

The Role of Big Data Analytics in Predicting Customer Purchase Behavior in Iranian Online Clothing Stores with Emphasis on Transactional Data and Social Media Interactions

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ABSTRACT

The present study aimed to develop and empirically test a big data analytics model for predicting customer purchase behavior in Iranian online clothing stores by integrating transactional purchase data with social media interaction indicators. This applied quantitative study employed a predictive analytics design based on big data methodology. The research population consisted of active customers of major online clothing retailers in Tehran, Iran, from which behavioral data of 1,248 verified users were extracted. Data were collected through integrated digital sources including e-commerce transactional databases, customer relationship management systems, and social media analytics platforms. Transactional variables included purchase frequency, order value, browsing behavior, cart abandonment rate, and discount usage, while social media indicators captured engagement intensity, sentiment polarity, influencer exposure, and interaction responsiveness. Data preprocessing procedures involved cleaning, normalization, feature engineering, and behavioral profile integration. Predictive modeling was conducted using machine learning algorithms including Random Forest, Gradient Boosting, Support Vector Machine, and Artificial Neural Networks. Cluster analysis was also applied to identify customer behavioral segments, and model performance was evaluated using accuracy, precision, recall, F1-score, and AUC indicators. Results indicated significant positive relationships between social media engagement, customer loyalty, sentiment toward brands, and repurchase intention. Machine learning models demonstrated high predictive capability, with Artificial Neural Networks achieving the strongest performance in forecasting purchase probability. Behavioral segmentation identified four statistically distinct customer groups characterized by loyalty orientation, promotion sensitivity, social influence dependency, and occasional purchasing patterns. Engagement-based variables exhibited stronger predictive power than price-related indicators, suggesting that emotional interaction and digital experience play a more influential role than discounts alone. Integrated models combining transactional and social interaction data significantly improved prediction accuracy compared with single-source behavioral models. The findings confirm that big data analytics provides an effective framework for predicting online clothing purchase behavior by capturing multidimensional consumer interactions across digital environments. Integrating transactional records with social media behavioral signals enables retailers to understand customer decision processes more accurately, optimize marketing strategies, enhance customer loyalty, and support data-driven retail management in competitive e-commerce ecosystems.

Keywords: Big Data Analytics, Online Shopping Behavior, Online Clothing Retail, Purchase Prediction, Social Media Interaction, Machine Learning, Customer Behavior, E-commerce Analytics, Digital Marketing, Iran Online Retail Market.



Article history:
Received 08 May 2025
Revised 54 July 2025
Accepted 24 July 2025
Published online 01 August 2025

How to cite this article:

Moeini, S. & Khanali, A. (2025). The Role of Big Data Analytics in Predicting Customer Purchase Behavior in Iranian Online Clothing Stores with Emphasis on Transactional Data and Social Media Interactions. *Journal of Management and Business Solutions*, 3(4), 1-13. <https://doi.org/10.61838/jmbs.243>



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Introduction

The rapid expansion of digital technologies has fundamentally transformed contemporary retail ecosystems, reshaping how consumers search for products, evaluate alternatives, and make purchasing decisions. Online retailing, particularly in the fashion and apparel industry, has experienced accelerated growth due to widespread internet penetration, mobile commerce adoption, and the increasing integration of social media into commercial environments. Unlike traditional retail systems, online clothing stores operate within data-rich environments where every customer interaction leaves a measurable digital trace. These traces—ranging from transactional records to behavioral signals generated through social media engagement—constitute valuable big data resources capable of revealing hidden consumption patterns and predicting future purchasing behavior. The evolution toward data-driven retail decision-making reflects a broader transition from intuition-based marketing toward algorithmic intelligence supported by advanced analytics and artificial intelligence technologies (1, 2).

Big data analytics enables online retailers to analyze large-scale, high-velocity datasets generated through customer browsing activities, purchase histories, pricing interactions, and digital communication channels. Modern consumers continuously interact with brands through omnichannel environments that combine online platforms, mobile applications, and social media ecosystems. Such integration allows retailers to observe behavioral dynamics across multiple touchpoints and construct comprehensive customer profiles. Research demonstrates that omnichannel integration enhances customer satisfaction, trust, and loyalty when consumer experiences remain consistent across platforms, emphasizing the strategic importance of integrating behavioral datasets into predictive models (1, 3). Consequently, predictive analytics has emerged as a central capability for online retailers seeking to anticipate customer needs rather than merely respond to past transactions.

