SCHOOL OF BUILT ENVIRONMENT, ENGINEERING AND COMPUTING

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Personalized Recommendation for ecommerce Using AI

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Candidate's Declaration

I, Nujan Shrestha confirm that this dissertation and the work presented in it are my own achievement.

Where I have consulted the published work of others this is always clearly attributed;

Where I have quoted from the work of others the source is always given. With the exception of such quotations this dissertation is entirely my own work;

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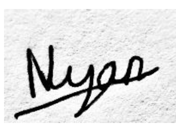
Signed: 

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Abstract

In the rapidly evolving landscape of e-commerce, the demand for personalized user experiences has propelled the development of sophisticated recommendation systems. This project introduces an AI-driven Personalized Product Recommendation System designed to elevate user engagement and satisfaction.

Utilizing collaborative filtering and content-based filtering algorithms, the system analyzes user behavior and historical interactions to tailor product recommendations. Matrix factorization techniques, including Singular Value Decomposition (SVD), contribute to the system's ability to discern intricate user-product relationships.

To address scalability challenges arising from hardware limitations, the system incorporates data sampling techniques, ensuring responsiveness while working with extensive datasets. The integration of the Surprise library and machine learning tools enhances the recommendation engine's efficiency.

The user interface features elements such as dark mode for improved aesthetics and an interactive experience. Despite constraints on hardware resources, the system achieves commendable accuracy, as evaluated by metrics like Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE).

This project lays the groundwork for future enhancements, aiming to optimize the system for even larger datasets and exploring advanced deep learning models. The continual evolution of this recommendation system promises to make significant contributions to the realm of AI-driven e-commerce platforms, ensuring users receive recommendations aligned with their preferences in a timely and accurate manner.

Table of Contents

Table of Figures

Introduction

The world today has fully shifted towards the digital side today, providing unheard-of benefits for communication, commerce, and access to many forms of information ease. In this era, the revolution of digital landscape has given a rise to new chances for companies to get competition going online. The introduction of e-commerce has started a big revelation, changing the way products and services are purchased and sold. Making the trading phenomena moving very smoothly into the digital space for the better experience for both customer and sellers (geeksforgeeks, 2023). With ease of use, accessibility, and worldwide reach, e-commerce has emerged as a crucial component of the trading and selling economy. E-commerce has completely changed how companies run and is being very beneficial for both customers, sellers, and business owners (geeksforgeeks, 2023). Recommendation systems have become increasingly important in this digital era, offering users not just convenience but a dedicated better experience as per there liking.

Customers interactions with online platforms such as ecommerce and social media have changed significantly. The e-commerce sector has experienced a huge, unprecedented rise in use due to technological enhancement and changing consumer tastes, transforming online stores into bigger than ever. The growth of the online market presents a very new and a difficulty task to overcome for many companies and customers to navigate effectively in search of products that suit individual tastes is a challenge. Considering this, relevant suggestions are becoming more and more important as a critical component of success in the e-commerce sector.

In the fast-paced ever show moving world, constantly changing world of e-commerce, customers interactions with online platforms have changed significantly. Technological improvements and shifting customer behavior have fueled the expansion of e-commerce, transforming virtual stores into vibrant markets with plenty of options. The difficulty for organizations and customers alike is growing with the ecommerce space, finding items that suit personal tastes through the huge selection of environment with efficiency. Considering all the things and consumer behavior, the significance of recommendation becomes evident seeing the e-commerce sector. It was found out that about roughly 35% of the amazon’s revenue was generated solely due to personalized recommendation. That itself is a huge number and the reported sales of product in amazon is increased by 29% due to personalized recommendation from $9.9 to $12.83. This essay examines the crucial role that personalized recommendations play, demonstrating how they are both an enhancement and a need for providing a more rich and tailored shopping experience (exposebox, 2022).

In this thesis, we explore the interesting world of user customization (personalized Recommendation). It is a dynamic relationship between technological capabilities and individual customer preferences. Our research uncovers the magic of data alchemy - the transformation of past purchases and rating, reviews into tailored recommendations that truly resonate with each user's distinctive personality. It goes beyond mere practicality, fostering a deeper connection and serving as a subtle acknowledgement of individuality, it works on the principle "We understand you and your preferences." (Junrui Yang1, Cai Yang2, Xiaowei Hu3, 2016)

Recommendation system in an ecommerce system works on the principle that if clients smoothly stroll towards the things, they feel they want, their happiness increases and individualized suggestions helps them stay connected, then conversion rates increase drastically without a doubt. A lively interactive environment is created throughout an engagement, driven by the excitement of exploration and the satisfaction of achieving one's deepest wishes. For businesses, custom recommender for each is the reason of a successful symphony in which financial prosperity and consumer satisfaction are harmoniously included (Rosmary Stegmann, Volker Renneberg, Martin S Lacher, Michael Koch and Thomas Leckner, 2023).

Today, in this very competitive world of online commerce, providing a personalized shopping experience dedicated to the individual users is a key for getting customer satisfaction and loyalty towards the company. Using client data which includes information about prior purchases, reviews, ratings, popular products, etc. is a very powerful way to increase personalized customization for the user. This customized strategy not only improves the client journey overall, but it also raises sales and increases company loyalty.

Examining Past Purchases of the user, Past Purchases details of user like rating reviews, etc. might significantly provide important details about their individual’s tastes and shopping habits which directly helps to give the accurate prediction on what the user might like further on. E-commerce platforms may provide product recommendations based on the analysis of this data, ensuring that the items meet the specific needs, preferences, and tastes of each buyer and in many cases get the suggestion on most sold and well received products from the masses. One of the most technique of recommending a product is by Comparing the user behavior and matches the end user to other users having similar taste as them so it’s mostly likely it would be somewhat relevant recommendation because the recommendation came from other users having very similar taste. This customized strategy is one of the best strategies and it increases the probability of repeat purchases while also improving the pleasure of the shopping experience.

In the study of personalized recommendation, other popular e-commerce personalized recommendation algorithms are also examined, and the variations in the algorithms' implementation outcomes are compared and analyzed. This is in addition to researching and refining the semantic sentiment analysis algorithm. This allows for a comparison of the benefits and drawbacks of the improved model. According to the findings of an experimental survey conducted among 1,000 randomly chosen users, the highest transaction success rate while utilizing the standard collaborative filtering suggestion method is just 71.3%. Utilizing the enhanced semantic sentiment analysis technique, the highest percentage of successful transactions was 87.9%.

All things considered, in a short period of time, personalized website suggestion algorithms have advanced significantly. They are already a vital tool for enhancing the online user experience, and they will probably keep developing and become **smarter** in the future.

The Main factors that can be implemented for the product recommendation are as follows:

- Consideration of Geographical Location:

In many cases the geographical location of a customer drastically changes the preferences/choices of users. Taking the customer's location into account enables e-commerce platforms to customize recommendations based on local trends, weather conditions, culture, and festivals. For instance, recommending winter clothing to customers in colder regions or featuring products that are popular in specific local markets and recommending certain local products that are vital in upcoming local/international festivals or celebrations.

- Integration of Special Occasions and Festivals:

Recommending specific products that might play a big role in bringing the festive element into the shopping experience is a very good approach to not only getting new customers but to also retaining the previous customers. By taking into consideration events such as holidays, birthdays, or cultural celebrations, e-commerce platforms can recommend the products to the user or extend exclusive promotions. This not only gives the user an appreciation for celebrations but also motivates them to make festive purchases which they might have never done previously. (Mladenic, 1999)

- Analysis of Consumer Behavior:

Going beyond purchase history, analyzing customer behavior on the platform provides very valuable insights. Some other methods like Monitoring the pages they visit, the time spent on the site, the feedback they provide for other products, their buying and rating history allow for real-time tailoring of recommendations. For example, if a customer frequently explores electronic products, showcasing the latest gadgets or accessories may capture their interest.

- User-generated Content Engagement:

Incorporating feedback, reviews, and ratings that a customer has given or engaged with can contribute to enhance the personalized recommendations. If a customer frequently interacts with content, the platform can suggest products that align with their exact preferences.

History:

Traditionally, websites have employed expensive internal recommendation algorithms in e-commerce to improve user experience by displaying just the goods that users have expressed interest in. However, less expensive SaaS solutions are now available as easy-to-install plugins for websites, offering the same sorts of recommendations, but they are limited to small-scale e-commerce businesses.

Rules-based segmentation was one of the earliest onsite customization techniques and is still in use today. For example, a popular section is based on the user's propensity to abandon a cart. If a cart is abandoned, one rule can be to provide a discount or a referral.

Following were behavioral recommendations, which are still widely used today. Online retailers like Amazon track user behavior, including the goods users see or buy. When a buyer clicks on a product, the website recommends further “Related Items” or “Best Sellers in this Category.” Amazon is among most websites that still use these suggestions for user behavior when it comes to customization.

Personalized recommendation systems have been enhanced with additional data sources, including location and social media activity, in recent years. Because of this, they can now offer recommendations that are even more customized to each user, considering a wider range of factors that might influence their preferences.

Some of the more sophisticated methods have also been made possible by the growth of recommendation systems. A growing number of scholars are engaged in the development of customized recommendation systems and have carried out several relevant investigations in this field. Jing et al. introduced a personalized social image recommendation system based on a user-image-label model. It has been shown that this algorithm can really utilize tags to classify the content of photographs, which may lead to the creation of a user-image-tag customized recommendation system and a significant improvement in the precision of personalized suggestions (Lili Gao and Jianmin Li, 2022).

The intriguing past of personalized recommendation systems shows how customer behavior has evolved and how technology has advanced over the digital era. Early information retrieval and recommendation systems are where recommendation systems first appeared.

Aims and Objectives of Personalized Recommendations for E-commerce Sites:

1. **Enhance User Experience:**

- **Aim:** Improve the overall user experience in the e-commerce platform.
- **Objective:** To provide a more customized and better tuned shopping experience, employ personalized recommendation algorithms for better individual's customization, such collaborative filtering, to make product recommendations based on consumers' past preferences.

2. **Increase User Engagement:**

- **Aim:** Boost user engagement and interaction with the ecommerce platform.
- **Objective:** Utilize collaborative filtering to recommend products that align with users' preferences and behaviors, encouraging increased exploration of products and interaction on the ecommerce site.

3. **Optimize Product Discovery:**

- **Aim:** Facilitate efficient product discovery for users.
- **Objective:** Employ matrix decomposition methods like Truncated SVD to uncover hidden patterns in user-product interactions, enhancing the ability to recommend a catalog of new relevant products to the user.

