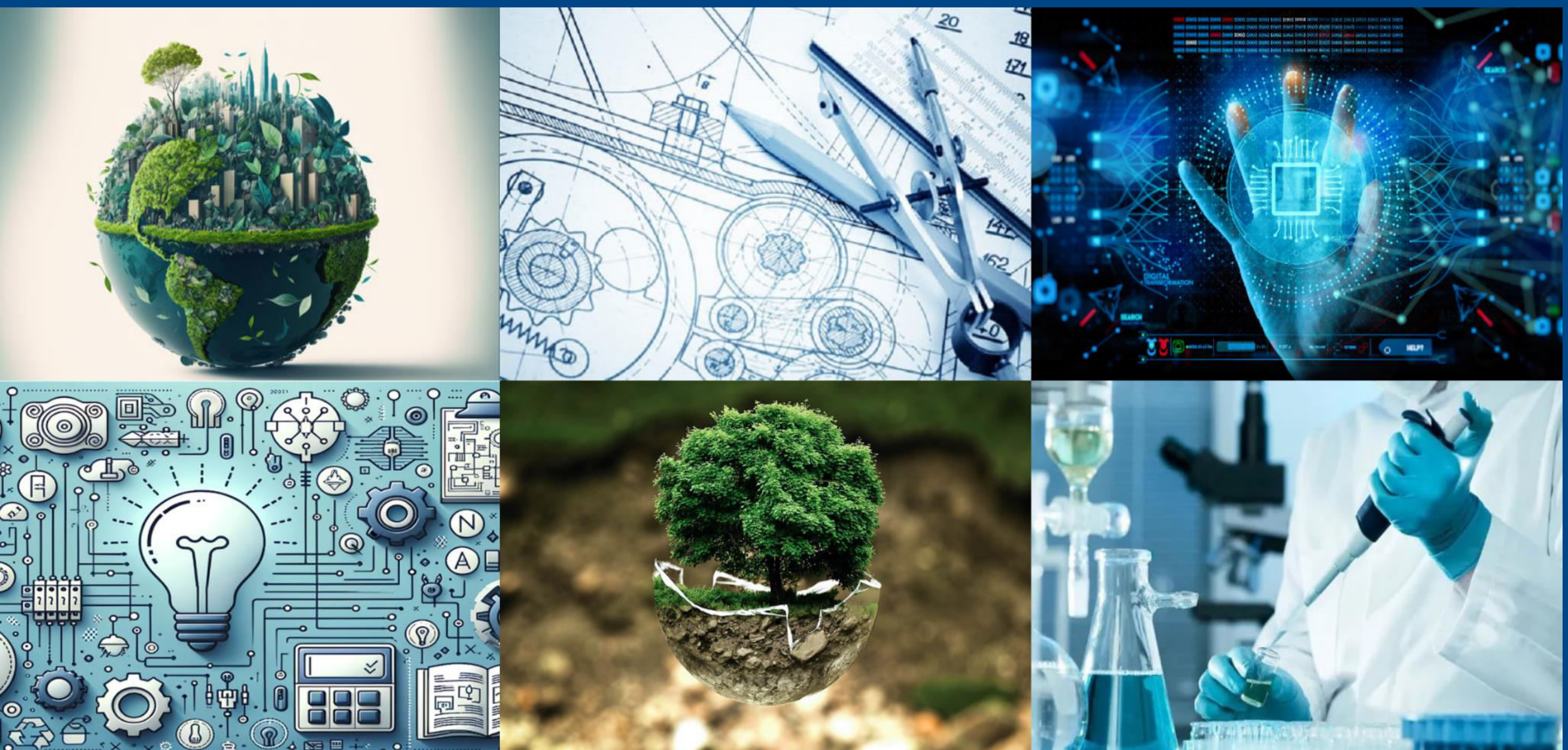
ISSN: 2582-7219

# International Journal of Multidisciplinary Research in Science, Engineering and Technology

*(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)*



Impact Factor: 9.864

Volume 9, Issue 5, May 2026

www.ijmrset.com ijmrset@gmail.com +91 6381 907 438 +91 63819 07438

© 2026 IJMRSET | Volume 9, Issue 5, May 2026| DOI:10.15680/IJMRSET.2026.0905042

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 9.864| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

# AI-Powered Recommender Systems in ECommerce: An Evolving Research Landscape

**Prof. Dr. Aniruddha Rumale [1], Dr. Dipak Bage[2], Gaurav Ravindra Patil [3], Krushna karbari Munjal [4], Ishan Rajendra Bharambe [5], Snehal Rajesh Nawase [6]**