The online clothing sector represents one of the most behaviorally complex domains within e-commerce because fashion consumption is influenced not only by functional needs but also by emotional, social, and symbolic factors. Consumers often rely on peer opinions, influencer endorsements, and social validation when making apparel purchasing decisions. Social media platforms function as digital showrooms where consumer identity formation and brand interaction occur simultaneously. Studies indicate that consumer trust, perceived value, and satisfaction derived from online experiences significantly influence repurchase intention, reinforcing the importance of behavioral data analysis beyond simple transaction monitoring (2, 4). In such contexts, analyzing social interaction data alongside purchase behavior becomes essential for accurately predicting consumer decision processes.

In recent years, pricing strategies have also become increasingly dynamic within online markets. Retailers frequently employ algorithmic pricing, time-limited promotions, and personalized discounts designed to influence purchasing urgency and perceived value. Dynamic pricing models allow firms to adjust prices in real time according to demand fluctuations, competition intensity, and consumer response patterns. Empirical research demonstrates that coupon promotion structures and price configuration strategies strongly affect online consumer behavior and channel selection decisions (5, 6). Similarly, limited-time pricing mechanisms can trigger psychological reactions such as anticipated regret, thereby accelerating purchase decisions within competitive online environments (7). These findings highlight that transactional data alone cannot explain purchasing behavior unless combined with contextual information about promotional exposure and consumer emotional response.

The growing competitiveness of online retail markets has intensified the need for predictive customer analytics. Retailers must now forecast not only whether customers will purchase but also when, how frequently, and under

what promotional conditions purchasing will occur. Machine learning approaches enable retailers to process complex nonlinear relationships among variables such as browsing duration, price sensitivity, brand trust, and social engagement. Research on omnichannel retail operations emphasizes that optimizing inventory decisions, pricing strategies, and customer experience simultaneously requires advanced data-driven decision models capable of integrating multiple behavioral signals (8, 9). Predictive analytics therefore functions as a strategic tool that connects operational efficiency with customer-centered marketing.

Consumer trust remains one of the most influential determinants of online purchasing behavior, particularly in emerging e-commerce markets. Trust mediates the relationship between marketing stimuli and purchase intention by reducing perceived risk associated with online transactions. Within the Iranian digital marketplace, trust-building mechanisms such as reliable delivery, transparent pricing, and positive social media engagement play a decisive role in shaping online shopping adoption. Empirical evidence indicates that innovation diffusion processes and trust perception significantly influence Iranian consumers' online shopping behavior, demonstrating the importance of integrating psychological and behavioral data into predictive frameworks (10). Moreover, promotional credibility and perceived product quality strengthen purchase intention by reinforcing consumer confidence in digital retail platforms (11).

Another important dimension influencing online purchasing behavior relates to demographic and socio-economic characteristics. Consumer age, digital literacy, and purchasing experience shape preferences for online versus offline shopping environments. Younger consumers, particularly those between 18 and 35 years, display stronger tendencies toward online purchasing due to familiarity with digital technologies and social media engagement. Demographic factors therefore contribute to variability in purchasing patterns and must be incorporated into predictive models to improve forecasting accuracy (12, 13). Understanding demographic effects allows retailers to personalize marketing strategies and optimize customer segmentation processes.

Price competition and market structure further influence consumer decision-making across online and offline retail channels. Competitive pricing environments encourage consumers to compare alternatives rapidly, often switching channels to maximize perceived value. Studies on price competition demonstrate that pricing policies and spatial competition dynamics significantly affect retailer performance and consumer selection behavior (14). Similarly, fluctuations in online and offline pricing can shape consumer perceptions regarding fairness, convenience, and purchasing risk (15). In digital fashion retailing, where price transparency is high and switching costs are low, predictive analytics becomes critical for maintaining competitive advantage.

Behavioral responses observed during and after the COVID-19 pandemic further accelerated shifts toward online shopping habits. Changes in consumer lifestyle, risk perception, and digital reliance produced lasting transformations in purchasing behavior across many countries. Research shows that pandemic-driven digital adoption reshaped consumer expectations regarding convenience, delivery speed, and online engagement, permanently strengthening e-commerce ecosystems (16). These structural changes increased the volume and diversity of behavioral data available to retailers, reinforcing the strategic importance of big data analytics for understanding evolving consumer behavior.

