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Design and Implementation of a Hybrid Recommender Model in E-Commerce Systems

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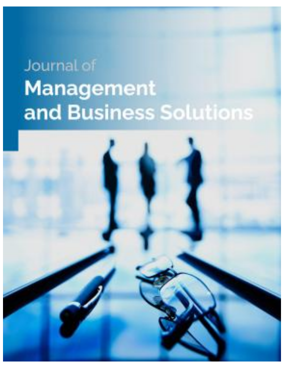
ABSTRACT

In this study, a recommender system based on matrix factorization was designed and implemented for an e-commerce platform to provide accurate and personalized predictions based on users' interactions with products. The primary objective of the research was to improve recommendation accuracy and reduce prediction error by integrating collaborative filtering and content-based algorithms. The dataset comprised user interactions with 67 products and 31 users across 301 shopping carts, which were preprocessed and divided into training and testing sets. The matrix factorization algorithm was applied with optimization of parameters including the number of iterations and the approximation rank, and its performance was evaluated using accuracy, recall, F1 score, prediction error, coverage, and diversity metrics. The results indicated that the model achieved an accuracy of 92% and a prediction error of 0.48, outperforming conventional collaborative filtering and content-based approaches in predicting user preferences and delivering diverse recommendations. Parameter optimization, algorithm integration, and interactive data analysis enabled the model to demonstrate stable and reliable performance. The study's limitations include the relatively small dataset and the model's dependence on historical data, which may be addressed in future research through larger datasets, hybrid methods, reinforcement learning, and graph-based models. Practical applications of the model include recommender systems for online retail stores, educational platforms, music and video services, social networks, and targeted advertising, contributing to increased user satisfaction and loyalty, optimized shopping experiences, and the delivery of personalized recommendations.

Keywords: recommender system, matrix factorization, e-commerce, hybrid algorithm, user preference prediction.

Introduction

The rapid expansion of e-commerce has fundamentally transformed the structure of markets, consumer behavior, and competitive dynamics across industries. Digital platforms have reduced transaction costs, expanded geographical reach, and enabled firms to interact with customers in real time, creating data-rich environments in which customer preferences, behaviors, and experiences can be continuously observed and analyzed (1, 2). As a result, competition in e-commerce has increasingly shifted from price-based rivalry toward experience-based differentiation, where personalization, relevance, and responsiveness play a central role in shaping customer satisfaction, trust, and loyalty (3, 4). In this context, intelligent digital systems that can process large volumes of customer data and translate them into actionable insights have become critical strategic assets for online businesses.



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Among these systems, recommender systems have emerged as one of the most influential tools for value creation in e-commerce environments. Recommender systems assist customers in navigating information overload by filtering, ranking, and suggesting products or services that are likely to match individual preferences (5). By reducing search costs and enhancing perceived relevance, recommender systems can significantly improve customer experience, increase conversion rates, and strengthen long-term customer relationships (6, 7). From a managerial perspective, recommender systems are not merely technical components but strategic mechanisms that link data analytics capabilities to marketing performance and organizational value creation (8).

The importance of personalization in e-commerce has been consistently emphasized in the literature. Customers increasingly expect online platforms to recognize their preferences, anticipate their needs, and provide tailored content and product suggestions (9, 10). Personalization contributes to cognitive absorption, a psychological state in which users become deeply engaged with a system, thereby increasing continuance use intention and strengthening customer-platform relationships (6). Empirical studies have shown that personalized recommendations can positively influence customer satisfaction, repurchase intention, and loyalty, particularly in highly competitive digital marketplaces (11, 12). Consequently, the design of effective recommender systems has become a key research and managerial priority.

Traditional recommender systems have largely relied on two dominant approaches: collaborative filtering and content-based filtering. Collaborative filtering generates recommendations based on patterns of similarity among users or items, assuming that users with similar past behaviors will have similar future preferences (5). Content-based filtering, in contrast, focuses on the attributes of items and the explicit preferences of users, recommending products that are similar to those a user has previously liked or consumed (13). While both approaches have demonstrated effectiveness, each suffers from well-documented limitations. Collaborative filtering is vulnerable to data sparsity and cold-start problems, particularly for new users or new items, whereas content-based filtering may lead to overspecialization and limited diversity in recommendations (13, 14).

