent systems. Consequently, explaining online consumer behavior requires an integrated framework that simultaneously considers technological capabilities, consumer perceptions, environmental readiness, and contextual constraints.

Artificial intelligence has significantly expanded the ability of retailers to collect, process, and interpret customer data. Machine learning algorithms, neural networks, natural language processing systems, recommendation engines, predictive analytics, intelligent customer relationship management systems, chatbots, virtual assistants, and generative artificial intelligence applications now support various stages of the consumer journey. These technologies can analyze large volumes of structured and unstructured data, identify latent behavioral patterns, segment customers dynamically, predict purchasing intentions, detect dissatisfaction, and deliver personalized content in real time. The use of artificial intelligence in behavioral analytics allows retailers to move from descriptive analysis of past transactions toward predictive and prescriptive models that estimate future behavior and recommend appropriate managerial actions. Research on artificial intelligence algorithms and neural networks has shown that these technologies can improve the prediction of customer preferences and behavioral responses by identifying complex relationships that may not be detectable through conventional analytical methods [3]. Similarly, artificial intelligence–based user and entity behavior analytics has expanded organizational capabilities for recognizing behavioral deviations, modeling user interactions, and generating more accurate customer profiles [4].

The development of artificial intelligence in marketing has also altered the conceptual basis of consumer analysis. Earlier applications of artificial intelligence were primarily predictive, focusing on forecasting demand, classifying customers, and estimating purchase probability. More recent generative systems can create text, images, product descriptions, personalized messages, conversational responses, and dynamic promotional content. This shift from predictive to generative artificial intelligence has expanded the influence of intelligent technologies from backstage analytical functions to direct customerfacing interactions. Artificial intelligence can now participate actively in the construction of the consumption experience by responding to questions, recommending products, generating persuasive content, and adapting communications to the characteristics of individual consumers. Accordingly, consumer responses are shaped not only by the accuracy of predictions but also by the perceived human-likeness, transparency, relevance, and ethical conduct of artificial intelligence systems [1]. The emergence of generative artificial intelligence has therefore created new managerial opportunities while raising questions about autonomy, persuasion, consciousness attribution, behavioral manipulation, and ethical responsibility [5].

Personalization is among the most prominent mechanisms through which artificial intelligence affects online consumer behavior. Intelligent personalization refers to the automated adaptation of products, recommendations, communication, website content, prices, and promotional offers according to individual customer data and inferred preferences. Effective personalization can reduce the cognitive burden associated with evaluating numerous alternatives, improve the relevance of information, shorten the purchasing journey, and increase the perceived convenience of digital shopping. When consumers believe that a platform understands their needs and offers useful recommendations, they are more likely to perceive greater value and develop favorable attitudes toward the platform. Artificial intelligence can also strengthen self-congruence by aligning the presented products and experiences with consumers' perceived identities, lifestyles, and personal values. Evidence indicates that perceived value and self-congruence are important mechanisms underlying consumers' engagement with artificial intelligence–based technologies, as customers are more willing to interact with intelligent systems when these systems are perceived as useful, relevant, and consistent with their self-concept [6]. Thus, personalization is not simply a technical process of recommendation accuracy; it is a psychological and relational process through which consumers assess whether the digital environment recognizes and supports their individual preferences.

However, the effectiveness of personalization depends on the quality of data-driven interaction. Online retail platforms continuously communicate with customers through automated messages, chatbots, recommendation systems, notifications, loyalty applications, and intelligent support services. These forms of interaction can provide immediate assistance, answer frequently asked questions, facilitate product comparison, and guide consumers through purchasing decisions. Intelligent interaction can also improve service availability because artificial intelligence systems can operate continuously without the time and capacity limitations associated with human employees. Nevertheless, the behavioral impact of such interaction depends on perceived responsiveness, empathy, accuracy, and ease of use. Consumers may respond positively to intelligent services when they provide relevant and efficient assistance, but poorly designed systems may create frustration, confusion, or perceptions of impersonality. The application of artificial intelligence in brand management and customer behavior analysis indicates that intelligent interactions influence not only individual transactions but also broader perceptions of brand competence, innovation, and customer orientation [7]. Therefore, retailers must treat artificial intelligence–mediated interaction as a strategic component of relationship management rather than merely an instrument for reducing service costs.

The anthropomorphic characteristics of artificial intelligence systems represent another important determinant of consumer responses. Anthropomorphism occurs when consumers attribute human-like appearance, intentions, emotions, or social capacities to nonhuman technologies. Chatbots with names, avatars, conversational language, and human-like expressions can increase social presence and make digital interactions more engaging. However, the effects of anthropomorphism are not uniform and may depend on product type, consumer expectations, and the perceived appropriateness of human-like design. Artificial intelligence products with anthropomorphic appearances can influence consumers' evaluations of both the technology and the associated brand, but the direction and strength of these effects vary across product categories and usage situations [8]. In retail contexts, anthropomorphic systems may reduce psychological distance and improve engagement, yet excessive human-likeness may also create discomfort or unrealistic expectations regarding intelligence and empathy. This duality highlights the need to examine intelligent customer experiences as multidimensional phenomena shaped by technological design, psychological interpretation, and situational fit.

Consumer trust is particularly important in online environments because purchasing decisions occur under conditions of information asymmetry and perceived risk. Customers must trust that the retailer will deliver the promised product, protect financial information, use personal data responsibly, and provide effective remedies when problems occur. Artificial intelligence may strengthen trust by improving service consistency, fraud detection, product relevance, and response speed. Conversely, opaque algorithms, unexplained recommendations, unauthorized data collection, and unclear responsibility for automated decisions may weaken trust. Consumers often have limited knowledge of how their information is processed, which variables are used to generate recommendations, and whether algorithmic outcomes serve their interests or primarily advance organizational objectives. Therefore, digital trust depends not only on technological security but also on transparency, procedural fairness, accountability, and perceived ethical conduct.

The disclosure of artificial intelligence involvement is one aspect of transparency that may significantly influence consumer judgments. When customers are informed that they are interacting with an artificial intelligence system rather than a human representative, their behavioral responses may change depending on their expectations, perceptions of responsibility, and social judgments. Research indicates that the disclosure of artificial intelligence identity can influence unethical consumer behavior, suggesting that customers may apply different moral standards when interacting with a machine than when interacting with a human agent [9]. This finding has major implications for online retail management because the use of artificial intelligence may affect not only purchase intention and satisfaction but also honesty, opportunistic behavior, complaint practices, and adherence to platform rules. Retailers must therefore consider how artificial intelligence identity is communicated and how transparency affects customers' perceptions of accountability and social obligation.

Privacy concerns constitute one of the principal intervening conditions in artificial intelligence–based retailing. The high level of personalization enabled by artificial intelligence depends on access to extensive customer data, including browsing histories, locations, preferences, financial transactions, social interactions, and behavioral patterns. Although such data can improve service relevance, consumers may perceive intensive data collection as intrusive, especially when they do not understand how the information was obtained or used. Privacy concerns can reduce willingness to disclose information, limit engagement with personalization features, and weaken trust in the platform. They may also produce a personalization paradox in which consumers value customized services while simultaneously resisting the data practices required to generate them. Ethical issues become particularly salient when artificial intelligence systems infer sensitive characteristics or influence behavior without adequate consumer awareness. The interrelationship among artificial intelligence, behavior, consciousness, and ethics demonstrates that technological innovation cannot be separated from questions of autonomy, informed consent, fairness, and human agency [5].