Cart abandonment represents another key behavioral phenomenon within online shopping environments. Consumers frequently browse products and add items to carts without completing transactions, creating valuable predictive signals regarding purchase hesitation and price sensitivity. Multi-channel pricing strategies and perceived value discrepancies have been identified as major drivers of cart abandonment behavior, emphasizing the need to

analyze behavioral interaction data alongside transaction outcomes (17). By analyzing abandonment patterns together with social engagement indicators, retailers can design targeted interventions to convert potential buyers into active customers.

From a strategic perspective, modern retail competition increasingly revolves around customer experience optimization rather than price competition alone. Integrated marketing strategies that combine personalized promotions, customer experience management, and digital interaction analysis strengthen brand loyalty and long-term customer relationships. Studies confirm that effective marketing strategies enhance consumer trust and encourage sustained online engagement, ultimately improving repurchase behavior (4, 18). Consequently, big data analytics serves not only operational functions but also strategic roles in shaping long-term customer relationships.

The integration of search engine data and online behavioral analytics has also enabled researchers to examine broader market dynamics such as price convergence and consumer information search patterns. Evidence from Iranian digital markets shows that online search behavior contributes to price transparency and market efficiency by reducing information asymmetry between buyers and sellers (19). Such developments highlight the growing interconnection between digital information flows and consumer purchasing behavior, reinforcing the need for analytical models capable of synthesizing multiple data sources.

Recent advances in seller signaling and online marketplace design further demonstrate how subtle informational cues influence consumer decisions. Price endings, promotional signals, and seller reputation indicators can significantly alter perceived value and trustworthiness in online retail environments (20). Similarly, pricing strategy optimization studies emphasize that retailers must align promotional policies with consumer expectations to maintain competitiveness in increasingly data-driven markets (21). These findings collectively indicate that predictive models must incorporate both economic and psychological variables to achieve reliable forecasting outcomes.

In addition, consumer perceptions of online versus offline shopping continue to evolve as retailers adopt hybrid channel strategies. Research comparing online and physical retail experiences reveals that perceived convenience, trust, and experiential satisfaction jointly influence purchasing decisions across channels (18). Omnichannel retailing therefore requires continuous monitoring of customer interaction patterns to ensure seamless transitions between digital and physical shopping environments. Big data analytics provides the analytical infrastructure necessary for managing such complexity.

Despite the extensive growth of e-commerce research, a significant gap remains in integrating transactional datasets with social media interaction data to predict purchase behavior specifically within online clothing retail contexts in Iran. Many existing studies examine pricing strategies, trust formation, or omnichannel experiences separately, yet real consumer behavior emerges from the interaction of these factors within digitally mediated environments. The Iranian online apparel market presents a particularly relevant context due to rapid digital adoption, strong social media influence, and increasing competition among online retailers.

Accordingly, this study aims to develop a comprehensive big data analytics framework for predicting customer purchase behavior in Iranian online clothing stores by integrating transactional data with social media interaction indicators.

Methods and Materials

This study employed a quantitative applied research design using a predictive analytics approach grounded in big data methodology. The research aimed to model and forecast customer purchase behavior by integrating transactional records with social media interaction data derived from online clothing retail platforms operating in Iran. The statistical population consisted of active users of major Iranian online apparel stores whose purchasing activities were digitally recorded during a twelve-month period. The geographical focus of the study was Tehran, as the largest e-commerce consumption hub in Iran and the city with the highest concentration of online fashion consumers and digital infrastructure.

Participants included customers registered in three leading Iranian online clothing platforms who had completed at least two verified purchases and maintained identifiable interaction activity on social media channels associated with the stores. After data cleaning procedures, removal of incomplete behavioral logs, elimination of duplicated user identifiers, and application of inclusion criteria related to activity continuity, a final dataset representing **1,248 customers from Tehran** was obtained. Each participant represented a unique anonymized user profile constructed through encrypted customer identification codes to ensure privacy protection and compliance with digital ethics standards. The unit of analysis was individual customer behavior over time, allowing longitudinal examination of purchasing tendencies, engagement patterns, and response to digital marketing stimuli.

