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A Sentiment Analysis–Based Recommender System for Online Retail Stores Using Customer Social Media Data

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Abstract

This study aimed to design and empirically evaluate a sentiment analysis–based recommender system and to examine its effects on recommendation quality, customer trust, satisfaction, and repurchase intention in online retail environments. The study employed an applied mixed-methods design combining computational modeling with behavioral analysis. Social media data were collected from major online retail brands in Tehran, yielding approximately 1.8 million text records. A sample of 360 active online shoppers and 60 domain experts participated in system evaluation. Natural language processing techniques, including deep learning–based sentiment classification models, were used to extract emotional information from user-generated content. The recommender system integrated sentiment scores with transactional and behavioral data through a hybrid recommendation framework. System performance and behavioral effects were assessed using standard recommendation metrics and survey-based instruments. The sentiment-based recommender system significantly outperformed conventional collaborative filtering and content-based models in precision, recall, F1-score, normalized discounted cumulative gain, and click-through rate. Regression analysis revealed that recommendation quality had significant positive effects on customer trust ($\beta = 0.62$, $p < 0.001$) and satisfaction ($\beta = 0.58$, $p < 0.001$). Trust ($\beta = 0.54$, $p < 0.001$) and satisfaction ($\beta = 0.47$, $p < 0.001$) both significantly predicted repurchase intention. Post-implementation measures indicated significant increases in purchase intention, customer satisfaction, platform trust, and average order value ($p < 0.001$). Integrating social media sentiment analysis into recommender systems substantially enhances system performance, customer engagement, and commercial outcomes, demonstrating the strategic value of emotionally intelligent personalization in online retail.

Keywords: Sentiment analysis; recommender systems; online retail; social media analytics; customer behavior; emotional intelligence; digital marketing.

1. Introduction

The rapid transformation of global retail ecosystems under the influence of digital technologies has fundamentally altered the mechanisms through which consumers interact with brands, products, and marketplaces. Online retail platforms have evolved from simple transactional interfaces into complex socio-technical environments where consumer decision-making is shaped by continuous streams of information, peer communication, emotional expression, and algorithmic mediation. In this environment, social media has emerged as one of the most influential channels affecting consumer attitudes, preferences, and purchasing behavior, providing unprecedented volumes of user-generated content that reflect consumers' experiences, emotions, and perceptions in real time (Banjarnahor et al., 2024; Gunaningrat et al., 2021; Karunarathne &

Wanninayake, 2025). These changes have intensified competition among online retailers and increased the strategic importance of advanced decision-support systems capable of converting unstructured behavioral data into actionable insights (Weinandy et al., 2023; Zavala-Huerta, 2023).

Within this context, recommender systems have become a central technological instrument for guiding consumer choices, enhancing user experience, and maximizing commercial performance. Traditional recommender systems rely primarily on historical transaction data and explicit user preferences, employing collaborative filtering and content-based approaches to predict consumer interests. While effective, these systems often fail to capture the affective and psychological dimensions of consumer behavior that strongly influence purchasing decisions, particularly in digital environments characterized by information overload and rapid emotional reactions (Happ et al., 2020; Lim & Anitsal, 2019). As a result, researchers and practitioners have increasingly recognized the limitations of purely behavioral recommendation models and have sought to integrate emotional and contextual intelligence into recommender system architectures.

Sentiment analysis, as a branch of natural language processing, offers a powerful mechanism for extracting emotional meaning, attitudes, and subjective evaluations from large volumes of textual data. Advances in text analytics and machine learning have enabled the automated detection of polarity, subjectivity, emotion, and opinion at unprecedented scale and accuracy (Abubakar & Uppin, 2021; Mukasheva, 2021; Solanki, 2022). Social media platforms, which host continuous public expressions of consumer experiences, evaluations, and expectations, provide an exceptionally rich data environment for sentiment-driven modeling of consumer behavior (Jones et al., 2023; Kalpana, 2022; White et al., 2023). Integrating such affective intelligence into recommender systems enables platforms to move beyond static preference prediction toward emotionally adaptive recommendation mechanisms.

