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EXPLAINABLE ARTIFICIAL INTELLIGENCE FOR PERSONALIZED RECOMMENDER SYSTEMS USING DEEP LEARNING MODEL

Dr. Deepjyoti Roy[1*], Prof. Dr. Rohini Pundalik Onkare[2], Muthumari[3], Amit S. Tiwari[4] , Shah Rakesh Jagdishchandra [5], Amartya Ghosh[6], Dr Nagendra Nath Giri [7]

[1*]Assistant Professor, Department of Computer Science and Engineering, Assam down town University, Panikhaiti, Guwahati, Assam. PIN: 781026. ORCID ID : https://orcid.org/0000-0002-8020-7145 Email ID: deepjyoti2roy@gmail.com

[2]Assistant Professor, Department of Electronics & Telecommunication Engineering, Dbatu Lonere / Padmabhooshan Vasntraodada Patil Institute of Technology, Budhgaon (Sangli), 416304, Maharashtra Specialization: Deep Learning, signal processing ORCID ID (if available): 0009000649485354 Email ID: rponkare.etc@pvpitsangli.edu.in

[3]Assistant Professor, Department of Karpaga Vinayaga, College of Engineering and Technology, India Electrical and Electronics Engineering Email Id: nilaakanu@gmail.com

[4]Assistant Professor, Department of Electronics and Computer Science, Shah and Anchor Kutchhi Engineering College, Mumbai, 400004, Specialization: Electronics and telecommunication, ORCID ID: 0009-0003-2014-7704, Email ID: amit.tiwari@sakec.ac.in

[5]Assistant Professor, Deaprtment of Computer Engineering, Silver Oak College of Engineering, Silver Oak University, Ahemdabad, Gujarat-382481 Specialization: Artificial Intelligence and Machine Learning Email ID: rakeshshah.ce@socet.edu.in

[6]Assistant Professor, Department Of Computer Science Engineering, Brainware University, ORCID ID: 0009-0002-2504-3325, Email ID: com.amartya@gmail.com

[7]Associate Professor, Department of Computer Science, Maharani Science College for Women, Mysore, Karnataka, india. Email ID: nagengiri123@gmail.com

Abstract

Personalized recommender systems play a central role in modern digital platforms, yet many high-performing models operate as opaque systems, limiting user trust and practical adoption. Explainable artificial intelligence has emerged as a promising approach to address this challenge by enhancing transparency while maintaining predictive capability. This study investigates the impact of integrating explainable features into a deep learning-based personalized recommender system to improve both performance and interpretability. Using the REASONER dataset, which includes user-item interactions enriched with user attributes, personality traits, and multi-aspect tags, a logistic regression model was implemented as a baseline and compared with a feedforward neural network. Model performance was evaluated using accuracy, precision, recall, F1 score, and ROC-AUC, with threshold tuning and feature importance analysis applied to optimize and interpret the neural network. The results show that the neural network achieved superior discriminative performance with a ROC-AUC of 0.729 and improved minority-class recall after optimization. Feature importance analysis revealed that interest tags, video tags, and reason-based attributes were the most influential predictors, whereas demographic variables contributed less significantly. These findings indicate that incorporating explainable, behavior-driven features enhances both the effectiveness and transparency of recommendation models. Overall, the study highlights the importance of combining deep learning with explainable inputs to develop more reliable, user-centered recommender systems.

Keywords: *explainable artificial intelligence, recommender systems, deep learning, personalization, transparency*

1. Introduction

The growth in the speed of artificial intelligence (AI) has altered the digital environment of the present, namely in information-heavy decision-making, e-commerce and online services, in an inconceivable way. One of such contributions is explainable artificial intelligence (XAI) that has emerged as one of the most important paradigms aimed at enhancing the transparency, interpretability, and trust of multi-layered machine learning models. In most cases, classical black-box-based AI systems are not interpretable, which limits their application in high-stakes and user-friendly applications. XAI is thus set to bridge this gap by providing humans with explanations on what algorithms do, in a way that is easily understandable to make their decisions more accountable and which their user's trust [1]. Recent studies have also singled out the emergence of the importance of explainability as AI systems are increasingly becoming a part of the world. The need for transparency is particularly when it comes to the example of the recommender system, where the decisions of the algorithms directly influence the decisions and actions of the user. Large-scale studies indicate that XAI is not only a way to increase trust but also allows the debugging, legal and ethical implementation of AI to be possible [2]. An achievement has a history of explainability in AI, beginning with the rule-based systems of the early 20th century up to the modern deep learning systems, where the interpretability of the predictions has become even more critical as the complexity of the models also rises [3]. The application of recommender systems has become a constitutive component of the e-commerce system in the modern world because it provides the possibility to offer customized content and enhance user experience. These types of systems utilize various approaches, which include collaborative filtering, content-based filtering, and hybrid techniques to arrive at relevant recommendations. They are popular in retail, streaming services, and online education, which underlines their appropriateness in the experiences and business outcomes of users [4]. In addition, systematic research on the topic of e-commerce recommender systems has shown that they are applicable to large-scale data processing and provide individual recommendations, depending on the preferences and behavioral patterns of the user [5].