Emerging neurotechnologies may further intensify these ethical and managerial challenges. Neurotechnology-based consumer research can potentially identify emotional, cognitive, and attentional responses that consumers may be unable or unwilling to articulate explicitly. Combined with artificial intelligence, neurological and biometric data may enable firms to decode complex behavioral reactions, improve product design, and predict consumer choices with greater precision. Nevertheless, these technologies raise serious concerns regarding mental privacy, manipulation, informed consent, and the ownership of sensitive behavioral information. The use of neurotechnology for decoding consumer behavior presents substantial opportunities for more accurate analysis but also introduces methodological, regulatory, and ethical challenges that require careful governance [10]. Although such technologies may not yet be widely implemented in all retail environments, their development illustrates the growing depth of artificial intelligence–based behavioral observation and reinforces the importance of incorporating ethical safeguards into consumer behavior models.

The effects of artificial intelligence on consumers are also shaped by perceived value. Perceived value reflects consumers' overall evaluation of the benefits received relative to the monetary, cognitive, emotional, temporal, and privacy-related costs incurred. Artificial intelligence may enhance functional value through speed, convenience, and recommendation accuracy; emotional value through enjoyable and personalized experiences; and social value through innovative and identity-consistent interactions. However, consumers may perceive lower value when automated services are inaccurate, difficult to use, excessively intrusive, or insufficiently transparent. Engagement with artificial intelligence–based services is therefore influenced by the balance between technological benefits and perceived sacrifices. The relationship among perceived value, self-congruence, and engagement behavior suggests that consumers respond more favorably when intelligent technologies deliver meaningful benefits that are compatible with their personal expectations and identities [6]. Perceived value consequently functions as a critical link between artificial intelligence capabilities and behavioral outcomes such as satisfaction, continued use, loyalty, and positive word of mouth.

Customer satisfaction and loyalty are among the most important outcomes of artificial intelligence–enabled retailing. Satisfaction emerges when the actual shopping experience meets or exceeds customer expectations regarding convenience, reliability, personalization, support, and product suitability. Artificial intelligence can improve satisfaction by reducing search costs, providing timely responses, predicting customer needs, and minimizing friction across the purchasing journey. Repeated satisfactory experiences can subsequently strengthen loyalty, increase repurchase intention, and reduce customer sensitivity to competing offers. Nevertheless, loyalty in digital markets is often fragile because switching costs are low and consumers can compare alternatives rapidly. Consequently, artificial intelligence must create more than momentary convenience; it must contribute to a coherent and trustworthy customer experience. Meta-analytic evidence regarding artificial intelligence and Industry 4.0–based products indicates that intelligent technologies can significantly affect consumer behavior characteristics, although the magnitude of their impact varies according to technological, demographic, and contextual conditions [2].

Environmental readiness for e-commerce represents a critical contextual condition that determines whether artificial intelligence capabilities can be translated into meaningful consumer outcomes. Environmental readiness includes the availability of reliable digital infrastructure, internet accessibility, secure payment systems, data-processing capabilities, logistics networks, regulatory support, and public technological literacy. Even advanced artificial intelligence systems may fail to generate customer value when platforms experience technical instability, payment insecurity, weak delivery systems, or insufficient integration among digital services. Similarly, consumers may be reluctant to use intelligent retail services when they lack confidence in digital technologies or encounter difficulties in accessing online platforms. Therefore, the effects of artificial intelligence should not be examined independently of the institutional and technological ecosystem in which online retailing operates. Artificial intelligence capabilities produce strategic value when they are supported by adequate infrastructure, organizational preparedness, and a culture of technology acceptance.

Economic and infrastructural limitations may also moderate the adoption and effectiveness of intelligent retailing. Implementing artificial intelligence requires investments in data architecture, software, cybersecurity, skilled personnel, integration, maintenance, and organizational learning. Large retail firms may possess the resources necessary to develop advanced systems, while smaller retailers may face substantial financial and technical barriers. Economic instability can additionally influence consumers' purchasing power, price sensitivity, risk perception, and willingness to experiment with new technologies. In such contexts, retailers must balance technological sophistication with affordability, usability, and local relevance. Models developed in technologically advanced markets may not adequately explain consumer behavior in environments characterized by uneven infrastructure, regulatory ambiguity, limited digital literacy, and distinctive cultural expectations. This limitation is especially important in emerging markets, where the adoption of artificial intelligence may occur alongside structural constraints that affect both firms and customers.

The Iranian retail industry provides a particularly important context for examining these relationships. The expansion of online retail platforms, digital payments, social commerce, and mobile shopping has created significant opportunities for intelligent personalization and data-driven marketing. At the same time, retailers operate within a complex environment characterized by economic pressures, infrastructural variation, privacy concerns, differences in technological literacy, and evolving consumer trust in digital transactions. Iranian consumers may appreciate the convenience and relevance created by artificial intelligence while remaining cautious about data collection, algorithmic decision-making, and the reliability of online platforms. Iranian research has increasingly emphasized the role of artificial intelligence in predicting customer behavior, managing brands, and analyzing user activity [3, 4, 7]. Nevertheless, there remains a need for an integrated model that connects intelligent capabilities with environmental readiness, constraints, customer experience, purchasing processes, and perceived value.

A significant gap in the literature concerns the fragmentation of existing explanations. Some studies focus primarily on predictive accuracy and behavioral analytics, whereas others examine personalization, anthropomorphism, trust, engagement, ethics, or brand evaluation. Although each perspective contributes important insights, online consumer behavior in artificial intelligence–enabled retailing is the product of simultaneous interactions among technological, psychological, organizational, environmental, and ethical factors. A comprehensive explanation must account for how intelligent capabilities initiate behavioral processes, how contextual conditions facilitate or inhibit their effects, how consumers experience algorithmically mediated purchasing, and how these experiences generate perceived value and behavioral consequences. Moreover, purely quantitative models may impose predetermined constructs without sufficiently capturing context-specific meanings, while exclusively qualitative studies may provide conceptual depth without statistically testing the relationships among the identified categories.

An exploratory mixed-methods approach is particularly appropriate for addressing this gap. Through qualitative inquiry, researchers can identify categories grounded in the experiences of retail managers and specialists and uncover locally relevant conditions that may not be adequately represented in existing theories. Through quantitative analysis, the resulting conceptual model can then be tested among consumers to evaluate the strength and significance of the proposed relationships. The integration of grounded theory with partial least squares structural equation modeling enables the development of a model that is both contextually meaningful and empirically testable. Such an approach is valuable for examining a rapidly evolving phenomenon in which established theories may not fully reflect the capabilities of generative artificial intelligence, emerging forms of data-driven interaction, changing consumer expectations, and ethical concerns.