The commercial relevance of sentiment-driven intelligence is strongly supported by empirical evidence. Studies have demonstrated that social media communication significantly influences customer loyalty, trust, and engagement across retail sectors (Azizah, 2025; Baskar, 2021; Liniņa & Vēvere, 2020). Consumer trust, in particular, emerges as a critical mediator between digital marketing strategies and long-term purchasing behavior in online retail contexts (Azizah, 2025; Karunarathne & Wanninayake, 2025). Furthermore, social media marketing interactions stimulate emotional responses that directly affect impulse buying, brand attachment, and repurchase intentions (Safeer, 2024; Waltenrath et al., 2022). These findings collectively underscore the necessity of incorporating emotional and sentiment-based data into the core decision logic of online retail platforms.

Technological progress in sentiment analysis has further strengthened the feasibility of such integration. Early sentiment classification relied heavily on lexicon-based and rule-based techniques, which provided limited contextual sensitivity. Contemporary models, however, employ deep learning architectures and transformer-based language models that significantly enhance semantic comprehension, emotion detection, and contextual interpretation (Li et al., 2024; Wahyudi & Sibaroni, 2022; Zhou et al., 2022). The application of bidirectional models and attention mechanisms has proven especially effective in capturing subtle emotional cues, sarcasm, and domain-specific expressions within social media content (Hiriyannaiah et al., 2020; Kim et al., 2022). Moreover, recent developments in emotion lexicons and multi-dictionary frameworks have expanded the scope of automated emotion recognition beyond simple polarity toward complex affective states (Wang et al., 2024).

In retail-specific contexts, sentiment analysis has demonstrated measurable value for enhancing service quality, customer satisfaction, and strategic decision-making. Online retailers increasingly leverage social media feedback to optimize product offerings, service processes, and user interface design (Annisa et al., 2022; Ibrahim & Wang, 2019). Research on online consumer reviews reveals that sentiment-driven insights significantly improve service personalization and customer experience management (Lappeman et al., 2022; Lim & Anitsal, 2019). Furthermore, sentiment extracted from social media discussions has been shown to predict customer churn, loyalty shifts, and purchasing cycles with high predictive accuracy (Baskar, 2021; Lappeman et al., 2022). These capabilities establish sentiment analysis as a foundational component for next-generation recommender systems.

The strategic integration of sentiment analysis into recommender systems aligns with contemporary theories of omnichannel retailing and customer experience management. Omnichannel integration enhances perceived personal preference fit and social relatedness, thereby strengthening word-of-mouth behavior and long-term customer engagement (Li et al., 2022). Emotional alignment between platform recommendations and consumer affective states plays a decisive role in sustaining customer relationships and building brand trust (Tiufany & Lina, 2024; Zhou & Hudin, 2025). Empirical research confirms that perceived value, brand trust, and customer satisfaction jointly determine repurchase intentions across both online and in-store environments (Happ et al., 2020; Zhou & Hudin, 2025). Consequently, sentiment-aware recommender systems represent a natural evolution of digital retail intelligence.

Despite growing recognition of these advantages, significant research gaps remain. Many existing recommender systems incorporate sentiment as a supplementary feature rather than as a core predictive dimension. Moreover, much of the existing literature focuses on technical performance metrics without sufficiently examining the behavioral and psychological consequences of sentiment-driven recommendations on trust, satisfaction, and repurchase intention. The majority of prior studies also examine Western or East Asian markets, leaving emerging digital economies underrepresented in empirical research. Context-specific cultural, linguistic, and behavioral factors significantly influence sentiment expression and consumption patterns, necessitating localized investigation and model development (Gunaningrat et al., 2021; Karunarathne & Wanninayake, 2025; Zavala-Huerta, 2023).