Even though they are effective, recommender systems have a number of limitations, such as scalability, information sparsity, and transparency. The goal of intelligent recommender systems is to eliminate these problems by incorporating the latest machine learning algorithms, but they are not usually transparent to end-users. This ambiguity creates issues with trust in the user, especially when the recommendations play a big role in the decision to make a purchase [6]. The basic literature in recommender systems further organizes the search techniques and applications used and shows the recurring issues on explainability, diversity, and user satisfaction [7]. Fairness and ethical considerations have become an issue in recent years, with regard to recommender system research. Prejudice in recommendation algorithms may cause inequity in both the users and service providers. Achieving fairness and at the same time preserving the accuracy of recommendations has emerged as an essential research direction, particularly in systems that operate on a large scale [8]. Also, personalization can be regarded as a prior goal, and it has been shown that combinational algorithms are effective to improve the accuracy of recommendations and increase the user interest in online learning and other spheres [9].

The continued progress in the field of recommender systems has been on the incorporation of new technologies into the system, like big data analytics and deep learning. According to systematic reviews, although such methods enhance predictive performance, they tend to increase the interpretability issue, and hence users cannot easily comprehend the rationale behind recommendations [10]. Equally, the use of collaborative filtering in IoTs underscores the increased complexity of the scenarios of recommendation, where the situation is further compounded by the heterogeneity in data sources, which in turn complicates the issue of transparency and explainability [11]. Recent studies have investigated how explanation interfaces can be used to improve user satisfaction. The feature-based explanations and various modalities of output have been found to play a significant role in the perceptions and trustworthiness of users with respect to recommender systems. Explain everything in a meaningful and clear way that can enhance the user acceptance and confidence in the decision-making process and hence, enhance the effectiveness of the entire recommendation system [12].

Although there has been a significant improvement, the explainable AI and recommender systems are at a critical point where there is a research gap. Although many studies have examined XAI and recommendation methods individually, limited research has been done to integrate explainability into recommender systems in a manner that supports the proposed trio of objectives: transparency, accuracy, and user satisfaction. Moreover, current methods do not usually focus on the effect of various explanation strategies on user trust and system usability in practice.

It is against this background that this paper delves into the explanatory concept of artificial intelligence that will be integrated in a recommender system, specifically, how it can contribute to the transparency and understanding of the user. It examines the weaknesses of the existing recommender systems methods due to the absence of explainability and explains how recommendable attributes can be leveraged to render recommendations more approachable and trustworthy. The study also determines the extent to which predictive modeling along with explanation-based features, can aid the enhancement of the performance and interpretability. By doing so, this analysis will contribute to providing a glimpse of the development of recommender systems to make them more open and easier to use.

2. Methodology

2.1 Research Design and Data Source

The data-driven experimental design has been taken in the analysis of the role of explainable features in personalized recommender system in this paper. The reasoning is that the predictive performance can be improved by the addition of signals that the user can understand, i.e. tags that correspond to user interest and reasoning, and interpretability in a deep learning system.

The experiments are conducted based on the REASONER dataset [13], which is a dataset that is supposed to be applied in the study of explainable recommendation and possesses user-item interactions crowned with multi-aspect tags, user attributes, and personality traits. These attributes make it suitable to explainable artificial intelligence studies in recommendation projects. There are four processes in the workflow to a greater extent, which include data preprocessing, feature engineering, model development, and evaluation.

