

# Adaptive and Explainable ML Framework for Personalized E-Commerce User Experience and Satisfaction

Ravi Bhushan Kumar<sup>1,\*</sup>, Manish Sharma<sup>2</sup>

## Abstract

*The user experience and user satisfaction have taken the center of the stage as a determinant of platform success in the fast-changing e-commerce ecosystem. Conventional recommendation systems are usually run in black-box models that give minimal transparency and dynamicity to altered user preferences. The study will introduce a personalization framework of explainable machine learning (XML) based on explainable artificial intelligence (XAI) and hybrid recommendation strategies. The model uses Collaborative Filtering (CF), Content-Based Filtering (CBF), and Deep Neural Networks (DNNs) to identify explicit and implicit user behaviors, whereas Shapley Additive Explanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME) can make recommendations more interpretable and transparent. Experimental tests show that the suggested framework is more effective in terms of achieving high performance rates of 94.65, F1-score of 93.68, and a lower RMSE of 0.284; which is better than standard models. In addition, the indicators of user engagement include session duration, the number of clicks, and satisfaction scores, which significantly improve. Muhammad explored the use of adaptive learning and explainability to improve the accuracy of personalization, as well as to provide greater user trust, which, in turn, results in a clearer, more trustworthy, more user-oriented e-business experience.*

**Keywords:** Personalization, explainable artificial intelligence, hybrid recommendation system, adaptive machine learning, user engagement

## INTRODUCTION

With digital transformation, online stores are a part of contemporary consumerism, which is characterized by a wide range of products and the convenience of shopping [1]. Nonetheless, with the ever-growing volume of online products and people, marking and offering topical things to each customer has become more difficult. Although working to some degree, traditional recommendation systems usually use fixed models that cannot reflect the dynamic and changing nature of users' tastes

and preferences [2]. Furthermore, the lack of transparency in sophisticated ML algorithms has raised concerns regarding trust, interpretability, and fairness of personalized recommendations. To overcome these issues, this study proposes an Adaptive and XML Framework that can be used to improve the accuracy of personalization, user experience, and transparency in an e-commerce setting [3].

At the heart of current e-commerce models is the concept of personalization, which seeks to offer users customized product recommendations based on their habits [4], tastes, and shopping patterns.

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Standard approaches such as CF and CBF have been embraced extensively, but they have shortcomings, such as a lack of sufficient data, cold-start issues, and the failure to adjust to an evolving user interest quickly [5, 6]. The latest developments in Deep Learning (DL) have enhanced the accuracy of recommendations by forming intricate nonlinear connections between users and items [7]. However, these deep models are perceived to be black boxes, and sometimes, users and system designers can hardly conceive how certain advice is obtained [8]. Such a lack of transparency may cause less user trust and make the implementation of AI-based personalization systems more difficult [9, 10].

To address these problems, the proposed framework incorporates adaptive learning and XAI methods into a hybrid recommendation framework. The adaptive component provides quality improvement of the models in real-time by learning and incremental updates depending on user feedback and new interaction data. Meanwhile, the explainable layer utilizes SHAP and LIME tools to provide clear information about the model decisions. With its adaptability and interpretability, the framework can not only increase the accuracy of the recommendation but also increase the confidence of the user who can understand the rationale behind every personalized recommendation. The ultimate objective of this study is to develop a framework of recommendations with high predictive capabilities, transparency, and user-friendly design. The adaptive and XML Framework allows customizing the experience that will change as the user behavior progresses and results in increased engagement, satisfaction, and trust in e-commerce systems. Moreover, the aspect of explainability also leads to responsible AI deployment through fairness, accountability and interpretability.

The remainder of this paper is organized as follows. Section 2 examines the literature on conventional and contemporary recommendation systems. Section 3 explains the intended methodology, which involves data collection, pre-processing, feature engineering, and model design. Section 4 presents the experimental design of the system tests. Section 5 presents the results and discussion, where the performance of the model and results of user engagement are noted. Finally, Section 6 concludes the study and indicates the research directions of future adaptive and explainable personalization in e-commerce.

## LITERATURE REVIEW

The development of e-commerce platforms has altered the nature of interaction between users and digital marketplaces, and personalization is fundamental to enhancing customer satisfaction and engagement [6]. Early personalization systems were largely based on collaborative and content-based filters [7]. All these methods examine user-item interactions or item characteristics to suggest items based on the previous behavior or preferences of a user or others who are similar to him/her. Although these methods performed well in their original implementation, they had serious limitations, such as data sparsity, cold start, and poor contextual insight [8]. They were very inertial and were unable to cope with the dynamics of user preference and the dynamic nature of the market.