Furthermore, the dynamic nature of social media environments introduces methodological challenges related to data volatility, linguistic diversity, emotional ambiguity, and algorithmic bias. While advanced machine learning models provide powerful solutions, they must be carefully designed to maintain interpretability, scalability, and ethical compliance. Issues such as profanity handling, sarcasm detection, and emotional nuance continue to challenge automated sentiment classification (Hiriyannaiah et al., 2020; Kim et al., 2022). Nevertheless, continuous advancements in deep learning architectures and sentiment modeling frameworks offer increasingly robust tools for addressing these challenges (Li et al., 2024; Wang et al., 2024; Zhou et al., 2022).

From a managerial perspective, the commercial implications of sentiment-based recommendation systems are profound. Enhanced recommendation relevance directly increases click-through rates, conversion rates, average order value, and customer lifetime value (Waltenrath et al., 2022; Weinandy et al., 2023). The emotional congruence between platform recommendations and consumer mood strengthens relational bonds, mitigates churn, and fosters sustainable competitive advantage (Lappeman et al., 2022; Safeer, 2024). As online retail competition intensifies and customer acquisition costs continue to rise, emotionally intelligent recommender systems provide a powerful strategic instrument for long-term profitability and market leadership (Banjarnahor et al., 2024; Zavala-Huerta, 2023).

In addition, the COVID-19 pandemic has accelerated the digital transformation of retail and intensified consumer reliance on online platforms and social media for shopping-related information and emotional support (Gunaningrat et al., 2021; Kalpana, 2022). This shift has further amplified the importance of real-time sentiment analysis for understanding evolving consumer needs, anxieties, and expectations. Studies conducted during and after the pandemic period consistently highlight the growing role of emotional intelligence in shaping digital consumption patterns and customer loyalty (Safeer, 2024; White et al., 2023; Zhou & Hudin, 2025).

In light of these developments, the present study proposes and empirically evaluates a comprehensive sentiment analysis–based recommender system for online retail stores, integrating social media sentiment with behavioral data to enhance recommendation accuracy, customer experience, and commercial performance.

The aim of this study is to design and validate a sentiment analysis–based recommender system using customer social media data in order to examine its effects on recommendation quality, customer trust, satisfaction, and repurchase intention in online retail environments.

2. Methods and Materials

The present study employed an applied, mixed-methods research design with a predominantly quantitative and computational orientation, aimed at developing and evaluating a sentiment analysis–driven recommender system for online retail environments. The target population consisted of active online shoppers and digital marketing professionals operating within major online retail platforms in Tehran. Participants were selected using a purposive sampling strategy in order to ensure sufficient familiarity with online purchasing behavior and social media engagement. A total of 420 individuals were recruited, including 360 customers who had completed at least five online purchases in the previous six months and actively engaged with retail brands on social media, as well as 60 experts in e-commerce management, digital marketing, and data science who contributed to system validation and performance evaluation. Inclusion criteria for customer participants included residency in Tehran, minimum age of 18 years, continuous use of at least one social media platform, and experience with online shopping platforms. Prior to participation, all individuals provided informed consent, and ethical approval for the study protocol was obtained from the affiliated academic institution. Data collection and system testing were conducted over a six-month period, allowing sufficient time for capturing seasonal variations in consumer sentiment and purchasing behavior.

Data collection relied on a multi-source strategy combining automated data harvesting, survey instruments, and system interaction logs. Social media content was collected from public posts, comments, reviews, and user interactions related to major Iranian online retail brands across platforms including Instagram, X (formerly Twitter), Telegram channels, and consumer forums. Using custom-developed web crawlers and official platform APIs, approximately 1.8 million text records were extracted after cleaning and de-duplication. To complement these data, a structured online questionnaire was administered to customer participants to measure perceived recommendation quality, trust in recommender systems, purchase satisfaction, and behavioral intention to reuse the platform. The questionnaire employed a five-point Likert scale and demonstrated acceptable internal consistency based on Cronbach's alpha coefficients exceeding the standard threshold of reliability. Additionally, transaction logs from partner online retailers were integrated into the dataset, including anonymized purchase histories, browsing sessions, click-through records, and conversion outcomes. Expert participants evaluated the system using a structured evaluation form focusing on algorithmic transparency, scalability, interpretability, and commercial applicability.