2.2 Data Preprocessing

The identifiers were unique, and hence the combination of the interaction, user, item and personality data into a single dataset was done. Records with values that were not entered in key fields were destroyed. The tag-based features that were originally expressed as a string representation of lists were converted to a structured numerical list. These tags are various dimensions of user engagement, such as reasoning, interest, and content attributes. These tag lists were then converted to multi-hot encoded vectors to be used as input into the model. Numerical variables, such as demographic variables and personality scores, were normalized in order to have similar scaling. The data was divided into a training and a testing set by stratified sampling to maintain the distribution of classes.

2.3 Feature Engineering

The feature set combines several sources of information to hit both behavioral and contextual points of user preferences. Explanation-based features contain the tags, which are the features of the reasoning, interest, and content related to the user, which present the interpretable cues of the user's decision-making. Tag-based representations of video characteristics are used as item features, whereas demographic attributes (age, gender, education, and income) are used as user features. Also, responses to the Big Five questionnaire are used to incorporate features of personality. These groups of features combined allow the model to be personalized in terms of learning and to be interpretable at the same time.

2.4 Model Development

There were two kinds of models used. The simplicity and interpretability of a logistic regression model were considered a baseline. A class-weighted version was also used to tackle the imbalance in the classes. To capture the nonlinear feature relationships, a feedforward neural network was developed. The model is composed of dropout regularization and fully connected layers using the activation of rectified linear units. The Adam optimizer was used to carry out training. A weighted binary cross-entropy loss function was applied in order to manage the imbalance of classes. A validation subset was also used to keep track of performance and choose the most appropriate model.

2.5 Model Optimization and Evaluation Metrics

Threshold tuning was also used to enhance model performance. Several decision thresholds were tested in order to determine the best balance between precision and recall. The choice was made according to the macro F1 score to have a balanced performance in the classes. Accuracy, precision, recall and F1 score were used to determine model performance. Moreover, the model was tested on ROC-AUC to determine whether the model can differentiate between classes regardless of the decision level.

2.6 Explainability Analysis

The importance of features was evaluated in terms of the learned weights of the neural network. The significance of every feature was calculated with the mean absolute contribution of input features. The given analysis determines the most influential factors affecting the predictions of the models and allows for interpretability.

3. Results

3.1 Dataset Characteristics

The data used in the current research consists of 58,497 user-item interaction between 2,997 users and 4,672 video items. There are 6,122 distinct tags to be used in describing content features and user preference. The mean score is 3.57, as the review of Table 1 highlights, which shows mostly positive customer reviews. Also, the percentage of positive interactions ("like") is 72.92, which shows an evident imbalance in classes. Figure 1 depicts the distribution of the binary outcome as the instances of "like" are far higher than the cases of "not like." Such an imbalance leads to the idea that models that are not trained with corrective actions can be biased toward the majority group. Figure 2 gives further insight into the behavior of the users in terms of rating. The ratings are skewed towards a higher number, especially 4 and 5, a notion that shows that the user would give positive reviews. This skewness supports the fact that effective modeling strategies are required that can manage imbalanced and positively biased data.

Table 1. Dataset Summary

Metric	Value
Total Interactions	58,497
Total Users	2,997
Total Items (Videos)	4,672
Unique Tags	6,122
Average Rating	3.57
Like Ratio (%)	72.92

