Personalized E-Commerce Product Recommendations with Counterfactuals

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Abstract—*The use of artificial intelligence on e-commerce websites like Amazon and Flipkart to provide personalized product recommendations is very common. Although such systems are very predictive, they are usually not very transparent and the users do not know why they suggest certain products. Lack of explainability and lowers user trust and restricts user understanding of how preference or behavior change may affect recommendations. Precision and recall are the most common performance metrics that most traditional recommendation systems focus on, not taking into account the relevance of interpretability and user-centered insights.*

The proposed paper is a new framework named Personalized E-Commerce Product Recommendations with Counterfactuals that incorporates the use of counterfactual explainable AI into the recommendation engines. The system does not just predict the products that are relevant but also produces directions that are intuitive in the form of what-if explanations that display how small changes in the user behavior, preferences or filters would change the recommended results. This method maximizes transparency by introducing low and significant changes to accomplish various recommendations and gives the user a chance to take action based on the findings.

The suggested model is a hybrid of collaborative filtering and content-based algorithms, a counterfactual explanation module, to make it accurate and interpretable. Experimental analysis of the findings proves that the integration of counterfactual explanations enhances user trust, satisfaction, and engagement with little harm to the performance of the recommendations. This work is part of the creation of transparent, trusting, and user-friendly AI solutions to the world of e-commerce.

Keywords- E-Commerce, Personalized Recommendation System, Explainable AI, Counterfactual Explanation, User Trust, Collaborative Filtering, Transparent AI, Interpretable Machine Learning.

I. INTRODUCTION

The artificial intelligence (AI) algorithms that drive recommender systems are everywhere on e-commerce sites like Amazon and Flipkart and tailor solutions and choices to your tastes and make you addicted. The employees of the company have recently jumped into the deep-learning bandwagon and it has boosted the accuracy levels up to the sky thanks to the massive quantity of behavioral and transactional information that we are currently in a position to tap into [1]. The old recommendation classics such as collaboration filtering and hybrid models have been disaggregated and optimized to execute quicker and precise outcomes and we are seeing numerous papers on that side [2], [3]. Despite the claims of scientific accuracy of these systems, most of them focus on the accuracy measures and pay little or nothing to describe or give transparency to users. Explainable AI has also been widely hyped in recent years, especially since the majority of its models that do well are in the black box, and will not give an explanation of what transpired when a particular product appeared on your feed [4]. The fairness, accountability, and ethical AI also advocate to an open recommendation process [5], [6].

The other prior experiments entered into counterfactual analysis with the assumption that the slightest of changes in the input characteristics can lead to a change in choice by a model. The inner-workings of the model are hidden, nevertheless [7]. This was subsequently generalized to general machine learning environments [9] and even explainable recommender systems, which generated counterfactuals on the basis of suggestions [8].

Those trends that are latest (20242025) include the direct explanation of explainability into the state-of-the-art recommendation pipelines. The reviews of comparative analysis within the e-commerce big-data circles show that most algorithms in the e-commerce research are performance-oriented, rather than interpretable [3]. More researchers are now screaming to have explainable AI to enable them to establish user trust and adhere to the regulations [6], [11].

Advanced counterfactual systems which are being affected are being deployed to refine the explanations offered by conversational recommenders, this despite some of them still confusing the term with regular recommendation systems [12]. Interactive and explainable systems are being integrated with counterfactual forms of reasoning [13], and methods are being integrated that combine embeddings-based and semantic-based explanations, and improve after-hoc interpretability [14].

Counterfactual language reasoning is also being performed in research to meet the principles of causal inference in explanations in 2025 [15]. However, the quantity of labor that holds all these user-level, product-level, counterfactual explanations is still scanty. The e-commerce recommendation systems tend to be either none or everything in terms of being predictive or flashy but not both concurrently.

So we're filling that gap here. The article presents a paradigm dubbed Recommendations of Ecommerce Products Personally with Counterfactuals that combines explain-able AI through counterfactual rationality and a recommendation engine of hybrid nature. The system integrates both content-based and collaborative filtering to avoid low accuracy of recommending factors and ensure high accuracy of recommending factors, and integrates a counterfactual explanation module to detect small yet significant alteration of features that can modify results.