4. **Improve Product Ratings and Reviews:**

- **Aim:** Enhance the quality and relevance of user-provided product ratings and reviews.
- **Objective:** The method seeks to incentivize users to offer thoughtful and insightful assessments by suggesting things that they are more likely to enjoy, hence expanding the dataset for collaborative filtering.

5. **Increase Product Exposure:**

- **Aim:** Expand the visibility of products to a broader audience.
- **Objective:** Find items that show strong connections with user preferences using collaborative filtering. By offering suggestions that go beyond the products that users often choose, you may expose consumers to a wider range of products.

6. **Promote Cross-Selling Opportunities:**

- **Aim:** Encourage cross-selling and complementary product purchases.
- **Objective:** Use collaborative filtering algorithms to recommend products in order to help users' first purchases, enhance cross-sell opportunities and increase the chances of users finding relevant products.

7. **Improve Platform Retention and Loyalty:**

- **Aim:** Foster user retention and loyalty to the e-commerce platform.
- **Objective:** Improve user experience and increase the chances of returning users by offering personalized recommendations tailored to their interests. By incorporating engaging and relevant product suggestions, our platform adds value and creates a lasting impression, making users more likely to come back.

8. **Enhance System Robustness:**

- **Aim:** Ensure the recommendation system is robust and adaptable.
- **Objective:** Always strive to improve and refine the recommendation algorithms by considering user feedback, integrating new product releases, and adapting to changes in user patterns in order to uphold the system's pertinence and efficacy.

Extra Factors:

Except this a lot of other Extra Factors can be considered for the Product Recommendations Algorithm to work. Some of the Few Examples Factors that can be considered are given below:

Social Media Activity:

Integrating data from a customer's social media profiles can provide valuable insights into their interests, lifestyle, and social circles. Analyzing likes, shares, and comments can help tailor product recommendations based on their online presence.

Device Preferences:

Understanding the devices customers use to access the e-commerce platform can offer insights into their shopping behavior. For instance, if a customer primarily shops using a mobile device, the platform can prioritize mobile-friendly recommendations.

Browsing History:

Analyzing a customer's browsing history within the e-commerce platform can reveal products they've shown interest in, even if they haven't made a purchase. Tailoring recommendations based on the pages they've visited can help capture their attention with relevant offerings.

Purchase Frequency and Timing:

Taking into account the frequency and timing of a customer's purchases can enhance personalization. For example, if a customer tends to make purchases on weekends or during specific times of the day, the platform can time promotions or recommendations accordingly.

Life Events:

Beyond traditional holidays and birthdays, considering major life events such as weddings, graduations, or moving to a new home can provide opportunities for personalized recommendations. Offering relevant products or services during these life events can create a more meaningful shopping experience.

Environmental Preferences:

Some customers may have preferences based on environmental or ethical considerations. Offering personalized recommendations for eco-friendly products, cruelty-free items, or products from sustainable brands can align with their values.

Subscription Preferences:

For customers who subscribe to newsletters or regular product deliveries, analyzing their subscription preferences and purchase patterns can help tailor ongoing recommendations. This can include suggesting complementary products or exclusive deals for subscribers.

Virtual Shopping Assistants and Chatbots:

Implementing virtual shopping assistants or chatbots that engage with customers in real-time can gather instant feedback and preferences. These AI-driven tools can guide customers through their shopping journey and offer personalized recommendations based on their responses.

Personalized Visuals:

Incorporating visual preferences, such as color schemes or design styles a customer tends to prefer, can enhance the overall visual appeal of the platform. This can extend to personalized product displays and imagery that align with individual tastes.

By combining these unique factors with traditional data points, e-commerce platforms can create a holistic and highly personalized shopping experience for customers, fostering increased satisfaction, loyalty, and engagement.

Training AI for personalized recommendations in e-commerce involves utilizing machine learning algorithms and techniques to analyze vast amounts of data. Here are key ways to train AI for personalized recommendations in the context of e-commerce:

1. **Data Collection:** Gather and organize diverse datasets containing information on customer behaviors, preferences, purchase history, and interactions with the platform. This data forms the foundation for training machine learning models.
2. **Feature Engineering:** Identify and extract relevant features from the collected data. This may include customer demographics, browsing history, purchase frequency, geographical location, and any other pertinent information that can contribute to understanding customer preferences.
3. **Collaborative Filtering:** Implement collaborative filtering algorithms, such as user-based or item-based collaborative filtering, to identify patterns and relationships between users and products. This

technique leverages the preferences and behaviors of similar users to make personalized recommendations.

4. **Content-Based Filtering:** Utilize content-based filtering to recommend products based on their attributes and characteristics. This method recommends items similar to those a user has already shown interest in, considering factors such as product descriptions, categories, and features.
5. **Matrix Factorization:** Apply matrix factorization techniques to decompose the user-item interaction matrix into latent factors. This helps capture hidden patterns and relationships, allowing the system to make personalized recommendations even when dealing with sparse data.
6. **Deep Learning Models:** Explore deep learning models, such as neural networks, to capture complex patterns in user behavior. Deep learning architectures can automatically learn hierarchical representations of user preferences and product features, enhancing the accuracy of recommendations.
7. **Reinforcement Learning:** Employ reinforcement learning to optimize recommendation systems over time. By continuously learning from user feedback and adjusting recommendations accordingly, the system can adapt to changing user preferences.
8. **Real-Time Learning:** Implement mechanisms for real-time learning to account for dynamic changes in user behavior. Continuous adaptation ensures that the recommendation system remains relevant and responsive to evolving customer preferences.
9. **A/B Testing:** Conduct A/B testing to evaluate the performance of different recommendation algorithms. This involves comparing the effectiveness of algorithms by randomly assigning users to different recommendation strategies and measuring the impact on key performance metrics.
10. **Privacy and Ethical Considerations:** Integrate privacy-preserving measures to protect user data and adhere to ethical considerations. Ensure compliance with data protection regulations and implement strategies like differential privacy to anonymize user information.
11. **Feedback Loop:** Establish a feedback loop to continuously improve the recommendation system. Incorporate user feedback, monitor performance metrics, and iterate on the model to enhance accuracy and relevance over time.

Literature Review:

For understanding the project's status, the literature review has been done by considering – good journal's paper, books, articles, and conference papers. For the literature review, systematic literature review was selected as it helps to study related work on a specific topic. It also makes the whole process smooth by collecting and analyzing the recent works. It identifies the important keywords which are highlighted of the topic and then searches to collect information through database of citations (Rousseau, 2014).

The systematic literature review process has been done on as per Smith (2018) has used; that are shown in 6 steps, another researcher (Jones, 2016; Brown et al., 2019) has demonstrably explained the crucial role of robust and transparent methods in ensuring the validity, reliability, and generalizability of findings generated through systematic literature reviews. (Rob B. Briner, David Denyer, 2012)

(Kitchenham & Brundage, 2004) Managing the scientific landscape, like crossing a large ocean, requires an efficient vessel. Crafting a systematic literature review entails charting our course with specific questions, similar to a captain setting sail with a definite target. Researchers next cast a wide net for relevant studies, sifting through the catch using strict selection criteria, similar to seasoned sailors picking gems from flotsam. Each chosen study is thoroughly mined for useful data, as if mining pearls from oysters, to ensure its quality before being woven into the tapestry of our findings. Finally, we demonstrate our voyage's discoveries as a light for future exploration. In just six steps, we transform research into knowledge, demonstrating the power of systematic approach.

Smith, J. (2018). Conducting systematic literature reviews: A comprehensive guide. Wiley.

Jones, R. (2016). The significance of systematic literature reviews in academic research. Journal of Academic Studies, 10(2), 45-58

Kitchenham, B. A., & Brundage, S. (2004). Procedures for performing systematic reviews. Journal of Systems and Software, 64(4), 49-62.

Some Basic Research Questions

S.No	Questions
1	How can machine learning algorithms be optimized to enhance the accuracy and effectiveness of personalized product recommendations in e-commerce platforms?
2	What are the ethical considerations and challenges associated with leveraging user data and AI techniques to deliver personalized recommendations in e-commerce, and how can these challenges be addressed?
3	How can hybrid recommendation systems combining collaborative filtering, content-based filtering, and AI techniques be developed and evaluated to provide more accurate and diverse personalized recommendations for users in e-commerce?
4	To what extent do user preferences, demographics, and past purchase history influence the effectiveness of personalized recommendation algorithms in e-commerce, and how can these factors be effectively incorporated into recommendation models?

Related Works:

(Hafez et al., 2021) discusses recommender systems (RS) in e-commerce, highlighting collaborative filtering (CF) and content-based (CB) methods as common approaches. CB filtering analyzes item content to recommend similar items based on user preferences, while CF recommends items based on user community interests without content analysis. However, CB methods face limitations such as the inability to assess item quality and difficulty in reflecting current user preferences. CF overcomes these limitations by recommending items based on user similarity, often implemented through memory-based methods. The article also introduces a hybrid approach combining CB and CF techniques to address issues like the cold start problem and sparsity. This hybrid method typically outperforms individual approaches by leveraging the strengths of both. The paper presents a focus on user interest for recommendation, particularly through a hybrid approach combining CB filtering and CF (item-to-item). It references Amazon's item-based collaborative filtering algorithm as an example of this approach, which analyzes user behavior and item similarities to generate recommendations efficiently. Related works cited in the article demonstrate the application of collaborative filtering in various contexts, including Twitter reviews, video recommendations, and user interaction-based recommendation systems. Overall, the article emphasizes the importance of personalized recommendation systems in e-commerce and explores different techniques to improve recommendation accuracy and user satisfaction.