Accordingly, the aim of this study was to explain and empirically test a comprehensive artificial intelligence–based model of online consumer behavior in Iran's retail industry by integrating intelligent capabilities, environmental readiness, environmental constraints, the intelligent purchasing process, intelligent customer experience, and consumers' perceived value.

Methodology

From the perspective of its objective, this study was applied research, and in terms of data collection, it employed a mixed-methods approach with a sequential exploratory design (Qualitative → Quantitative). The mixed-methods approach enables researchers to obtain an in-depth understanding of the meaning of phenomena through qualitative data while enhancing the generalizability of the findings through quantitative data.

Qualitative Phase: Exploratory Component

In the qualitative phase, grounded theory was employed to identify the dimensions and components of artificial intelligence–based online purchasing behavior. This method was selected because of its exploratory nature and the theoretical gap in explaining consumer behavior in interactions with artificial intelligence.

Population and sample: The participants consisted of 15 managers and specialists in the online retail industry who were selected through purposive role-based sampling.

Data collection: The primary data collection instrument consisted of semi-structured interviews, which continued until theoretical saturation was reached—that is, until no new data emerged that could contribute to the further development of the categories.

Reliability: Cohen's kappa coefficient was used to assess the reliability of the coding process. The resulting coefficient of 0.78 indicated an acceptable level of agreement and stability in the qualitative analyses.

Quantitative Phase: Explanatory Component

In the quantitative phase, a survey method was employed to test the conceptual model derived from the qualitative phase and generalize it to the consumer population.

Population and sample: The statistical population consisted of customers of online retail platforms. Based on Cochran's formula and the calculations performed using G*Power software, the required sample size was determined to be 384 participants, who were selected through convenience-based random sampling.

Data collection instrument: A researcher-developed questionnaire was designed based on the components extracted during the qualitative phase. The validity of the questionnaire was confirmed through confirmatory factor analysis, and its reliability was verified using Cronbach's alpha coefficient.

Finally, by integrating the qualitative findings, including the extracted themes, with the quantitative results, including the path coefficients and model confirmation, the final artificial intelligence–based online consumer behavior model was explained. This two-phase process ensured that the research model was not only qualitatively rich but also statistically reliable.

Findings and Results

To integrate the findings of the qualitative phase, which was based on grounded theory, into a single table, the most appropriate approach is to present a paradigmatic model. This model represents the essence of the research findings and, in accordance with the standards of qualitative research articles, is generally summarized in a comprehensive table. In the following table, all identified categories have been integrated into the standard grounded theory classifications proposed by Strauss and Corbin.

Figure 1

Research Paradigmatic Model

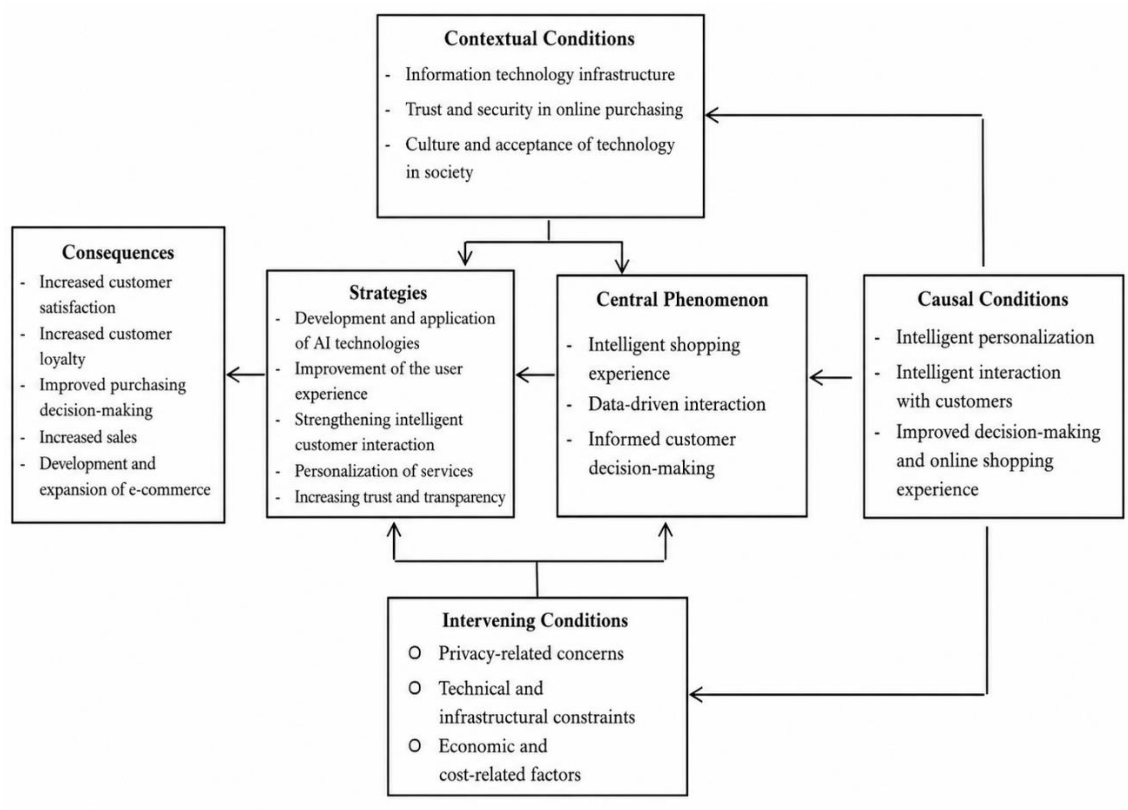

Table 1

Comprehensive Paradigmatic Model

Component of the Paradigmatic Model	Main Category or Theme	Subcategories and Key Concepts
Causal conditions	Behavioral drivers	Intelligent personalization; intelligent customer interaction, including chatbots and intelligent customer relationship management systems; online shopping experience motivations, including convenience and attractiveness
Contextual conditions	Influential contextual factors	Technological and big-data infrastructure; digital security and trust; the level of technological culture and literacy in society
Intervening conditions	Constraints and challenges	Privacy concerns; infrastructural deficiencies; economic constraints and implementation costs
Central phenomenon	Intelligent customer behavior	Intelligent purchasing experience; data-driven interaction; informed algorithm-based decision-making
Strategies	Retailers' actions	Development of artificial intelligence technologies; improvement of the user experience and user interface; personalization of services and recommendations; transparency regarding privacy
Consequences	Model outcomes	Increased satisfaction and loyalty; improved decision-making; growth in sales and profitability; development of the e-commerce ecosystem

The paradigmatic model of this study was developed based on the paradigmatic framework proposed by Strauss and Corbin. In light of these factors and conditions, the model and process of marketing intelligence based on the new product development process in the automotive industry were designed. Explaining the factors contributing to the emergence of this phenomenon was also a major concern of the present study. The research paradigmatic model is presented in Figure 1.

Given the large number of variables and based on the feedback received from experts and interview participants, the following summarized process model was extracted from the paradigmatic model and empirically tested. Accordingly, based on the model presented below, the research hypotheses in the quantitative phase were formulated as follows:

Hypothesis 1: Intelligent capabilities have a significant effect on environmental readiness for e-commerce.

