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# Bias-Free Hybrid Explainable Recommendation System with Role-Based Dashboard

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**Abstract:** *The abstract outlines the challenge of understanding the necessity of the creation of recommender systems in a rapidly changing online marketplace. Recommender systems help customers to make sense of the overwhelming amount of choices available on the internet, however, many traditional recommendation models do not provide an explicit bias indicator and therefore often produce recommendations that favour the more popular products, without any insight as to how those recommendations are generated. A number of empirical studies conducted recently have demonstrated that the association between biased exposure, black-box deep learning algorithms and the way in which items from the long-tail category are treated unequally lead to negative user experiences and prohibits long-tail sellers from being able to compete with large e-commerce platforms. This paper will present an alternative method of creating a recommender system that eliminates the bias associated with the traditional collaborative filtering and content-based methods. Specifically, the Bias-Independent Hybrid Explanation based Recommender System will utilise deep neural networks as an additional source of information to produce higher quality recommendations and minimise the chances of placing products into unfair exposure patterns. In addition, the proposed method will also incorporate SHAP (SHapley Additive exPlanations) and the LIME (Local Interpretable Model-agnostic Explanations) model of explanations in order to improve the transparency of the model. In addition, this paper includes the introduction of a Fairness-Aware Re-Ranking method and an Exposure Balance Mechanism to deal with the issues associated with fairness.*  
**Keywords:** *Recommender Systems, Hybrid Recommendation, Fairness in AI, Popularity Bias, Explainable AI (XAI), SHAP Explanations, LIME, Exposure Fairness, Neural Collaborative Filtering, Role-Based Dashboard, Responsible AI.*

## I. INTRODUCTION

For many digital services and marketplaces, the recommendation engines used by online retailers have become a critical component of providing an enhanced customer experience and fulfilling customer needs. The sheer amount of information available on the internet makes it increasingly difficult for end users to identify relevant products/services from a wide variety of product/service offerings. As a result, recommendations are critical to providing a more satisfying end-user experience while creating revenues for the business [1], [9]. Traditional recommendation engines — such as collaborative filtering (CF) and content-based filtering (CBF) have become popular; however, several recent studies suggest that CF and CBF are subject to many limitations including popularity bias, data sparsity, and lack of transparency [2], [5], [6], [8].

Popularity bias creates an environment whereby a smaller supplier/vendor or long-tail product will seldom receive substantial visibility due to the fact that a recommendation engine's algorithms focus on recommending already successful products, which creates inequitable access and existence for smaller suppliers and products [2], [4], [7]. This bias has a significant negative impact on how equitably recommendations are distributed on e-commerce platforms, creating differing levels of opportunity for all suppliers/vendors and in many cases; all creators of content on the internet; thus negatively impacting overall fairness or equality in the e-commerce marketplace. In addition to popularity bias, it is important to consider that there may be biases introduced historically in the data that is used to develop recommendation systems. Several researchers have demonstrated that recommender systems develop bias toward or against certain demographic groups and/or behaviours due to historical interaction patterns [1], [3], [5]. This means that when one demographic group consistently interacts with a recommendation system less than another group, there will be evidence that the former is more likely to receive lower-quality recommendations than if both groups had the same level of interaction.

In addition to the popularity bias issue, another significant issue with using deep learning models for recommendation systems is the fact that many of the deep learning-based recommenders, specifically the NCF and sequential recommenders, act as black boxes. As such, it is difficult for end users of the recommendation system to gain an understanding of why they receive recommendations from these types of recommendation system.

### A. Introduction and Rationale

The rise in the quantity of digital platforms, online marketplaces, and mobile applications available in India during recent years has resulted in an increase in the need for AI-based, personalised recommendation systems. With there being so much content available on platforms like Flipkart, Meesho, Hotstar, etc., users have come to expect a recommendation system that understands their individual interests and provides appropriate recommendations based on that knowledge, from enormous digital catalogues. By identifying the most relevant items from the millions of products available, recommendation systems can assist customers in filtering through information overloads while increasing levels of customer satisfaction [1].