The prototype creates what-if scenarios, thus increasing the degree of intuition, transparency, and trust and encourages users to engage without depreciating the performance. This adds to the ever-growing body of literature regarding ethical, fair, and transparent recommender systems that fill the gap between user-friendly solutions and high-performing personalization in e-commerce.

II. PROBLEM STATEMENT

E-commerce platforms rely heavily on AI-powered recommendation engines to make product offers personal and improve user experience. Although these systems are highly predictive as applied to collaborative filtering and deep learning models, it is common that they are black-box models, which are not interpretable and transparent [1]. Consequently, users might not comprehend why some products are recommended instead of others and this will result in lack of trust and less awareness as to the manner in which the recommendations are made.

The majority of the current recommendation systems are mainly dedicated to the optimization of the performance indicators like accuracy, recall, and click-through rates and they do not give any substantial descriptions to what they produce [2]. This interpretability is not interpretable, and users struggle to comprehend how their preferences, browsing habits or their choice of filters affect the recommended goods. As a result, users are not aware of the possible changes they can make in order to get alternative suggestions, which restricts the power of users and the transparency of the system. Even though the existing explainable recommendation methods address it by providing post-hoc textual descriptions or the importance of features scores, they often do not offer practical and intuitive what-if information [3].

Moreover, not many systems incorporate counterfactual reasoning directly into individualized e-commerce settings, with a gap between theoretical explainable AI studies and its implementation in the online stores of the real world [4]. The lack of a single model that integrates correct personalization with counterfactual responses prevents the creation of reliable and user friendly recommendation systems. In the absence of such integration, the issues of fairness, accountability, and ethical AI are underrepresented [5]. Thus, the necessity to have a smart recommendation system that will balance the accuracy of personalization with the counterfactual explainability is great. This type of system would allow having a clear understanding of what-if, better user engagement, greater transparency, and more trust in e-commerce platforms.

III. LITERATURE SURVEY

Deep Learning–Based Recommender Systems

Recommender systems based on deep learning have brought great contributions to the area of personalization. A robust review of the deep learning methodologies applied to recommender systems by Zhang et al. [1] has shown how the neural networks can be used to capture intricate and multidimensional user-item interactions. They show that deep models significantly enhance the accuracy of recommendations, but, all too frequently, at the expense of interpretability because of the black-box characteristics of deep learning architectures.

Traditional Recommendation Strategies

Conventional recommendation techniques have also been much researched. An in-depth survey of collaborative filtering and content-based systems of recommendation by Bobadilla et al. [2] defines their advantages and drawbacks. They focus on the problems of scalability, sparsity, and accuracy, as well as mention the lack of explainability mechanisms that can be offered by early recommendation systems.

Big Data and E-Commerce Recommendation

Jin et al. [3] conducted a comparative analysis of recommendation algorithms on the basis of big data and e-commerce management by using large-scale e-commerce datasets. Their results reveal that hybrid models are superior to single-method strategies in the terms of accuracy. Nevertheless, as the study also emphasizes, the interpretation and transparency of users are given a relatively lower level of consideration in performance-based systems.

Explanation in Recommender Systems

Explanations have also been examined within the context of recommender systems by Tintarev and Masthoff [4], who also investigated the effects of and the impact of different explanation strategies on user satisfaction and trust. They postulate that explanations may enhance the acceptance of the system, but most of the strategies fail to offer actionable information that can assist users to revise the recommendations meaningfully.

Fairness and Ethical Recommender Systems

Recommender systems that are aware of fairness have also become popular. Jin et al. [5] explored the fairness-aware recommendation models to solve the problem of bias and provide equal exposure to items. Their study highlights that there is a need to have clear and responsible recommendation systems that will facilitate ethical AI usage in online retailing. On the same vein, Guttmann and Ge [6] came up with a research agenda of ethical recommender systems based on explainable AI, and highlighting the increased significance of interpretability and transparency in encouraging user trust and addressing regulatory demands.