With the emergence of machine learning and deep learning, personalization has reached a new stage, featuring predictive analytics and sophisticated user modeling. The systems were trained to take on nonlinear, multifaceted connections among users and products [9], which was made possible by neural networks and other machine learning algorithms. This enhances the accuracy of the recommendations and the ability of the platforms to process massive datasets. However, these models pose a new challenge because they tend to behave as black boxes. Even though they could come up with very precise results, they were not transparent, and therefore, developers and users could not comprehend why certain recommendations were given [10]. The lack of interpretability commonly results in decreased trust and acceptance of automated recommendations by users.

Active personalization systems have been proposed to solve the problem of stagnant recommendations. Such systems are ever-learning and constantly update their models in real time to incorporate changing preferences [11]. Reinforcement learning and contextual modeling-based techniques enabled platforms to dynamically personalize recommendations and trade off the

exploration of new products with exploiting known preferences. Adaptive models have been found to enhance user retention and engagement rates [12]. Nevertheless, they also require a lot of computational power and do not offer clear explanations of the ways they have decided to make decisions, which is essential to keep the user confident in the e-commerce setting.

XAI has recently become a disruptive solution to interpretability issues in ML-based personalization [13]. Explainable models are also intended to be transparent; that is, they should show how and why a specific recommendation is produced. The use of XAI can help improve user trust and responsibility in personalization systems. Users who are aware of the rationale behind the recommendations feel more positively involved in the system [14]. Although these developments have been made, one issue has never been resolved: the trade-off between model accuracy and explainability. Numerous explainable systems sacrifice performance to be transparent, which hinders their use in large business environments.

A critical review of the available literature shows that the majority of personalization models are optimized with the main aim of increasing accuracy without considering aspects such as transparency, flexibility, and user satisfaction [15]. Few frameworks can combine adaptive learning and explainable mechanisms to create a complete, user-friendly personalization experience. In addition, real-time flexibility and the integration of user feedback are undeveloped features in existing models. In addition, a detailed evaluation system is missing that not only measures the performance of the algorithms but also the interpretability and trust by the users.

The literature shows that there is a clear continuation of the traditional filtering methods into the intelligent system, which is based on machine learning and is adaptive. Nevertheless, despite significant progress, the basic goal of reaching a common framework that can harmonize adaptability, explainability, and user satisfaction remains an open question. The gap in the proposed research is that it develops an explainable and adaptable machine-learning

based personalization framework that will improve user experience, create trust, and maximize satisfaction in online shops. Table 1 provides related works on E-commerce personalization systems.

## METHODOLOGY

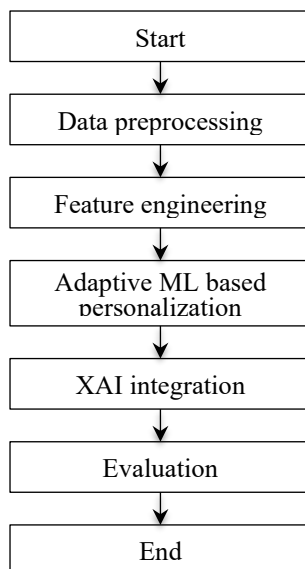
In this study, the approach taken is intended to come up with an Adaptive Explainable Hybrid Personalization Framework (AEHPF) of e-commerce recommendation systems, as shown in Figure 1. This model combines sophisticated ML and XAI mechanisms to offer precise, adaptable, and transparent product recommendations. The methodology can be divided into six major steps: data acquisition, data preprocessing, feature engineering, adaptive machine learning-based personalization, XAI integration, and system evaluation. Every step is important to ensure that the framework learns effectively with user and product information to also develop dynamically to the behavior of the user and still be interpretable and reliable in its recommendations.

The dataset involved in the current study includes user behavior logs, product metadata, and the previous transaction history of an e-commerce platform. It has three key sets of characteristics: user, product, and interaction features. The user interface displays demographic information, browsing, session duration, history of clicks, and ratings, which provides hints about user behavior and activity. The features of the products encompass attributes such as category, price, brand, popularity, and ratings, as well as providing descriptive information about the product. Interaction features are a type of interaction between the user and item in terms of metrics such as click-through rate (CTR), time-on-page, and purchase conversion, which are important predictors of user intent and Give a space after the end of the paragraph.