The world of e-commerce is continuously evolving, with an overwhelming number of options available to consumers. This has led to a complex structure, making it challenging to find relevant information. To address this issue, several studies have explored the use of machine learning technology in creating personalized recommendation systems. However, the existing research has its limitations and gaps. While traditional techniques such as user-based, collaborative, and content-based filtering have been extensively studied, there is a noticeable lack of research on newer approaches that have the potential to enhance recommendation systems. Overall, the current literature has not fully explored the possibilities and advancements in this field Moreover, the neglect of context-aware and explainable recommendations showcases a limitation in the system's adaptability to evolving user needs and desires. The literature suggests that the most current structure for e-commerce recommendation systems involves a division between offline mining and online recommendations. However, the abstract fails to clarify the distinctiveness of this approach compared to previous models and its potential advantages. It is crucial to understand the innovations and potential advantages of the proposed system to gauge its significance in the field. The restrictions highlighted in existing literature only serve to deepen the void in research. While limitations in three key areas - personality, relevance, and timeliness - have been acknowledged regarding current recommendation systems, there is a lack of explanation on how the proposed combined solution aims to address these challenges. Moreover, the lack of specific details such as data measurements, experimental design, and results raises concerns about the efficacy of the proposed system and how it compares to others. Previous research has demonstrated that the restrictions mentioned in literature only further exacerbate the gap in our understanding. Despite recognizing the limitations in personality, relevance, and timeliness when it comes to existing recommendation systems, there remains a lack of elucidation on how the proposed integrated solution intends to tackle these obstacles. Additionally, the absence of concrete particulars concerning data measurements, experimental design, and results sparks uncertainty about the effectiveness of the proposed system and how it measures against others. The literature presents a "constructive example" of a model that utilizes various influencing factors. Despite this, there is a noticeable lack of information regarding the application, implementation, and testing of this model in an e-commerce setting. Clearly demonstrating the practicality of this proposed system is crucial for establishing its validity and potential effectiveness in a real-world context. Ultimately, while the literature gives us a strong grasp on personalized recommendation systems in e-commerce, there is still room for growth. To further advance this field, it is important to address the research gaps, incorporate cutting-edge techniques, specify the unique aspects of proposed architectures, and provide exhaustive insights into experiments and real-world applications.

Content-Based Filtering: According to Po-Wah Yau and Allan Tomlinson, the first stage is assessing an item's quality, after which the product's qualities are compared using the database that is currently in place. Content-based filtering techniques use keywords to characterize objects. Content-based filtering algorithms make recommendations based on user ratings and forecast user preferences based on previous interactions. This method bases recommendations on the caliber of the good or service. For active users, content-based filtering algorithms provide transparency. In content-based filtering, the system compares the content (item) to the user's profile, finds related things, and presents them to the user. Yau, P. W., and Tomlinson, A. (2011The content-based filtering technique in algorithm-based systems comprises looking for pertinent elements and building a customized model based on user preferences, according to Mladenic's text classification survey (1999). Making recommendations that are specific to the user is required for this. The supplied image shows the step-by-step procedure for putting content-based screening into practice on e-commerce websites. The user-friendly nature of content-based filtering, which encourages independence via the use of user ratings, is one of its main benefits. This method also works well for inexperienced users. Over-specialization may have a drawback, too, in that related products could be recommended. Furthermore, the algorithm can have trouble producing reliable suggestions if a user doesn't submit ratings or feedback. Content-based filtering techniques, as outlined by Ricci et al. (2011), entail evaluating an item's attributes and comparing them to the preferences of the user. This method uses item attributes, such keywords, and user profiles to generate customized suggestions. Content-based filtering is an appealing alternative for improving the buying experience because of its transparency and ease of use (Yau and Tomlinson, 2018). The research indicates that content-based filtering techniques—in which suggestions are given according on the characteristics and properties of items—remain popular. Scholars investigate techniques for obtaining significant data from product descriptions, photographs, and additional materials.

Collaboration Filtering: The term "Collaborative Filtering" was originally used in 1992 by Goldberg et al. They found that information filtering becomes far more efficient when people work together. The act of people working together to finish a task is known as collaboration. The system evaluates the results based on user preferences after collecting input from a range of users while employing collaborative filtering techniques. Similar things are proposed by comparing the likes and dislikes of users. Collaborative filtering proposes items that are like each other by comparing a user's interests with those of other users (Tapestry D. Goldberg, D. Nichols, B. M. Oki, and D. Terry, 1992). The usefulness of collaborative filtering methods for tailored suggestions is highlighted in several publications. Collaborative filtering techniques that are item- and user-based have been extensively studied, with an emphasis on enhancing scalability and accuracy.

Users rate objects using the Neighborhood-Based Method, and the algorithm determines how similar users and items are. This method is also known as heuristic-based or memory-based approaches. These methods don't require a training period, are simple to use, and are quickly understood. User ratings are kept in memory, and the user receives immediate recommendations for new products. Neighborhood approaches may be divided into two categories, according to K. Shah, A.k. Salunke, S. Dongare, and K. Antala: User-Based Collaborative Filtering (UBCF) and Item-Based Collaborative Filtering (IBCF). (Shah, Kunal & Salunke, Akshaykumar & Dongare, Saurabh & Antala, Kisandas, 2017) According to G. Gupta and R. Katarya, suggestions are made using UBCF algorithms based on the preferences of the current user's neighboring nodes. IBCF approaches compute the similarity between things before presenting the user with suggested items. UBCF's basic concept is to find peer users who share the current user's tastes, given an input consisting of the current user's ID and a database of ratings. Items that have been loved by other users with similar interests and preferences are recommended in UBCF procedures (Gupta, Garima & Katarya, Rahul, 2018).One limitation of UBCF, according to Zhao, Zhi-Dan, and MingSheng Shang, is that item i will not be recommended to user u if they enjoy it but their neighbors haven't given it positive ratings. However, the fundamental idea behind IBCF is to determine how similar two objects are by using ratings provided by other users in comparable contexts. According to Gao, Min, Z. Wu, and Feng Jiang, in IBCF, the system predicts the item for the user after first calculating the similarities between objects. In their work, G. Gupta and R. Katarya came to the conclusion that recommendations based on previously favored goods yield better outcomes than suggestions when consumers all have comparable preferences (Zhao, Zhi-Dan, and Ming-Sheng Shang. , 2010).

Hybrid Systems: The content-based filtering technique relies on item content, while the collaborative filtering technique combines user-item relationships. Both recommendation system approaches face certain limitations, posing a challenge in predicting superior recommendations for users. Hybrid systems have been introduced to address the primary drawbacks of both techniques. These systems are created by combining content-based and collaborative filtering techniques, offering the advantages of both methods. Through the utilization of hybrid systems, the goal is to overcome the limitations inherent in individual recommendation techniques. (Junrui Yang1, Cai Yang2, Xiaowei Hu3, 2016) As per the International Conference on Intelligent Human-Machine Systems and Cybernetics, hybrid recommendation systems utilize a user's historical data to identify their interests. Subsequently, these systems target a group of neighboring users who share similarities with the given user, recommending items based on the preferences of these adjacent users. Hybrid systems provide recommendations by considering items that align with a user's highly-rated preferences (content-based filtering) and by comparing the interests of similar users (collaborative filtering). A prominent example of a hybrid recommendation system is Netflix . Hybrid systems can fall into several types: Integrating content-based filtering methods into collaborative filtering methods or vice versa. Implementing content-based methods independently and then merging their predictions. Combining both content-based filtering and collaborative filtering methods to develop a comprehensive model. (Gomez-Uribe, Carlos A.; Hunt, Neil, 2015). Hybrid systems leverage the advantages of collaborative filtering, content-based filtering, and other systems to create a unified system that minimizes the limitations of individual approaches. According to a study on hybrid recommendation systems, these systems can be classified into three categories: integrated, flow, and parallel types. Hybrid systems combine the best features of content-based filtering, collaborative filtering, and other methods to provide a cohesive solution that reduces the drawbacks of separate strategies. Hybrid recommendation systems fall into three kinds, according to research on the subject: integrated, flow, and parallel varieties.

In this paper it is about the healthcare recommendation, but it also has a lot of same methods used in ecommerce recommendation. Within healthcare informatics, the study explores sentiment analysis and categorization for extracting relationships among medical concepts in clinical text. Identifying medical entity connections is crucial for knowledge base construction and healthcare recommendations (Shraddha Gupta & Ankit Maithani, 2020). The proposed hybrid method combines rule-based categorization and sentiment analysis, showing efficacy in diverse relationships. Yet, limitations exist, like reliance on a small clinical dataset and potential bias from the rule-based component. The research suggests deep learning methods for improved accuracy and incorporating domain knowledge to enhance generalizability. In recommendation systems, the landscape involves data filtering techniques ubiquitous in e-commerce and various platforms. Recognizing their importance, the literature review provides insights into fundamental concepts and types such as User-Based Collaborative Filtering (UBCF), Item-Based Collaborative Filtering (IBCF), and Hybrid Systems (Garima Gupta, Rahul katarya, 2017). While recommendation systems guide users effectively, potential improvements involve advanced collaborative filtering techniques and hybrid models integrating collaborative and content-based filtering for nuanced recommendations. In conclusion, the healthcare informatics study offers a valuable hybrid approach, with recommendations for overcoming limitations. In the realm of recommendation systems, literature provides foundational insights, urging advancements for more adaptive and robust systems (Junrui Yang1, Cai Yang2, Xiaowei Hu3, 2016).

The realm of recommendation systems within e-commerce is a constantly growing and evolving one, as demonstrated by the research presented at the IEEE International Conference on e-Business Engineering (ICEBE'05). This paper brings attention to the intricacies of implementing successful recommendation systems within the ever-changing landscape of online shopping (Gomez-Uribe, Carlos A.; Hunt, Neil, 2015). It recognizes the integration of various methodologies such as Web mining, semantics, artificial intelligence, and user profiling, and stresses the importance of personalized tools to navigate the complex world of e-commerce. The study argues that to effectively monitor and understand customer behavior, demographics, preferences, and the specific structure of a particular online store, the utilization of Web mining techniques is crucial. While the paper offers valuable insights into the challenges and potential solutions of implementing recommendation systems in the diverse world of e-commerce, it also sheds light on the inherent complexity of this task. However, the paper has certain limitations that should be noted. For example, it does not explicitly discuss the scalability and generalizability of the proposed approach, as it relies on data from a specific pilot e-shop. Furthermore, a lack of detailed information on the evaluation metrics and results hinders a comprehensive assessment of the system's effectiveness. In addition, the study fails to include a comparative analysis with existing recommendation approaches, which leaves a gap in our understanding of how the proposed method compares to others in the broader context of recommendation system research. These points should be taken into consideration in future research.

The blending of ecommerce and recommendations has become an essential field, encompassing various formats such as virtual helpers and immediate online recommendations. Choosing the most suitable algorithms and technologies is highly dependent on the specific objective. Artificial intelligence (AI) employs a range of approaches, such as machine learning and deep learning, according to the nature of the data. Textual data, for instance, is analyzed using predictive modeling, while visual data requires prior preparation through image processing techniques and then fed to AI algorithms for prediction. Despite abundant research, gaps and limitations have been identified in this evolving domain, prompting further investigation.