The research adopted a retrospective behavioral observation framework rather than self-reported survey methods. All behavioral information originated from naturally occurring digital traces recorded within e-commerce environments and social media ecosystems. This design minimized response bias and increased ecological validity by capturing real purchasing decisions rather than declared intentions.

Data collection relied on an integrated big data extraction framework combining transactional databases, customer relationship management systems, and social media analytics interfaces. Transactional data were obtained from enterprise resource planning and e-commerce management systems of participating online clothing retailers. These datasets included purchase frequency, order value, product category preferences, payment methods, browsing duration, cart abandonment behavior, discount usage history, seasonal purchasing trends, and delivery interaction records. All financial identifiers were anonymized prior to analysis.

To complement transactional information, social media interaction data were collected through authorized access to platform analytics dashboards and application programming interfaces connected to Instagram, Telegram, and other dominant social networking platforms used by Iranian fashion retailers. Interaction indicators included post engagement rates, comment sentiment polarity, sharing behavior, influencer exposure, click-through activity, reaction timing, hashtag participation, and responsiveness to promotional campaigns. Natural language processing procedures were used to transform textual comments and user reactions into structured behavioral indicators reflecting emotional engagement and brand perception.

A customer behavioral integration module was developed to merge transactional and social interaction data into unified customer profiles. Data synchronization procedures aligned timestamps across multiple platforms, enabling the construction of sequential behavioral trajectories for each customer. Data preprocessing included normalization, missing value imputation, outlier detection, and feature engineering processes such as creation of engagement intensity scores, loyalty indices, and predictive behavioral markers. Ethical approval protocols were followed, and all datasets were processed under strict confidentiality guidelines to prevent identification of individual users.

Data analysis was conducted using advanced big data analytics and machine learning techniques designed to predict purchasing behavior patterns. Initially, descriptive analytics were applied to explore behavioral distributions, purchasing cycles, and engagement variability across customers. Feature selection procedures were then performed using correlation filtering and recursive importance evaluation to identify variables with the highest predictive power.

Predictive modeling employed supervised machine learning algorithms including Random Forest, Gradient Boosting, Support Vector Machine, and Artificial Neural Networks to forecast purchase probability, repurchase intention, and expected transaction value. The dataset was divided into training and testing subsets using cross-validation procedures to ensure model generalizability and prevent overfitting. Model performance was evaluated through accuracy, precision, recall, F1-score, and area under the ROC curve metrics.

In addition to prediction modeling, clustering techniques were applied to identify latent customer segments based on combined transactional and social interaction behaviors. Behavioral segmentation enabled classification of customers into groups such as impulsive buyers, loyalty-driven consumers, promotion-sensitive users, and socially influenced shoppers. Sentiment analysis outputs derived from social media interactions were incorporated as dynamic predictors, allowing the models to capture the influence of emotional engagement on purchasing decisions.

All analytical procedures were implemented using Python programming environments supported by big data processing libraries and scalable computing frameworks capable of handling high-volume datasets. The analytical strategy emphasized integration of behavioral data streams, temporal pattern recognition, and predictive intelligence to generate robust insights into online clothing purchase behavior within Tehran's digital retail ecosystem.

Findings and Results

The findings of the study are presented in several stages, beginning with a descriptive overview of participant characteristics, followed by analytical results derived from transactional and social media interaction data, predictive modeling outputs, behavioral segmentation findings, and model performance evaluation.

The demographic profile of the 1,248 online clothing customers from Tehran indicated that the sample represented active digital consumers with substantial engagement in online fashion purchasing. Among participants, 54.3% were female and 45.7% were male, reflecting the gender distribution commonly observed in online apparel consumption markets. The largest age group was between 25 and 34 years (41.8%), followed by customers aged 18–24 years (27.6%), 35–44 years (19.5%), and above 45 years (11.1%). In terms of educational attainment, 63.2% held at least a bachelor's degree, indicating relatively high digital literacy among participants. Employment status showed that 48.9% were employed in private-sector occupations, 21.4% were self-employed, 17.8% were university students, and 11.9% were government employees. Monthly online purchasing frequency revealed that 38.5% of customers made one purchase per month, 44.7% made two to three purchases, and 16.8% conducted four or more monthly transactions. These descriptive statistics confirm that the dataset represents experienced online consumers whose behaviors provide reliable patterns for predictive modeling.