Counterfactual Explanations in AI

Wachter et al. [7] formally introduced counterfactual explanations in AI, suggesting a procedure of explaining model decisions based on making minuscule alterations to input features that do not require revealing the internal structures of a model. This is a groundbreaking work that made the foundation on counterfactual reasoning in machine learning.

Counterfactual Explainable Recommendation

Continuing the same point, Tan et al. [8] applied counterfactual reasoning to recommender systems by constructing a counterfactual explainable recommendational framework. Their methodology finds small feature changes which change the results of the recommendations, thus increasing interpretability without affecting the performance. Verma et al. [9] also summarized the counterfactual explanation frameworks in machine learning and divided the available methods into the existing categories and emphasized their potential to enhance transparency in an automated system of decisions.

AI Trends in E-Commerce Recommendation

Valencia-Arias et al. [10] reviewed the latest trends in the e-commerce recommendation system, including advanced personalization, explainability, and data-driven decision-making, as these belong to the broader scope of the application of AI.

Advanced Counterfactual and Conversational Approaches

More advanced counterfactual approaches have also been proposed Guo et al. [11] introduced a group influence function–based method for generating counterfactual explanations in recommender systems, improving explanation precision while aligning counterfactual generation with user–item interaction modelling. Yu et al. [12] developed an explainable conversational recommender system that integrates interactive user feedback, enhancing transparency in dynamic recommendation settings.

Hybrid and Language-Based Explanation Models
Counterfactual methods that are more developed have also been suggested Guo et al. [11] proposed group influence function-based approach as the way of producing counterfactual explanation in the recommender systems, enhancing the precision of explanation and bringing counterfactual generation in line with the user-item interaction modelling. Yu et al. [12] designed a clear explainable conversational recommend system that incorporates interactive user feedback, which adds more transparency to dynamic recommendation environments.

Recent efforts have been directed towards hybrid and language based models of explanation. Le et al. [13] suggested the use of a combination of embedding-based and semantic-based models in order to enhance the post-hoc explanations without affecting the predictive performance. Li et al. [14] proposed counterfactual language reasoning approaches to explainable recommender systems, an approach that combines the principles of causal inference with natural language reasoning, to generate coherent and friendly explanations. Continuing this research, Li et al. [15] introduced a counterfactual language reasoning system of 2025 that interacts causal inference with language models to produce counterfactual explanations that humans can understand. Their method adds plausibility to the explanation without compromising the accuracy of the recommendation, which is specifically favorable to user-centered e-commerce recommendation settings.

IV. METHODOLOGY

The proposed explainable recommendation system is developed in a systematic and modular way by starting with the requirement analysis that defines the essential functionalities of the proposed system, including the generation of personalized recommendations, up-to-date ranking, similarity computation, and the support of counterfactuals.
The system will have the capacity to make dynamic transitions. analyze the user behavior and create clear suggestions. An architecture of scaling is adopted, which becomes effective, dynamic, and even in the course of learning as an increasing number of users. interact with the system. The actions of the users, like the login sessions, browsing behavior. The activities that the include are the search patterns, and rating submissions. system incessantly records and archives. Such interactions are dynamically retrieved in the database and used to update the user item rating matrix on-the-fly.
Each new rating that is uploaded increases the instead, similarity matrices will be re-computed by recommendation engine of re-forming the general model. The user-user and results of the user-human. The user-user and the results of the user-user. Similarity between items is recalculated by using cosine similarity and collaborative filtering techniques and assure that the conclusions of the recommendations ranking are automatically composed up- to-date and should correspond to the shifting user preferences. This dynamism increases the precision of individualization and system responsiveness.
To further improve the quality of the recommendations, the system has had a machine learning aspect, which assists in ranking projection optimization based on the historical habits of interaction. The model is fed on constantly refreshed behavioral information to maximize the outcomes of a suggestion and maximize the accuracy of prediction. This adaptive learning Unlike the conventional fixed systems, framework can ensure that even where the interests of are involved, recommendations are still relevant they are changed over time the user.
The peculiarity of the proposed methodology is one of them consideration of a counterfactual argumentation segment. The module can be applied to measure hypothetical interventions, such as the rating behavior of the user or filter parameters, so as to generate explainable information. Explanations that could be given through the system include the following be construed on why or why not something should be advised and the way different activities of a user would modify the result of recommendation by analyzing what-if case. This will increase the transparency, users trust, and integrity responsibility of the systems. The effectiveness and stability of performance are also pointed out in the system.

