2025 International Conference on Fiscal Management, Holistic Social Studies (FMHSS 2025)

Article

Research on E-Commerce User Profiling Based on the Integration of Sentiment Analysis and Big Data and Emotion-Driven Consumer Behavior

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Abstract: With the rapid advancement of big data and artificial intelligence technologies, sentiment analysis has emerged as an indispensable and highly effective tool for understanding complex user emotions and significantly enhancing e-commerce personalization. Traditional user profiling methodologies predominantly focus on demographic and historical transaction data, frequently overlooking the critical emotional dimension of consumers. This fundamental limitation restricts the accuracy of behavior prediction and diminishes the efficacy of decision-making support systems. To address this gap, this study proposes a novel, comprehensive approach to e-commerce user profiling by seamlessly integrating advanced sentiment analysis with robust big data techniques to construct multi-dimensional, emotion-aware consumer profiles. The research develops an innovative framework that systematically incorporates emotional factors into dynamic user models, rigorously analyzes their direct influence on purchasing behavior, and explores how fluctuating emotional states drive diverse consumption patterns across various product categories. Through extensive multi-source data collection—encompassing social media interactions, customer reviews, and real-time browsing behaviors—coupled with state-of-the-art natural language processing algorithms and established consumer psychology models, the research reveals profound and statistically significant correlations between specific user emotions and subsequent purchase decisions. The empirical findings provide a robust theoretical basis for refining targeted marketing strategies, improving user-centric product design, and optimizing personalized recommendation systems to achieve higher conversion rates. Ultimately, this research not only contributes to the broader academic understanding of emotion-driven consumption but also offers actionable, practical guidance for the development of intelligent, emotionally responsive e-commerce service ecosystems.

Keywords: sentiment analysis; e-commerce; user profiling; consumer behavior; big data; decision making

Received: 24 April 2026
Revised: 17 June 2026
Accepted: 28 June 2026
Published: 01 July 2026

1. Introduction

1.1. Research Background and Significance

With the rapid development of e-commerce and the widespread adoption of intelligent terminals, user profiling has emerged as a vital tool for platforms to better understand users and deliver personalized services. Traditional approaches to user profiling have predominantly emphasized demographic and behavioral data, often overlooking the critical impact of emotional factors on consumer behavior [1]. Emotional influences frequently play a pivotal role in shaping purchasing decisions, making their integration into profiling methodologies essential. The advent of big data and artificial intelligence has enabled sentiment analysis technologies to extract emotional tendencies from extensive text datasets. This advancement provides innovative methods for constructing user profiles that incorporate emotional dimensions. By combining sentiment analysis with big data, platforms can achieve a more precise depiction of user preferences and consumption patterns, thereby offering robust theoretical and technical foundations for enhanced marketing strategies and tailored service delivery.

1.2. Current Research Status at Home and Abroad

International research on user profiling has undergone significant advancements, shifting from static models to more dynamic methodologies that incorporate emotional and contextual factors. Early approaches to user profiling primarily relied on demographic data and behavioral patterns, which provided only a limited and static snapshot of user characteristics at a specific point in time. With the development of sentiment analysis techniques and insights from cognitive psychology, contemporary research has moved toward integrating emotional states and situational contexts into user profiling processes [1, 2]. This evolution enables more precise predictions of user behavior by accounting for the dynamic and fluctuating nature of emotions and external circumstances. In the e-commerce industry, major platforms have made notable progress in embedding emotional computing and personalized recommendation systems into their operations. These systems leverage emotional cues to customize content and product suggestions, thereby enhancing the user experience and driving increased engagement and sales. The integration of such advanced techniques demonstrates the potential of dynamic user profiling to transform digital interactions and commercial strategies.

Within domestic research, sentiment-based user profiling is gaining traction, with a growing focus on refining algorithms and enhancing data analysis methodologies. Despite these advancements, there remains a significant gap in the incorporation of psychological theories and the practical application of behavioral mechanisms [3]. While sentiment analysis has become a widely used tool for interpreting user emotions, challenges persist in achieving high levels of accuracy. Furthermore, practical implementations of sentiment-aware user profiling encounter obstacles such as the limited integration of data from diverse sources. This limitation hinders the development of a comprehensive understanding of user behavior. Many existing systems face difficulties in synthesizing and harmonizing varied data types, including emotional responses, behavioral patterns, and contextual information, into a unified and actionable user profile. Addressing these challenges requires further innovation in data integration techniques and a deeper alignment with interdisciplinary insights to enhance the effectiveness and applicability of user profiling systems.