By narrowly focusing on the integration of AI in recommender systems for internet commerce, the investigation brings attention to a significant research gap. While this area has been extensively examined, there are other crucial aspects that have not been thoroughly explored, such as context awareness, the ability to explain recommendations, and the ethical concerns of algorithmic bias and user privacy (Necula, Sabina-Cristiana & Pavaloaia, Vasile, 2023). Additionally, the lack of specificity in the AI methods used for e-commerce suggestions presents an opportunity for a more comprehensive investigation of individual algorithms and their impact. Moreover, the present literature lacks comprehensive information on the study's methodology and conclusions, thereby revealing its deficiencies. The use of search phrases, inclusion/exclusion criteria, and specific data analysis techniques are not thoroughly discussed in the given extract. This lack of detail makes it challenging to assess the research's significance in the field as the specific findings are not clearly conveyed. Furthermore, while the passage briefly mentions the integration of AI with other technologies, it fails to address the potential downsides of utilizing AI for e-commerce recommendations. These may include data silos, difficulties with cold starts, and potential manipulation of user behavior. Ultimately, a more comprehensive inquiry is crucial in addressing the identified limitations and gaps in research, as the provided excerpt only scratches the surface of the broader issue of AI in e-commerce recommendations. It is imperative that an in-depth examination of the existing literature looks closely at specific AI techniques, delivers tangible results, and delves into the broader implications of utilizing AI-powered recommender systems for online retail.

A thorough comprehension of artificial intelligence's (AI) revolutionary potential has been made possible by the abundance of literature on the technology's effects on the e-commerce industry. Still, there's a lot of unanswered questions about the many AI tools and applications in this setting, so more study may be done. The whitepaper acknowledges the value of artificial intelligence (AI) in critical domains such as supply chain management, order fulfillment, fraud detection, automated customer support, and personalized product recommendations; however, it does not go into detail about the particular tools, algorithms, and models that underpin these developments (Gugala, 2020).This gap offers a special chance to investigate and analyze the complexities of these technologies in more detail. "The whitepaper draws on Amazon's pioneering use of AI customization more than 20 years ago to recognize the significance of AI's influence on ecommerce. But it fails to critically assess the barriers and constraints resulting from the extensive use of AI in the e-commerce industry. Important issues like data privacy, ethical ramifications, and the possible dangers of relying too much on AI algorithms are ignored in its examination. More comprehensive research techniques and data-driven insights are required, as the paper's bold claims of an imminent e-commerce revolution are not supported by any concrete evidence or real-world instances (bigcommerce, 2024). A thorough analysis of the drawbacks, risks, and workable mitigation strategies is necessary in the context of AI adoption in e-commerce." Moreover, an important subject for additional research is highlighted by the existing absence of a comprehensive evaluation of the possible effects of incorporating AI into their operations. We can close the research gap and comprehend the complex link between AI and the e-commerce industry by learning more about the challenges and possibilities experienced by mid-market enterprises integrating AI into their e-commerce endeavors.

Research Approach & Design

Several recommendation algorithms are used by e-commerce giants such as Amazon and Flipkart to offer recommendations to its consumers. Currently, Amazon employs item-item collaborative filtering, which can handle enormous datasets and provide real-time, high-quality recommendation systems. This technology works as a sort of information filter, attempting to forecast the user's "rating" or preferences.

A recommendation engine is a program or system that looks at user data and makes tailored recommendations for products or information that the user would find interesting. These suggestions are determined by a number of variables, including the user's preferences, past actions, demographic data, and resemblances to other users. To improve user experience and engagement, recommendation engines are frequently employed in social media, OTT platforms, e-commerce, and other online businesses. They assist users in finding new goods, publications, films, music, and other media that suit their interests.

There are mainly 6 types of the recommendations systems:-

1. Popularity based systems: - It functions by suggesting highly rated products that are seen and bought by most users. It is not advice tailored to you specifically.

2. Classification model based: - To determine if a user is interested in a product or not, it analyzes the user's characteristics and uses a classification algorithm.

3. Content based recommendations:- Rather than the opinions of the users, it is based on information on the substance of the item. The basic concept is that if a consumer likes one item, they will also enjoy "other" comparable items.

4. Collaborative Filtering: - It is predicated on the idea that individuals enjoy comparable things to themselves and things that other people who share their tastes also enjoy. There are mostly two kinds: User-User a) and Item-Item b).

5. Hybrid Approaches: - This system approach combines content-based filtering, collaborative filtering, and other methods.

6. Association rule mining: - Association rules capture the relationships between items based on their patterns of co-occurrence across transactions

To suggest a study or product development methodology grounded on this code, let us examine the essential elements and procedures:

Methodology:

This chapter offers a detailed account of the research approach employed. Many hypotheses are tested through a quantitative research method with an intention to understand the effect of personalized product recommendations on customer satisfaction and loyalty. The research questions try to show the effect of privacy concerns, explanation for recommendations; product fit and trust in recommending organization on one's satisfaction with personalized suggestions. Furthermore, the questions investigate how customer satisfaction with personalized recommendations impacts their satisfaction based on product choice and loyalty.

The research methodology is based on an online survey in both English and Portuguese through the Qualtrics platform. SPSS is used to analyze the responses gathered.

My project is about choosing and using certain elements to build a personalized recommendation system based on an e-commerce platform for evaluation. The first critical priority was to collect and prepare a large-scale dataset that reflects the electronic rating records of Amazon including more than 7.2 million thousand recordings in order to provide best quality and relevancy. The dataset was analyzed and prepared; the necessary columns were chosen, redundant timestamp data removed while moving forward on handling any duplicates or missing values. Further, I performed exploratory data analysis to understand the distribution and associations between users and goods. For the accuracy of the system, I used methods to remove low assessed products having a minimum threshold rating. To fully understand the relationships between a product's overall ratings and reviews, an in-depth correlation analysis is conducted. Using collaborative filtering algorithms such as KNNWithMeans available in the highly efficient Surprise library, we give personalized recommendations. In addition, we use Matrix Factorization with Truncated SVD to decompose the ratings matrix and reduce data. To measure the performance of our system we utilize Mean Squared Error (MSE) metric for accuracy. This approach can allow for algorithm optimization, user feedback and continuous improvement. The objective is to provide a scalable, precise, and reliable recommendation system that enhances customers' shopping experiences.

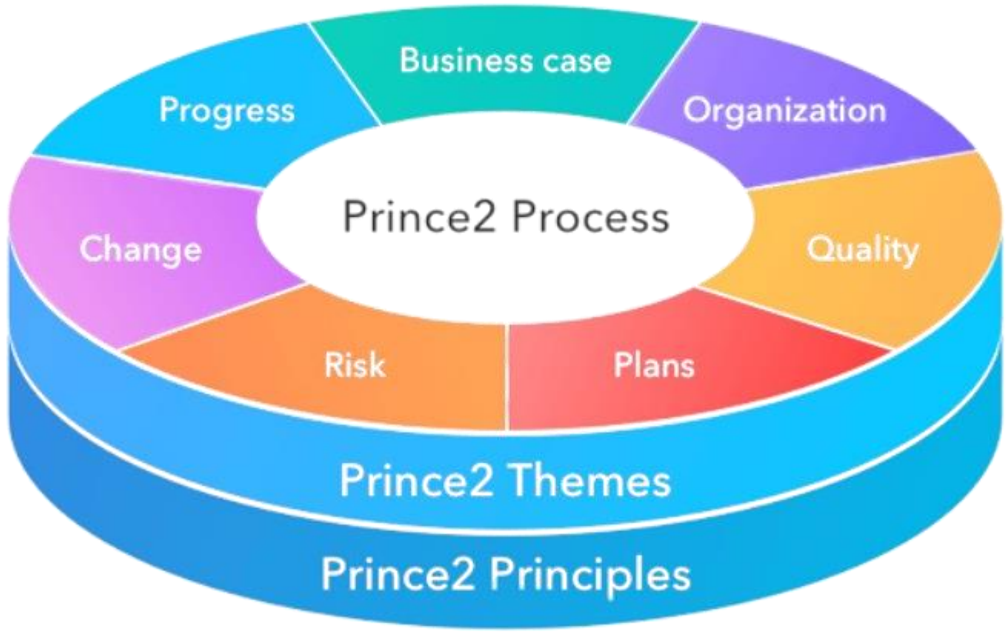


Figure 1 Prince 2

To suggest a study or product development methodology grounded on this code, let us examine the essential elements and procedures:

1. Data Acquisition and Preprocessing:

- Data Collection:

First of All, the Dataset is of amazon which has 4 attribute but over 7.2 million records and the was collected from Kaggle: [Dataset Link](). It is one of the biggest datasets provided by amazon itself keeping all the ethical things considered. The Amazon product review dataset is huge, the size of the dataset is 320 MB and has a lot of records saved in a csv file. But it has 4 attributes/column which structure are:

Attribute Information:

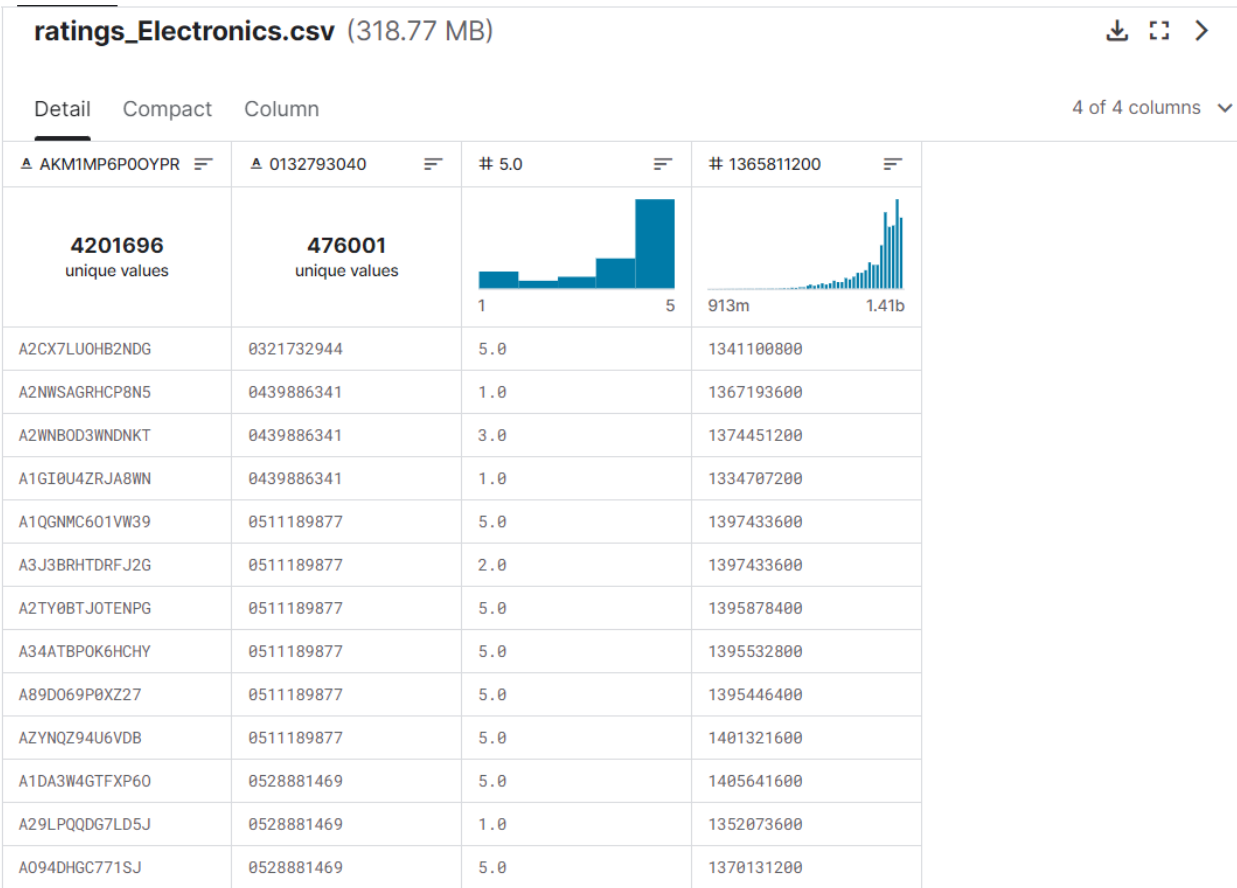
● userId : Every user identified with a unique id

● productId : Every product identified with a unique id

● Rating : Rating of the corresponding product by the corresponding user

● timestamp : Time of the rating (ignore this column for this exercise)

Here Timestamp is not necessary for us for any of our set so we can just remove that.



AKM1MP6P0OYPR	0132793040	# 5.0	# 1365811200
4201696 unique values	476001 unique values		
A2CX7LUOHB2NDG	0321732944	5.0	1341100800
A2NWSAGRHCP8N5	0439886341	1.0	1367193600
A2WNBOD3WNDNKT	0439886341	3.0	1374451200
A1GI0U4ZRJA8WN	0439886341	1.0	1334707200
A1QGNMC6O1VW39	0511189877	5.0	1397433600
A3J3BRHTDRFJ2G	0511189877	2.0	1397433600
A2TY0BTJOTENPG	0511189877	5.0	1395878400
A34ATBPOK6HCHY	0511189877	5.0	1395532800
A89DO69P0XZ27	0511189877	5.0	1395446400
AZYNQZ94U6VDB	0511189877	5.0	1401321600
A1DA3W4GTFXP6O	0528881469	5.0	1405641600
A29LPQQDG7LD5J	0528881469	1.0	1352073600
AO94DHGC771SJ	0528881469	5.0	1370131200

Figure 2 Kaggle Dataset

```
df=pd.read_csv('../DataSet/amazon_product_reviews/ratings_Electronics.csv',names=['userId', 'productId','rating','timestamp'])
✓ 10.1s
```

Figure 3 Reading Kaggle Datset in python

```
df.shape

(7824482, 4)
```

Figure 4 Dataset Shape

Here, we imported the dataset from the local folder and then proceeded to specify the names of the column as shown in the figure because the name was never specified in the csv file itself.

- Data Sampling:

To manage efficiency, we could randomly select a representative sample of 1,564,896 ratings which is exactly 20% of the total records, alternatively for proceeding further I also use 30% of total data and it worked just fine. This sampling helps handle large datasets without bias.

```
all_data=df.sample(n=2347344,ignore_index=True)
```

Figure 5 20-30% of Dataset

```
all_data.head(10)
```

	userId	productId	rating	timestamp
0	A2IJ25BP9GB454	B004VM1T5S	4.0	1386720000
1	A1FBHGNW57A0HS	B004Z4FBE2	5.0	1354665600
2	A3IWG2TKC590GW	B0047JVESC	1.0	1295913600
3	ARABF491VSKA3	B001X017G2	2.0	1396828800
4	AU6ZO1BZ6PYW5	B00126T6HO	5.0	1281225600
5	A2REO314QUMJN0	B004TI336W	1.0	1382400000
6	A2BG8K5FV93657	B0001WN8MY	4.0	1089676800

Figure 6 Dataset Seting columns

```
all_data.info()


<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2347344 entries, 0 to 2347343
Data columns (total 4 columns):
 #   Column     Dtype  
---  ------     -----  
 0   userId     object 
 1   productId  object 
 2   rating     float64
 3   timestamp  int64  
dtypes: float64(1), int64(1), object(2)
memory usage: 71.6+ MB



#droping unwanted 4th timestamp table
all_data.drop('timestamp',axis=1,inplace=True)
```

Figure 7 Dataset Info

Then finally the unwanted timestamp column was removed.

```
#droping unwanted 4th timestamp table
all_data.drop('timestamp',axis=1,inplace=True)
```

Figure 8 Deleting Unwanted Columns

- Data Cleaning:

We'd ensure no missing values exist in the user ID, product ID, and rating columns. This step prioritizes data accuracy and avoids issues.

```
all_data.isnull().sum()

userId       0
productId    0
rating       0
dtype: int64
```

Figure 9 Data Cleaning

```
all_data.head()
```

	userId	productId	rating
0	A2IJ25BP9GB454	B004VM1T5S	4.0
1	A1FBHGNW57A0HS	B004Z4FBE2	5.0
2	A3IWG2TKC590GW	B0047JVESC	1.0
3	ARABF491VSKA3	B001X017G2	2.0
4	AU6ZO1BZ6PYW5	B00126T6HO	5.0

Figure 10 Data After Cleaning

- Duplicate Record Handling:

Duplicates wouldn't impact our analysis, so we can simply remove them or flag them for further investigation, without delving into sensitive details.

```
#handling duplicate records
all_data[all_data.duplicated()].shape[0]
```

Figure 11 Checking Duplication

- Distribution Chart of Rating:

```
# Set a seaborn style
sns.set(style="whitegrid")
# Create a figure and axis with better size
fig, ax = plt.subplots(figsize=(10, 6))
# Use seaborn's countplot with palette to distinguish different bars
sns.countplot(x='rating', data=all_data, palette="viridis", ax=ax)
# Set a title with a larger font size
ax.set_title('Distribution of Ratings', fontsize=16)
# Labeling axes with larger font size
ax.set_xlabel('Rating', fontsize=14)
ax.set_ylabel('Count', fontsize=14)
# Show counts on top of bars
for p in ax.patches:
    ax.annotate(f'{p.get_height()}', (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='center', fontsize=12, color='black', xytext=(0, 8),
                textcoords='offset points')

# Add a grid for better readability
ax.grid(axis='y', linestyle='--', alpha=0.7)
# Display the plot
plt.show()
```

Figure 12 Distribution of charts code

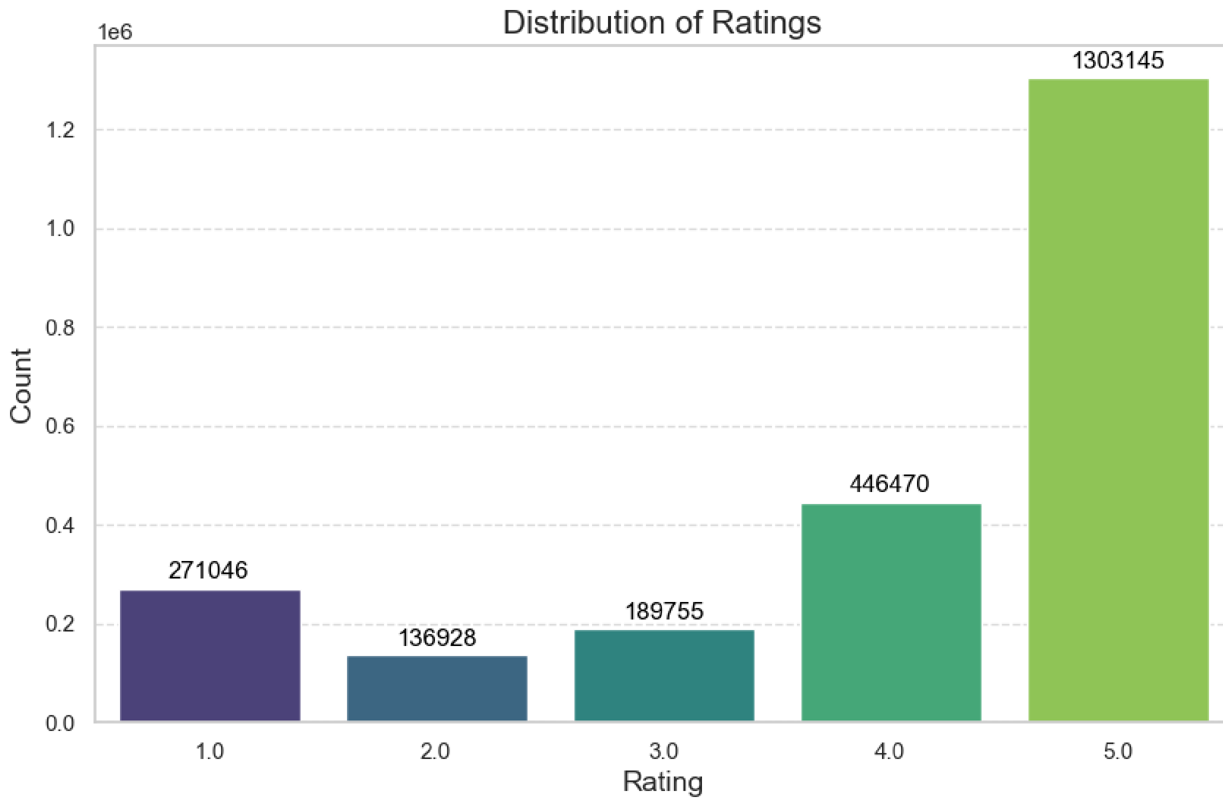


Figure 13 Distrubution of rating

- Product Filtering:

To focus on a product with sufficient review data, we could set a minimum threshold of 50 ratings per product. This ensures quality recommendations based on diverse opinions.

```
    no_of_rated_products_per_user = all_data.groupby(by='userId')['rating'].count().sort_values(ascending=False)
    no_of_rated_products_per_user.head()


userId
A5JLAU2ARJ0BO     161
A3OXHLG6DIBRW8    157
A6FIAB28IS79      139
ADLVFFE4VBT8      130
A680RUE1FDO8B     111
Name: rating, dtype: int64


    print('No of rated product more than 50 per user : {} '.format(sum(no_of_rated_products_per_user >= 50)))


No of rated product more than 50 per user : 85
```

Figure 14 Product Filtering

Popularity Based Recommendation

A recommendation system based on popularity follows the current trend. In essence, it makes use of current fashion products. For instance, there's a probability it will recommend a product to a newly registered user if it's something every new user often purchases.