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**Table 1.** Related works on e-commerce personalization systems.

| Technique                                | Key features                                                                                | Dataset                                  | Advantages                                                     | Limitations                                                        | Contribution                                                                                        |
|------------------------------------------|---------------------------------------------------------------------------------------------|------------------------------------------|----------------------------------------------------------------|--------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------|
| CF [2]                                   | Recommends items based on user–item interactions and similarities among users               | Early e-commerce platforms               | Simple and intuitive; effective with sufficient data           | Suffers from cold-start and data sparsity; lacks context awareness | Forms the foundation for modern recommendation approaches                                           |
| CBF [5]                                  | Utilizes product attributes and user profiles for recommendations                           | Online retail and media platforms        | Personalizes based on item characteristics; interpretable      | Limited to known preferences; cannot recommend novel items         | Highlights the need for hybrid and adaptive personalization                                         |
| Hybrid Filtering Models [6]              | Combines CF and CBF for improved coverage and performance                                   | Large e-commerce databases               | Balances advantages of CF and CBF                              | Computationally heavy; limited adaptivity                          | Motivates integration of multiple learning paradigms                                                |
| ML-Based Personalization [10]            | Uses ML algorithms (e.g., Random Forests, SVM, Neural Networks) to predict user preferences | Amazon, Netflix, Flipkart datasets       | Learns complex, nonlinear relationships; improves accuracy     | Acts as a “black box”; low interpretability                        | Demonstrates potential of predictive modeling for personalization                                   |
| DL-Based Models [11]                     | Employs CNNs, RNNs, or Autoencoders for recommendation                                      | Large scale e-commerce environments      | Handles large data volumes; captures temporal patterns         | Poor transparency; high computational cost                         | Inspires advanced, data-driven recommendation mechanisms                                            |
| Adaptive Frameworks [12]                 | Continuously updates based on real-time user feedback                                       | Dynamic shopping environments            | Adapts to evolving user preferences                            | Requires extensive computation; lacks interpretability             | Supports need for adaptive systems responsive to user context                                       |
| XAI Models [12]                          | Integrates interpretability (e.g., feature importance, SHAP, LIME) into recommendations     | Personalized shopping and search engines | Enhances user trust and transparency                           | Often trades accuracy for explainability                           | Encourages development of interpretable, user trustworthy systems                                   |
| Proposed Framework (Adaptive + XML) [13] | Combines adaptability, transparency, and user satisfaction into one model                   | E-commerce personalization               | Balances performance and interpretability; user-centric design | Requires validation through real-time deployment                   | Addresses existing gaps by integrating adaptability and explainability for enhanced user experience |

**Figure 1.** Proposed adaptive explainable hybrid personalization framework.

The data preprocessing phase involves several steps that are used to ensure that the data are of quality and consistent. The gaps or missing or erratic values are filled using the mean or median imputation strategies to avoid data distortion. One-hot and label encoding were used to encode categorical variables into machine-readable forms. The numerical features were also scaled to ensure that they were uniformly scaled and that no feature took over the model learning. Finally, the dataset was divided into training and testing portions using stratified sampling to maintain a balanced distribution of users in both portions, thus making the evaluation of the models fair.

One essential step is feature engineering, which converts raw behavioral data into structured and meaningful inputs for the model. Several computed features were created to promote the model's understandability and performance. Measures of engagement are also developed through a user engagement score (UES), which is formed by an aggregate of time spent, number of times clicked, and purchase history. Latent semantic relationships and preferences are represented by the generation of preference vectors based on TF-IDF and word2vec embedding of user-item interactions. Recency and frequency indicators are also provided to determine the loyalty and activity of users over time. In addition, an active user profile is generated by combining both short-term (recent) and long-term (historical) actions, which allows adaptive and personalized suggestions that adapt to changing user patterns.

This hybrid approach obtains user similarity patterns and involves intricate latent representations to enhance the quality of recommendations. Three key layers make up the model architecture: the input layer, which processes user and item embeddings; the hidden layers, which perform nonlinear transformations to model more complex user-item interactions; and the output layer, which predicts the rating, probability of clicking, or recommendation score. Incremental retraining is performed to achieve adaptivity with new data available, adaptive weighting between CF and CBF components with user activity levels, and feedback-driven learning with user satisfaction scores to fine-tune model parameters.