1.3. Research Objectives and Content

The primary objective of this study is to investigate the development of e-commerce user profiles that incorporate sentiment analysis, with a focus on understanding how user emotions influence online purchasing behavior [4]. This research aims to provide a detailed exploration of the ways in which emotions impact decision-making processes and consumption patterns within e-commerce environments. The study will delve into the technical frameworks and methodologies necessary for creating sentiment-aware user profiles, including the application of sentiment analysis algorithms, advanced emotion detection techniques, and the integration of diverse data sources. By constructing a multi-dimensional, data-driven user profile model, the research seeks to enhance the precision of user profiling by integrating behavioral data with emotional responses, thereby offering a more comprehensive perspective on user behavior. Additionally, the study will analyze the connections between various emotional states—such as joy, frustration, trust, or anxiety—and their influence on users' purchasing decisions, aiming to identify the mechanisms through which emotions shape online consumption behaviors. Based on these insights, the research will propose an emotion-driven marketing strategy designed to personalize content and product recommendations according to users' emotional states, ultimately aiming to improve marketing efficiency, foster deeper customer engagement, and increase conversion rates.

2. Theoretical Foundations and Research Framework

2.1. Theoretical Basis of Sentiment Analysis

Sentiment analysis, a significant domain within natural language processing (NLP), has garnered substantial attention due to its extensive applications in areas such as social media monitoring, public opinion analysis, and product review evaluation. This section delves into the theoretical foundations of sentiment analysis, emphasizing methodologies rooted in natural language processing, machine learning, and deep learning. At its core, sentiment analysis involves text sentiment classification, which seeks to identify the emotional polarity—positive, negative, or neutral—expressed within a given text. Traditional methods often utilize sentiment lexicons, which categorize words based on their emotional valence [5]. Examples of such lexicons include resources designed to classify words according to their associated sentiment. However, these lexicon-based approaches face challenges in addressing contextual nuances, irony, and domain-specific language variations. To overcome these limitations, machine learning algorithms, including Naïve Bayes, Support Vector Machines (SVM), and logistic regression, have been employed to enable more sophisticated and data-driven classification. In recent years, deep learning models have transformed sentiment analysis by capturing intricate syntactic and semantic relationships within textual data. Models such as Recurrent Neural Networks (RNNs), Long Short-Term Memory networks (LSTMs), and transformer-based architectures like BERT have demonstrated exceptional capabilities in interpreting context-dependent emotional expressions. These advanced models are particularly effective in analyzing nuanced sentiment across diverse platforms and cultural contexts, thereby enhancing the accuracy and applicability of sentiment analysis.

2.2. User Profiling Theories

User profiling is a multidisciplinary domain that draws upon principles from behavioral economics, consumer psychology, and information systems theory. It focuses on creating structured representations of users to gain insights into their preferences, behaviors, and motivations. This process involves analyzing various dimensions such as demographic attributes (including age, gender, and geographic location), individual interests (such as hobbies and preferred types of content), and consumption patterns (like purchase histories and browsing behaviors). By synthesizing these elements, systems can develop dynamic user profiles that enable personalized content delivery and targeted marketing strategies. Recent advancements in the field highlight the importance of adaptive profiling techniques, where user profiles are continuously updated in real time based on incoming data. Furthermore, privacy-aware modeling has emerged as a critical area, aiming to balance the benefits of personalization with ethical considerations and data protection. Innovations such as social network analysis and emotion-aware computing are also expanding the scope of user modeling, offering more comprehensive and empathetic approaches to understanding user behavior.