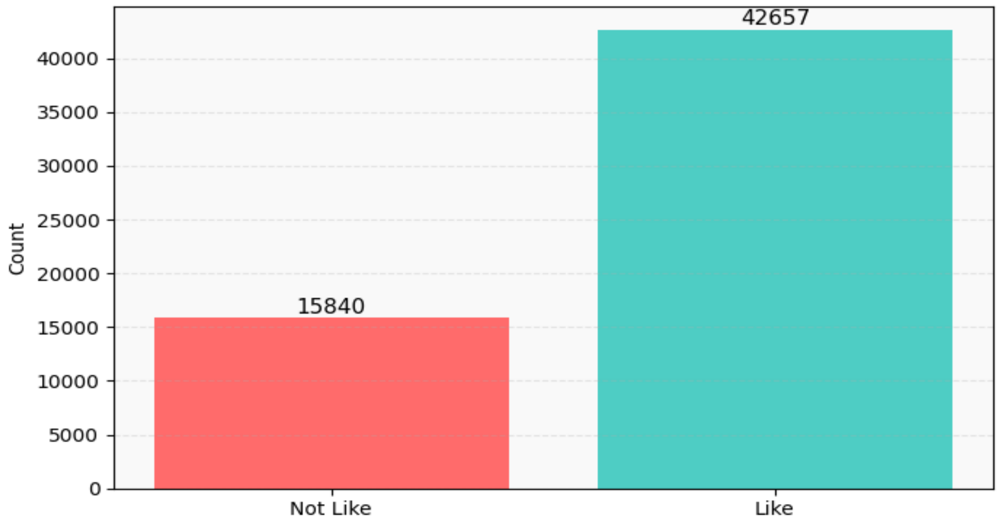

Figure 1. Distribution of Binary User Feedback (Like vs. Not Like)

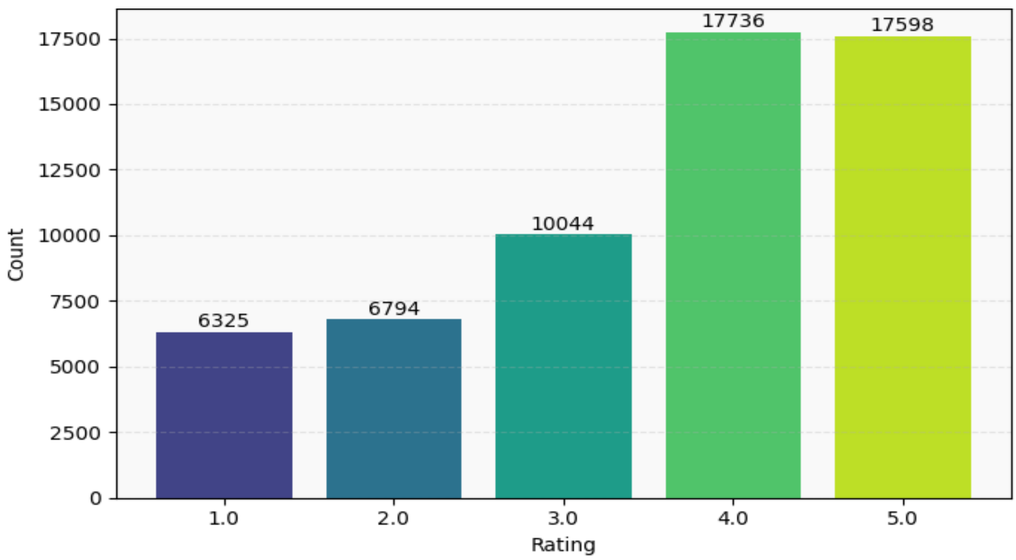

Figure 2. Distribution of User Ratings Across Interaction Data

3.2 Baseline Model Performance

To develop a baseline, a logistic regression model was first. The model also attained an accuracy of 0.726, but this was mainly because the positive class was dominant. The model had very low recall on the minority group ("not like"), which implies that it does not generalize negative interactions. In order to overcome this limitation, the class-balanced logistic regression was used. According to Table 2, this change enhanced the model to detect cases of the classes of minorities, which were more effective in recall. This was, however, accompanied by a reduction in the overall accuracy, and this indicates the natural trade-off between predictive accuracy and class balance.

Table 2. Model Performance Comparison

Model	Accuracy	ROC-AUC
Logistic Regression (Basic)	0.726	0.624
Logistic Regression (Balanced)	0.593	0.625
Neural Network (Balanced)	0.685	0.729
Neural Network (Tuned Threshold)	0.712	0.729

3.3 Deep Learning Model Performance

A neural network model was created to represent more intricate patterns of data. The first form of the model had a similar behavior as the baseline, with the majority class being favored. Thus, weighted loss functions and stratified validation were used to have a balanced approach to training. The balanced neural network had a test ROC-AUC of 0.729, as shown in Table 2, which shows that it has a better discriminative ability than the logistic regression models. This affirms the benefit of deep learning in the modeling of nonlinear relations in multi-modal feature space.

The optimization of model performance was also based on threshold optimization. As depicted in Figure 3, the decision threshold affects the classification performance of the decision to a large extent. The model obtained a better-balanced precision and recall trade-off when it chose the best possible threshold of 0.45 on the macro F1 score. The last tuned model has an accuracy of 0.712 but has a ROC-AUC of 0.729. Notably, the recall of the minority group rose to 0.54 and the majority group maintained performance. This establishes that threshold tuning is effective in reducing the effect of class imbalance and does not affect the overall predictive results.