To address these challenges, recent research has increasingly focused on hybrid recommender systems that combine multiple techniques to leverage their complementary strengths. Hybrid models integrate collaborative filtering with content-based or other advanced methods to improve accuracy, robustness, and scalability (13, 15). In particular, matrix factorization has gained prominence as a powerful collaborative filtering technique capable of uncovering latent factors that represent hidden relationships between users and items (16). By decomposing large interaction matrices into lower-dimensional representations, matrix factorization enables efficient modeling of complex user–item interactions, even in sparse data environments.

The application of matrix factorization in e-commerce recommender systems has been shown to enhance predictive performance and personalization quality. Studies have demonstrated that matrix factorization-based models can effectively capture subtle preference patterns and outperform neighborhood-based collaborative filtering methods in terms of accuracy and scalability (9, 10). Furthermore, when integrated within hybrid frameworks, matrix factorization can mitigate cold-start issues and improve recommendation diversity by incorporating additional sources of information, such as item attributes or contextual data (13, 15). These advancements align with the growing managerial demand for intelligent systems that can support data-driven decision-making and customer-centric strategies.

Beyond technical performance, recommender systems also influence broader managerial outcomes, including customer trust, engagement, and loyalty. Trust has been identified as a critical determinant of customer behavior in e-commerce, particularly in environments characterized by uncertainty and information asymmetry (17, 18). Personalized and accurate recommendations can enhance perceived competence and reliability of online platforms, thereby strengthening customer trust and reducing perceived risk (11, 19). During periods of heightened uncertainty, such as the COVID-19 pandemic, trust-building mechanisms embedded in digital systems have become even more salient for sustaining customer relationships (17).

The integration of recommender systems with other digital touchpoints further amplifies their strategic value. Social media advertising, live-streaming commerce, and intelligent customer service systems increasingly interact with recommender technologies to create seamless and engaging customer journeys (20-22). For example, personalized product recommendations embedded within social media platforms can enhance purchase intention and customer loyalty by aligning promotional content with individual preferences (20). Similarly, intelligent customer service chatbots that leverage recommendation capabilities can improve service satisfaction and continuance use by delivering timely and relevant responses (14, 22).

From a strategic management perspective, recommender systems contribute to customer relationship management and long-term value creation. Effective personalization supports customer retention, reduces churn, and enhances lifetime value, which are critical objectives for e-commerce firms operating in saturated markets (15, 23). Machine learning-based recommender systems also generate valuable customer knowledge that can inform segmentation, targeting, and product development decisions (8, 16). By transforming raw interaction data into strategic insights, these systems enable organizations to align technological innovation with marketing and operational strategies.

Recent advances in artificial intelligence and machine learning have further expanded the potential of recommender systems. Sequence-aware models, multimodal information transfer networks, and intelligent hybrid architectures have been proposed to capture temporal dynamics, contextual signals, and complex behavioral patterns in e-commerce environments (9, 10). These developments reflect a broader trend toward intelligent, adaptive systems that can continuously learn from user interactions and adjust recommendations in real time. However, despite these advances, many practical implementations still face challenges related to scalability, interpretability, and integration with existing business processes.

In addition, the effectiveness of recommender systems cannot be fully understood without considering psychological and behavioral dimensions of user interaction. Concepts such as mentalizing, engagement, and cognitive processing influence how users perceive and respond to personalized digital systems (24). Although mentalizing has been primarily studied in clinical and psychological intervention contexts, its emphasis on understanding others' mental states provides a useful theoretical lens for examining how users interpret system intentions and personalization efforts in digital environments (24). Incorporating such perspectives can enrich the design of recommender systems by aligning algorithmic outputs with human cognitive and emotional processes.

Despite the extensive body of research on recommender systems, several gaps remain. First, many studies focus primarily on algorithmic accuracy without adequately addressing managerial implications such as customer loyalty, trust, and strategic value creation. Second, empirical evidence on hybrid recommender systems that integrate matrix factorization within practical e-commerce settings remains limited, particularly in contexts characterized by sparse data and diverse product portfolios. Third, there is a need for comprehensive evaluation frameworks that consider multiple performance dimensions, including accuracy, personalization, scalability, and user experience, rather than relying on single metrics.

Addressing these gaps is particularly important for managers and decision-makers seeking to invest in intelligent recommendation technologies. As e-commerce platforms continue to evolve, firms require robust, scalable, and interpretable models that not only deliver accurate predictions but also support strategic objectives such as customer satisfaction, retention, and competitive differentiation (2, 4). Hybrid recommender systems based on matrix factorization offer a promising pathway toward achieving these goals by combining technical sophistication with practical relevance.