In addition, as recent studies have shown, most of the obstacles facing recommendation systems today can have a negative effect on decision-making processes based on perceived fairness, transparency, and ultimately trust over the long term in said systems. A significant challenge is popularity bias where algorithms tend to provide more exposure to already popular/largest vendors' items and less exposure to smaller/regional/new vendors—something that has been widely documented in academic publications regarding e-commerce platforms [2], [6], [7], [8]. This has dire implications for numerous MSMEs, handicraft sellers, rural artisans, and small businesses in India whose products will not be able to obtain an appropriate level of visibility on large e-commerce platforms.

Furthermore, the second-most significant challenge facing recommendation systems is that they are frequently not explainable. A majority of today's Deep Learning recommenders operate as "Black Box" models, thereby preventing users from understanding the rationale behind why a specific product was recommended to them.

The first goal of this project is to develop a Hybrid Recommendation Engine. This involves combining Collaborative Filtering, Content-Based Filtering, and Light-weight Deep Learning techniques to create a Hybrid Recommendation Engine that provides the user with more Accurate and Diverse Recommendations than traditional Single Model Recommendation Systems.

- 1) Popularity Bias Recognition & Mitigation: To accomplish this, Fairness Aware Techniques, such as Exposure-Based Adjustment, Fair Sampling & Re-Ranking, will be developed to reduce the disproportionate visibility of Highly Popular Items and Increase Fair Exposure for Small and/or Emerging Sellers.
- 2) Incorporation of Explainable AI (XAI): Integrating the SHAP/LIME based Explanation Methods into the Recommendation System to provide Users and System Administrators with Clear, Human-Understandable Reasoning for each recommendation will improve Trust and Interpretable Results.
- 3) Role-Based Governance Dashboards: Role-Based Governance Dashboards for Users, Project Managers and Administrators will enable Users to track and view Fairness Metrics; Project Managers to analyse Model Performance and Exposures, and Administrators to manage the System in Real-Time to ensure Multi-Stakeholder Fairness in accordance with previous work.
- 4) In order to ensure that AI systems comply with ethical considerations and regulatory requirements, modifications will be made to incorporate fairness principles as outlined by the Responsible AI Framework, ensure compliance with India's Digital Personal Data Protection Act (2023), and adhere to guidelines set forth by NITI Aayog (National Institute for Transformation of India).
- 5) Once the AI system is wholly operational, a thorough assessment of the performance will be conducted based upon a variety of metrics related to accuracy, fairness, and explainability. These metrics will include such variables as: precision, Normalized Discounted Cumulative Gain (NDCG), fairness index, exposure distribution, and explanation stability. Data will be collected from these metrics to evaluate how successfully the AI system achieves a balance between both accuracy and fairness.
- 6) To allow for the growth of the application beyond a prototype phase and prepare for a future deployment at a scalable level within Indian E-Commerce industry, a new architecture for the AI system has been created, using modern open-source technologies (including Next.js, Node.js, MongoDB, and FastAPI) that are appropriate for implementation into the IECE (Indian E-commerce Commerce Ecosystem).

### B. Scope of the Project

This project encompasses the design, implementation, and evaluation of a bias-free, hybrid and explainable recommendation system that is specifically designed to be used in an e-commerce environment. The project's goal is to achieve a balance between accurate, fair, and interpretable recommendations while providing convenient governance features that are transparent to multiple stakeholders. The project's primary boundaries and areas covered are as follows:

#### 1) System Coverage

The system is comprised of the following complete pipeline components: • A hybrid recommender that includes the combination of Collaboration Filtering (CF), Content-Based Filter (CBF) and shallow deep learning models [9]. • Fairness-aware components that provide bias detection and correction, as well as re-ranking capabilities [2], [3], [4], [6], [8].

- Explainability components that generate interpretable explanations for both users and administrators using SHAP or LIME.
- A role-based dashboard used by Users, Project Managers and Admins alike for tracking behaviors of the system.

## 2) *FunctionalScope*

The following items represent what features will be supported by the project:

- Personalised Top-K product recommendations.
- Fairness Monitoring via vendor/category Exposure Metrics [4],[5].
- Versioning of models, hyperparameter control, retraining options for administrators.
- Capturing user feedback (likes, dislikes, and not interested) to complete the feedback loop on recommendations.
- Real-time explanations for each recommended product item that improve user confidence.