Professor, Department of Information Technology, Sandip Institute of Technology and Research Center, Nashik, India[1,2]

UG Scholars,Department of Information Technology, Sandip Institute of Technology and Research Center, Nashik, India [3,4,5,6]

**ABSTRACT:** The continuous growth of digital commerce platforms has significantly increased the number of products available to online consumers. Although this expansion improves accessibility and convenience, it also creates difficulty for users in identifying products that match their interests and requirements. Recommendation systems play a vital role in solving this issue by delivering personalized product suggestions based on user behavior and product characteristics. Conventional recommendation approaches such as collaborative filtering and content-oriented filtering have shown useful results, but they often struggle with challenges including sparse datasets, cold-start conditions, and limited capability to understand complicated user-item interactions.

This research introduces an intelligent hybrid recommendation framework developed for the NEUROCART AI E-Commerce Platform. The proposed framework integrates collaborative filtering, content-oriented recommendation, neural collaborative filtering, and sentiment analysis into a unified architecture. The system is organized into multiple layers, namely the data management layer, processing layer, recommendation engine, and user interaction layer, to improve scalability and flexibility. Performance evaluation using metrics such as Precision, Recall, F1-Score, and Mean Average Precision demonstrates that the proposed hybrid approach performs better than traditional recommendation techniques. The study emphasizes the growing significance of artificial intelligence in improving recommendation quality, enhancing customer experience, and enabling adaptive personalization in online shopping environments.

**KEYWORDS:** Artificial Intelligence, Recommendation Systems, E-Commerce Personalization, Deep Learning, Hybrid Recommendation Model, Neural Collaborative Filtering, Sentiment Analysis, Adaptive Recommendation

## I. INTRODUCTION

Electronic commerce has transformed the way consumers purchase products and services across the world. The rapid development of internet infrastructure, mobile technologies, and digital payment systems has enabled online marketplaces to provide access to millions of products from different categories. As a result, customers can now compare prices, features, and reviews from multiple vendors within seconds. While this digital transformation has improved customer convenience, it has also introduced the challenge of excessive information availability, where users face difficulty in identifying products that truly satisfy their preferences.

To address this issue, recommendation systems have become an essential component of modern e-commerce platforms. These systems analyze user activities such as browsing behavior, ratings, search history, and purchase patterns to generate personalized recommendations. Earlier recommendation methods mainly relied on popularity-based strategies that suggested widely purchased products to every customer. Over time, more advanced methods such as collaborative filtering and content-based filtering were introduced to provide customized recommendations.

Collaborative filtering methods generate recommendations by identifying similarities among users or products based on historical interaction data. On the other hand, content-based recommendation systems focus on product attributes and user preferences to suggest similar items. Although these approaches are widely adopted, they suffer from several practical limitations. Collaborative filtering techniques are affected by data sparsity and cold-start problems, while content-based approaches often produce repetitive recommendations with low diversity.

Recent advancements in artificial intelligence and deep learning have created opportunities to improve the effectiveness of recommendation systems. AI-driven models can process complex behavioral patterns, learn non-linear relationships, and continuously adapt to changing user interests. This research proposes the NEUROCART AI E-Commerce Platform, which combines multiple recommendation techniques into a hybrid architecture. The platform integrates collaborative filtering, content-based filtering, neural collaborative filtering, and sentiment analysis to improve recommendation accuracy and user satisfaction.

In addition to recommendation functionality, the platform also includes intelligent product search, multilingual support, and an AI-powered conversational assistant for natural language interaction. The system architecture follows a layered approach to ensure maintainability, scalability, and modular development

## II. LITERATURE REVIEW

Research in recommender systems has progressed significantly over the past few decades. Different approaches have been developed to improve personalization, recommendation quality, scalability, and adaptability. This section discusses important recommendation techniques and their contributions.

### A. Collaborative Filtering

Collaborative filtering is one of the most commonly used recommendation approaches. This method predicts user preferences by analyzing similarities between users or products. User-based collaborative filtering identifies users with similar interests and recommends products preferred by those users. Item-based collaborative filtering focuses on similarities between products based on customer interactions.

These methods are simple to implement and capable of capturing community-driven preferences. However, collaborative filtering faces major challenges in sparse datasets because users typically interact with only a small percentage of available products. The approach also struggles when new users or products are introduced into the system.

### B. Content-Based Recommendation

Content-based recommendation systems focus on the characteristics of products previously preferred by users. Product descriptions, categories, specifications, and other attributes are analyzed to build user preference profiles. Similarity measures such as cosine similarity and TF-IDF are commonly used to compare product features.