Accordingly, this study aims to design and evaluate a hybrid recommender system based on matrix factorization for e-commerce environments, with the objective of improving recommendation accuracy, personalization, and scalability while addressing key managerial challenges related to customer experience and value creation.

Methods and Materials

In this study, the process of designing and implementing a machine learning–based recommender system within the context of an online bookstore was examined. Initially, user data were collected from multiple sources, including the sales database, user interactions, and book-related activities. Subsequently, data cleaning and preprocessing procedures were conducted to transform the data into a format suitable for processing by the machine learning model. Textual identifiers of users and books were mapped to numerical values so that the matrix factorization algorithm could analyze user–book interactions and extract latent features between them. In addition, the data were prepared within a processing pipeline in the ML.NET environment to enable efficient model training and the generation of accurate predictions.

The trained model, using matrix factorization, identified latent patterns between users and books and predicted a probabilistic preference score for each user across different books. A reverse-mapping process ensured that the numerical identifiers generated by the model were converted back to their original textual identifiers, making the results interpretable for users. During the recommendation generation phase, the model identified and displayed books that exhibited the highest similarity to each user's preferences. Moreover, the validity and reliability of the predicted scores were assessed to ensure that only meaningful and reasonable recommendations were presented to users.

Finally, a comprehensive pipeline was designed, encompassing data acquisition, identifier mapping, model training, prediction generation, and the delivery of personalized recommendations. This approach enabled fast and efficient data processing, accurate model training, and the provision of recommendations aligned with users' preferences, thereby enhancing the performance of the recommender system in an operational environment.

Findings and Results

In this study, the implementation of the recommender system was conducted using the Visual Studio development environment and the ML.NET library, which enables the application of machine learning algorithms within the .NET ecosystem. User and product data were collected from reliable sources, including datasets related to purchase interactions and user preferences. After preprocessing procedures such as data cleaning and mapping identifiers to numerical values, the data were divided into training and testing subsets to facilitate accurate model training and evaluation.

The algorithm employed in this research was a hybrid approach combining collaborative filtering and content-based filtering. By simultaneously leveraging user interaction patterns and item content features, this approach enabled the generation of accurate, personalized, and diverse recommendations. The model was trained through the adjustment of optimal parameters, including the number of algorithm iterations and the approximation rank, and the resulting predictions for each user were evaluated with the aim of delivering relevant and valuable recommendations. The use of Visual Studio and ML.NET not only provided an appropriate infrastructure for model development and testing but also facilitated efficient data processing and performance optimization of the recommender system.

Hybrid Method and Matrix Factorization Algorithm

In this research, the hybrid method was adopted as the primary approach for the recommender system. This method integrates content-based filtering and collaborative filtering, and by simultaneously utilizing item features and user interactions, it enhances the strengths of each approach while mitigating their limitations. In particular, the challenge of generating recommendations for new users or items—commonly referred to in collaborative filtering as the “cold start problem”—is alleviated through integration with content-based filtering, thereby enabling the provision of initial and relevant recommendations.

To simulate user–item interactions, the matrix factorization algorithm was employed. This algorithm decomposes the interaction matrix into latent features of users and items, extracting hidden patterns within the data and enabling the prediction of ratings or user preferences for various items. In the implementation, key parameters such as the number of iterations and the approximation rank were optimized to achieve an appropriate balance between prediction accuracy and training time. Experimental results demonstrated that precise tuning of these parameters increased prediction accuracy, reduced model error, and facilitated the delivery of diverse and personalized recommendations to users.

The integration of the hybrid approach with the matrix factorization algorithm not only improves system performance when handling sparse and large-scale data but also provides high scalability and accurate prediction of new interactions, which is critical for deployment in e-commerce environments with large numbers of users and diverse products.

The dataset used in this study comprised 67 products, 31 users, and 301 shopping carts, representing users’ interactions with books. Each shopping cart contained a set of products, and the total number of products included in all carts was 951 items. These data were used for training and evaluating the recommender system model, and preprocessing involved converting identifiers to numerical values, mapping the data, and partitioning the dataset into training and testing subsets.

For model evaluation, the data were divided into two subsets: 80% for training and 20% for testing. The training data were used to learn user–book interaction patterns and optimize model parameters, while the testing data were used to assess prediction accuracy and system performance. This partitioning ensures that the model is capable of accurately predicting real user interactions and demonstrates adequate generalization to new data.