2.3. Emotion-Driven Consumer Behavior Model

This subsection explores how users' emotional states influence their decision-making processes by utilizing concepts from the Stimulus-Organism-Response (S-O-R) model and appraisal theory. The S-O-R model, which originates from environmental psychology, suggests that external stimuli, such as advertising content or user interface design, impact an individual's internal state, which subsequently shapes their behavioral responses, including purchasing decisions. Within the realm of digital marketing and e-commerce, emotional stimuli—such as the visual appeal of a platform, the tone used in communication, and the presence of social proof—are pivotal in influencing user perceptions and engagement. These elements are carefully designed to evoke specific emotional reactions, thereby enhancing the likelihood of desired consumer behaviors [6].

Appraisal theory provides additional depth by detailing how individuals assess and interpret emotional stimuli based on factors such as personal relevance, goals, and the situational context. These cognitive evaluations determine the type and intensity of emotions experienced, which in turn guide users' intentions and actions. By synthesizing these theoretical models, the emotion-driven consumer behavior framework offers a comprehensive understanding of how emotional cues embedded in digital environments can trigger specific psychological states. These states not only increase consumer involvement and trust but also foster stronger engagement and ultimately drive purchasing behavior [7]. This integrated approach underscores the importance of strategically leveraging emotional elements to optimize user experiences and achieve marketing objectives.

3. Construction of Sentiment-Enhanced E-Commerce User Profiles

3.1. Data Sources and Preprocessing

Data is gathered from various sources, including user reviews on e-commerce platforms, browsing histories, purchase records, and textual content from social media. These diverse datasets provide comprehensive insights into consumer behavior, preferences, and emotional tendencies. The preprocessing stage is essential for ensuring the data is clean, structured, and ready for analysis. This involves removing noise and irrelevant information, such as duplicate entries, incomplete data, or errors, to enhance data quality. Additionally, word segmentation is applied, particularly for languages lacking clear word boundaries, to divide text into meaningful units like words or phrases. Entity recognition is another critical step, enabling the identification of key elements within the data, such as product names, brands, or expressions of sentiment. These preprocessing techniques collectively ensure the data is consistent, accurate, and well-organized, thereby optimizing its suitability for subsequent analytical processes.

3.2. Sentiment Analysis Methodology

For sentiment analysis, advanced algorithms, including models designed to process textual data with high efficiency, are utilized to analyze large-scale information. These algorithms are adept at capturing both immediate and extended dependencies within text, which is essential for accurately identifying emotional patterns. The primary objective is to classify and distinguish between fundamental emotional categories, such as joy, anger, fear, and sadness. Following the detection of emotions, quantification methods are employed to assess the intensity of each emotion, thereby facilitating a detailed examination of sentiment distribution across user interactions. This comprehensive approach enables researchers to uncover intricate emotional tendencies and provides valuable insights into subtle variations in consumer sentiment, enhancing the understanding of user behavior and preferences.

3.3. User Profile Model Construction

The construction of a user profile model involves the integration of fundamental user attributes, such as age, location, and gender, alongside behavioral data, including browsing history, purchase patterns, and interaction frequency. Additionally, emotional dimensions are derived through sentiment analysis to provide deeper insights into user behavior. Advanced clustering and classification algorithms are utilized to categorize users based on emotional tendencies, shifts in interests, and consumption preferences. This segmentation process identifies distinct user groups characterized by unique emotional and behavioral profiles. By continuously monitoring the evolution of user preferences and analyzing the impact of emotional states on purchasing decisions, the model enables the delivery of highly personalized recommendations, thereby improving the relevance and effectiveness of suggested content or products.