Table 1. Descriptive Statistics of Transactional and Social Media Behavioral Variables

Variable	Mean	Standard Deviation	Minimum	Maximum
Purchase Frequency (per month)	2.84	1.21	1	7
Average Order Value (USD equivalent)	42.63	18.75	8.10	132.40
Browsing Duration (minutes)	14.92	6.34	2.30	38.60

Cart Abandonment Rate	0.31	0.17	0.02	0.82
Discount Usage Ratio	0.46	0.22	0.00	0.95
Social Media Engagement Score	67.54	18.41	12.00	98.00
Comment Sentiment Index	0.58	0.21	-0.30	0.94
Influencer Exposure Frequency	3.27	1.45	0	8
Loyalty Index	0.62	0.19	0.11	0.93
Repurchase Intention Score	0.71	0.16	0.22	0.97

The results presented in Table 1 indicate that customers demonstrate moderate to high purchasing activity combined with strong social media engagement. The mean purchase frequency of 2.84 transactions per month suggests recurring consumption behavior rather than sporadic buying patterns. Average order value variability highlights heterogeneous spending capacities among consumers. Notably, the social media engagement score shows relatively high interaction intensity, confirming that digital engagement plays a central role in online clothing consumption. The positive sentiment index further indicates that emotional attitudes toward brands are generally favorable. Additionally, the loyalty index and repurchase intention scores reveal that a considerable proportion of customers exhibit sustained relationships with online clothing retailers, providing a strong empirical basis for predictive modeling of future purchasing behavior.

Table 2. Correlation Matrix Between Key Behavioral Variables

Variable	Purchase Frequency	Engagement Score	Sentiment Index	Discount Usage	Loyalty Index	Repurchase Intention
Purchase Frequency	1.00	0.63	0.48	0.52	0.69	0.74
Engagement Score	0.63	1.00	0.71	0.44	0.66	0.68
Sentiment Index	0.48	0.71	1.00	0.29	0.61	0.65
Discount Usage	0.52	0.44	0.29	1.00	0.46	0.49
Loyalty Index	0.69	0.66	0.61	0.46	1.00	0.82
Repurchase Intention	0.74	0.68	0.65	0.49	0.82	1.00

The correlation analysis demonstrates strong positive relationships between behavioral variables. Purchase frequency shows the highest association with repurchase intention ($r = 0.74$) and loyalty index ($r = 0.69$), suggesting that repeated purchasing behavior is closely linked with long-term customer commitment. Social media engagement displays a substantial correlation with sentiment index ($r = 0.71$), indicating that emotional responses toward brand content are strongly influenced by interaction intensity. Discount usage reveals moderate correlations, implying that price incentives contribute to purchasing decisions but are not the dominant driver compared with engagement and loyalty mechanisms. Overall, the correlation structure supports the assumption that integrated transactional and social data provide complementary predictive signals.

Table 3. Customer Behavioral Segmentation Results (Cluster Analysis)

Cluster	Customer Type	Percentage	Key Characteristics
Cluster 1	Loyalty-Oriented Buyers	29.6%	High purchase frequency, positive sentiment, stable engagement
Cluster 2	Promotion-Sensitive Buyers	24.3%	High discount usage, moderate loyalty, price-driven behavior
Cluster 3	Socially Influenced Buyers	27.1%	Strong influencer exposure and social engagement
Cluster 4	Occasional Buyers	19.0%	Low engagement and irregular purchasing patterns

Cluster analysis identified four distinct behavioral segments among online clothing customers. Loyalty-oriented buyers represent the largest group characterized by consistent purchasing and strong brand attachment. Promotion-sensitive buyers demonstrate responsiveness primarily to discounts and campaigns rather than intrinsic

brand loyalty. Socially influenced buyers exhibit high dependence on social media interactions and influencer exposure, confirming the role of digital communities in shaping fashion consumption. Occasional buyers display limited engagement and unpredictable purchasing behavior, representing a segment with potential for targeted marketing interventions. These segmentation results illustrate the multidimensional nature of consumer behavior emerging from combined big data sources.