Hypothesis 2: Intelligent capabilities have a significant effect on environmental constraints.

Hypothesis 3: Intelligent capabilities have a significant effect on the intelligent purchasing process.

Hypothesis 4: Environmental readiness for e-commerce has a significant effect on the intelligent enhancement of the customer experience.

Hypothesis 5: Environmental readiness for e-commerce has a significant effect on the intelligent purchasing process.

Hypothesis 6: Environmental constraints have a significant effect on the intelligent enhancement of the customer experience.

Hypothesis 7: Environmental constraints have a significant effect on the intelligent purchasing process.

Hypothesis 8: The intelligent purchasing process has a significant effect on the intelligent enhancement of the customer experience.

Hypothesis 9: The intelligent enhancement of the customer experience has a significant effect on the perceived value of online consumers.

Partial least squares structural equation modeling was employed to analyze the data. Three indicators were considered for evaluating convergent validity: factor loadings, average variance extracted, and composite reliability, also referred to as construct reliability. Average variance extracted is a measure of convergence among a set of observed indicators representing a construct. In other words, it represents the proportion of variance explained among the indicators. The average variance extracted must be greater than 0.50 for convergent validity to be supported (Fornell & Larcker, 1981). According to Fornell and Larcker (1981), composite reliability should also be 0.70 or higher, indicating adequate internal consistency. Table 2 presents the convergent validity, reliability, and model-fit indicators. Convergent validity means that the indicators of each construct ultimately provide an appropriate distinction in measurement relative to the other constructs in the model. In simpler terms, each indicator should measure only its corresponding construct, and their combination should enable all constructs to be clearly distinguished from one another. The average variance extracted values indicated that all the constructs under investigation had AVE values greater than 0.50. Composite reliability and Cronbach's alpha coefficients were used to evaluate the reliability of the questionnaire. All these coefficients were greater than 0.70, demonstrating the reliability of the measurement instrument. Therefore, based on the values presented in the table, construct validity and reliability were confirmed.

Table 2

Results of the Assessment of Construct Validity and Reliability

Latent Variable	AVE	CR	R^2	Cronbach's Alpha
Trust and security in online purchasing	0.76	0.90	0.727	0.88
Increased trust and transparency in online purchasing	0.65	0.85	0.799	0.73
Increased customer satisfaction	0.68	0.89	0.748	0.84
Increased sales and profitability of online retailers	0.81	0.93	0.491	0.88
Increased customer loyalty	0.70	0.88	0.717	0.79
Online shopping experience motivations	0.65	0.88	0.797	0.82
Improved user experience on purchasing platforms	0.67	0.86	0.626	0.90
Improved purchasing decision-making	0.71	0.88	0.684	0.80
Artificial intelligence–based intelligent purchasing experience	0.75	0.93	0.813	0.86
Informed customer decision-making in the online purchasing environment	0.73	0.86	0.760	0.88
Data-driven interaction between the customer and the retail platform	0.79	0.85	0.807	0.80
Intelligent customer interaction	0.79	0.86	0.819	0.91
Strengthening intelligent customer interaction	0.68	0.89	0.814	0.84
Development and application of artificial intelligence technologies	0.63	0.84	0.751	0.72
Development and expansion of e-commerce	0.61	0.86	0.397	0.79
Information technology infrastructure	0.55	0.86	0.679	0.79
Personalization of services and recommendations	0.76	0.90	0.437	0.84
Intelligent personalization of the purchasing experience	0.64	0.84	0.641	0.72
Economic and cost-related factors	0.81	0.93	0.491	0.88
Culture and acceptance of technology in society	0.70	0.80	0.717	0.77
Technical and infrastructural constraints	0.65	0.88	0.790	0.80
Privacy-related concerns	0.76	0.81	0.650	0.83

In addition to examining the correlation coefficients, Table 2 addresses discriminant validity. According to this criterion, the variance of each latent variable should be greater for its own indicators than for the indicators of other variables. To determine this condition, the square root of the AVE for each latent variable is first calculated and then compared with the correlations between that latent variable and the other latent variables. The square root of the AVE must be greater than the corresponding correlation coefficients. This procedure must be performed for all latent variables. The results of the Fornell–Larcker criterion are presented in the following table. The diagonal values in this table represent the square root of the average variance extracted. Discriminant validity is confirmed when the square root of the average variance extracted for each variable is greater than all its correlation coefficients with the remaining variables. As shown in the table, for all variables, the square root of the average variance extracted is greater than the correlations between that variable and the other variables. In addition to examining correlation coefficients, Table 3 evaluates discriminant validity. According to this criterion, the variance of each latent variable should be greater for its own indicators than for the indicators associated with the other variables. To evaluate this condition, the square root of the AVE for each latent variable is first calculated and then compared with the correlations between that latent variable and the remaining latent variables. The square root of the AVE must be greater than the corresponding correlation coefficients. This process must be conducted for all latent variables. The findings for the Fornell–Larcker criterion are reported in the following table. The diagonal values in the table represent the square root of the average variance extracted. Discriminant validity is confirmed when the square root of the average variance extracted for each variable is greater than all the correlation coefficients between that variable and the remaining variables. As presented in the table, the square root of the average variance extracted for all variables is greater than the correlations between the corresponding variable and the other variables.

Table 3

Correlation Matrix and Square Roots of the Average Variance Extracted for the Main Model

Component	1	2	3	4	5	6	7	8	9	10	11
1. Trust and security in online purchasing	0.834										
2. Increased trust and transparency in online purchasing	0.535	0.771									
3. Increased customer satisfaction	0.696	0.477	0.830								
4. Increased sales and profitability of online retailers	0.632	0.467	0.564	0.791							
5. Increased customer loyalty	0.609	0.588	0.525	0.470	0.640						
6. Online shopping experience motivations	0.414	0.376	0.347	0.222	0.450	0.801					
7. Improved user experience on purchasing platforms	0.524	0.418	0.463	0.306	0.456	0.319	0.794				
8. Improved purchasing decision-making	0.411	0.222	0.450	0.404	0.394	0.190	0.299	0.796			
9. AI-based intelligent purchasing experience	0.719	0.498	0.621	0.553	0.593	0.406	0.485	0.469	0.849		
10. Informed customer decision-making in the online purchasing environment	0.635	0.490	0.518	0.510	0.549	0.333	0.501	0.394	0.593	0.670	
11. Data-driven interaction between the customer and the retail platform	0.812	0.556	0.664	0.594	0.580	0.400	0.542	0.447	0.784	0.679	0.799
12. Intelligent customer interaction	0.641	0.487	0.535	0.414	0.462	0.297	0.628	0.295	0.494	0.588	0.597
13. Strengthening intelligent customer interaction	0.479	0.327	0.432	0.437	0.432	0.246	0.533	0.450	0.476	0.481	0.511
14. Development and application of AI technologies	0.728	0.445	0.735	0.604	0.583	0.357	0.460	0.348	0.616	0.553	0.663
15. Development and expansion of e-commerce	0.786	0.547	0.582	0.574	0.627	0.418	0.463	0.398	0.682	0.544	0.681
16. Information technology infrastructure	0.702	0.481	0.618	0.524	0.654	0.432	0.408	0.368	0.606	0.562	0.698
17. Personalization of services and recommendations	0.576	0.396	0.431	0.367	0.414	0.263	0.597	0.341	0.531	0.514	0.568
18. Intelligent personalization of the purchasing experience	0.643	0.584	0.556	0.511	0.578	0.359	0.563	0.501	0.667	0.628	0.684
19. Economic and cost-related factors	0.575	0.748	0.441	0.468	0.611	0.357	0.408	0.255	0.501	0.428	0.563
20. Culture and acceptance of technology in society	0.457	0.416	0.446	0.289	0.495	0.468	0.618	0.225	0.490	0.467	0.537
21. Technical and infrastructural constraints	0.689	0.700	0.611	0.570	0.598	0.347	0.434	0.414	0.637	0.619	0.695
22. Privacy-related concerns	0.544	0.431	0.408	0.453	0.415	0.131	0.373	0.393	0.483	0.624	0.501