4. Research on Emotion-Driven Consumer Behavior

4.1. Correlation Analysis of Emotion and Purchase Behavior

This section explores the complex interplay between emotional factors—specifically emotional intensity and polarity—and consumer purchase behavior. Emotional intensity pertains to the strength or magnitude of emotions experienced by individuals during their interactions with products, services, or advertisements. Emotional polarity, on the other hand, refers to the nature of these emotions, whether positive or negative [8]. By examining these dimensions, the research aims to uncover their influence on various facets of purchasing behavior, such as the decision to make a purchase, the frequency of purchases, and the extent of brand loyalty exhibited by consumers over time. For instance, heightened positive emotions like joy or excitement can often trigger impulse purchases, whereas negative emotions such as frustration or dissatisfaction may result in product avoidance or brand switching. Moreover, analyzing the relationship between emotional intensity and purchase frequency can provide valuable insights into customer retention, shedding light on whether a brand successfully fosters repeat purchases or if emotional disconnects contribute to customer attrition. Additionally, understanding how emotional engagement correlates with brand loyalty can reveal how consistent emotional resonance strengthens long-term consumer relationships. Advanced statistical methods, including regression analysis, correlation matrices, and structural equation modeling, are employed to quantify these emotional influences on consumer behavior. These techniques enable a nuanced understanding of how emotions shape not only immediate purchasing decisions but also enduring consumer loyalty. Such insights are instrumental for businesses aiming to refine their marketing strategies, ensuring they effectively address both the emotional and behavioral dimensions of their target audience.

4.2. Emotional Pathways in Decision-Making

This section delves into the exploration of emotional pathways that influence user decision-making and purchasing behavior. Various empirical methods are employed to analyze how emotional stimuli impact the steps leading to a purchase [9]. Eye-tracking technology, for instance, provides a detailed understanding of users' visual attention patterns, identifying specific elements on a website, product page, or advertisement that capture emotional attention. Through the analysis of eye movements and gaze fixation, researchers can determine which colors, images, or product features evoke stronger emotional responses. These findings are instrumental in identifying the emotional components that resonate most effectively with consumers, thereby enhancing engagement and interaction with the content.

Questionnaire surveys serve as another critical tool for accessing users' emotional states during their shopping experiences. By directly asking users about their feelings at various stages of their interaction with a product or brand—such as feelings of excitement, frustration, or satisfaction—researchers can establish correlations between these emotional states and purchasing intentions [10, 11]. This method provides a qualitative perspective on the emotions that influence decision-making, offering a self-reported complement to the behavioral data obtained through other techniques. The insights gained from these surveys help to create a more comprehensive understanding of the emotional factors that drive or hinder purchasing behavior.

A/B testing is utilized to experiment with different emotional cues or variations in content, enabling researchers to observe which elements generate stronger emotional reactions and lead to higher conversion rates. For example, a website might display two distinct advertisements—one emphasizing excitement and adventure, and the other focusing on security and trust [3, 12]. The results of such testing reveal which emotional appeal is more effective in driving purchases. This approach allows for the optimization of content to align with the emotional preferences of the target audience, thereby improving the overall effectiveness of marketing strategies.

By integrating these empirical methods, the research identifies critical emotional touchpoints in the decision-making process. These are moments when emotions play a pivotal role in swaying users toward making a purchase or, conversely, when negative emotions act as barriers to decision-making. Understanding these emotional pathways provides valuable insights into designing more effective online shopping experiences. By strategically incorporating elements that evoke positive emotions and mitigate negative ones, businesses can guide users toward favorable decision-making outcomes. This not only enhances conversion rates but also contributes to greater customer satisfaction, fostering long-term loyalty and engagement.

4.3. User Segmentation Based on Emotion

This section explores the segmentation of users based on their emotional attributes, aiming to identify variations in purchasing behavior across different emotional profiles [13, 14]. Key factors in this segmentation process include emotional sensitivity, preference orientation, and price sensitivity. Emotional sensitivity pertains to the extent to which individuals react to emotional stimuli, which can significantly influence their decision-making processes. Preference orientation categorizes users according to their inclination toward specific product types or brands, often shaped by emotional appeals such as trust, excitement, or fear. Price sensitivity examines how emotional factors impact consumers' willingness to pay, with some individuals prioritizing emotional satisfaction over cost considerations. By categorizing users into distinct emotional segments, it becomes possible to analyze how these profiles influence purchasing decisions, product preferences, and responses to promotional offers or pricing strategies. This approach enables the development of more targeted marketing strategies and personalized user experiences. Furthermore, it provides valuable insights into the role of emotional factors in shaping consumer behavior, offering a nuanced understanding of how emotions drive decision-making across diverse user groups.