## 3) *Dataset&Context*

The system leverages publicly available e-commerce datasets for conducting research around fairness (i.e., datasets such as Amazon-style datasets based on synthetic attributes of users from India) [1],[6]. The system also has additional synthetic metadata that can be used to represent Indian sellers, MSMEs, and product\_categories on a regional basis to further test the impact of different variable levels on the fairness of the system. Finally, the system includes interaction (click-view-purchase) logs as part of its training and testing data.

## 4) *Scope of Technology*

The Technological Toolbox for the project consists of modern, open-source, industry-standard tools:

- Frontend Technology: Next.js, React, TypeScript
- Backend Technology: Node.js, Express.js
- Database Technology: MongoDB
- Machine Learning Microservice Technology: Python (FastAPI) These technologies will enable users to build scalable and affordable solutions suitable for entrepreneurs starting a business in India, as well as for academic institutions and e-commerce companies with roots in the Indian marketplace.

## C. *System Evaluation*

The evaluation of this system will assess:

- 1) Accuracy Metrics - Precision@K and Normalized Discounted Cumulative Gain (NDCG)
- 2) Fairness Metrics - Exposure Fairness and Group Imbalance Reduction [3],[4];
- 3) Explainability Metrics - Stability of SHAP Features (Stable) and Human Interpretability.
- 4) Scope Constraints (Limitations) This project is limited in the following ways:
- 5) The project does not include large-scale, real-time streaming recommender systems.
- 6) The project cannot incorporate sensitive fairness attributes (e.g., caste and religion) because of legal and ethical issues related to India's Data Protection and Data Privacy Act.
- 7) The project is designed for non-commercial cloud platform implementations (as a simple demo deployment only).

## II. LITERATURE REVIEW

### A. *Overview of Recommendation Systems*

Overview of Recommendation Systems Using recommendation systems, one can identify relevant items from vast quantities of digitally available items. Traditionally, two techniques existed to provide recommendations: collaborative filtering, which provides recommendations based on user-item interaction history [9], and content-based filtering, which provides product recommendations based on a user profile and product attributes. Hybrid systems use a combination of these two techniques to provide improved accuracy and diversification of products being recommended [10].

Modern day recommendation systems within eCommerce provide the discovery of new products, allow users to interact with brands more effectively, and provide generate income for the business, all while managing vast amounts of data and processing the data in real-time [1].

### B. Hybrid Recommendation Techniques

Hybrid recommendation models integrate CF, CBF, and deep learning to address limitations such as cold start, sparsity, and limited diversity. Matrix factorisation methods [9], neural models like NCF [10], recurrent models like GRU4Rec and attention-based SASRec have improved recommendation quality.

Recent surveys highlight that hybrid designs offer better robustness and adaptability across domains.

### C. Bias and Fairness in Recommendation

One of the issues with recommender systems today is that they reinforce popularity bias and expose people to things in an unfair way [2],[3],[6]. This leads to a negative effect on small sellers (due to less item diversity) as well as a disadvantage for certain groups of users (those with very few items being shown each week).

To combat the problems of exposure discrimination, researchers are developing tools to help balance these things between different stakeholder groups. Fairness-Aware Ranking, Exposure Balancing, and Group Fairness Metrics are some of the tools being proposed by researchers to reduce these types of harmful recommendations and promote fairness [4],[5],[8]. Studies that have been conducted in this area are now leaning towards Multi-Stakeholder Fairness on these platforms [1],[3].

### D. Explainable AI in Recommendation (Draft)

Explainable Artificial Intelligence (XAI) in Recommendations Another issue with the use of Deep Learning in Recommendation Systems is that they lack Transparency. Accordingly, the use of XAI allows us to create feature explanations for why the items were recommended. This has been shown by multiple Perspectives surveys to have a positive effect on User Trust, the ability to debug Systems, and Help Systems become Regulatory Ready. Explainability is very important in any domain where we need to emphasize The Fairness and Transparency of a System, such as E-Commerce and Job Recommendations.