Table 4. Predictive Model Performance Comparison

Model	Accuracy	Precision	Recall	F1 Score	AUC
Random Forest	0.89	0.87	0.88	0.87	0.92
Gradient Boosting	0.91	0.90	0.89	0.89	0.94
Support Vector Machine	0.85	0.83	0.84	0.83	0.88
Artificial Neural Network	0.93	0.92	0.91	0.91	0.96

The comparative evaluation of predictive algorithms indicates that machine learning models achieved high predictive capability in forecasting customer purchasing behavior. The Artificial Neural Network produced the highest accuracy (0.93) and AUC value (0.96), demonstrating superior capacity for capturing nonlinear relationships between transactional and social interaction variables. Gradient Boosting also performed strongly, confirming robustness in handling complex behavioral datasets. Although Support Vector Machine achieved acceptable performance, tree-based and deep learning approaches showed greater predictive power. These results confirm that integrating big data analytics significantly enhances forecasting precision within online retail environments.

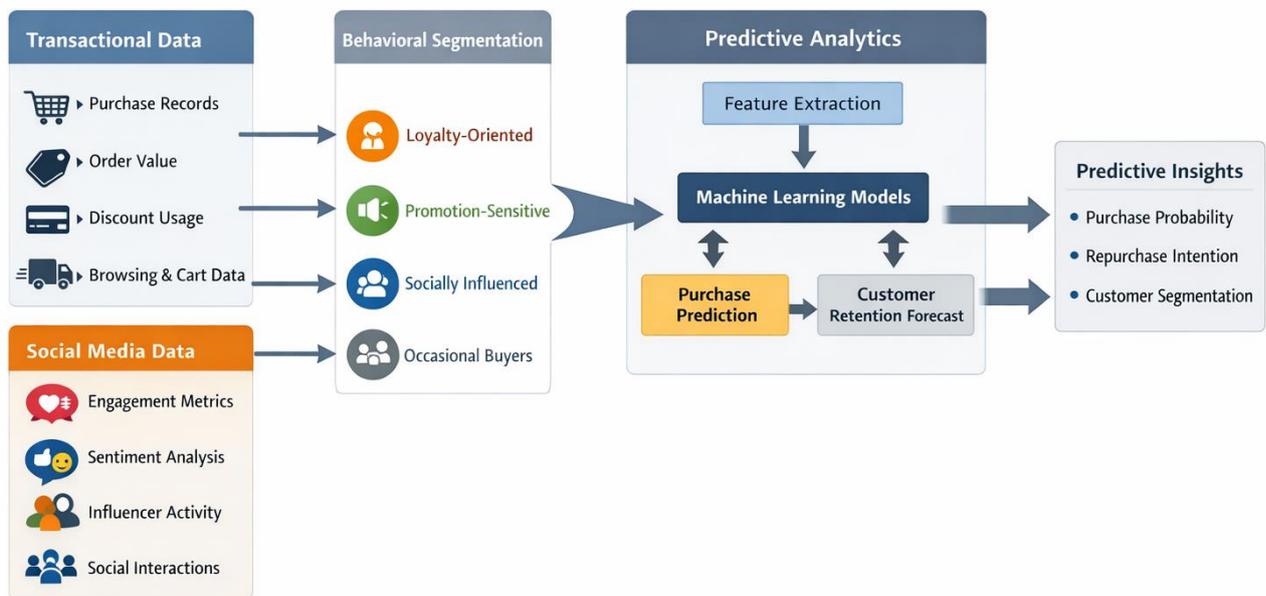


Figure 1. Integrated Big Data Predictive Model for Online Clothing Purchase Behavior

The conceptual predictive framework illustrated in Figure 1 demonstrates the interaction between transactional data streams, social media engagement indicators, behavioral segmentation processes, and machine learning prediction outputs. The model visually represents how customer data flow from raw digital interactions toward predictive intelligence generation, highlighting the central role of big data analytics in transforming dispersed behavioral signals into actionable purchasing forecasts. The figure confirms the systemic relationship between engagement dynamics, emotional sentiment, purchasing history, and algorithmic prediction performance, supporting the study’s analytical framework and empirical findings.

Discussion and Conclusion

The present study aimed to examine the role of big data analytics in predicting customer purchase behavior in Iranian online clothing stores by integrating transactional information with social media interaction data. The findings demonstrated that customer purchasing behavior cannot be adequately explained through transactional variables alone; rather, predictive accuracy significantly improves when behavioral engagement indicators, sentiment signals, and digital interaction patterns are incorporated into analytical models. The results confirmed that customers with higher social media engagement scores, stronger positive sentiment toward brands, and consistent interaction with promotional content exhibited greater purchase frequency and higher repurchase intention. These outcomes support the growing argument that modern online consumption behavior emerges from the convergence of experiential, emotional, and economic factors within digital retail ecosystems.