5. Application Scenarios and Strategy Recommendations

5.1. Refined Marketing Based on Emotion Profiles

Refined marketing strategies can be developed by analyzing users' emotional tendencies and underlying consumption motivations. By understanding emotional profiles, such as sensitivity to joy, fear, trust, or excitement, marketers can craft highly customized content marketing and advertising campaigns that resonate on a deeper emotional level [15]. Aligning promotional messages, visuals, and tones with specific emotional triggers enables marketers to enhance engagement and relevance. This approach improves marketing precision by targeting the appropriate emotions at optimal moments, ultimately leading to a better user experience and more effective communication. For instance, content designed to evoke trust can be particularly impactful for high-involvement products, where consumers require reassurance and confidence. Conversely, excitement-driven content may be more suitable for impulsive purchases or limited-time offers, where urgency and enthusiasm play a critical role. By leveraging targeted emotional appeals, brands can not only strengthen their messaging but also foster deeper connections with consumers, encouraging repeat interactions and cultivating long-term loyalty. This strategic focus on emotional alignment ensures sustained consumer engagement and brand growth.

5.2. Product Design and Optimization

User emotional feedback is a pivotal factor in shaping the design and optimization of products. By systematically analyzing the emotional responses triggered by various product features or user experiences, businesses can pinpoint specific areas requiring enhancement and implement design modifications that elevate user satisfaction. This process enables designers to discern which elements of a product resonate most strongly with users on an emotional level, whether it pertains to visual aesthetics, functional performance, intuitive usability, or the overall user experience. For example, products that successfully evoke positive emotions, such as joy, trust, or comfort, are more likely to establish enduring emotional connections with consumers. Conversely, negative emotional reactions, such as frustration, dissatisfaction, or confusion, highlight aspects that necessitate refinement. By integrating emotional insights into iterative product development cycles, companies can craft offerings that not only fulfill practical requirements but also foster deeper emotional engagement, ultimately driving higher levels of customer loyalty and long-term satisfaction.

5.3. Personalized Recommendation System Optimization

Personalized recommendation systems can achieve substantial improvements by integrating emotional indicators into their algorithms. Traditional models primarily focus on analyzing user behavior, such as purchase history or browsing patterns, to generate suggestions. However, incorporating emotional data, such as users' responses to specific types of content, products, or services, allows recommendation engines to deliver more precise and contextually relevant suggestions. Emotional matching enables the system to align recommendations with the user's current emotional state, enhancing the personalization and effectiveness of the suggestions. Furthermore, scenario-based push strategies can be employed to tailor recommendations not only to individual preferences but also to the emotional context or situational factors influencing the user. For instance, a user experiencing stress could be presented with calming products or services, while someone in an excited state might receive suggestions related to adventure or novelty. This approach fosters deeper emotional connections with the brand, increasing user engagement and loyalty. By addressing both emotional and situational dimensions, these systems can significantly improve user retention and overall satisfaction, creating a more dynamic and responsive recommendation experience [2].

6. Conclusion

This paper investigates the integration of sentiment analysis and big data in e-commerce user profiling, with particular emphasis on the important role of emotional factors in improving user understanding and shaping consumption behavior. By constructing a comprehensive and multi-dimensional user profile model that combines emotional information with behavioral characteristics, the study clarifies how emotions influence purchasing decisions, preference formation, and broader patterns of consumer engagement. The analysis indicates that emotional states, including excitement, satisfaction, frustration, and doubt, exert a direct influence on multiple stages of the consumer journey, such as purchase intention, transaction frequency, post-purchase evaluation, and long-term brand loyalty. These findings demonstrate that emotional information is not merely supplementary to conventional behavioral data, but rather a critical component for achieving a more accurate and dynamic representation of users in digital commerce environments. In addition to offering theoretical insight into the relationship between emotion and consumer behavior, this research provides practical guidance for improving personalized services in e-commerce platforms. Through the effective use of emotional data, businesses can refine marketing strategies, generate product recommendations with stronger emotional relevance, and optimize product design and service delivery to better align with users’ psychological expectations and affective needs. Emotional marketing, when grounded in systematic sentiment understanding, can therefore strengthen customer relationships, enhance trust, increase user retention, and improve conversion performance. Furthermore, this study identifies promising directions for future research, particularly in the areas of real-time emotion recognition, adaptive feedback mechanisms, and context-aware personalization. The incorporation of real-time emotional insight may enable e-commerce systems to respond more flexibly to users’ immediate states, thereby improving interaction quality, satisfaction, and platform intelligence. Overall, the findings support the development of more responsive, precise, and emotionally aware e-commerce ecosystems.