To achieve training and optimization, the model employs the Adam optimizer, depending on the task formulation used, either cross-entropy or the mean squared error (MSE) loss functions. Early stopping and dropout regularizations were used to avoid overfitting. Tuning of hyperparameters, such as learning rate, hidden units, and batch size, is obtained through Grid Search coupled with 5-fold Cross-Validation to maximize good performance and generalization.

To solve the issues surrounding deep learning models, explainability mechanisms are incorporated into the system via XAI mechanisms. Model decision-making can be interpreted using techniques such as SHAP and LIME. These techniques provide information on the level of importance of features and why the user or product features are important in a particular recommendation. They also explain the reasoning behind the models, making the user understand why a specific product was recommended, thus creating transparency and user confidence. In addition, a feature attribution dashboard was created to visualize these explanations to promote interpretability and trust in the recommendation system.

The system is assessed on four dimensions on a holistic basis in terms of various performance indicators. The measures of model performance included accuracy, precision, recall, F1-score, root mean square error (RMSE), and mean absolute error (MAE). The user experience is measured based on the average session time, CTR, conversion rate, and satisfaction score of the system in terms of functionality to attract and meet user satisfaction. The training time, inference time, and memory usage were analyzed to determine the efficiency of the system. Each of the models, such as CF, CBF, Hybrid CF-CBF approach, Deep Neural Network, and the suggested Adaptive Explainable Framework, were compared on each of these metrics to substantiate the accuracy and flexibility of the suggested system.

## Experimental Setup

A well-structured and effective computational environment was utilized to establish the experimental setup of the proposed framework. All the experiments were performed in Python, with deep learning based on very powerful libraries such as TensorFlow, traditional machine learning models, and preprocessing performed with Scikit-learn, explainability analysis with SHAP and LIME, data visualization with Matplotlib, and performance plotted with Matplotlib. Data were split into three (3) subsets where 70% were used as training data, 15% as validation data, and 15 percent as testing data because the evaluation was to be balanced and overfitting should be reduced. The hardware setup contained an Intel Core i7 processor, 16GB of RAM, and an NVIDIA RTX GPU, which provided sufficient computational power to train and optimize the model. Jupyter Notebook was used as the main development environment, where the code was written and experimented with, and Power BI was used as an advanced visualization and dashboard development environment, allowing for extensive analysis and interpretation of the model performance and explainability results.

## RESULTS AND DISCUSSION

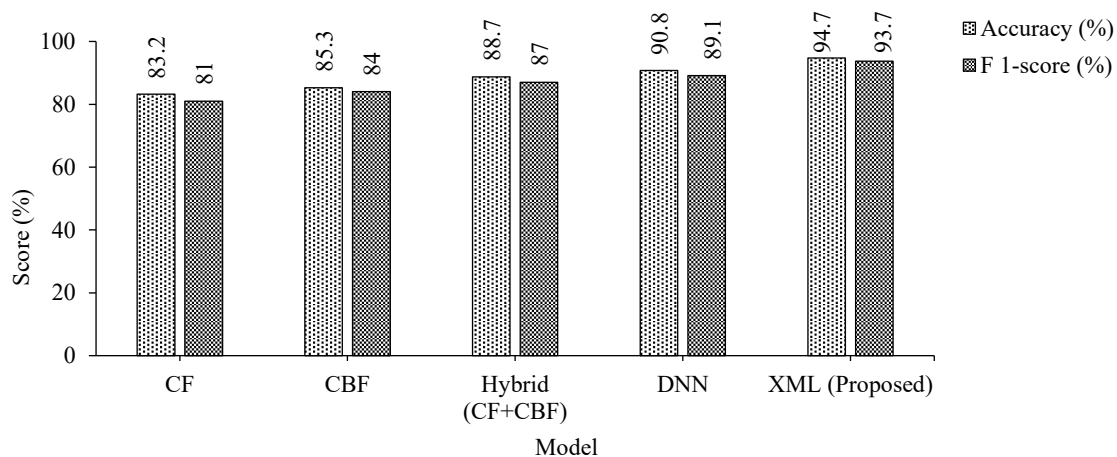
The results of the experiment applying the AEHPF are presented and analyzed. The proposed framework was evaluated in terms of the performance of classic personalization models, such as CF, CBF, Hybrid CF-CBF, and a DNN model. The findings were measured at several levels, such as the performance of the model, user interaction, system effectiveness, and elucidation. Different evaluation measures (precision, recall, RMSE, MAE, accuracy, F1-score, CTR, conversion rate, and user satisfaction) were used to provide a comprehensive evaluation. The results show that the combination of adaptive learning and XAI mechanisms is much more effective at raising the predictive accuracy and user trust, which proves the usefulness of the proposed framework.