One advantage of content-based methods is their ability to recommend newly introduced products without relying on interactions from other users. However, these systems often produce overly specialized recommendations and fail to provide sufficient diversity.

### C. Matrix Factorization and Neural Collaborative Filtering

To improve recommendation quality, model-based approaches such as matrix factorization were introduced. Matrix factorization techniques decompose the user-item interaction matrix into latent feature representations, allowing systems to identify hidden preference patterns.

Deep learning further enhanced recommendation systems through Neural Collaborative Filtering (NCF). Instead of using traditional linear similarity calculations, NCF applies neural networks to learn complex and non-linear relationships between users and products. This approach improves personalization accuracy, especially in large-scale recommendation environments.

© 2026 IJMRSET | Volume 9, Issue 5, May 2026| DOI:10.15680/IJMRSET.2026.0905042

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 9.864| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

**D. Graph Neural Networks and Reinforcement Learning**

Graph Neural Networks (GNNs) have become increasingly popular in recommendation research. In these systems, users and products are represented as nodes within a graph structure. Relationships between nodes enable the model to capture multi-level interaction patterns that traditional techniques may overlook.

Reinforcement learning has also been applied to recommendation systems. In this approach, the recommendation engine acts as an intelligent agent that continuously learns from user feedback such as clicks, purchases, and viewing duration. The system dynamically adjusts its recommendation strategy to maximize user engagement.

**E. Large Language Model-Based Recommendation**

Recent developments in large language models have opened new possibilities in recommendation systems. GPT-based models can understand conversational inputs, analyze product descriptions, and process user reviews to generate context-aware recommendations. These systems are capable of supporting conversational product discovery, generating human-readable recommendation explanations, and interacting with users through multi-turn dialogue. Despite their advantages, large language model-based systems require substantial computational resources and deployment infrastructure.

**F. Comparative Analysis**

Table 2.1 presents a comprehensive comparison of major recommendation approaches analyzed in the literature survey

| Method | Key Idea | Advantages | Limitations |
|---|---|---|---|
| Collaborative Filtering | Uses interaction patterns between users and products | Easy to implement and effective | Suffers from sparsity and cold-start issues |
| Content-Based Filtering | Recommends items with similar attributes | Effective for new items | Limited diversity |
| Neural Collaborative Filtering | Uses deep neural networks for learning interactions | Improved personalization | Requires large datasets |
| Graph Neural Networks | Models recommendation data as graphs | Captures deeper relationships | Computationally expensive |
| Reinforcement Learning | Learns recommendations from feedback | Supports adaptive recommendation | Complex training process |
| LLM-Based Recommenders | Uses large language models for recommendations | Context-aware and conversational | High computational cost |

**Table 2.1: Comparative Study of Recommendation Approaches**

## III. PROBLEM STATEMENT AND OBJECTIVES

Traditional recommendation systems encounter several difficulties that reduce their effectiveness in modern online shopping platforms.

© 2026 IJMRSET | Volume 9, Issue 5, May 2026| DOI:10.15680/IJMRSET.2026.0905042

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 9.864| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

One major challenge is the cold-start problem. Recommendation systems cannot provide reliable suggestions for newly registered users because there is little or no interaction history available. Similarly, newly added products cannot be recommended effectively due to the absence of ratings or purchase records.

Another significant issue is data sparsity. In large e-commerce platforms, each user interacts with only a small fraction of products. As a result, the interaction matrix becomes extremely sparse, reducing the accuracy of collaborative filtering algorithms.

Conventional recommendation techniques also struggle to capture complicated and non-linear relationships between users and products. Many systems lack adaptability and fail to update recommendations according to changing user interests. Furthermore, users often receive recommendations without understanding why certain products were suggested.

**Objectives**

The primary objective of this research is to design and develop an intelligent hybrid recommendation platform capable of overcoming the limitations of conventional methods. The key objectives are:

1. To develop a hybrid recommendation framework integrating collaborative filtering, content-based filtering, neural collaborative filtering, and sentiment analysis.
2. To improve recommendation accuracy and personalization using artificial intelligence and deep learning techniques.
3. To implement adaptive recommendations that respond dynamically to user behavior.
4. To integrate a conversational AI assistant for natural language product discovery.
5. To evaluate system performance using metrics such as Precision, Recall, F1-Score, and Mean Average Precision

## IV. PROPOSED METHODOLOGY

The proposed NEUROCART AI E-Commerce Platform follows a layered architecture to ensure modularity, scalability, and efficient data processing. The system consists of four major layers:

1. Data Layer
2. Processing Layer
3. AI Recommendation Engine

User Interface Layer.