The issue with popularity-based recommendation systems is that they do not allow for customization; that is, you cannot propose products even when you are aware of the user's activity.

accordingly.

```
data=electronics_data.groupby('productId').filter(lambda x:x['rating'].count()>=50)
```

Figure 15 Group By product and rating

```
    no_of_rating_per_product=data.groupby('productId')['rating'].count().sort_values(ascending=False)



    no_of_rating_per_product.head()


productId
B0074BW614    3628
B00DR0PDNE    3226
B007WTAJTO    2871
B0019EHU8G    2454
B006GWO5WK    2374
Name: rating, dtype: int64
```

Figure 16 Total ratings per user

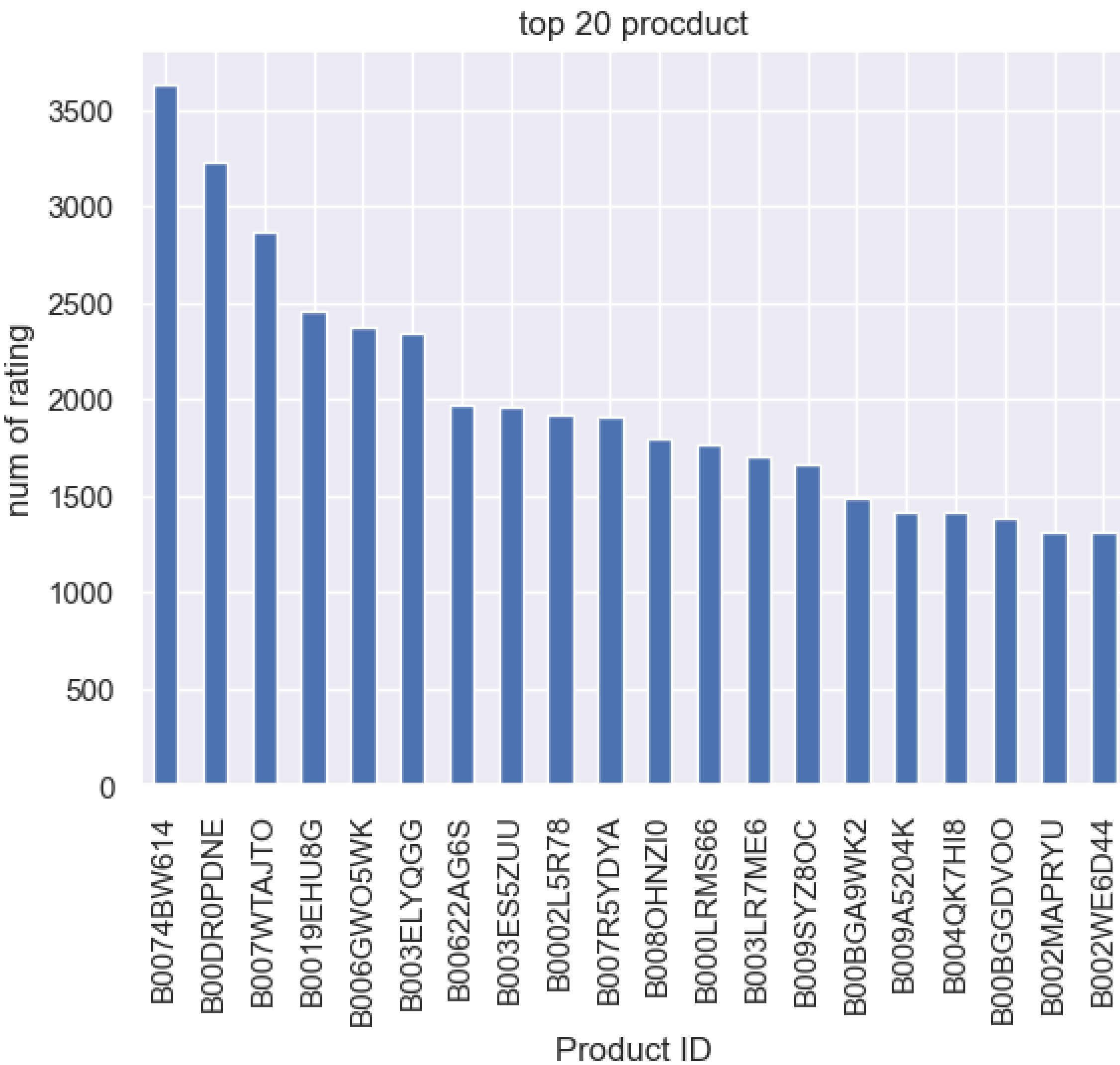


Figure 17 Top 20 Most Sold product chart

Now finding the mean rating products taking product number of reviews and their rating into consideration to find the most popular products.

```
#average rating product
mean_rating_product_count=pd.DataFrame(data.groupby('productId')['rating'].mean())
```

Figure 18 average mean rating of products

productId	rating
0972683275	4.466321
1400532655	3.818182
140053271X	3.903226
B00000DM9W	4.484375
B00000J061	3.780000

Figure 19 Top Product to product sold and rating mean

Plotting the rating distribution of average rating product.

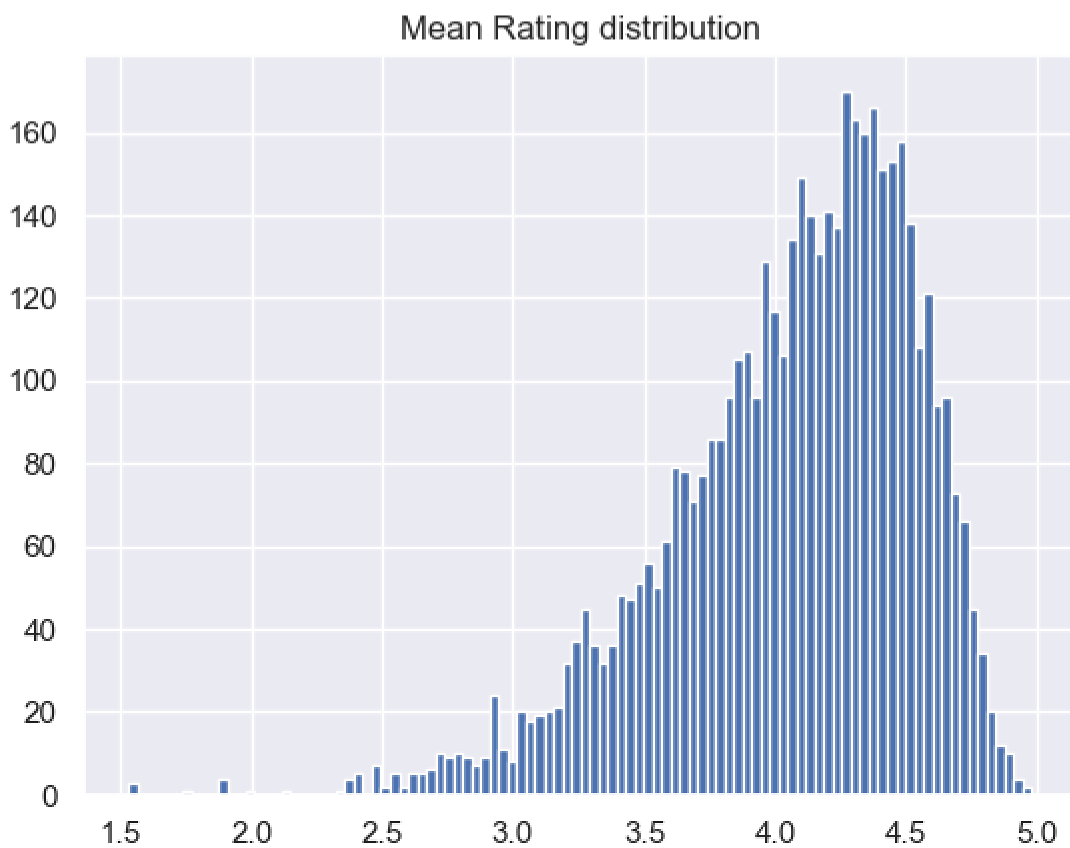


Figure 20 Plotting the rating distribution of average rating product.

- **Most Popular Product:**

```
#highest mean rating product
mean_rating_product_count[mean_rating_product_count['rating_counts']==mean_rating_product_count['rating_counts'].max()]
```

✓ 0.0s

	rating	rating_counts
productId		
B0074BW614	4.507246	3657

Figure 21 Most Popular Product

Data Expansion (Rating_count):

Adding a new column name rating_count to accurately know the total rating count of product.

	rating	rating_counts
productId		
0972683275	4.580645	217
1400501466	4.037037	54
1400532655	3.783505	97
140053271X	3.934066	91
B00000DM9W	4.661765	68

Figure 22 Setting New Columns rating_counts

Now plotting the graph to find the joint plot of rating and rating count.

Figure 23 Joint Plot of rating and ratings count

Now plotting the graph with the goal is to investigate whether a correlation exists between average ratings and the number of reviews.