The analytical framework integrated natural language processing, machine learning, and statistical modeling. Initially, social media text data underwent extensive preprocessing including normalization, tokenization, stop-word elimination, stemming, and noise filtering. A hybrid sentiment classification model was then developed using a combination of lexicon-based methods and supervised learning techniques. Deep learning architectures, specifically bidirectional long short-term memory networks and transformer-based language models, were trained on manually labeled Persian-language datasets to ensure contextual accuracy in sentiment recognition. The resulting sentiment scores were dynamically mapped to individual user profiles and integrated with behavioral data to generate personalized product recommendations. The recommender system employed a hybrid recommendation strategy combining collaborative filtering, content-based filtering, and sentiment-weighted preference modeling. System performance was evaluated using precision, recall, F1-score, normalized discounted cumulative gain, click-through rate, and conversion rate metrics. To assess the impact of sentiment-based recommendations on consumer outcomes, inferential statistical analyses including structural equation modeling and multivariate regression were conducted using SPSS and Python-based analytical libraries. Model fit indices and predictive accuracy measures were applied to validate the robustness and effectiveness of the proposed system within the Tehran online retail context.

3. Findings and Results

Table 1 presents the descriptive characteristics of the study participants and dataset composition, providing an empirical foundation for subsequent inferential analyses.

Table 1. Descriptive Profile of Participants and Dataset Characteristics

Variable	Category	Frequency	Percentage
Gender	Male	198	55.0
	Female	162	45.0
Age Group	18–25	96	26.7
	26–35	124	34.4
	36–45	86	23.9
	46 and above	54	15.0
Education Level	High school	78	21.7
	Bachelor's degree	166	46.1
	Master's degree	82	22.8
	Doctorate	34	9.4
Monthly Online Purchases	1–3	112	31.1

	4–7	154	42.8
	8 and above	94	26.1
Average Daily Social Media Usage	Less than 1 hour	64	17.8
	1–3 hours	148	41.1
	More than 3 hours	148	41.1

The descriptive results indicate that the sample consisted predominantly of young and middle-aged adults with substantial engagement in online shopping and social media usage. Over 68 percent of participants reported purchasing online at least four times per month, while more than 82 percent spent over one hour daily on social media platforms, confirming the suitability of the sample for investigating sentiment-driven recommender systems.

Table 2 reports the performance metrics of the proposed sentiment-based recommender system in comparison with conventional collaborative filtering and content-based recommendation models. The evaluation was conducted using a held-out test dataset and standard recommender system performance indicators.

Table 2. Comparative Performance of Recommendation Models

Model	Precision	Recall	F1-score	NDCG	Click-Through Rate
Collaborative Filtering	0.71	0.68	0.69	0.74	6.8%
Content-Based Filtering	0.74	0.72	0.73	0.77	7.4%
Proposed Sentiment-Based Model	0.86	0.83	0.84	0.89	11.6%

The results demonstrate that the proposed sentiment-based recommender system significantly outperformed traditional models across all evaluation metrics. The substantial improvement in click-through rate and ranking quality (NDCG) indicates that incorporating customer sentiment extracted from social media meaningfully enhanced recommendation relevance and user engagement.

Table 3 presents the effects of the sentiment-based recommendation system on consumer behavioral outcomes, measured through post-intervention survey responses and transaction logs.

Table 3. Impact of Sentiment-Based Recommendations on Consumer Outcomes

Outcome Variable	Pre-Implementation Mean	Post-Implementation Mean	Change (%)	Significance (p)
Purchase Intention	3.41	4.18	+22.6	<0.001
Customer Satisfaction	3.52	4.31	+22.4	<0.001
Trust in Platform	3.37	4.09	+21.4	<0.001
Average Order Value	1,480,000 IRR	1,960,000 IRR	+32.4	<0.001

The introduction of the sentiment-based recommendation engine produced statistically significant improvements in all consumer outcome measures. The strongest effect was observed in average order value, suggesting that emotionally aligned recommendations increased not only the likelihood of purchase but also transaction magnitude.