Component	12	13	14	15	16	17	18	19	20	21	22
1. Trust and security in online purchasing											
2. Increased trust and transparency in online purchasing											
3. Increased customer satisfaction											
4. Increased sales and profitability of online retailers											
5. Increased customer loyalty											
6. Online shopping experience motivations											
7. Improved user experience on purchasing platforms											
8. Improved purchasing decision-making											
9. AI-based intelligent purchasing experience											
10. Informed customer decision-making in the online purchasing environment											
11. Data-driven interaction between the customer and the retail platform											
12. Intelligent customer interaction	0.818										
13. Strengthening intelligent customer interaction	0.531	0.841									
14. Development and application of AI technologies	0.532	0.401	0.857								
15. Development and expansion of e-commerce	0.496	0.466	0.624	0.856							
16. Information technology infrastructure	0.505	0.383	0.654	0.614	0.757						
17. Personalization of services and recommendations	0.599	0.529	0.457	0.495	0.443	0.808					
18. Intelligent personalization of the purchasing experience	0.621	0.581	0.597	0.603	0.588	0.539	0.757				
19. Economic and cost-related factors	0.503	0.364	0.437	0.585	0.504	0.357	0.526	0.816			
20. Culture and acceptance of technology in society	0.521	0.416	0.440	0.354	0.437	0.486	0.539	0.381	0.734		
21. Technical and infrastructural constraints	0.611	0.476	0.568	0.632	0.570	0.418	0.666	0.751	0.422	0.796	
22. Privacy-related concerns	0.488	0.355	0.360	0.400	0.431	0.419	0.492	0.468	0.252	0.649	0.814

The goodness-of-fit index demonstrates the compatibility between the quality of the structural model and that of the measurement model and is calculated

A goodness-of-fit value greater than 0.40 indicates an acceptable model fit. The calculated goodness-of-fit index was 0.739, which was greater than the threshold value of 0.40 and therefore indicated an appropriate model fit. In simpler terms, the data obtained in this study demonstrated an appropriate fit with the factor structure and the underlying theoretical framework of the research, indicating consistency between the questionnaire items and the theoretical constructs.

The second category of findings was devoted to testing the structural model and the research hypotheses. For this purpose, path coefficients and coefficients of determination were calculated using the partial least squares algorithm in SmartPLS software. Figure 2 tests all the measurement equations, including the first-order and second-order factor loadings and the path coefficients, using the *t* statistic. According to this model, a factor loading is statistically significant at the 95% confidence level when the corresponding *t* statistic falls outside the range of −1.96 to +1.96.