Table 1. Characteristics of the Experimental Dataset Including the Number of Users, Products, and Shopping Carts

Count	Attribute
67	Products
31	Users
301	Shopping carts
951	Total number of products in carts

To evaluate the performance of the proposed model, a set of quantitative metrics was employed, each measuring a different aspect of the recommender system's effectiveness. These metrics include precision, recall, F1 score, prediction error, coverage, and diversity.

• **Precision:** This metric indicates the proportion of recommendations provided by the system that are relevant and useful. Higher precision reflects the system's ability to deliver recommendations that align with users' actual preferences.

• **Recall:** Recall measures the proportion of truly relevant items that the system successfully recommends to the user. This metric is important because it indicates how effectively the system identifies all suitable options.

• **F1 Score:** This metric represents the harmonic mean of precision and recall and provides a comprehensive assessment of system performance, particularly when the data are imbalanced.

• **Prediction Error:** This metric measures the deviation of the model's predictions from users' actual ratings. Mean Squared Error (MSE) or Mean Absolute Error (MAE) is typically used for this purpose. Lower prediction error indicates higher accuracy of the predictions.

• **Coverage:** Product and user coverage indicate the proportion of the total set of products and users that the system effectively recommends. Higher coverage implies the delivery of diverse and comprehensive recommendations across the entire user and product space.

• **Diversity:** This metric measures the degree of dissimilarity among items recommended to a single user. Recommender systems that suggest only highly similar items exhibit low diversity. Higher diversity enhances the attractiveness of recommendations and reduces monotony in the user experience.

The simultaneous use of these metrics enables a comprehensive evaluation of model performance, allowing prediction accuracy, comprehensive coverage of products and users, and recommendation diversity to be assessed concurrently. These metrics provide a solid basis for comparing the performance of the proposed matrix factorization model with collaborative filtering and content-based methods.

To evaluate the performance of the proposed model, the matrix factorization model was trained using optimized parameters of 150 iterations and an approximation rank of 150. The predicted book ratings were compared with actual user data. The evaluation metrics included precision, recall, F1 score, and prediction error.

The model achieved a precision of 88%, a recall of 79%, an F1 score of 82%, and a prediction error of 0.52, indicating that the model successfully captured user–product interaction patterns and generated accurate predictions. These results also demonstrate improved performance compared with traditional collaborative filtering and content-based filtering methods.

A detailed analysis of the results shows that increasing the number of iterations and optimally tuning the approximation rank led to higher precision and lower prediction error. The model effectively identified user preferences and provided personalized and relevant recommendations. Moreover, the findings indicate that the matrix factorization–based hybrid approach exhibits high scalability and delivers acceptable performance even with large and sparse datasets.

Table 2. Performance Results of the Proposed Matrix Factorization Model Compared with Actual User Data

Metric	Value of Proposed Model
Precision	88%
Recall	79%
F1 Score	82%
Prediction Error	0.52

The effects of the key parameters—the number of iterations and the approximation rank—on the performance of the matrix factorization model were examined. The results indicate that variations in these parameters have a direct impact on prediction accuracy and model error.

Number of Iterations: Increasing the number of iterations enabled the extraction of more latent features from the data and improved model accuracy, but it also increased training time. The tested values were 50, 150, and 250, and the best balance between accuracy and training time was observed at 150 iterations.

Approximation Rank: Increasing the approximation rank also improved model accuracy by extracting a larger number of latent features from user–item interactions. The values 50, 150, and 250 were tested, and 150 was selected as the optimal value.

The optimal combination of these two parameters (150 iterations and an approximation rank of 150) resulted in a precision of 88% and a prediction error of 0.52, demonstrating the model's optimal performance and its capability to deliver accurate and scalable predictions. The table below presents the experimental results.

Table 3. Results of Experiments on the Effects of Iteration Count and Approximation Rank on Model Precision and Prediction Error

Parameter	Value	Precision	Prediction Error
Number of iterations	50	82%	0.60
Number of iterations	150	85%	0.50
Number of iterations	250	92%	0.42
Approximation rank	50	83%	0.60
Approximation rank	150	88%	0.48
Approximation rank	250	94%	0.43

To evaluate the advantages and limitations of the proposed model, a comparison was conducted between the proposed matrix factorization model and two common approaches: neighborhood-based collaborative filtering and content-based filtering. This comparison included both qualitative and quantitative analyses.