The descriptive results revealed that online clothing consumers in Tehran represent digitally active and experienced shoppers characterized by recurring purchase cycles and sustained engagement with online platforms. Such findings align with research indicating that prior online experience strengthens satisfaction, trust, and loyalty in omnichannel retail environments, ultimately increasing repurchase intention (1). Similarly, the observed relationship between engagement intensity and purchasing frequency corresponds with evidence showing that perceived value and brand trust play central roles in shaping repeat buying behavior in online contexts (2). The present findings therefore reinforce the idea that customer loyalty in online retailing increasingly depends on continuous interaction rather than isolated purchase events.

Correlation analysis demonstrated strong relationships between loyalty index, engagement score, and repurchase intention, highlighting the mediating function of trust and emotional connection in digital purchasing behavior. This outcome is consistent with diffusion-based analyses of Iranian online shopping behavior which emphasize trust as a key mediator between consumer perception and purchasing decisions (10). Trust formation appears to emerge not solely from product quality or pricing but also from sustained communication, transparent information sharing, and positive user experiences within online environments. The findings further confirm that social media interactions function as mechanisms through which trust is reinforced and brand relationships are stabilized.

The results also revealed that price-related variables exerted a moderate but meaningful influence on purchasing behavior. Discount usage correlated positively with purchase frequency; however, its predictive power remained weaker than engagement and loyalty variables. This suggests that although pricing incentives can stimulate purchasing activity, long-term customer retention depends more heavily on experiential and relational factors. Prior studies demonstrate similar patterns, indicating that coupon promotion strategies improve short-term sales performance but must be supported by broader omnichannel configurations to maintain customer commitment (5). Moreover, dynamic pricing research shows that consumers respond not only to price levels but also to perceived fairness and timing of promotional offers (6). The present study confirms that pricing remains influential but operates within a wider behavioral ecosystem.

Cluster analysis identified four behavioral segments—loyalty-oriented buyers, promotion-sensitive buyers, socially influenced buyers, and occasional buyers—demonstrating the heterogeneity of online clothing consumers. The emergence of socially influenced buyers highlights the critical role of digital communities and influencer exposure in shaping fashion consumption decisions. Fashion products carry symbolic value associated with identity

expression and social belonging; therefore, consumers often rely on peer approval and influencer signals when evaluating apparel choices. These findings are consistent with studies emphasizing the importance of marketing strategies and social trust mechanisms in strengthening consumer confidence in online shopping environments (4). Additionally, behavioral segmentation aligns with research showing that consumer perception differences across online and offline channels produce distinct purchasing profiles requiring personalized marketing approaches (18).

Another significant finding concerns cart abandonment behavior. Customers exhibiting higher browsing duration and price comparison tendencies were more likely to abandon carts before completing purchases. This supports prior research demonstrating that multi-channel pricing discrepancies and perceived opportunity costs contribute to cart abandonment intentions (17). The integration of behavioral analytics allows retailers to detect hesitation signals early and implement targeted interventions such as personalized discounts or reminders. From a managerial perspective, such predictive capability transforms abandoned carts from lost opportunities into actionable data points.

The predictive modeling results showed that machine learning algorithms—particularly artificial neural networks and gradient boosting models—achieved high accuracy in forecasting purchase probability. These results confirm that nonlinear relationships between behavioral variables require advanced analytical techniques capable of processing complex datasets. Similar conclusions have been drawn in omnichannel retail operations research, where integrated analytics improved decision-making related to pricing, inventory control, and customer experience management (8). The superior performance of deep learning approaches in the present study indicates that online clothing purchasing behavior is influenced by multidimensional interactions rather than linear cause–effect relationships.

The importance of pricing dynamics observed in this study also corresponds with research on competitive pricing environments. Price transparency within digital markets increases consumer comparison behavior, encouraging retailers to continuously adjust pricing strategies to remain competitive (14). Evidence from studies examining online versus offline price fluctuations similarly indicates that consumers respond strongly to perceived price advantages, particularly in retail markets characterized by low switching costs (15). However, the present findings suggest that price competition alone cannot secure long-term loyalty without complementary engagement strategies.