Figure 2

Research Structural Model in the Significance-Coefficient Mode

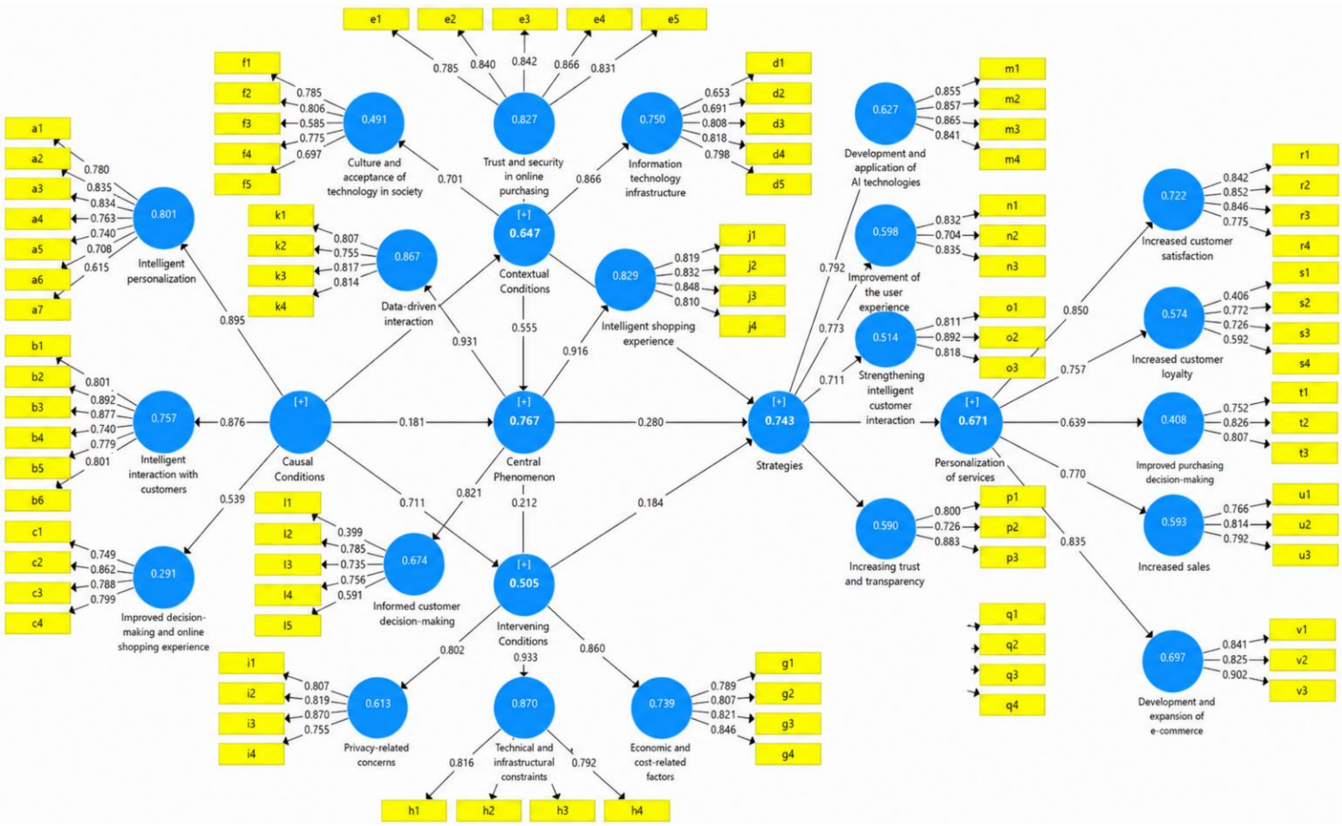

Figure 3

Research Structural Model in the Standardized-Coefficient Mode

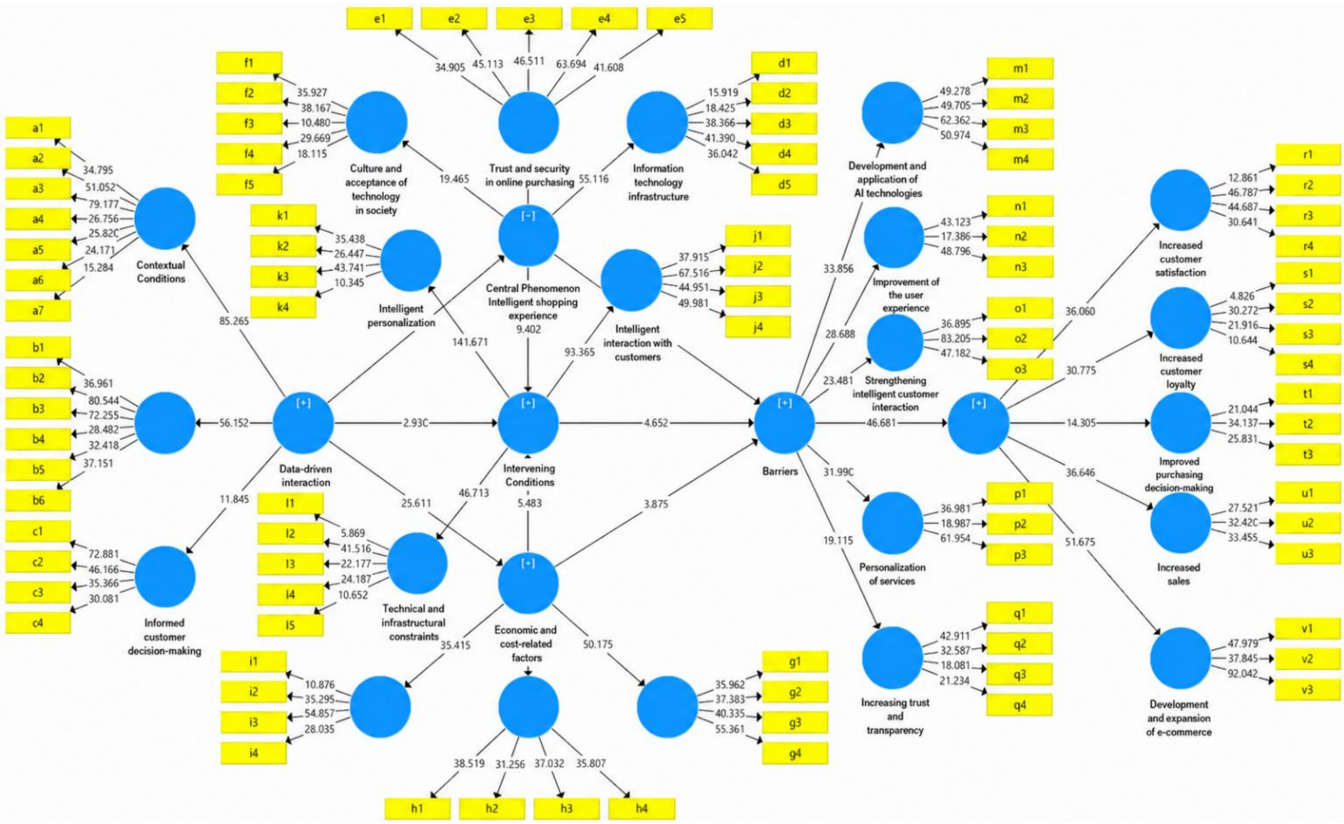

Figure 3 presents the research structural model in the standardized-coefficient mode. Accordingly, the estimated standardized factor loadings should be greater than 0.30 and, ideally, equal to or greater than 0.70 (Fornell & Larcker, 1981). All variables had factor loadings of at least 0.40. Therefore, at this stage, the consistency of the questionnaire items in measuring the corresponding concepts was considered acceptable.

Discussion and Conclusion

The present study aimed to explain a comprehensive model of online consumer behavior in Iran's retail industry by integrating artificial intelligence capabilities, environmental readiness for e-commerce, environmental constraints, the intelligent purchasing process, intelligent customer experience, and consumers' perceived value. The qualitative findings produced a paradigmatic model consisting of causal conditions, contextual conditions, intervening conditions, a central phenomenon, strategies, and consequences. Intelligent personalization, intelligent customer interaction, and shopping-experience motivations emerged as the principal causal conditions. Technological infrastructure, digital trust and security, and the culture of technology acceptance were identified as contextual conditions, whereas privacy concerns, technical and infrastructural weaknesses, and economic constraints constituted the major intervening conditions. The central phenomenon was characterized as intelligent customer behavior, reflected in an artificial intelligence–enabled shopping experience, data-driven interaction, and informed algorithm-supported decision-making. The quantitative findings subsequently confirmed the structural relationships extracted from the qualitative phase. In particular, intelligent capabilities significantly affected environmental readiness for e-commerce, environmental constraints, and the intelligent purchasing process. Environmental readiness significantly influenced both the intelligent purchasing process and the intelligent enhancement of customer experience. Environmental constraints also significantly affected these two constructs. Furthermore, the intelligent purchasing process significantly influenced the intelligent customer experience, which, in turn, exerted a significant effect on consumers' perceived value. Collectively, these findings demonstrate that the effects of artificial intelligence on consumer behavior are neither isolated nor exclusively technological; rather, they operate through an interconnected system of technological capabilities, contextual preparedness, perceived constraints, purchasing processes, and experiential evaluations.

The identification of intelligent capabilities as a primary causal condition indicates that artificial intelligence plays a foundational role in shaping online consumer behavior. These capabilities include intelligent personalization, automated interaction, predictive analytics, recommendation systems, chatbots, intelligent customer relationship management, and the use of behavioral data to anticipate customer needs. The significant effect of intelligent capabilities on the intelligent purchasing process suggests that artificial intelligence changes how consumers search for information, compare alternatives, evaluate products, and make final purchasing decisions. By processing extensive behavioral data, artificial intelligence can reduce information overload, prioritize relevant alternatives, and simplify the consumer journey. This interpretation is consistent with research showing that artificial intelligence and neural-network algorithms can identify complex patterns in customer data and improve the prediction of purchasing behavior [3]. It is also aligned with evidence that artificial intelligence and Industry 4.0–based products influence multiple dimensions of consumer behavior, including attitudes, adoption, decision-making, and consumption responses [2]. Therefore, the intelligent purchasing process identified in this study can be understood as a behavioral outcome of the platform's ability to transform fragmented customer data into relevant, timely, and actionable support.