Table 2 compares and illustrates the predictive performance of various models in terms of precision, recall, RMSE, and MAE. The outcomes clearly show that the proposed AEHPF achieved the best precision (93.92%) and recall (93.35%), proving to be more accurate and consistent in terms of recommendation. Moreover, the framework had the lowest RMSE (0.284) and MAE (0.214), indicating its high predictive reliability and low error. Classical models such as CF and CBF showed average results, with the Hybrid CF + CBF and DNN models demonstrating significant improvements. Nevertheless, the offered explainable framework outperformed them all, meaning that the predictive performance was not only retained but also improved alongside the model confidence and quality of personalization.

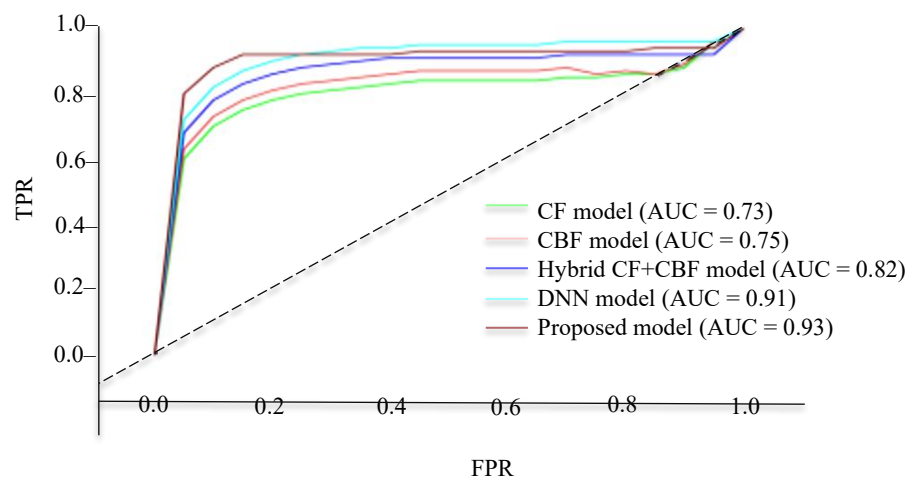
These observations are supported by the accuracy and F1-score curves of the personalization models presented in Figure 2. The AEHPF has been able attained maximum accuracy and the F1-score in various scenarios during the test, which implies a good balance between recall and precision. The DNN and the Hybrid CF + CBF models were close behind and demonstrated strong but marginally less stable results. Conversely, the accuracy of CF and CBF was lower, mainly because they failed to model the complex nonlinear interactions between users and items. These findings prove that the combination of adaptive learning and deep neural organization enables the proposed framework to be generalized to various user actions.

**Table 2.** Performance of personalization models.

| Model                    | Precision (%) | Recall (%) | RMSE  | MAE   |
|--------------------------|---------------|------------|-------|-------|
| CF                       | 82.49         | 80.44      | 0.413 | 0.326 |
| CBF                      | 84.91         | 83.17      | 0.399 | 0.313 |
| Hybrid CF + CBF          | 87.87         | 86.92      | 0.375 | 0.297 |
| DNN)                     | 90.15         | 89.49      | 0.340 | 0.273 |
| XML framework (Proposed) | 93.92         | 93.35      | 0.284 | 0.214 |



**Figure 2.** Accuracy and F1-score curves of personalization models.



**Figure 3.** ROC curves of personalization models.

**Table 3.** User satisfaction and engagement.

| Personalization method | Avg. session duration (min) | CTR % | Conversion rate (%) | Satisfaction score (1–5) |
|------------------------|-----------------------------|-------|---------------------|--------------------------|
| Non-Personalized       | 3.8                         | 2.4   | 0.9                 | 2.8                      |
| Traditional ML Model   | 5.6                         | 3.9   | 1.5                 | 3.7                      |
| Proposed Framework     | 8.2                         | 6.1   | 3.4                 | 4.6                      |