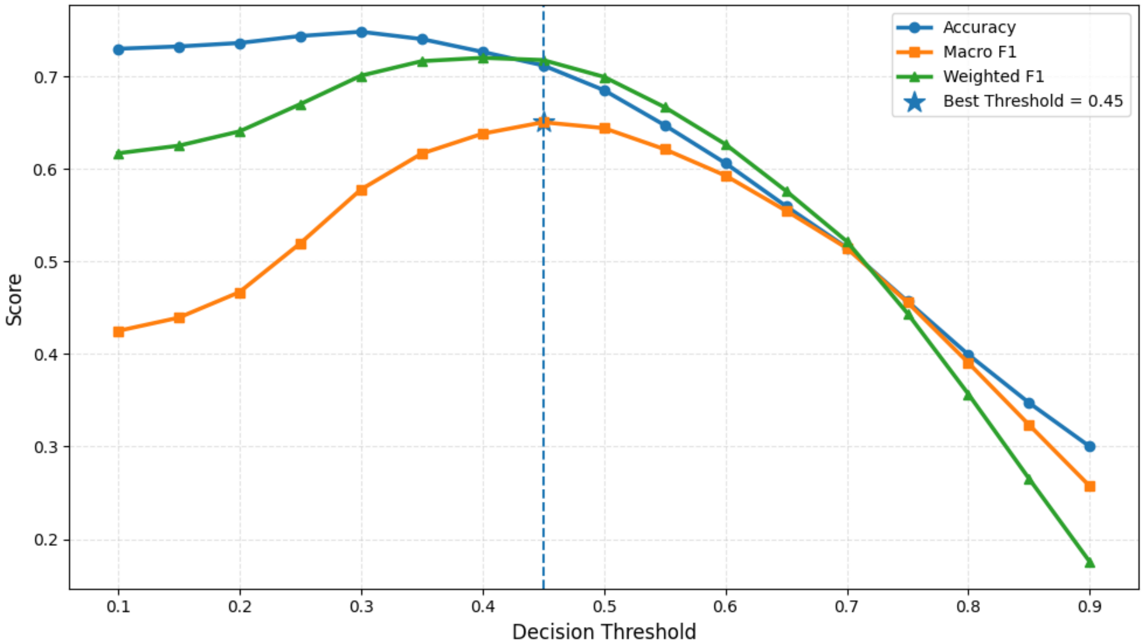

Figure 3. Threshold Tuning Performance of the Neural Network Model

3.4 Explainability Analysis

To explain how the neural network arrived at the decision, the weights of the first layer were used to analyze feature importance. Table 3 provides the results, and Figure 4 gives a summary of the results visually. The discussion shows that the key features of the model predictions are the ones related to explanation, especially the aspects related to user interest and video features. Such features as interest tag 1," video tag 18," and "interest tag 0" are among the most significant, which suggests that user engagement indicates and content descriptors are essential to the precision of the recommendations.

Features based on reasoning, which emulate the motivations of the user before engagement, are also very important. That implies the fact that, in addition to the ability of the model to predict preferences, the concept of user reasoning should be introduced. Demographic variables, on the contrary, like career and age, are relatively less significant. Although these features promote personalization, they do not have as much influence as behavior-driven and explanation-based signals. The features that are significant are related to explanation. This helps to support the fact that explainable features not only enhance transparency but also predictive performance.

Table 3. Top Important Features

Rank	Feature	Importance Score
1	interest tag 1	0.119
2	video tag 18	0.112
3	interest tag 0	0.111
4	video tag 11	0.105
5	reason tag 10	0.105
6	video tag 17	0.103
7	reason tag 11	0.103
8	reason tag 9	0.102
9	reason tag 2	0.101
10	reason tag 8	0.098
11	video tag 15	0.093
12	video tag 13	0.091
13	video tag 16	0.091
14	career	0.090
15	reason tag 4	0.088