The significant effect of intelligent capabilities on environmental readiness for e-commerce shows that the organizational use of artificial intelligence can contribute to the broader preparation of the digital retail environment. Although environmental readiness is often considered an antecedent of technological adoption, the present findings suggest a reciprocal developmental process in which the deployment of intelligent capabilities encourages retailers to strengthen their data infrastructure, digital service architecture, payment systems, information security, and customer-support mechanisms. In other words, artificial intelligence implementation generates new organizational requirements that may accelerate technological and managerial readiness. Retailers that adopt recommendation engines, automated support systems, or predictive analytics must improve data quality, system integration, cybersecurity, and human expertise. This finding corresponds with the argument that artificial intelligence has become a central marketing-management capability rather than a peripheral technical function [7]. It is also consistent with research emphasizing that artificial intelligence–based user and entity behavior analytics requires integrated data environments capable of collecting, classifying, and interpreting behavioral information [4]. Thus, intelligent capabilities and environmental readiness appear to reinforce one another within the transition toward intelligent retailing.

The significant relationship between intelligent capabilities and environmental constraints indicates that greater use of artificial intelligence simultaneously exposes or intensifies existing technical, economic, ethical, and infrastructural challenges. As intelligent systems become more sophisticated, retailers become increasingly dependent on high-quality data, stable technological infrastructure, specialized expertise, continuous system maintenance, and substantial financial investment. Artificial intelligence adoption may therefore make deficiencies in infrastructure and organizational capacity more visible. Moreover, increased personalization and behavioral tracking may intensify customer concerns about privacy, surveillance, and unauthorized data use. This result supports the view that artificial intelligence creates both opportunities and risks for firms and consumers. The literature on the behavioral and ethical implications of generative artificial intelligence emphasizes that technological advancement cannot be separated from issues such as transparency, responsibility, autonomy, and potential behavioral manipulation [5]. Similarly, the application of neurotechnology and artificial intelligence to consumer-behavior decoding has been associated with significant concerns regarding consent, mental privacy, data ownership, and the ethical boundaries of persuasion [10]. Therefore, environmental constraints should not be interpreted merely as external barriers; they are partly generated or amplified by the increasing depth of intelligent consumer analysis.

The findings also demonstrated that environmental readiness for e-commerce significantly influenced the intelligent purchasing process. This result indicates that artificial intelligence capabilities do not automatically produce effective consumer outcomes unless they are supported by reliable technological and institutional conditions. Consumers can benefit from intelligent recommendations and automated decision support only when the platform offers stable access, secure payments, accurate information, rapid processing, dependable delivery, and adequate protection of customer data. Environmental readiness reduces friction across the customer journey and enables intelligent tools to perform consistently. Inadequate infrastructure, by contrast, can undermine even advanced artificial intelligence applications. For example, a sophisticated recommendation system may have little behavioral value when the platform is slow, transaction procedures are unreliable, inventory information is inaccurate, or delivery systems are weak. The importance of behavioral analytics and data-driven customer prediction identified in earlier studies assumes the existence of an adequate information infrastructure and reliable data-processing capabilities [3, 4]. The present findings therefore extend this literature by demonstrating that environmental readiness functions as a key mechanism through which intelligent capabilities are translated into improved purchasing processes.

Environmental readiness also had a significant effect on the intelligent enhancement of customer experience. This finding suggests that the customer experience is not determined solely by visible artificial intelligence features, such as chatbots or personalized recommendations, but by the overall reliability and coherence of the digital retail ecosystem. Customers evaluate their experience across multiple touchpoints, including registration, product search, comparison, payment, communication, delivery, return procedures, and post-purchase support. Artificial intelligence can enhance these touchpoints only when technological systems are integrated and aligned with consumer expectations. The development of artificial intelligence from predictive applications toward direct, generative, and interactive systems has increased its influence on the visible customer experience [1]. Generative systems can now produce personalized messages, explanations, product descriptions, and conversational responses, but their effectiveness depends on accuracy, responsiveness, and integration with the broader service process. Consequently, environmental readiness provides the operational foundation required for customers to perceive intelligent services as useful, seamless, and trustworthy.

The significant effects of environmental constraints on both the intelligent purchasing process and the intelligent customer experience reveal the central role of contextual barriers in shaping consumer responses. Privacy concerns, economic limitations, technical weaknesses, and insufficient digital literacy can alter how customers interpret and use artificial intelligence–enabled services. Even when intelligent technologies increase convenience, consumers may avoid them if they believe that the platform collects excessive personal information or uses opaque algorithms. Likewise, consumers may not fully benefit from personalized services when internet access is unstable, digital interfaces are complex, or online payment systems are perceived as unsafe. The significant relationship found in this study may also reflect the possibility that constraints do not always eliminate artificial intelligence use but change the nature and intensity of its effects. For instance, privacy concerns may make customers more cautious, encourage selective disclosure, or increase demand for transparency. Research has shown that disclosing the artificial intelligence identity of an interaction partner can influence consumers' judgments and even their unethical behavior, because consumers may apply different social and moral expectations to machines and humans [9]. Accordingly, the effects of environmental constraints involve not only technological access but also moral judgment, trust formation, and perceptions of accountability.

The qualitative identification of privacy and transparency as critical components is especially important. Artificial intelligence–based personalization requires extensive behavioral data, yet consumers may not clearly understand how recommendations are generated or how their information is stored and processed. This tension can weaken trust and reduce perceived control. The findings suggest that retailers must establish a balance between personalization and privacy protection. Excessive personalization without transparent explanations may be perceived as intrusive, whereas relevant recommendations delivered within a trustworthy governance framework may improve the experience. The relationship between artificial intelligence identity disclosure and consumer behavior reported by Li et al. indicates that transparency regarding the nature of the intelligent agent can alter consumer responses [9]. Similarly, ethical discussions surrounding generative artificial intelligence emphasize the importance of informed interaction, human oversight, and the prevention of manipulative behavioral influence [5]. The present study therefore supports the view that algorithmic transparency is not simply a legal or technical obligation but a central component of consumer-experience management.

Another major finding was the significant effect of the intelligent purchasing process on the intelligent enhancement of customer experience. This result implies that customer experience is shaped by how effectively artificial intelligence supports the sequence of purchasing activities rather than merely by the presence of innovative features. When artificial intelligence helps customers clarify their needs, find relevant products, compare alternatives, evaluate information, and complete transactions efficiently, the entire experience becomes more coherent and satisfying. Consumers are likely to evaluate intelligent retailing positively when the technology reduces effort and uncertainty while preserving autonomy. This finding is aligned with the transition from predictive to generative artificial intelligence described in the literature, through which intelligent systems increasingly participate directly in customer decision processes [1]. It is also consistent with the evidence that anthropomorphic design affects consumer behavior and brand evaluation by altering the perceived social and experiential qualities of interactions with artificial intelligence products [8]. Human-like conversational features may improve the purchasing experience when they facilitate decisions, although their effectiveness depends on product type and consumer expectations.

The role of intelligent interaction can also be explained through anthropomorphism and social presence. Consumers may experience chatbots and virtual assistants as social actors, particularly when these systems use natural language, personalized responses, human-like names, or avatars. Such design features can increase engagement and reduce the psychological distance between the consumer and the platform. However, the effects are conditional. If an anthropomorphic system performs poorly, provides irrelevant responses, or appears deceptive, human-like design may intensify dissatisfaction. Research has demonstrated that the anthropomorphic appearance of artificial intelligence products influences both consumer behavior and brand evaluation, with different effects across product categories [8]. Thus, intelligent customer experience depends on congruence among system appearance, functional performance, and the nature of the purchasing task. Retail managers should not assume that greater human-likeness is always preferable; rather, anthropomorphic elements should support clarity, efficiency, and trust.