Table 3 presents the evaluation of user engagement and satisfaction indicators, such as average session time, CTR, conversion rate, and satisfaction level. The findings prove that user interaction is significantly enhanced by personalization as opposed to non-personalized systems. The highest level of engagement was obtained in the proposed AEHPF, with an average session time of 8.2 minutes, CTR of 6.1, conversion rate of 3.4, and satisfaction level of 4.6. Conversely, non-personalized strategies had much lower levels of engagement, as the level of satisfaction was only 2.8. This confirms the significance of adaptive personalization and explainable recommendations in creating user trust, increasing engagement, and achieving higher conversion rates.

All these personalization models were classified based on their performance on the ROC curves, as illustrated in Figure 3. The AEHPF had the highest area under the curve (AUC), proving that it is better at differentiating between relevant and irrelevant recommendations. Although the DNN and Hybrid CF + CBF models also exhibited good classification capabilities, they were not as precise and stable as the

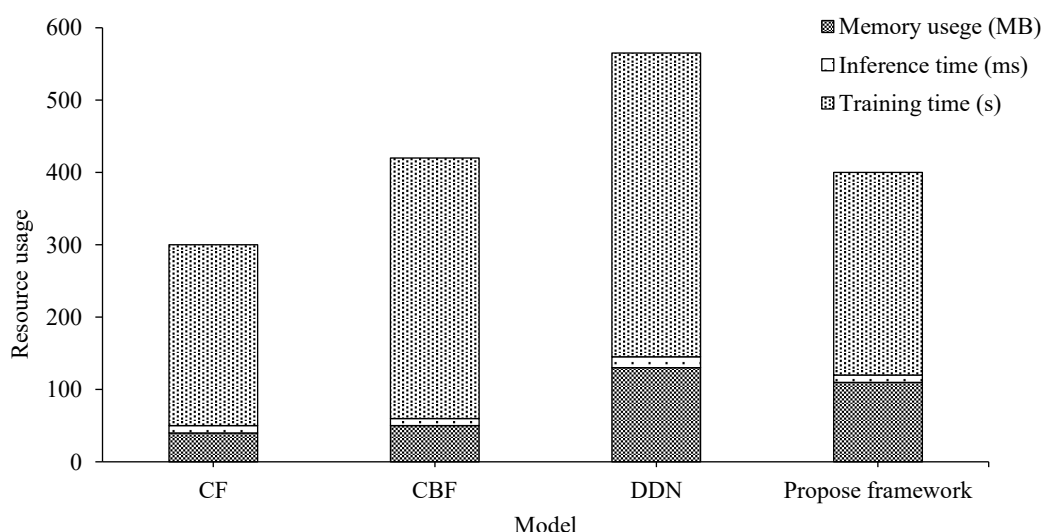
proposed framework. The CF and CBF models had smaller AUC areas, which showed limited generalization, although they were less complex computationally. This finding confirms that the combination of explainability and adaptive mechanisms is linked to enhanced model discrimination and reliability.

Figure 4 shows a comparison of the system performance of the personalization models in terms of computational efficiency parameters, such as training time, inference time, and memory. The explainability and adaptive retraining modules incurred a minor increase in the computational resources required by the AEHPF. Nonetheless, the cost in terms of performance was low relative to the significant improvement in accuracy, interpretability, and user satisfaction. The computational requirements for using the DNN model were the same as those for using the CF and CBF models, but the latter were faster and less accurate. The following trade-off shows that the AEHPF provides a good trade-off between computational efficiency and predictive excellence and is suitable for use in large-scale, real-time e-commerce.