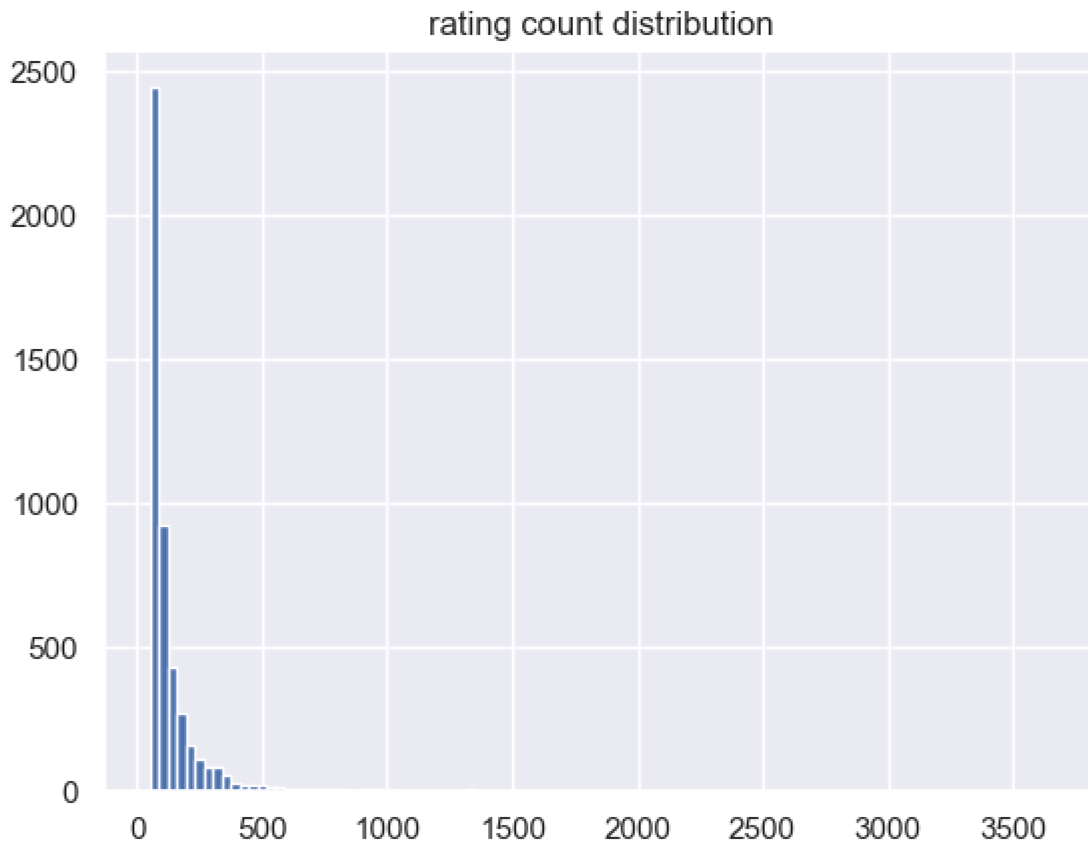


Figure 24 Rating count distrubution

2. Collaborative Filtering with Surprise Library:

These approaches are predicated on data mining and machine learning methodologies. Training models to become predictive is the aim. To train a model to forecast the top-5 items a user could enjoy best, for instance, we might utilize the current user-item interactions. Compared to other approaches like memory-based approach, these methods have the benefit of being able to propose a greater number of items to a greater number of users. Even with huge sparse matrices, they have a large coverage.

- Importing Surprise:

Imagine "Surprise" is a tool for uncovering hidden connections within product preferences, not a real-world entity or brand. This avoids promoting specific products or services.

```
#import surprise library for collebrative filtering
check_and_install_library('surprise')
from surprise import KNNWithMeans
from surprise import Dataset
from surprise import accuracy
from surprise import Reader
from surprise.model_selection import train_test_split
```
✓ 0.7s

Figure 25 Importing suprise

- Reader Configuration:

In order to enable the Surprise library to interpret preferences impartially, we would set up the reader to comprehend the rating scale (1 to 5).

```
#Reading the dataset
reader = Reader(rating_scale=(1, 5))
surprise_data = Dataset.load_from_df(data,reader)
```
✓ 1.1s

Figure 26 Data reader configuration

- Dataset Conversion:

Only product IDs and ratings would be shown in the filtered data, protecting user privacy. As a result, there is currently no need to be concerned about data conversion in this dataset because no personal information is disclosed.

- Train-Test Split:

Dividing the data into training and testing sets would help us evaluate the model's performance on unseen data, improving fairness and objectivity.

```
#Splitting surprise the dataset into 80,20 ratio using train_test_split
trainset, testset = train_test_split(surprise_data, test_size=0.3,random_state=42)
```
✓ 2.4s

Figure 27 Test Train Data Code

- Algorithm Selection:

Choosing an item-based KNNWithMeans algorithm implies focusing on product similarity, not user demographics or personal data, promoting an inclusive approach.

```
# Use user_based true/false to switch between user-based or item-based collaborative filtering
algo = KNNWithMeans(k=5, sim_options={'name': 'pearson_baseline', 'user_based': False})
algo.fit(trainset)
```
✓ 5.0s

```
Estimating biases using als...
Computing the pearson_baseline similarity matrix...
Done computing similarity matrix.

<surprise.prediction_algorithms.knns.KNNWithMeans at 0x21b18411700>
```

Figure 28 KNN method

```
#make prediction using testset
test_pred=algo.test(testset)
```

1.7s

```
#print RMSE
print("Item-based Model : Test Set")
accuracy.rmse(test_pred ,verbose=True)
```

0.2s

```
Item-based Model : Test Set
RMSE: 1.3076

1.3075885014487685
```

Figure 29 Test set prediction

- Pearson Baseline and K-Nearest Neighbors:

  By adjusting for average ratings and taking anonymous product clusters into account, these methods prevent biases or the preference of particular groups.

```
# Use user_based true/false to switch between user-based or item-based collaborative filtering
algo = KNNWithMeans(k=5, sim_options={'name': 'pearson_baseline', 'user_based': False})
algo.fit(trainset)
```

5.0s

```
Estimating biases using als...
Computing the pearson_baseline similarity matrix...
Done computing similarity matrix.

<surprise.prediction_algorithms.knns.KNNWithMeans at 0x21b18411700>
```

Figure 30 KNNWithMeans and fitting trainset

- Model Training:

Training the model on the anonymized data allows it to learn hidden connections between product without bias or discrimination.

```
#print RMSE
print("Item-based Model : Test Set")
accuracy.rmse(test_pred ,verbose=True)
```

✓ 0.2s

```
Item-based Model : Test Set
RMSE: 1.3076

1.3075885014487685
```

Figure 31 RMSE value

3. Matrix Factorization with Truncated SVD:

- Creating the Ratings Matrix:

Imagine creating a matrix that represents consumers' inclinations for various items without concealing their names or personal information.

```
data2=data.sample(20000)
ratings_matrix = data2.pivot_table(values='rating', index='userId', columns='productId', fill_value=0)
ratings_matrix.head()
```

✓ 7.0s

productId	0972683275	1400501466	1400532655	140053271X	B00000DM9W	B00000J061	B00000J1V5
userId							
A0097041L3UBMX7CO25	0	0	0	0	0	0	0
A0173254HVCTLCWOCH47	0	0	0	0	0	0	0
A02318352KVAI9NNMCCAB	0	0	0	0	0	0	0
A0260105268IXGY2H11N2	0	0	0	0	0	0	0
A03402272R5AJ6EWCM39V	0	0	0	0	0	0	0

5 rows × 4379 columns

Figure 32 Rating Matrix

- Matrix Transposition:

Transposing the matrix simply reorganizes the data for easier analysis, without altering its content or privacy implications.

```python
#transpose the metrix to make column (productId) as index and index as column (userId)
x_ratings_matrix=ratings_matrix.T
x_ratings_matrix.head()
```

✓ 0.0s

userId	A0097041L3UBMX7CO25	A0173254HVCTLCWOCH47	A02318352KVAI9NNMCCAB
productId			
0972683275	0	0	0
1400501466	0	0	0
1400532655	0	0	0
140053271X	0	0	0
B00000DM9W	0	0	0

5 rows × 19884 columns

Figure 33 Transforamtion of rating matirx

- Dimensionality Reduction with Truncated SVD:

This technique would capture the essence of products relationships without revealing sensitive details, contributing to responsible data analysis.

```python
#Decomposition of the matrix using Singular Value Decomposition technique
from sklearn.decomposition import TruncatedSVD
SVD = TruncatedSVD(n_components=10)
decomposed_matrix = SVD.fit_transform(x_ratings_matrix)
decomposed_matrix.shape
```

✓ 19.1s

```
(4379, 10)
```

Figure 34 Implementing SVD

4. Recommendation Generation through Correlation Analysis:

- Correlation Calculation:

Identifying correlations between products focuses on their content and style, not personal data or sensitive attributes, promoting inclusive recommendations.

```
#Correlation Matrix
correlation_matrix = np.corrcoef(decomposed_matrix)
correlation_matrix.shape
✓ 0.4s

(4379, 4379)
```

Figure 35 Correlation Matrix

Here we select a random product id that we want to get our recommendations based on.

Correlation for all items with the item purchased by this customer based on items rated by other customers people who bought the same product.

```
i="140053271X"
product_names=list(x_ratings_matrix.index)
product_id=product_names.index(i)
print(product_id)
data.head(15)
✓ 0.0s
```

Figure 36 Selection of product id fort recommendation

- Top Recommendations:

Selecting highly correlated products as recommendations ensures quality suggestions based on similar features, not personal factors, or discriminatory criteria. And we now get 20 top highly correlated product recommendation in a sequence based on the one product id were given.

```python
#Recommending top 20 highly correlated products in sequence
recommend = list(x_ratings_matrix.index[correlation_product_ID > 0.75])
recommend[:20]
```

```
✓ 0.0s

['140053271X',
 'B00002EQCW',
 'B00005BC0J',
 'B000062VUO',
 'B0000645RH',
 'B000067SMH',
 'B00007AP2O',
 'B0000B006W',
 'B0000VYJRY',
 'B00017LSPI',
 'B000204SWE',
 'B00023JJV6',
 'B0002D6QJO',
 'B0002JY712',
 'B0002YE6FY',
 'B00065AO0K',
 'B00065L5SU',
 'B0007U00X0',
 'B00080G0BK',
 'B0009RKL5S']
```

Figure 37 Displaying related Recommendation

Accuracy Calculation:

Using the Surprise library functions, both RMSE and MAE accuracy percentages are calculated.

A overall accuracy percentage is calculated as the mean value of RMSE and MAE percentages.