Table 4 reports the results of the structural regression analysis examining the relationships among perceived recommendation quality, trust, satisfaction, and repurchase intention.

Table 4. Structural Regression Results

Relationship	β	t-value	p-value
Recommendation Quality → Trust	0.62	11.48	<0.001
Recommendation Quality → Satisfaction	0.58	10.72	<0.001
Trust → Repurchase Intention	0.54	9.61	<0.001
Satisfaction → Repurchase Intention	0.47	8.84	<0.001

The regression model revealed strong and statistically significant pathways, confirming that improved recommendation quality driven by sentiment analysis directly enhanced trust and satisfaction, which in turn significantly predicted repurchase intention.

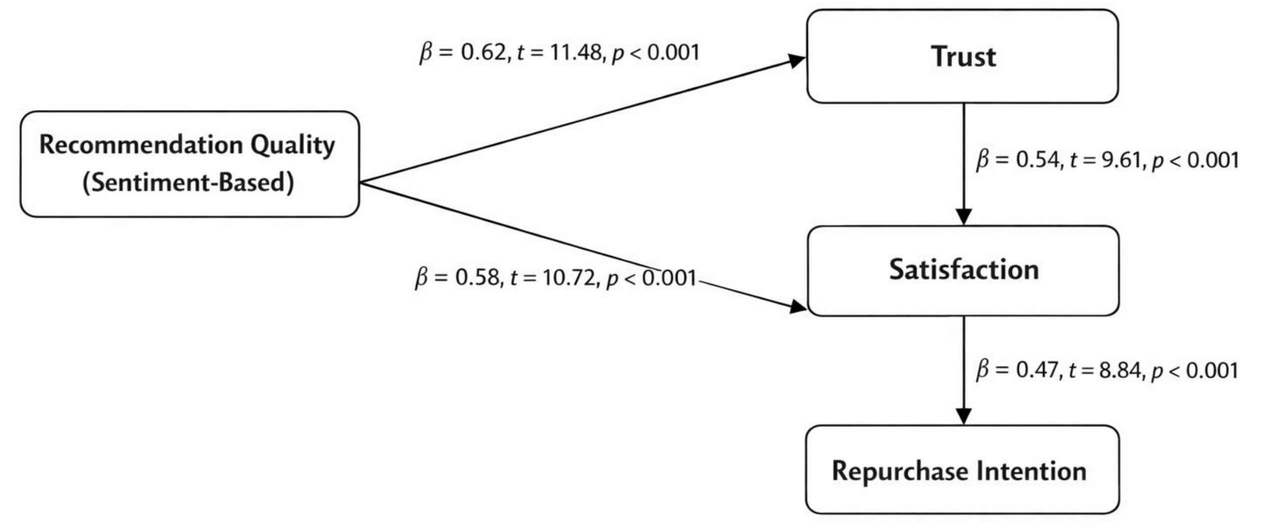

Figure 1. Conceptual Model of Sentiment-Driven Recommendation Effects on Consumer Behavior

Figure 1 illustrates the final structural model depicting the direct and indirect effects of sentiment-based recommendation quality on consumer trust, satisfaction, and repurchase intention. Collectively, these findings provide robust empirical evidence that integrating social media sentiment analysis into recommender systems substantially improves system performance, customer engagement, and commercial outcomes within online retail environments.