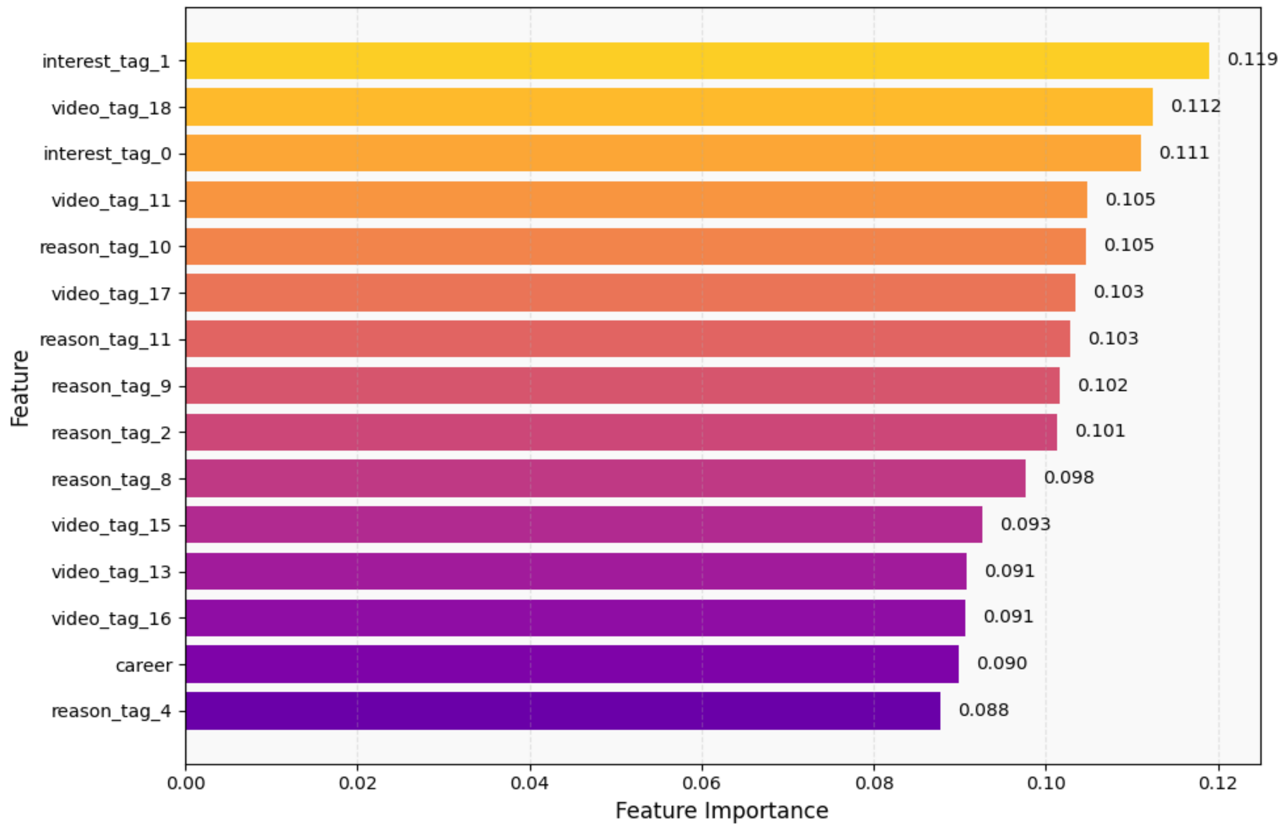

Figure 4. Feature Importance Analysis of the Proposed Explainable Model

4. Discussion

The findings indicate that explainability items included in the recommender systems enhance predictive and interpretability. The improved model capability, including its capacity to align itself to the user preferences through interest tags and the reason attributes, suggests that explanation-based contributions play a significant role in optimization of the quality of the recommendations. The system also has the advantage of utilizing feature of user intent and reasoning in contrast to utilization of historical interaction data alone. It implies that explainability is not an activity that should be performed separately, but a crucial component that can contribute to the effectiveness of the recommendation algorithms. In addition, predictive mechanisms within the model are most appropriate to fit the true behaviour of the users; imbalanced post-optimal results are expected to show the power of the model, which implies the discussed necessity. The system could be brought nearer to diverse tastes and become more reflective by being more concerned with less noticeable user actions. It substantiates the idea that explainable recommenders would be used to balance the process of making decisions and make it more user-centric.