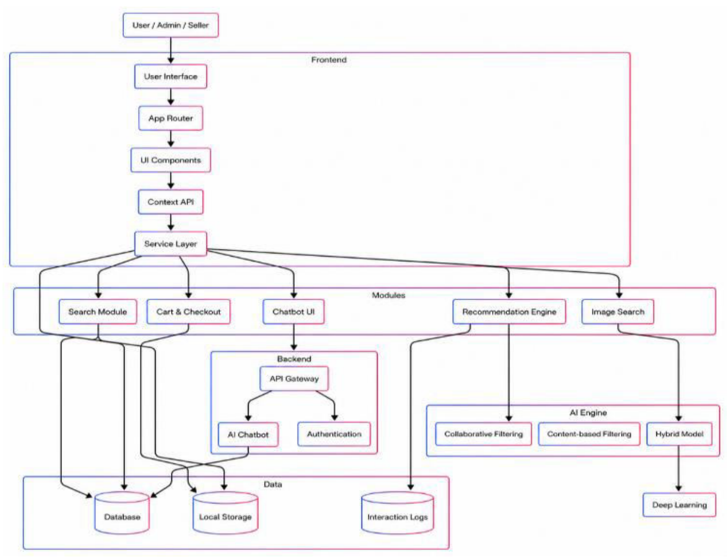



Figure 1: System Architecture

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 9.864| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

**A. Data Layer**

The data layer is responsible for storing and managing all information required by the recommendation system. This includes:

- User information such as browsing history, ratings, purchases, and search activity.
- Product details including descriptions, specifications, categories, prices, and images.
- Interaction records such as clicks, cart additions, reviews, and wishlist data.

The platform uses a PostgreSQL-compatible database system to maintain reliable and secure data storage

**B. Processing Layer**

The processing layer prepares collected data for machine learning operations. Important preprocessing tasks include:

- Removing duplicate and inconsistent data.
- Handling missing values.
- Encoding categorical variables into numerical form.
- Extracting useful features from user and product information.
- Applying dimensionality reduction techniques for computational efficiency.

**C. AI Recommendation Engine**

The recommendation engine represents the core intelligence of the system. It combines multiple recommendation approaches into a unified framework.

**Collaborative Filtering Module**

This module identifies similarities between users and products using historical interaction data.

**Content-Based Recommendation Module**

This module analyzes product features and user preference profiles to generate similar product recommendations.

**Neural Collaborative Filtering Module**

Deep neural networks are applied to learn complex user-item relationships and improve recommendation accuracy.

**Sentiment Analysis Module**

Natural language processing techniques are used to analyze customer reviews and extract sentiment information that enhances recommendation quality.

**D. User Interface Layer**

The user interface is developed using React and TypeScript to provide a responsive shopping experience across different devices. Personalized recommendations are displayed through product carousels, recommendation widgets, and related product sections.

The interface also includes an AI chatbot that enables users to search for products using natural language queries.

**E. Mathematical Formulations**

The recommendation system is grounded in several mathematical formulations that provide the theoretical foundation for its predictive capabilities. The following equations define the core models employed by the various recommendation submodules.

**Collaborative Filtering Prediction:**

$$\frac{\sum_v \mathrm{sim}_{uv} vi \ \ \bar{r}_v (r - )}{\sum_v \mathrm{sim}_{uv} ||} r_{ui} \bar{r}_u \ = \ +$$

**Content-Based Cosine Similarity:**

$$\frac{p_u \ \cdot \ x_i}{\|p_u\| \ \|x_i\|} \mathrm{score}_{ui} p_u x_i \ = \ \cos(,) \ =$$

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 9.864| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

**Hybrid Model Score:**

$$S_{hybrid} w_1 w_2 w_3 w_4 \ = \times \ CF \ + \times \ CB \ + \times \ DL \ + \times \ Sentiment$$

**Sentiment-Enhanced Rating:**

$$\bar{r}_{ui} w_s s_i r_{ui}^{sentiment} \ = \ + \ \times$$

## V. RESULTS AND DISCUSSION

The proposed hybrid recommendation system was tested using datasets containing user-product interactions, ratings, browsing records, and purchase history. Performance was evaluated using standard recommendation metrics.

### A. Evaluation Metrics

Precision measures the proportion of recommended products that are relevant to the user.

**Recall**

Recall measures how many relevant products are successfully recommended.

**F1-Score**

F1-Score provides a balanced measure combining precision and recall.