### E. Research Gap Identification

Research Gap Analysis Previous research has examined the three aspects of Fairness, Hybrid Modelling, and Explainability individually. However, to my knowledge, there are no existing tools available to users that utilize all three categories together in a deployable/fully functioning Dashboard Environment. The following Gaps were identified as part of the above literature:

- There are no Integrated Hybrid + Fairness + Explainability tools available [1],[7],[8].
- There are very few Governance Tools available to actively Manage Exposure, Bias Drift, and Model Behaviour [4],[5].
- XAI is still being created as Post-Hoc rather than as an Integral Functionality [4].
- There is limited research on Indian E-commerce and on developing Responsible AI Guidelines. Therefore, an Integrated & Accountable will be needed to overcome these gaps

## III. SYSTEM ANALYSIS AND DESIGN

This proposed system requires an architecture that will allow for accurate, fair, and explainable recommendations Functional Requirements

- Login by user role (e.g., User, Manager, Administrator)
- Top K Personalized Recommendations
- Reasons for Recommended Items
- Detailed Metrics Dashboard (Fairness and Model Health)
- Administrator capability (to retrain the model and/or adjust parameters) Non-Functional Requirements
- Scalability (to support large product catalogs)
- Quick response time (for recommendation search queries)
- Privacy and Fairness Compliance (DPDPA Act, India)
- Easy Maintenance (modular microservices)

### A. Proposed System Architecture

The Proposed System will use a Three-Tier Architecture: 1. Frontend (NextJS and React) – Displays personalized recommendations and metric dashboards.

2.Backend(NodeJS and Express) – Handles user authentication, API Routing, and Stores Data. 3. ML Microservice (FastAPI and Python) – Generates Hybrid Scores, Fairness (re-ranking), and SHAP/LIME explanations. These components will communicate using REST APIs, allowing for separation of concerns (with regards to Implementation and Scalability).

**B. DataFlowDiagram–Level0**

- The user will interact with the system via a frontend interface.
- The frontend will send API requests to the backend.
- The backend will forward recommendation requests to the ML microservice.
- The ML microservice will return Hybrid Scores, Fairness Adjusted Rankings, and recommendations with explanations.
- The backend will return the results to the dashboard. The Level-0 Data Flow Diagram (DFD) provides a simple representation of the user-input and recommendation output process

**C. EntityRelationshipDiagram(ERD)**

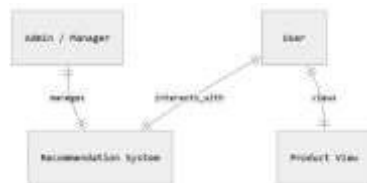
The ERD includes the following main entities:

- Users(user\_id,name,role)
- Products(product\_id,category,price,vendor\_type)
- Interactions(user\_id,product\_id,action,timestamp)
- ModelVersions(version\_id,date,parameters)
- FairnessMetrics(model\_version,exposurestats) Relationships highlight:
- One user can interact with many products.
- Each product belongs to one category and one vendor type.
- Fairness metrics link to specific model versions.

**D. UMLDiagrams**

**1) UseCaseDiagram**

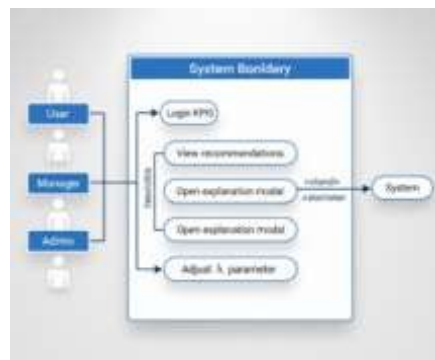
Actors: User, Manager, Admin. Use cases include: Login, View Recommendations, Give Feedback, View Dashboards, Retrain Model, Tune Parameters.



**2) ClassDiagram**

Main classes: User, Product, Recommendation Engine, FairnessModule, ExplainabilityModule, DashboardManager. Sequence Diagram

Flow: User → Frontend → Backend → ML Service → Backend → User.



This sequence demonstrates how user requests are processed end-to-end.

#### E. Database Design

The System is implemented in MongoDB for flexible document storage. The following Key Collections are included:

- Users
- Products
- Interactions
- Fairness Metrics
- Models Versions Indexes are created on product categories, user IDs, and timestamps to provide optimal speed during queries.