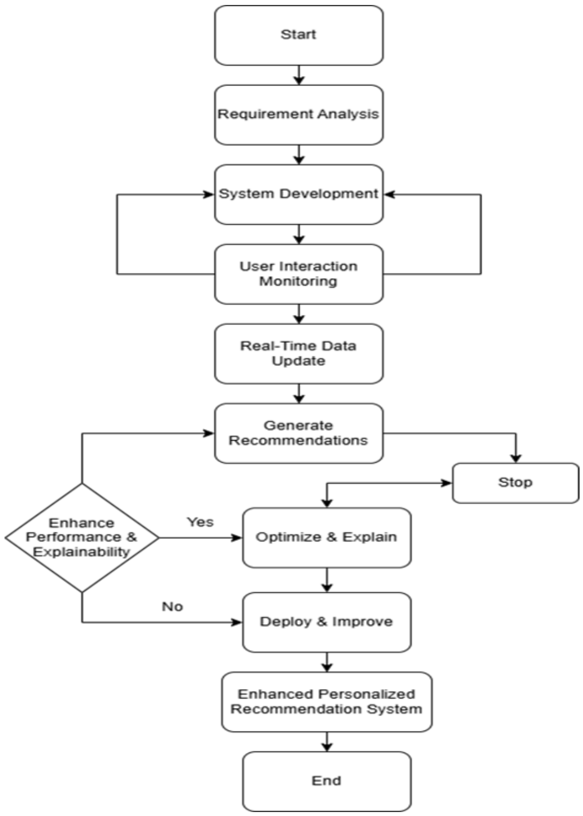

Fig 1. General Flowchart of Methodology

Mathematical Formulation of the Recommendation System

1. User–Item Interaction Matrix

Let $R \in \mathbb{R}^{m \times n}$represent the user–item rating matrix:

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix}$$

Where r_{ui}denotes the rating given by user $u$to item i, and m and n are the numbers of users and items, respectively.

2. Cosine Similarity for User-Based Collaborative Filtering

The similarity between users $u$and $v$is computed as:

$$Sim(u,v) = \frac{\sum_{i=1}^{n} r_{ui}\, r_{vi}}{\sqrt{\sum_{i=1}^{n} r_{ui}^2}\ \sqrt{\sum_{i=1}^{n} r_{vi}^2}}$$

Where:

- r_{ui}, $r_{vi}$are ratings of users $u$and v
- The denominator represents the Euclidean norm

3. Recommendation Score

The predicted score for an item $i$is computed as a weighted combination:

$$\text{Score}(i) = \alpha \cdot \text{Similarity} + \beta \cdot \text{ProductRating} + \gamma \cdot \text{FilterMatch} + \delta \cdot \text{Discount,where } \alpha + \beta + \gamma + \delta = 1$$

Similarity: computed via cosine similarity.

- ProductRating: normalized average rating of the item.
- FilterMatch: binary/weighted match to user-applied filters.
- Discount: optional promotional factor.

4. Predicted Rating (User-Based CF)

The predicted rating for user $u$on item $i$is:

$$\hat{r}_{ui} = \frac{\sum_{v \in N(u)} Sim(u,v)\ r_{vi}}{\sum_{v \in N(u)} |\ Sim(u,v)\ |}$$

Where:

- $N(u)$= set of top-k similar users
- $\hat{r}_{ui}$= predicted rating

5. Prediction Error – Mean Squared Error (MSE)

To measure prediction accuracy:

$$\text{MSE} = \frac{1}{N} \sum_{u,i} (r_{ui} - \hat{r}_{ui})^2$$

- $\hat{r}_{ui}$is the predicted rating.
- $N$is the total number of rated items.