**Mean Average Precision**

Mean Average Precision evaluates the ranking quality of recommendation lists

### B. Performance Analysis

Experimental analysis indicates that the hybrid recommendation framework performs better than individual recommendation methods.

- Collaborative filtering produced reliable recommendations for users with extensive interaction history.
- Content-based recommendation effectively handled new products.
- Neural collaborative filtering improved the understanding of complex user-product relationships.
- Sentiment analysis enhanced recommendation accuracy by incorporating customer review information.

The system also demonstrated adaptability by updating recommendations according to changing user behavior. As users interacted with products, the recommendation engine continuously refined prediction models.

### C. Comparative Performance

Compared with conventional recommendation techniques, the hybrid framework achieved significant improvements in recommendation quality. The integration of multiple AI techniques improved personalization, diversity, and recommendation relevance.

The inclusion of sentiment analysis contributed additional improvements in recommendation performance, especially for products containing large volumes of customer reviews.

## VI. CONCLUSION AND FUTURE SCOPE

This research presented the NEUROCART AI E-Commerce Platform, an AI-driven hybrid recommendation framework designed for modern e-commerce environments. By integrating collaborative filtering, content-based recommendation, neural collaborative filtering, and sentiment analysis, the proposed system addresses the limitations of traditional recommendation methods.

The layered architecture improves scalability, modularity, and maintainability while supporting adaptive personalization. Experimental evaluation demonstrates that the hybrid recommendation model provides improved recommendation accuracy, better personalization, and enhanced user experience.

The integration of conversational AI further strengthens the shopping experience by enabling users to discover products through natural language interaction.

### A. Future Scope

Several future enhancements can further improve the proposed platform:

1. Integration of advanced large language models for improved conversational recommendation.
2. Real-time recommendation updates using streaming data processing.
3. Cloud deployment for handling large-scale user and product datasets.
4. Application of reinforcement learning for long-term user engagement optimization.
5. Integration of computer vision for image-based product recommendation.
6. Development of privacy-preserving recommendation methods using federated learning.
7. Implementation of explainable AI techniques to improve recommendation transparency.

These advancements can contribute to the development of intelligent and highly adaptive e-commerce ecosystems.

## REFERENCES

[1] Y. Koren, R. Bell, and C. Volinsky, "Matrix Factorization Techniques for Recommender Systems," Computer, vol. 42, no. 8, pp. 30-37, 2009.

[2] X. He, L. Liao, H. Zhang, L. Nie, X. Hu, and T.-S. Chua, "Neural Collaborative Filtering," in Proceedings of the 26th International Conference on World Wide Web (WWW), 2017, pp. 173-182.

[3] R. Burke, "Hybrid Recommender Systems: Survey and Experiments," User Modeling and User-Adapted Interaction, vol. 12, no. 4, pp. 331-370, 2002.

[4] P. Covington, J. Adams, and E. Sargin, "Deep Neural Networks for YouTube Recommendations," in Proceedings of the 10th ACM Conference on Recommender Systems (RecSys), 2016, pp. 191-198.

[5] Y. Chen, Y. Zhang, H. Zhang, and X. Li, "Reinforcement Learning for Recommender Systems: A Survey," IEEE Transactions on Knowledge and Data Engineering, vol. 31, no. 5, pp. 864-882, 2019.

[6] A. Ezeife and K. Karlapalepu, "Sequential Pattern Mining in Recommender Systems," Journal of Big Data, vol. 10, no. 2, pp. 1-20, 2023.

[7] S. Gajula, "Sentiment-Aware Recommendation Systems Using NLP and Deep Learning," International Journal of Advanced Computer Science and Applications, vol. 16, no. 4, pp. 45-54, 2025.

[8] X. Le, Y. Wang, and H. Zhang, "Knowledge Graph-Based Recommender Systems: A Survey," ACM Computing Surveys, vol. 57, no. 1, pp. 1-36, 2024.

[9] W. Wu, S. Liu, and J. Zhang, "Graph Neural Networks in Recommender Systems: A Survey," Information Fusion, vol. 87, pp. 32-58, 2024.

[10] Y. Li, X. Wang, and Z. Chen, "Large Language Model Based Recommender Systems: Trends and Challenges," Journal of Artificial Intelligence Research, vol. 76, pp. 123-156, 2023.

[11] P. Resnick and H. R. Varian, "Recommender Systems," Communications of the ACM, vol. 40, no. 3, pp. 56-58, 1997.

[12] L. Gao, H. Li, and Q. Wang, "Generative Adversarial Networks for Recommendation Systems," IEEE Access, vol. 8, pp. 100345-100356, 2020.