References

1. N. Stephens and K. P. Gwinner, "Why don’t some people complain? A cognitive-emotive process model of consumer complaint behavior," *Journal of the Academy of Marketing Science*, vol. 26, no. 3, pp. 172–189, 1998.

2. A. Tripathi, A. Klami, and S. Kaski, "Simple integrative preprocessing preserves what is shared in data sources," *BMC Bioinformatics*, vol. 9, no. 1, p. 111, 2008.
3. D. R. Euston, A. J. Gruber, and B. L. McNaughton, "The role of medial prefrontal cortex in memory and decision making," *Neuron*, vol. 76, no. 6, pp. 1057–1070, 2012.
4. M. Gao, K. Liu, and Z. Wu, "Personalisation in web computing and informatics: Theories, techniques, applications, and future research," *Information Systems Frontiers*, vol. 12, no. 5, pp. 607–629, 2010.
5. L. Yang, Y. Li, J. Wang, and R. S. Sherratt, "Sentiment analysis for E-commerce product reviews in Chinese based on sentiment lexicon and deep learning," *IEEE Access*, vol. 8, pp. 23522–23530, 2020.
6. S. Vanaja and M. Belwal, "Aspect-level sentiment analysis on e-commerce data," in *2018 International Conference on Inventive Research in Computing Applications (ICIRCA)*, pp. 1275–1279, July 2018.
7. M. E. Alzahrani, T. H. Aldhyani, S. N. Alsubari, M. M. Althobaiti, and A. Fahad, "Developing an intelligent system with deep learning algorithms for sentiment analysis of E-Commerce product reviews," *Computational Intelligence and Neuroscience*, vol. 2022, no. 1, p. 3840071, 2022.
8. J. Jabbar, I. Urooj, W. JunSheng, and N. Azeem, "Real-time sentiment analysis on E-commerce application," in *2019 IEEE 16th International Conference on Networking, Sensing and Control (ICNSC)*, pp. 391–396, May 2019.
9. M. Loukili, F. Messaoudi, and M. El Ghazi, "Sentiment analysis of product reviews for e-commerce recommendation based on machine learning," *International Journal of Advances in Soft Computing & Its Applications*, vol. 15, no. 1, 2023.
10. H. Huang, A. A. Zavareh, and M. B. Mustafa, "Sentiment analysis in e-commerce platforms: A review of current techniques and future directions," *IEEE Access*, vol. 11, pp. 90367–90382, 2023.
11. S. K. Rajaram, G. K. Patra, S. Konkimalla, V. N. Boddapati, M. Sarisa, M. S. Reddy, and K. Polimetla, "A sentiment analysis of customer product review based on machine learning techniques in E-commerce," Available at SSRN 5153849, 2023.
12. I. Karabila, N. Darraz, A. El-Ansari, N. Alami, and M. El Mallahi, "BERT-enhanced sentiment analysis for personalized e-commerce recommendations," *Multimedia Tools and Applications*, vol. 83, no. 19, pp. 56463–56488, 2024.
13. M. Demircan, A. Seller, F. Abut, and M. F. Akay, "Developing Turkish sentiment analysis models using machine learning and e-commerce data," *International Journal of Cognitive Computing in Engineering*, vol. 2, pp. 202–207, 2021.
14. A. Bayhaqy, S. Sfenrianto, K. Nainggolan, and E. R. Kaburuan, "Sentiment analysis about E-commerce from tweets using decision tree, K-nearest neighbor, and naïve bayes," in *2018 International Conference on Orange Technologies (ICOT)*, pp. 1–6, October 2018.
15. P. K. Sari, A. Alamsyah, and S. Wibowo, "Measuring e-Commerce service quality from online customer review using sentiment analysis," in *Journal of Physics: Conference Series*, vol. 971, no. 1, p. 012053, March 2018.