These are not unexpected based on recent developments in explainable AI in recommender systems, where deep learning models are being designed with added interpretability and predictive accuracy. Research has revealed that explainability can be used alongside deep architectures to improve transparency and performance of the system, especially in complex recommendation settings [14]. Equally, the explainable machine learning approach to personalization is based on the idea that the perception of user preferences on a more granular level brings forth more valuable and interesting recommendations [15]. Explainable recommender systems have been useful in domain-specific applications to enhance transparency and user interaction. As an example, explainable models within the context of e-learning have been demonstrated to improve personalization as well as the confidence of users in recommendations [16]. The concept of deep models being interpretable with the help of explicit explanation mechanisms is further supported by structural improvements in explainable neural networks [17], which remove the classic black-box limitations associated with deep learning.

New studies also point to the implementation of more sophisticated AI methods, including reinforcement learning and large language models, to come up with more adaptive and explainable suggestions. Those methods underline that explainability must be incorporated throughout the process of making the recommendations instead of being an additional feature in a post hoc manner [18]. Besides, the research in the field of energy-related uses proves that explainable tips enhance the level of user acceptance and comprehension, which supports the necessity of transparency in decision support systems [19]. Such results are further corroborated by cross-domain evidence. Explainable AI has also been depicted to facilitate superior decision-making in agriculture recommendation systems by giving clear reasons why they recommend what they recommend, especially in uncertain and data-intensive settings [20]. Likewise, personality-conscious and customized recommendation systems suggest that the customization of explanations to a single user boosts confidence and effectiveness of the system [21]. The concept of a combination of explainable recommendations with a better user experience and engagement has been associated with retail and augmented reality settings, which underscores the usefulness of the concept in practice in the real-world setting [22].

There are some significant implications of the results in the research and practice. Technically, they indicate that, by adding the aspects of explanation to model design, it is possible to enhance their performance and interpretability at the same time. This is contrary to the classical trade-off between accuracy and transparency, which implies that the two can be balanced by adopting a considerate system design. The explainable recommender systems may be helpful regarding the growth of trust, satisfaction, and confidence in the decision made by the user. Such systems provide information on the reason why some of the recommendations are provided, and this makes people make conscious choices and reduce skepticism to automated decisions. This is more so in those areas that endorse grave consequences of recommendations, such as education, health care, and finances. Speaking of the organizational perspective, explainable recommender systems are to be implemented to improve user retention and engagement, as it increases the transparency and accountability. Explainability can also assist the business to build a better relationship with the users, ensuring that the recommendations procedure is conducted in a manner that satisfies the user's expectations and ethics.

Even though the outcomes were encouraging, several drawbacks should be mentioned. To begin with, the study would be restricted by the fact that only one dataset was used, and it may not be generalizable to other fields and groups of users at all times. Second, feature importance provides an insight into the model operation, but fails to provide the whole picture of the model decision-making, specifically when it comes to the individual prediction level. Third, the review is more performance-measuring, and not much is taken to gauge the perception of the user and the actual usability of the explanations. Limitations of future studies must be corrected by taking into account explainable recommender systems in alternative data and areas of implementation. More detailed information on the role of explanations in promoting trust and decision-making would be provided by the introduction of user-based evaluation tools (surveys and behavioral experiments). In addition, to obtain even greater transparency of the system, it may be helpful to explore hybrid approaches that will include intrinsic and post hoc explainability approaches. The new technologies of interactive and real-time explanatory systems, in particular in the immersive environment, are also capable of providing the prospects of user engagement and satisfaction.

5. Conclusion

One of the possible solutions that can be undertaken to increase the predictive and interpretability is the incorporation of explainable artificial intelligence in the personalized recommender system. The findings indicate that deep learning can go so far as to outperform conventional training using regularized behavior, context, and explanation characteristics. In particular, user interest tags, content prompt and reason-based functionality proved to have the strongest influence, which suggests that self-explanatory and valuable cues can encourage rather than inhibit the quality of recommendation. The results also suggest that model balancing and threshold tuning are required in the control of the imbalance of classes, as well as for more reliable performance among user responses. The results indicate that explainability is not merely an added interface that must be introduced in recommender systems. These systems will be able to support increased trust levels, satisfaction and realistic usability by relating the recommendations to the item- and user-level factors that can be comprehended. At the same time, it must be further validated on a larger scale of data and in practical situations to guarantee the generalizability and the effect of the use by the users. Generally, the article proves that deep learning must be complemented with explainable properties that can be used to develop more transparent, effective, and user-friendly recommendation models.

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