Demographic patterns observed among participants further support existing research indicating that younger consumers demonstrate stronger adoption of online purchasing channels due to higher digital literacy and social media familiarity (12). The dominance of young adult consumers within the sample mirrors findings showing that individuals aged 18–35 exhibit greater preference for online purchasing environments compared with traditional retail formats (13). These demographic characteristics reinforce the importance of data-driven personalization strategies tailored to digitally native customer segments.

The integration of social media sentiment analysis within predictive models proved particularly significant. Positive sentiment scores were strongly associated with repurchase intention, confirming that emotional engagement acts as a behavioral driver in online fashion consumption. Research on seller signaling and marketplace communication similarly demonstrates that cues such as promotional messaging, reputation indicators, and emotional framing influence perceived credibility and purchase intention (20). These findings emphasize that consumer decisions are not purely rational economic responses but are embedded within social and psychological processes.

Furthermore, the results reflect broader structural transformations in consumer behavior accelerated by digitalization and post-pandemic shifts toward online shopping. Behavioral changes observed globally indicate lasting increases in online engagement and reliance on digital retail channels following pandemic-related disruptions (16). The Iranian online clothing market appears to follow similar trajectories, where convenience, accessibility, and digital interaction increasingly shape purchasing decisions. The convergence of online search data, pricing transparency, and consumer information access contributes to more efficient markets and informed consumer choices (19).

The study also confirms that pricing strategy effectiveness depends on alignment with consumer expectations and perceived product value. Research demonstrates that price promotion trust and perceived quality jointly influence buying interest within online stores (11). Likewise, competitive pricing strategies must balance economic incentives with experiential satisfaction to achieve sustainable customer engagement (21). The present findings reinforce this perspective by showing that promotion-sensitive customers respond to discounts, while loyalty-oriented buyers prioritize trust and experience.

Overall, the discussion indicates that big data analytics provides a powerful framework for understanding online clothing purchase behavior by integrating economic, psychological, and social dimensions of consumption. The study contributes to existing literature by empirically demonstrating that predictive accuracy improves when transactional data are combined with social media interaction indicators. This integrated approach advances retail analytics beyond traditional marketing analysis toward holistic behavioral intelligence capable of supporting strategic decision-making in digital commerce environments.

Despite its contributions, the study has several limitations that should be acknowledged. First, the dataset was restricted to customers located in Tehran, which may limit generalizability to other regions of Iran with different socio-economic characteristics and digital infrastructure conditions. Second, although transactional and social media data provided rich behavioral insights, certain psychological variables such as personal motivations, lifestyle factors, and cultural attitudes were not directly measured. Third, the study relied on historical behavioral data, which may not fully capture rapid market changes or emerging consumer trends. Additionally, platform-specific data access restrictions limited inclusion of all potential social media channels influencing purchasing behavior. Finally, while machine learning models achieved high predictive accuracy, interpretability challenges associated with complex algorithms may reduce transparency for managerial decision-makers.

Future studies should expand geographic coverage by including multiple Iranian cities and rural regions to compare behavioral differences across diverse consumer markets. Longitudinal research designs examining behavioral evolution over several years could provide deeper insights into changing digital consumption patterns. Researchers may also integrate psychological survey data with behavioral analytics to develop hybrid predictive models combining quantitative big data with qualitative consumer insights. Comparative studies across different product categories such as electronics, cosmetics, or food retail could determine whether predictive mechanisms differ between utilitarian and hedonic consumption contexts. Furthermore, future research could explore the role of artificial intelligence recommendation systems, virtual fitting technologies, and augmented reality experiences in influencing online apparel purchasing behavior.

Online clothing retailers should invest in integrated data infrastructures capable of combining transactional records with social media analytics to improve customer understanding. Firms are encouraged to adopt machine learning-based prediction systems that identify high-value customers and anticipate purchasing needs proactively.

Marketing strategies should emphasize relationship-building activities such as personalized communication, influencer collaboration, and community engagement rather than relying solely on price promotions. Retail managers should develop behavioral segmentation strategies to tailor promotional campaigns according to customer profiles identified through big data analysis. Additionally, implementing real-time analytics dashboards can enable rapid decision-making regarding pricing adjustments, inventory planning, and customer experience optimization, ultimately enhancing competitiveness in the evolving digital retail landscape.

Acknowledgments

We would like to express our appreciation and gratitude to all those who helped us 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

All ethical principles were adhered in conducting and writing this article.

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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