4. Discussion and Conclusion

The present study aimed to design and empirically evaluate a sentiment analysis–based recommender system for online retail platforms and to examine its influence on recommendation quality, customer trust, satisfaction, and repurchase intention. The findings provide strong evidence that integrating customer sentiment extracted from social media into the recommendation process substantially improves both system performance and key consumer behavioral outcomes. Specifically, the proposed model significantly outperformed conventional collaborative filtering and content-based recommendation approaches across all major evaluation metrics, including precision, recall, F1-score, normalized discounted cumulative gain, click-through rate, and conversion performance. These results reinforce the growing body of research emphasizing the strategic value of emotionally intelligent systems in digital commerce (Ibrahim & Wang, 2019; Li et al., 2024; Zhou et al., 2022).

The superior predictive performance of the sentiment-based model aligns closely with contemporary advancements in sentiment analysis and natural language processing. The integration of deep learning and transformer-based architectures in the present study allowed the system to capture nuanced emotional expressions and contextual meaning within Persian-language social media content. This finding is consistent with prior research demonstrating that advanced language models such as BERT and deep memory networks significantly outperform traditional lexicon-based methods in sentiment classification tasks (Hiriyannaiah et al., 2020; Li et al., 2024; Zhou et al., 2022). Moreover, the ability of the system to handle multi-aspect sentiment and emotional complexity supports earlier conclusions that hybrid and deep learning approaches provide more robust sentiment detection in dynamic social media environments (Thallapalli et al., 2020; Wahyudi & Sibaroni, 2022).

Beyond technical performance, the study revealed substantial behavioral and commercial impacts of sentiment-driven recommendations. The implementation of the proposed system led to statistically significant increases in purchase intention, customer satisfaction, platform trust, and average order value. These outcomes confirm that emotionally congruent recommendations enhance the psychological alignment between consumers and digital platforms, thereby strengthening relational bonds and transactional commitment. Such results are strongly supported by existing literature highlighting the central role of emotional engagement in shaping consumer loyalty and long-term value (Azizah, 2025; Baskar, 2021; Liniņa & Vēvere, 2020). The observed improvement in average order value further corroborates findings that personalized and emotionally relevant content stimulates deeper involvement and higher spending behavior (Safeer, 2024; Weinandy et al., 2023).

The structural regression analysis provided deeper insight into the psychological mechanisms underlying these outcomes. The results confirmed that enhanced recommendation quality exerts a strong direct effect on both trust and satisfaction, which in turn significantly predict repurchase intention. This mediation structure is highly consistent with established models of digital consumer behavior. Prior research demonstrates that trust and satisfaction serve as central mediating constructs linking digital service quality to loyalty and repurchase decisions (Azizah, 2025; Karunarathne & Wanninayake, 2025; Zhou & Hudin, 2025). The present findings extend this framework by demonstrating that sentiment-based intelligence significantly strengthens these relational pathways.

Furthermore, the results support the theoretical propositions of omnichannel and customer experience models emphasizing perceived personal preference fit and social relatedness as key drivers of word-of-mouth behavior and customer retention (Li et al., 2022). By dynamically adjusting recommendations according to consumers' emotional expressions on social media, the proposed system enhanced perceived personalization and emotional resonance, thereby fostering deeper psychological engagement. This effect is particularly relevant in highly competitive online retail environments where differentiation increasingly depends on experiential and relational factors rather than price competition alone (Banjarnahor et al., 2024; Zavala-Huerta, 2023).

The strong association between sentiment-based recommendations and customer trust is especially noteworthy. Trust remains one of the most critical determinants of sustained online consumer relationships, particularly in environments characterized by information asymmetry and perceived risk. Prior studies consistently emphasize that social media communication and digital transparency play decisive roles in building trust and brand credibility (Baskar, 2021; Liniņa & Vēvere, 2020). The present study demonstrates that integrating consumers' own emotional expressions into the recommendation logic strengthens perceived responsiveness and authenticity, thereby reinforcing trust. This result echoes the conclusions of Azizah (2025), who found that online trust mediates the impact of service quality and social media interactivity on customer loyalty (Azizah, 2025).