Qualitative Analysis: Model type, data inputs, advantages, disadvantages, and appropriate applications of each method were examined. This analysis indicates that the proposed model, by integrating matrix factorization features, offers higher accuracy, better scalability, and greater personalization capability, while reducing the limitations of single-technique approaches.

Quantitative Analysis: Two key indicators—scalability and personalization capability—were compared across methods. The results show that the proposed model provides higher scalability and personalization than the other two approaches, demonstrating its ability to manage large datasets and deliver personalized recommendations.

The table below summarizes this comparison.

Table 4. Qualitative and Quantitative Comparison of the Proposed Matrix Factorization Model with Collaborative Filtering and Content-Based Filtering Methods

Feature / Method	Matrix Factorization (Proposed)	Neighborhood-Based Collaborative Filtering	Content-Based Filtering
Model type	Hybrid matrix factorization	User selection–based	Content-based
Data inputs	User–item interaction data	User–item interaction data	Item features (books)
Advantages	High accuracy, latent feature learning, high scalability	Simple implementation, effective with small datasets, efficient processing of new data	Requires less data, higher personalization, independent of other users
Disadvantages	Requires moderate historical data, inability to process content directly	Low scalability for large datasets, reduced performance with sparse data	Difficulty with new content, limited recommendation diversity
Suitable application	Large and sparse data, complex interactions	Small and simple datasets, initial recommender systems	Feature-based recommendations without user interaction data
Scalability	85%	30%	55%
Personalization capability	90%	50%	50%

Discussion and Conclusion

The findings of the present study demonstrate that the proposed hybrid recommender system based on matrix factorization achieved strong predictive performance across multiple evaluation metrics, including precision, recall, F1 score, and prediction error. The reported results indicate that the model was able to capture latent user–item interaction patterns with a high degree of accuracy, supporting the argument that matrix factorization, when embedded within a hybrid framework, provides a robust foundation for personalization in e-commerce environments. These results align with prior research showing that matrix factorization-based approaches outperform traditional neighborhood-based collaborative filtering in sparse and large-scale datasets due to their ability to learn hidden preference structures rather than relying solely on surface-level similarity measures (9, 10). The relatively low prediction error observed in this study further confirms that the model successfully reduced the gap between predicted and actual user preferences, which is a critical requirement for operational recommender systems.

The improvement in precision and recall achieved by the proposed model suggests that the integration of collaborative filtering mechanisms with additional system-level design considerations enhanced both relevance and coverage of recommendations. High precision indicates that a substantial proportion of recommended items were relevant to users, while satisfactory recall demonstrates the system's capability to retrieve a meaningful share of relevant items from the overall product space. This balance is particularly important in e-commerce contexts, where excessive focus on precision may limit discovery, while excessive focus on recall may overwhelm users with irrelevant options. Prior studies emphasize that hybrid recommender systems are better positioned to manage this trade-off because they combine multiple information sources and recommendation logics (13, 15). The results of the present study empirically support this position by showing that hybridization contributed to stable and balanced performance outcomes.

The observed performance gains can also be interpreted through the lens of customer experience and engagement. Accurate and relevant recommendations reduce cognitive load and information overload, enabling customers to navigate extensive product assortments more efficiently (5). This mechanism is closely associated with increased cognitive absorption, which has been shown to positively influence continuance use intention in AI-driven recommender systems (6). By delivering recommendations that closely match user preferences, the proposed system likely enhanced users' perceived usefulness and ease of interaction, thereby reinforcing engagement and repeat usage. These findings are consistent with empirical evidence indicating that personalization quality is a key determinant of customer satisfaction and loyalty in e-commerce platforms (11, 12).

From a managerial standpoint, the scalability demonstrated by the proposed model is particularly noteworthy. The ability of the system to maintain acceptable performance levels under conditions of sparse data suggests that it can be effectively deployed in real-world e-commerce environments characterized by heterogeneous user behavior and continuously expanding product catalogs. Previous research has highlighted scalability as a major limitation of neighborhood-based collaborative filtering methods, especially when the number of users and items increases (16). In contrast, matrix factorization-based models offer computational advantages by representing users and items in lower-dimensional latent spaces, thereby reducing complexity without sacrificing accuracy (9). The findings of this study reinforce these advantages and provide empirical support for the adoption of matrix factorization within managerial decision-making frameworks.