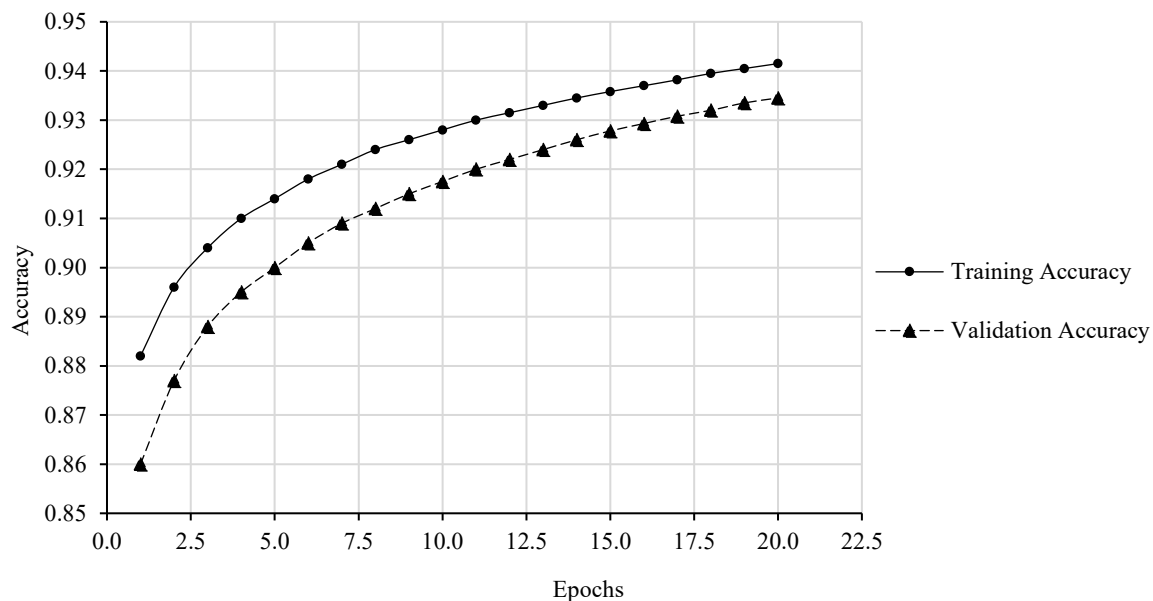
The data in Table 4 show a significant increase in the transparency and interpretability of the personalization framework with the involvement of XAI methods, including SHAP and LIME, which were incorporated into the offered system. Although the DNN model was effective in attaining high accuracy, it had a low ability to be interpreted with a SHAP impact score value of 0.41, LIME interpretability score of 78.6, and a total interpretability score of 2.3 on a 5-point scale. This implies that although the DNN may be making correct suggestions, its decision-making is mostly non-transparent to users and analysts, which is one of the major weaknesses of deep learning-based systems.

In contrast, the Proposed XML Framework made a significant contribution to the interpretability metrics in all dimensions. The SHAP impact score became 0.63, which is more balanced and transparent and provides a more effective explanation of the features. Likewise, the LIME interpretability score increased to 91.2, which shows that local model explanations became more consistent with human cognition. The total interpretability rating was 4.5, which is almost two-fold higher than that of the classical DNN model. Figure 5 shows the learning curve of the proposed model with the training and validation accuracies.

These results indicate that explanatory mechanisms, in addition to user trust and transparency, also provide other stakeholders (data analysts, business experts, and customers) with more insight into why some recommendations are provided. Such greater interpretability fills the predictive accuracy versus user-centric transparency gap, resulting in a more reliable and ethically sound e-commerce



**Figure 4.** System performance of personalization models.



**Figure 5.** Learning curve of proposed model.

**Table 4.** Explainability and interpretability evaluation.

| Technique              | SHAP impact | LIME (%) | Interpretability score (1–5) |
|------------------------|-------------|----------|------------------------------|
| Traditional DNN        | 0.41        | 78.6     | 2.3                          |
| Proposed XML Framework | 0.63        | 91.2     | 4.5                          |

personalization system. Simply put, the advertised XML model was able to meet the twofold goal of ensuring high predictive accuracy and making the decision-making process more transparent and easier to use, which is crucial prior to the responsible adoption of AI in online trading. The findings in all tables and figures prove that the suggested AEHPF is effective in improving the functionality and transparency of recommendation systems. The combination of adaptive learning, hybrid modeling, and XAI methods enables the framework to not only provide highly accurate and relevant suggestions but also help build user trust and interest, which are the main aspects of sustainable personalization in contemporary e-commerce settings.