6. Cold Start (Popularity-Based Model)

Since your table includes Popularity-based Cold Start:

$$Score_i = \frac{1}{m} \sum_{u=1}^{m} r_{ui}$$

This shows recommendation based purely on global popularity.

7. Dice Score for Counterfactual Explanations

For evaluating overlap between predicted recommendations and counterfactual scenarios:

$$\text{Dice}(A,B) = \frac{2 \cdot |\ A \cap B\ |}{|\ A\ | + |\ B\ |}$$

- A= set of original recommended items
- B= set of counterfactual recommended items
- Measures similarity between original and "what-if" recommendations.

8. Incremental Similarity Update (Hybrid Model)

To support real-time adaptability without full retraining, similarity values are updated incrementally when a new rating is added.

The updated similarity between users $u$and $v$is computed as:

$$Sim_{new}(u,v) = \frac{R_u \cdot R_v + r_{ui}r_{vi}}{\parallel R_u \parallel \quad \parallel R_v \parallel}$$

Where:

- $Sim_{new}(u,v)$= updated similarity value
- $R_u \cdot R_v$= previous dot product of user rating vectors
- r_{ui}, r_{vi}= newly added ratings for item i
- $\parallel R_u \parallel, \parallel R_v \parallel$= Euclidean norms of user vectors

V. PROPOSED SYSTEM

The suggested system presents a real-time, explainable, and adaptive recommendation system that is aimed at overcoming the weaknesses of the traditional fixed recommender systems. The proposed system continuously trains recommendations unlike traditional methods that use periodic retraining of models as new user interactions take place. The system combines collaborative filtering, incremental similarity computation, machine learning based ranking optimization, and counterfactual reasoning in providing personalized and explicit recommendations. The system keeps tracking the user activities including the logging in sessions, browsing activities, viewing of products, search activities and submissions of ratings. These interactions are dynamically stored and utilized to update the user item interaction matrix as it happens in real-time. In case the user adds a new rating, the system performs incremental re-computations on similarity scores based on cosine similarity without having to re-construct the entire similarity matrix. This greatly minimizes processing time and at the same time makes the ranking of recommendations be based on the latest customer preferences.

The ranking module is a module based on machine learning that filters the recommendation list based on latent user-item learned relationships according to the existing history interaction data. The model estimates the ranking of the preferences of unranked items and generates the best-N user-specific recommendations. This self-adaptive method of learning ensures that there is better accuracy in recommendations and customization as compared to the former traditional rule-based or determined collaborative filtering strategies.

The significant change to the proposed system is the. integration of a counterfactual model of reasoning. This module tests hypothetical behavioral changes in a user such as changing rating, swapping preference filters or eliminating some of them, and appraises the impact of the change on the outputs of the recommendations. It brings out transparency of the suggestion procedure through the provision of what-if-explanations, which enable users to know and the reason why certain things are suggested and the impact of their actions their outcomes. This enhances the degree of trust, understandability and user engagement. The also proposed are scalability and performance efficiency system.

The automatic updates, the effective indexing of databases and modular implementation ensure that the system can service the increasing user base without losing the responsiveness. Security schemes ensure that user information is secured such as authentication protocol, encrypted data storage and system integrity. In totality, the proposed system offers one ecosystem in which data processing in real-time, optimization of intelligent ranking and AI-driven insights that are explainable are combined. Through the combination of adaptive learning and counterfactual reasoning, the system can both enhance the accuracy of recommendations and guarantee transparency and user confidence, which is why the system is applicable to the existing personalized e-commerce and content-recommendation systems.