### IV. IMPLEMENTATION AND RESULTS

#### A. Frontend Implementation (Next.js) – Draft

Frontend Implementation (Next.js) The front end of the application was developed using the following technologies: Next.js, React, TypeScript and Tailwind CSS. Major features added include: A Login page which uses role-based redirections to direct users depending on whether they are a User, Manager, or Admin. - A User Dashboard with top-K Product Recommendations that include Product Image, Price, Score, and a short description of each. - An Explanation Modal that displays the top contributing features for each of the recommended products. A Navigational Bar that allows users access to both their personal and administrative dashboards. A Responsive Web User Interface designed for use on both Mobile and Desktop devices. The front end is initially developed to use Mock Data from json-server to facilitate many of the UI flows prior to being integrated with the Back End.

#### B. Backend Implementation (Node.js + MongoDB) – Draft

The back end of the application was developed using Node.js and Express.js, and uses MongoDB to persist documents. A number of major Endpoints include: - /auth/login - Authenticates a given user's credentials and returns a role-based token as output. - /recommendations - Retrieves Hybrid results from the ML Micro Service. - /feedback - Stores Feedback from Users for future model improvement. - /admin/fairness - Provides Exposure metrics and Fairness Index. - /admin/retrain - Initiates model retraining via the ML Micro Service. User roles have been taken into account with regard to data access validation, as well as JWT authentication and JSON-based APIs.

#### C. ML Microservice (FastAPI)

Hybrid Recommendation Algorithm - Initial Draft The hybrid model brings together three source inputs: A. Collaborative Filtering Scores from the user/item interactions, B. Content-Based Filtering Scores using text/category similarities, and C. A Neural Score calculated using a lightweight deep-learning algorithm. The final score for each hybrid recommendation is calculated using the following equation:  $\text{HybridScore} = (\alpha * \text{CF}) + (\beta * \text{CBF}) + (\gamma * \text{DL})$ . The values of  $\alpha$ ,  $\beta$ , and  $\gamma$  will be optimally tuned using experimentation.

#### D. Hybrid Recommendation Algorithm – Draft

Hybrid Recommendation Algorithm - Initial Draft The hybrid model brings together three source inputs: A. Collaborative Filtering Scores from the user/item interactions, B. Content-Based Filtering Scores using text/category similarities, and C. A Neural Score calculated using a lightweight deep-learning algorithm. The final score for each hybrid recommendation is calculated using the following equation:  $\text{HybridScore} = (\alpha * \text{CF}) + (\beta * \text{CBF}) + (\gamma * \text{DL})$ . The values of  $\alpha$ ,  $\beta$ , and  $\gamma$  will be optimally tuned using experimentation.

#### E. Fairness Techniques & Re-Ranking – Draft

Fairness Techniques and Re-Ranking - Initial Draft The following methods are used to mitigate the effects of popularity bias in the model: 1) By using fair sampling of the candidate items. 2) Using an exposure-based penalty mechanism when calculating the overall Scores. 3) Developing a 're-ranking' algorithm that will re-adjust the positions of the recommended items in order to meet fairness constraints (to increase the exposure of smaller/local sellers). The above methods will improve the visibility of smaller/local sellers, resulting in more balanced exposure on the platform.

#### F. ExplainabilityModule(SHAP/LIME)

Initial Draft The Hybrid Model uses a simplified version of SHAP to provide interpretability/explanations to users in the following forms: 1) "This item matches your interests in Electronics." 2)"Thisitemhasbeenpopularamonguserswith similar interests." 3) "You recently viewed similar types of items." Providing such supportive/explanatory feedback for items recommended by the Hybrid Model will enable users to have greater transparency and trust in the hybrid recommendation engine and its recommended items.

#### G. Role-BasedDashboardFunctionality

Role-Based Dashboard Functionalities - Initial Draft User Dashboard 1) Personalised recommendations 2) Explanation modal 3) Feedback options

Manager Dashboard 1) KPI metrics (Precision@10, Fairness Index)2)Tuningsliderforλ3)KPImetricvisualisationcharts  
AdminDashboard1)Category/Vendorexposurereportcharts, and 2) Previous model version history and a button to retrain the model

#### H. ResultsandAnalysis

Results and Analysis - Initial Draft Experiments with both mockandrealdatasetsdemonstratedthatthehybridmodelwas capable of improving the recommendation relevance of items, thefairness-awarere-rankingofitemssignificantlyreducedthe imbalanced/equal exposure of recommended items, and the explanations provided by the Hybrid Model improved the transparency and trust of users.