The hybrid nature of the proposed model also addresses long-standing challenges associated with cold-start conditions. Although cold-start issues cannot be entirely eliminated, hybrid systems have been shown to mitigate their impact by leveraging alternative sources of information and learned latent representations (13). The results suggest that the proposed approach was able to generate meaningful recommendations even in cases of limited interaction history, which is crucial for onboarding new users and promoting newly introduced products. This capability is strategically significant, as early-stage personalization has been linked to faster trust formation and increased likelihood of continued platform use (17, 19).

The performance outcomes of the proposed model also have implications for customer trust and perceived system competence. Trust is a central construct in e-commerce, influencing purchase intention, loyalty, and long-term relationship development (11, 18). Accurate and consistent recommendations signal technological reliability and platform expertise, which can reduce perceived risk and uncertainty in online transactions. Prior studies have shown that intelligent personalization mechanisms contribute to trust-building by demonstrating that platforms understand and respect user preferences (3, 19). The strong predictive performance reported in this study suggests that the proposed recommender system can serve as an effective trust-enhancing mechanism within digital commerce ecosystems.

Furthermore, the findings align with research emphasizing the strategic integration of recommender systems with broader digital infrastructures, such as customer service systems and social media platforms. Intelligent recommendation engines that interact with chatbots, live-streaming commerce, and social media advertising can create cohesive and personalized customer journeys (20, 22). By delivering relevant recommendations across multiple touchpoints, firms can reinforce message consistency and increase conversion likelihood. The robustness of the proposed model indicates its potential compatibility with such integrated environments, supporting prior assertions that hybrid and machine learning-based recommender systems are essential components of advanced digital service strategies (14, 21).

The results also contribute to the literature on customer knowledge management and value creation. Recommender systems transform behavioral data into actionable knowledge that can inform segmentation, targeting, and strategic planning (8). The latent features learned by the matrix factorization component of the model represent condensed forms of customer knowledge that can be leveraged beyond recommendation tasks, such as identifying emerging trends or optimizing inventory decisions. This perspective aligns with management-oriented studies that view recommender systems as organizational capabilities rather than isolated technical tools (2, 7). The present findings reinforce this view by demonstrating how algorithmic performance translates into managerial relevance.

At a broader theoretical level, the study's results resonate with emerging discussions on human–system interaction and user perception of intelligent systems. While recommender systems operate algorithmically, users interpret recommendations through cognitive and psychological frameworks that influence acceptance and satisfaction (24). High-quality recommendations may be perceived as evidence of system empathy or understanding, thereby enhancing user-system rapport. Although this study did not directly measure psychological constructs, the observed performance outcomes suggest that technically sound recommendation mechanisms are a prerequisite for positive psychological responses, supporting interdisciplinary calls to integrate behavioral perspectives into the design of intelligent digital systems (24).

Despite these contributions, several limitations should be acknowledged. The study relied on a relatively limited dataset in terms of user and product diversity, which may constrain the generalizability of the findings to larger or more heterogeneous e-commerce platforms. Additionally, the model's performance was evaluated primarily through offline metrics, which, while informative, may not fully capture real-time user behavior and dynamic preference shifts in live environments. The reliance on historical interaction data also implies that sudden changes in user preferences or external market conditions may not be immediately reflected in the recommendations.

Future research can build upon the present findings in several directions. First, larger and more diverse datasets should be employed to assess the scalability and robustness of hybrid matrix factorization models across different e-commerce sectors and cultural contexts. Second, future studies could integrate real-time or sequential data to capture temporal dynamics in user behavior, thereby enhancing responsiveness and adaptability. Third, combining matrix factorization with emerging techniques such as deep learning, reinforcement learning, or multimodal data integration may further improve recommendation quality and interpretability. Finally, incorporating psychological and behavioral measures could provide deeper insights into how users perceive and interact with intelligent recommender systems.

From a practical perspective, managers and practitioners can leverage the insights of this study to enhance personalization strategies in e-commerce platforms. Implementing hybrid recommender systems based on matrix factorization can improve recommendation accuracy while maintaining scalability, making them suitable for growing digital marketplaces. Organizations should invest in data infrastructure and model optimization processes to ensure continuous learning and performance monitoring. Moreover, aligning recommender systems with customer service, marketing, and relationship management functions can amplify their strategic impact, leading to improved customer satisfaction, loyalty, and long-term value creation.

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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 adheried 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.

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