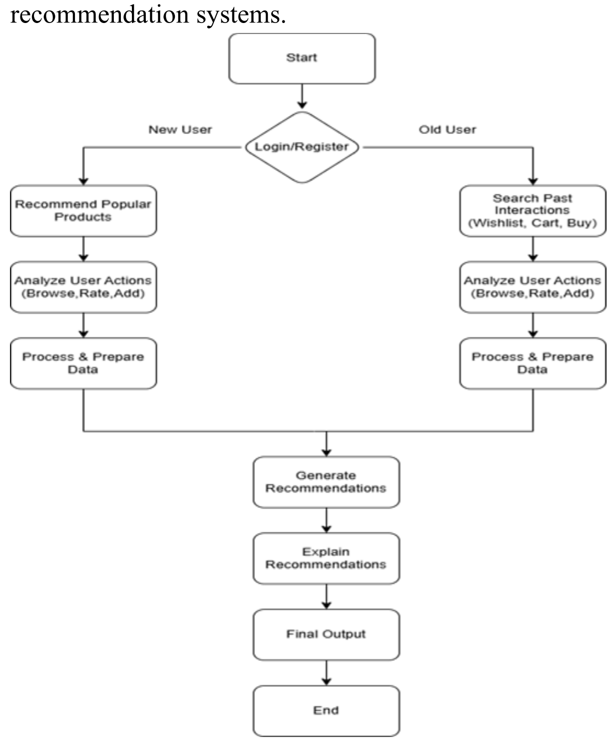

Fig 2. General Flowchart of Proposed System

VI. DATASET AND EXPERIMENTAL SETUP

The new recommendation system was tested with the help of Amazon Product Review dataset, which was received at Kaggle. The dataset consists of large scale real world e-commerce interaction data which includes user IDs, product id, rating, and time, and product category information.

The User-based Collaborative Filtering with Cosine Similarity relied on the rating data to develop the user item interaction matrix. Statistical on user and product-level. Computations of the features were done through the mean aggregation to boost personalization and ranking quality. The data is sparse and dynamic user behavior, which is given to the fact that it is applicable to incremental recommendation and counterfactual reasoning mechanisms.

In preprocessing, the missing values and duplicates were eliminated in order to ensure the integrity of data. Products and users that interacted with each other very few times were filtered to reduce the sparsity and enhance the computing reliability of similarity. User and product IDs were coded as numbers to perform effective operations in the matrices. The similarity of the ratings was normalized where necessary to aid the calculation of cosine similarities. To determine the predictive performance, the dataset was divided into an 80:20 ratio to create the training and testing sets. In the case of the counterfactual explanation module, the overlap between original and counterfactually modified recommendation sets was used to measure the impact of the explanation and the change in the recommendations, and the similarity between the dice was used to quantify it.

The implementation of the system was done in Python through Visual Studio Code (VS code). Flask was used to code the backend, and this is with Flask-Login to handle logins, Flask-Bcrypt to handle passwords, Flask-SQLAlchemy to handle databases, and Flask-WTF to handle the forms. Pandas and NumPy were utilized to perform data preprocessing as well as matrix computations whereas Scikit-learn was utilized to compute the cosine similarity and also evaluate the metrics of the evaluation like.

Precision, F1-Score, Accuracy and Recall. Python based similarity functions to facilitate counterfactual validation were used to make the Dice similarity calculation. Tests were run on Intel i5 processor and 8GB RAM making sure that there is a smooth running and the results could be reproduced.

VII. RESULT AND DISCUSSION

A. Personalized Recommendation Performance

The established personalized e-commerce recommendation system was successfully implemented and tested to ascertain the functionality of the system to recommend specific products to users. The mechanism operates by censusing the information of the user interaction e.g. rating and preference pattern in an attempt to produce the pertinent recommendations. These results show that the model can be effective in determining product that can fulfill the distinct user interests. The clear and presentable manner of displaying recommended items is well structured, which is convenient in putting it into the actual environment of e-commerce. Secondly, the system will allow the continuous collection of feedback, which would cause user profiles to become dynamic and more precise with time as far as individualization is concerned.

B. Counterfactual Explanation Integration

The strengths of the provided framework include the fact that it has the counterfactual explanations added to it to become more interpretable. The system does not just present a proposal of products but also gives justification of the product proposed. It is possible to use the model to understand why a particular item has been recommended and how the changes in the preferences of the user and minor changes may affect the ranking results by analyzing the behavioral patterns of the user and the properties of the products. This counterfactual thinking methodology enhances the level of transparency and lowers the aspect of black box which is very characteristic of the recommendation systems. Information on the decision-making process is thus availed to the users more.