The significant effect of intelligent customer experience on consumers' perceived value represents one of the most important findings of the study. Perceived value emerges when consumers conclude that the benefits obtained from an online purchasing experience exceed the monetary, temporal, cognitive, emotional, and privacy-related costs. Artificial intelligence can increase functional value by improving speed and accuracy, emotional value by creating an enjoyable and responsive experience, and relational value by making customers feel recognized and understood. The findings are consistent with evidence that perceived value and self-congruence influence consumers' engagement with artificial intelligence–based technologies [6]. Consumers are more likely to engage with intelligent platforms when the services correspond with their needs, lifestyles, and self-perceptions. Thus, personalization contributes to perceived value not only by recommending suitable products but also by creating a sense of alignment between the platform and the consumer's identity.

The qualitative findings further indicated that increased satisfaction, loyalty, decision quality, sales, and profitability were expected consequences of intelligent consumer behavior. Although the quantitative model focused directly on perceived value as the final construct, these broader consequences can be interpreted as subsequent behavioral and organizational outcomes. When consumers perceive greater value, they are more likely to report satisfaction, return to the platform, recommend it to others, and maintain a long-term relationship with the retailer. Artificial intelligence can therefore contribute to customer loyalty indirectly by improving the purchasing process and experience. Meta-analytic evidence confirms that artificial intelligence and Industry 4.0–based products influence consumer behavior characteristics across different settings [2]. Furthermore, the use of artificial intelligence in brand and marketing management suggests that intelligent customer analysis can strengthen targeting, communication, and brand–consumer relationships [7]. However, these positive outcomes depend on whether consumers perceive the system as beneficial, fair, and consistent with their expectations.

The findings also highlight the strategic importance of combining technology with ethics. Artificial intelligence in retailing should not be understood simply as an automation tool but as an organizational capability that shapes customer knowledge, decision environments, and relationships. The increasing ability to decode consumer behavior through advanced analytics, neural networks, and potentially neurotechnology creates powerful opportunities for prediction and personalization [3, 10]. Nevertheless, the same capabilities may threaten consumer autonomy when firms use behavioral insights to influence decisions without sufficient transparency. The interweaving of behavior, cognition, and ethics in artificial intelligence applications underscores the need for responsible governance [5]. Accordingly, the present model shows that sustainable intelligent retailing requires simultaneous investment in analytical capabilities, infrastructure, cybersecurity, privacy protection, explainability, and ethical oversight.

Overall, the mixed-methods findings provide an integrated explanation of online consumer behavior in artificial intelligence–enabled retailing. The qualitative phase clarified the contextual meaning of intelligent behavior in Iran's retail environment, whereas the quantitative phase confirmed the significance of the relationships among the principal constructs. The findings indicate that artificial intelligence influences consumer behavior through a sequential and context-dependent mechanism. Intelligent capabilities shape environmental conditions and facilitate intelligent purchasing; environmental readiness and constraints determine how effectively these capabilities can be used; the intelligent purchasing process shapes customer experience; and the resulting experience creates perceived value. This explanation contributes to the literature by moving beyond isolated examinations of personalization, trust, or adoption and presenting artificial intelligence–based consumer behavior as a multidimensional system. It also reinforces the view that technological innovation becomes strategically meaningful only when it is embedded within a reliable, transparent, culturally compatible, and ethically governed retail environment.

The present study was subject to several limitations. First, the quantitative participants were customers of online retail platforms in Iran, and the specific economic, cultural, technological, and regulatory characteristics of this context may limit the generalizability of the findings to other countries or more technologically mature markets. Second, the quantitative data were collected using a self-report questionnaire, which may have been affected by social desirability, response bias, imperfect recall, or differences between stated attitudes and actual online behavior. Third, the cross-sectional design did not permit the examination of changes in consumer perceptions over time or the establishment of definitive causal relationships among the constructs. Fourth, although theoretical saturation was achieved in the qualitative phase, the number of experts was limited, and the inclusion of additional stakeholder groups, such as policymakers, artificial intelligence developers, logistics providers, and consumer-rights specialists, might have produced additional categories. Fifth, the model combined multiple forms of artificial intelligence under the general concept of intelligent capabilities and did not distinguish systematically among predictive algorithms, recommendation systems, chatbots, generative artificial intelligence, and other applications. Finally, the study did not directly incorporate objective behavioral data, such as clickstream records, transaction histories, recommendation acceptance rates, or customer retention indicators.

Future studies should test the proposed model in different national, cultural, and industrial contexts to determine the stability and boundary conditions of the identified relationships. Longitudinal and experimental designs are recommended to examine causal mechanisms and changes in trust, perceived value, and loyalty after repeated interactions with intelligent retail systems. Researchers should distinguish among different artificial intelligence applications and compare consumer reactions to predictive recommendation engines, generative assistants, anthropomorphic chatbots, automated pricing systems, and virtual shopping agents. Multigroup analyses could investigate whether the structural relationships differ according to age, gender, income, digital literacy, shopping frequency, product involvement, and prior experience with artificial intelligence. Future research should also integrate questionnaire data with objective digital traces, including browsing duration, click patterns, abandoned carts, purchasing records, and repurchase behavior. Additional models may examine algorithmic transparency, perceived fairness, technological anxiety, consumer autonomy, and willingness to disclose personal information as moderators or mediators. Qualitative studies involving consumers, platform developers, regulators, and privacy experts could further clarify the ethical and governance dimensions of intelligent retailing.

Retail managers should approach artificial intelligence implementation as a coordinated strategic transformation rather than the isolated acquisition of software. Investment in recommendation systems, chatbots, and predictive analytics should be accompanied by improvements in data quality, cybersecurity, platform stability, payment reliability, logistics, and employee competencies. Retailers should design personalization processes that provide clear consumer benefits while minimizing unnecessary data collection. Customers should be informed in understandable language about when artificial intelligence is being used, what information is collected, how recommendations are generated, and how they can control or withdraw their data. Intelligent interfaces should simplify product discovery and decision-making without restricting consumer autonomy or creating excessive dependence on algorithmic recommendations. Human support should remain available for complex, sensitive, or high-risk transactions. Managers should continuously evaluate artificial intelligence systems using customer-experience indicators, complaint patterns, recommendation accuracy, retention, perceived fairness, and privacy-related concerns. Small and medium-sized retailers should prioritize scalable applications with clear operational value rather than adopting costly technologies without adequate infrastructure. Ultimately, intelligent retailing should be developed around a dual commitment to technological efficiency and ethical responsibility.

Acknowledgments

We would like to express our appreciation and gratitude to all those who cooperated in carrying out this study.

Authors' Contributions

All authors equally contributed to this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants. Written consent was obtained from all participants in the study.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

Funding

This research was carried out independently with personal funding and without the financial support of any governmental or private institution or organization.

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