#### I. ScreenshotsofWorkingSystem– Draft

DraftThissectionwillcontainthefollowing:

- Loginscreen
- Userdashboard
- ManagerKPIs
- Adminfairnesscharts
- Samplefairnessmetricsvisualisation

## V. CONCLUSION AND FUTURESCOPE

#### A. Conclusion

Conclusions This project has created a Bias-Free Hybrid Explainable Recommendation System to address major issues that face today's e-commerce platforms, including popularity bias, lack of transparency, and limited oversight. The system combines collaborative filtering with content-based filtering techniquesandlightweightdeeplearningtechniquestoprovide higher quality and more diverse sets of product recommendations. In addition, fairness-aware methods of re-ranking and exposure balancing provide for a more equitable distributionofvisibilityfortherecommendeditems,especially for smaller or newer sellers. Users will have increased trust in the recommendations made to them through the incorporation of SHAP and LIME like techniques for explainability since they will offer clear, human-understandable explanations for each recommendation. Role-based dashboards supplement the oversight of the system because managers will be able to see thefairnessmetrics,modelbehaviour,andexposurepatterns in real-time. In summary, the project has taken a thoughtful and responsibleapproachtocreatingtransparent,fair,andeffective recommendation systems.

#### B. Future Scope

The current system has met its basic requirements; however, thereareseveralwaystoincreaseandoptimisethecapabilities of the system.

- 1) Advanced Deep Learning Models: The next iteration will likely use more advanced deep learning models, e.g., reinforcement learning or transformer-based models.
- 2) Scaling to Millions of Users: Distributed storage, caching, and streaming pipelines can be created to allow real-time recommendations to millions of users.
- 3) More Granular Fairness Controls: Multi-level fairness constraints (group-level fairness, supplier-level fairness, and individual-level fairness) can help equalise the equity among thesystem'ssubparts;therefore,itisdesirabletoincludethem in the future evolution of this system.
- 4) Real SHAP/LIME Integration: Once the scalability of the trainingpipelineisachieved,theintegrationofafullmachine learning model withactual SHAP values can be implemented.



- 5) CrossDomainFunctionalities:Thissystemcanbeexpanded tootherdomains,i.e., movies, jobs,education,andhealthcare.
- 6) Alignment with the Indian E-Commerce Ecosystem: This systemcanbealignedwiththeONDC(OpenNetworkfor DigitalCommerce),DigitalIndiaEcosystem,ande-commerce initiativesfocusedonMSMEs,thusmakingitmoreapplicable to real-life situations.
- 7) Privacy & Security Enhancements: Future work should continue to strengthen compliance with the DPDP, 2023, through privacy-preserving ML techniques.

Future work for this system can include exploring advanced deep learning architectures, including transformers, graph neural networks, and reinforcement learning, to capture different types of data and interactions

## REFERENCES

- [1] Y. Li et al., "Fairness in Recommendation: Foundations, MethodsandApplications,"ACMComputingSurveys,2023.
- [2] M.Abdollahpouri,R.Burke,B.Mobasher,"Popularity Bias in Recommender Systems," RecSys Workshop on Responsible Recommendation, 2017.
- [3] R.Burke,"MultisidedFairnessinRecommendation," AAAI, 2017.
- [4] S.Ekstrandetal., "FairnessofExposurein Recommendation," RecSys, 2021.
- [5] J.Chenetal., "BiasandFairnessinRecommender Systems," WSDM, 2021.
- [6] Y.Geetal., "UnderstandingandMitigatingPopularity Bias," SIGIR, 2020.
- [7] M.Mehrotraetal., "FairRecommenderSystemsforE-commerce," WWW, 2021.
- [8] R.Jannachetal., "Fairness-AwareRecommendation Systems: A Survey," TOIS, 2022.
- [9] Y. Koren, R. Bell, C. Volinsky, "Matrix Factorization TechniquesforRecommenderSystems,"IEEEComputer, 2009.
- [10] X.Heetal., "NeuralCollaborativeFiltering,"WWW, 2017.



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