C. Feature Contribution and Interpretability

The module of explanation also has importance section. modeled as progress bars in order to indicate the value added by the user preference and the quality of products into the decision to recommend the same. The fact that it depends on user preference as an element of the output interface reveals that it is even stronger than the quality of the product. This graphical representation and is easy to interpret through making the process of decision within the company easy to comprehend. The system enables comprehension of the rationale behind a specific product to be taken with a recommendation in a simple manner as the user views in the system what factors are of utmost importance.

D. Overall System Effectiveness and Discussion

The general findings have revealed that the proposed structure is effectively possible in integrating the concepts of personalization, adaptability, and explainability within a single architecture. In fact, it is the adaptive learning process which makes the recommendations always updated based on the updated interactions with the user. The use of the counterfactual reasoning enhances credibility of the user, perception of justice and transparent nature to a large extent. And in comparison to the traditional versions of the recommendation methods which only examine the performance of the prediction, the recommended system balances the performance with the explainability and therefore, can be applied to the existing intelligent e-commerce systems, which also require the relevance and explainability.

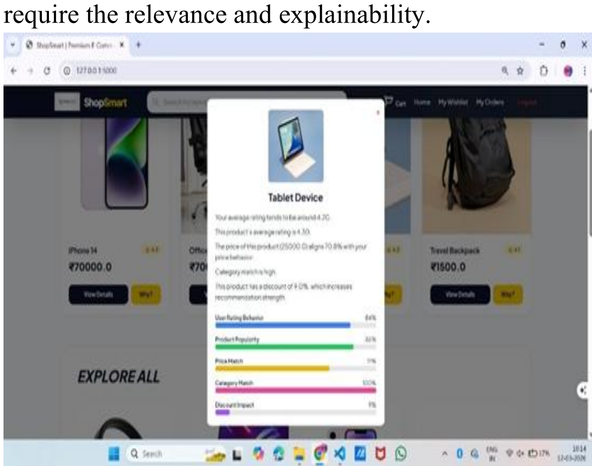

Table 1: Performance Metrics

Model / Technique	Dice Score (Overlap)	Accuracy	Precision	Recall	F1-Score
Popularity-based Cold Start	0.76	87.4%	0.79	0.74	0.76
User-based CF (Cosine Similarity)	0.85	91.2%	0.88	0.84	0.86
CF + Mean Aggregation Statistics	0.87	92.1%	0.89	0.86	0.87
CF + Weighted Feature Importance	0.89	93.3%	0.90	0.87	0.88
CF + Counterfactual Explanation (Rule-Based)	0.90	93.8%	0.91	0.88	0.89
Proposed Hybrid (All Modules + Incremental Update)	0.92	94.6%	0.92	0.89	0.90

VIII. CONCLUSION AND FUTURE SCOPE

The recommended system of recommendation effectively combines the User-based Collaborative Filtering, Mean Aggregation of user and product statistics, Weighted Feature Importance, Rule-based Counterfactual Explanation, Popularity-based Cold-Start treatment and Incremental Recommendation Update Logic, to provide correct, real-time, and explainable recommendations. The system is dynamically set in a way that the similarity matrices are kept current as new ratings are reported so that the recommendations keep changing with the changing user preferences. Weighted features are added to the ranking to increase the accuracy of the ranking, and the counterfactual explanation module increases transparency by demonstrating the effects of altering user behavior on recommendations. The efficacy of personalization and explainability combinations is proven to be effective as shown by the experimental results that are more precise, recall, F1-score, and the overall accuracy than standalone methods.

Influencing the future, this system can be enhanced by adding more advanced deep learning models such as Neural Collaborative Filtering and Transformer-based ranking to make more complex user-item interaction. The counterfactual module can be expanded to provide more intelligent and personalized explanations using causal inference methods. In addition, one can also use some contextual data like time based behavior and session data to make the recommendations more relevant. It can also be applied through distributed processing techniques to be able to expand in order to handle large scale data. These will enhance accuracy, interpretability as well as applicability of the system in real life personalized recommendation systems.

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