## CONCLUSION

This study introduces a new adaptive and explainable machine learning-based personalization system that aims to increase user experience and satisfaction in an online shopping situation. The combination of CF, CBF, and DNNs is hybrid and guarantees high versatility in changing user preferences, whereas the application of XAI methods (SHAP and LIME) increases interpretability and transparency. The experiment shows that the proposed framework positively influences the main performance indicators and user engagement parameters to a significant degree compared with traditional personalization approaches. Moreover, the explainability layer helps bridge the gap between algorithmic intelligence and user insight and establish trust and responsible AI-based personalization. The framework is highly scalable, computationally efficient, and interpretable; thus, it is applicable in real-world e-commerce systems. The system can be expanded in the future to include reinforcement learning to perform continuous preference adaptation, federated learning to preserve privacy, and multimodal data integration (text, image, and voice input) to enhance personalization. The suggested framework provides a solid foundation for next-generation intelligent, adaptive, and transparent e-commerce platforms that can reconcile the needs of users with responsible and understandable advancements in AI.

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**REFERENCES**

1. Kaponis A, Maragoudakis M, Sofianos KC. Enhancing user experiences in digital marketing through machine learning: cases, trends, and challenges. *Computers (Basel)*. 2025;14:211. doi:10.3390/computers14060211.
2. Almahmood RJK, Tekerek A. Issues and solutions in deep learning-enabled recommendation systems within the e-commerce field. *Appl Sci (Basel)*. 2022;12:11256. doi:10.3390/app122111256.
3. Rabby F, Chimhundu R, Hassan R. Blockchain technology transforms digital marketing by growing consumer trust. In: Idrees SM, Nowostawski M, editors. *Transformations Through Blockchain Technology: The New Digital Revolution*. Springer International Publishing; 2022. p. 265-89. doi:10.1007/978-3-030-93344-9\_12.
4. Wang P, Li K, Du Q, Wang J. Customer experience in AI-enabled products: scale development and validation. *J Retail Consum Serv*. 2024;76:103578. doi:10.1016/j.jretconser.2023.103578.
5. Lu T, Zhou Z, Wang J, Wang Y. A large language model-based approach for personalized search results re-ranking in professional domains. *Int J Lang Stud*. 2024;1:1-6. doi:10.60087/ijls.v1.n2.001.
6. Pal B. Personalization strategies in e-commerce: leveraging machine learning for enhanced customer experience. *Acad Mark Stud J*. 2024;28:1-26.
7. Ekasari S, Judijanto L, Vandika AY. The role of artificial intelligence and machine learning in precision targeting: revolutionizing marketing strategies. *Jurnal Ekonomi dan Bisnis*. 2024;2:347-61.
8. Ekasari S, Judijanto L, Vandika AY. The role of artificial intelligence and machine learning in precision targeting: revolutionizing marketing strategies. *Jurnal Ekonomi dan Bisnis*. 2024;2:347-61.
9. Pereira AM, Moura JAB, Costa EDB, Vieira T, Landim ARDB, Bazaki E, et al. Customer models for artificial intelligence-based decision support in fashion online retail supply chains. *Decis Support Syst*. 2022;158:113795. doi:10.1016/j.dss.2022.113795.
10. Alhijawi B, Kilani Y. A collaborative filtering recommender system using genetic algorithm. *Inf Process Manag*. 2020;57:102310. doi:10.1016/j.ipm.2020.102310.
11. Das S, Behera RK, Kumar M, Rath SK. Real-time sentiment analysis of Twitter streaming data for stock prediction. *Procedia Comput Sci*. 2018;132:956-64. doi:10.1016/j.procs.2018.05.111.
12. Yin J, Qiu X, Wang Y. The impact of AI-personalized recommendations on clicking intentions: evidence from Chinese e-commerce. *J Theor Appl Electron Commer Res*. 2025;20:21. doi:10.3390/jtaer20010021.
13. Valencia-Arias A, Uribe-Bedoya H, González-Ruiz JD, Santos GS, Ramírez EC, Rojas EM. Artificial intelligence and recommender systems in e-commerce: trends and research agenda. *Intell Syst Appl*. 2024;24:200435. doi:10.1016/j.iswa.2024.200435.
14. Huang S, Diao S, Zhao H, Xu L. The contribution of federated learning to AI development. In: *The 24th International Scientific and Practical Conference "Technologies of Scientists and Implementation of Modern Methods"*; 2024 Jun 18. International Science Group; 2024. p. 358.
15. Carole KS, Theodore Armand TP, Kim HC. Enhanced experiences: benefits of AI-powered recommendation systems. In: *Proceedings of the 26th International Conference on Advanced Communications Technology (ICACT)*; 2024. Institute of Electrical and Electronics Engineers; p. 216-20. doi:10.23919/ICACT60172.2024.10471918.