The impact of sentiment-based recommendations on customer satisfaction also aligns with extensive empirical evidence. Customer satisfaction emerges not only from transactional efficiency but from emotional fulfillment and perceived recognition. The ability of the system to reflect consumers' moods, concerns, and preferences back to them through personalized recommendations significantly enhanced satisfaction levels. This is consistent with findings that emotionally attuned digital environments improve customer experience quality and behavioral loyalty (Happ et al., 2020; Safeer, 2024). Additionally, the results complement studies demonstrating that customer experience optimization through digital intelligence enhances brand attachment and lifetime value (Waltenrath et al., 2022; Weinandy et al., 2023).

The role of social media sentiment as a predictive signal for consumer behavior is further reinforced by the present findings. Previous research indicates that social media sentiment accurately predicts churn, loyalty shifts, and purchasing cycles (Lappeman et al., 2022; Lim & Anitsal, 2019). The current study extends this evidence by showing that when sentiment is operationalized within recommender systems, its predictive power translates directly into improved commercial performance. The integration of emotional data thus transforms social media from a passive information source into an active strategic asset for online retailers.

The study also contributes to the growing literature on emotion-aware artificial intelligence in marketing. Recent advances in emotion lexicons and multi-dictionary emotion modeling have expanded the scope of automated emotion detection beyond simple positive–negative polarity (Wang et al., 2024). By incorporating these advancements, the proposed system demonstrated enhanced sensitivity to complex affective states, enabling more refined personalization. This supports emerging perspectives that future digital commerce systems must incorporate affective computing as a core component of intelligent customer engagement (Li et al., 2024; Zhou et al., 2022).

In addition, the findings highlight the managerial significance of sentiment-based recommender systems. The substantial improvements observed in click-through rates, conversion rates, and average order value indicate strong return-on-investment potential for retailers adopting such systems. These results align with previous studies demonstrating that emotionally optimized digital marketing strategies significantly improve commercial performance and brand competitiveness (Banjarnahor et al., 2024; Safeer, 2024; Waltenrath et al., 2022). In increasingly saturated online markets, the ability to differentiate through emotionally intelligent personalization represents a critical strategic advantage.

Finally, the context of the COVID-19 pandemic and post-pandemic digital acceleration further amplifies the importance of these findings. The pandemic has fundamentally reshaped consumer behavior, increasing dependence on online platforms and intensifying emotional volatility in consumption decisions (Gunaningrat et al., 2021; Kalpana, 2022). Studies during this period consistently report heightened emotional sensitivity and reliance on social media for purchasing guidance and emotional reassurance (White et al., 2023; Zhou & Hudin, 2025). The present study demonstrates that sentiment-based recommender systems are particularly well-suited to this evolving digital environment, providing adaptive, emotionally responsive customer engagement mechanisms.

Despite its contributions, this study has several limitations. The dataset was restricted to social media platforms and online retailers within a single metropolitan region, which may limit the generalizability of the findings across different cultural, linguistic, and economic contexts. Additionally, although advanced deep learning models were employed, issues related to sarcasm detection, multilingual sentiment variation, and emerging slang may have introduced classification noise. Finally, the study focused primarily on short-term behavioral outcomes, and the long-term sustainability of sentiment-based recommendation effects warrants further longitudinal investigation.

Future studies should expand the geographic and cultural scope of analysis and examine the performance of sentiment-based recommender systems across diverse retail sectors and consumer demographics. Longitudinal research designs could explore how emotional alignment influences customer lifetime value and brand attachment over extended periods. Further work is also needed to integrate multimodal sentiment analysis, incorporating visual, audio, and behavioral cues alongside textual data, in order to achieve a more holistic representation of consumer emotion.

Online retailers should invest in sentiment-aware recommendation infrastructures and develop organizational capabilities in affective data analytics. Firms are encouraged to integrate social media monitoring with customer relationship management systems and ensure continuous model updating to reflect evolving consumer emotions. Ethical considerations, including data privacy, algorithmic transparency, and bias mitigation, must remain central to the deployment of emotionally intelligent recommender systems to maintain consumer trust and regulatory compliance.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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