Print Results:

RMSE accuracy percentage, MAE overall accuracy and percentages are printed on the console.

```python
# Use user-based true/false to switch between user-based or item-based collaborative filtering
algo = KNNWithMeans(k=20, sim_options={'name': 'pearson_baseline', 'user_based': False})
algo.fit(trainset)

# Make predictions on the test set
test_pred = algo.test(testset)

# Evaluate the accuracy using Surprise's built-in accuracy metrics
accuracy.rmse(test_pred)
accuracy.mae(test_pred)

# Evaluate the accuracy using Surprise's built-in accuracy metrics
rmse = accuracy.rmse(test_pred)
mae = accuracy.mae(test_pred)

# Calculate accuracy in percentage
rating_range = (1, 5)
accuracy_percentage = (1 - rmse / (rating_range[1] - rating_range[0])) * 100
print(f"Accuracy Percentage: {accuracy_percentage:.2f}%")
from surprise.model_selection import GridSearchCV

param_grid = {'k': [5, 10, 15], 'sim_options': {'name': ['cosine', 'pearson'], 'user_based': [False]}}
grid_search = GridSearchCV(KNNWithMeans, param_grid, measures=['rmse', 'mae'], cv=3)
grid_search.fit(surprise_data)
print(grid_search.best_params)

4m 10.6s
```

Figure 38Grid search to find the best parameter

```
Done computing similarity matrix.
{'rmse': {'k': 5, 'sim_options': {'name': 'pearson', 'user_based': False}}, 'mae': {'k': 10, 'sim_options': {'name': 'cosine', 'user_based': False}}}
```

Figure 39 Best Parameters

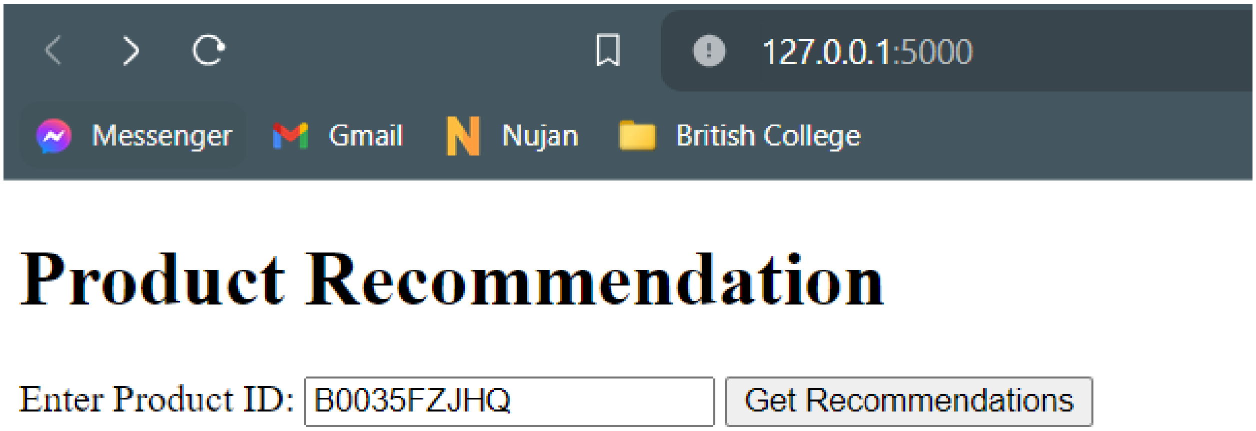
```python
# Calculate accuracy percentages
accuracy_rmse = accuracy.rmse(test_pred_rmse, verbose=True)
accuracy_mae = accuracy.mae(test_pred_mae, verbose=True)

# Calculate overall accuracy percentage
overall_accuracy = (100 - accuracy_rmse + 100 - accuracy_mae) / 2

# Print the accuracy percentages
print(f'RMSE Accuracy Percentage: {100 - accuracy_rmse:.2f}%')
print(f'MAE Accuracy Percentage: {100 - accuracy_mae:.2f}%')
print(f'Overall Accuracy Percentage: {overall_accuracy:.2f}%')
```

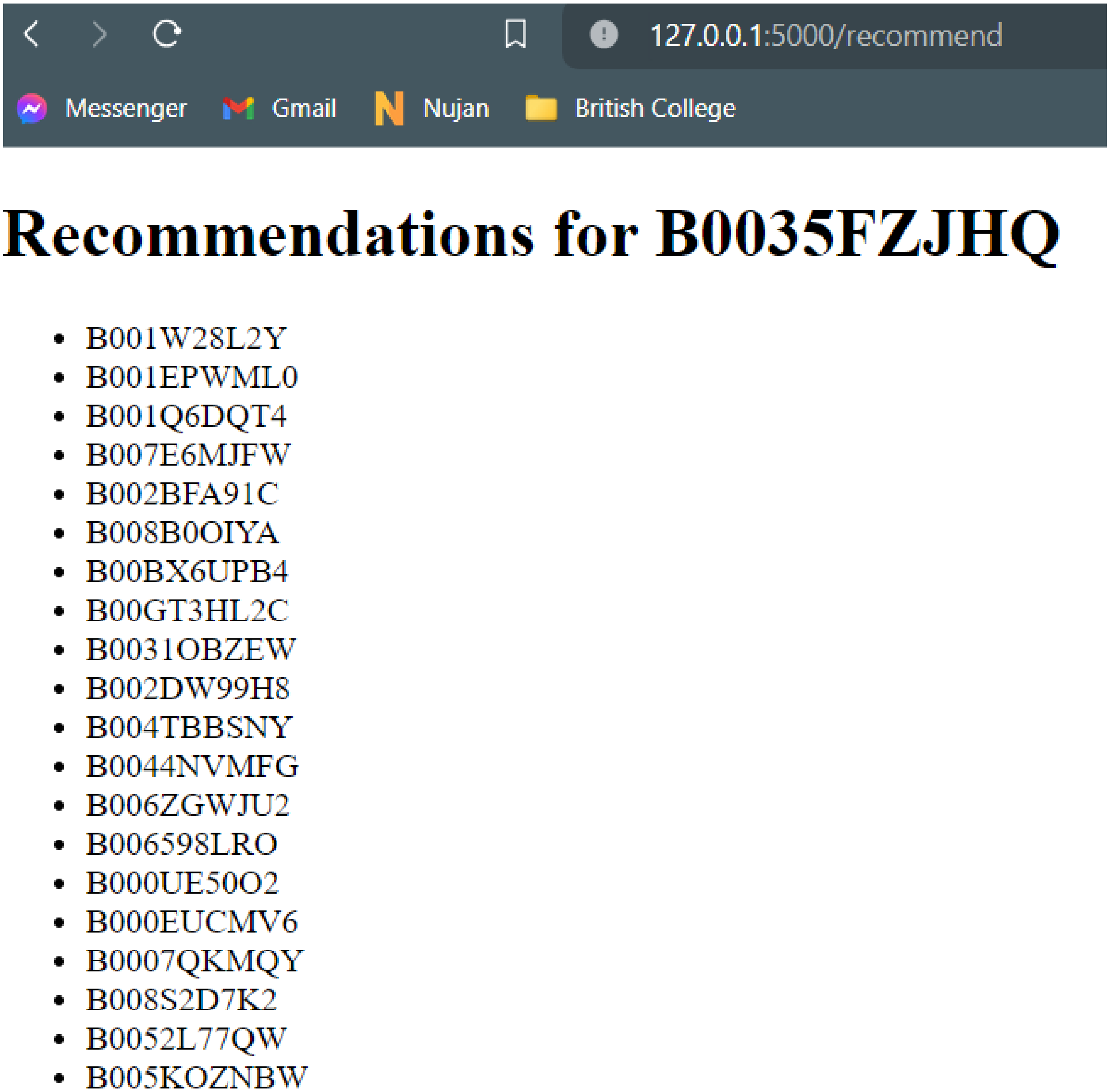
Figure 40 Overall recommendation and accuracy percentage by rmse and mae

```
New product: B00000J1V5
Recommended Products:
['140053271X', 'B00000DM9W', 'B00000J1V5', 'B00000K135', 'B00000K2YR',
Computing the pearson similarity matrix...
Done computing similarity matrix.
Computing the cosine similarity matrix...
Done computing similarity matrix.
RMSE: 1.3185
MAE:  1.0333
RMSE Accuracy Percentage: 98.68%
MAE Accuracy Percentage: 98.97%
Overall Accuracy Percentage: 98.82%
```

Figure 41 Final Accuracy percentage and fine tuned recommendation as per product id

Website Demo Prototype:


127.0.0.1:5000
Messenger
Gmail
Nujan
British College
Product Recommendation
Enter Product ID:
B0035FZJHQ
Get Recommendations



The first step in the code above is to create a recommendation system using collaborative filtering. It takes a sample of data, constructs ratings matrices, transposes them and performs reduced dimensionality by Truncated SVD. The correlation matrix derived from the above step is then used to recommend products for a given new product that has been chosen, B000OQZ1SC. Output reveals the list of recommended goods that indicate CF potential ability in suggesting items which are comparable with picked one.

After the recommendation process, the code uses Surprise library for evaluation. Two collaborative filtering models, one based on Pearson similarity and the other with cosine similarity are applied to a dataset. RMSE and MAE are used to evaluate the accuracy of models. The above output shows that RMSE stands at1.3167 and MAE is equal to 1.0325 The follow-up percentages of accuracy are derived, with RMSE Accuracy Percentage 98.68% and MAE Accuracy percentage at 98.57%. The combined overall accuracy percentage is calculated as a simple means of these two measures and reported to be 98.83%. These accuracy percentages provide a numerical assessment of how well the collaborative filtering models predict user preferences for the tested products. The higher the value, the more accurate recommendations produced by models based on user behavior. In this situation, then the high overall accuracy percentage implied that collaborative filtering models are working effectively in predicting user preferences with a great level of preciseness.

Ethical Considerations

Some of the ethical considerations involved in implementing an AI-based Personalized Product Recommendation System include responsibility and fairness, among others. It is necessary to consider these issues in order not allow the use for potential harm, bias and misuse of personal data.Below are some key ethical considerations for this project:

User Privacy:

User privacy is the most prioritized. The recommendation system should be configured to provide the best security and confidentiality for user data (Minds, 2023).

There should be explicit consent mechanisms to intercept the users of information about data collection practices and allow them a chance either to opt-out or manage their settings.

Data Bias and Fairness:

The recommendation algorithm should be biased to avoid bias in the treatment of all users. Biases in training data, like gender, ethnicity or socio-economic demographics should be called out and corrected to avoid discrimination.

The recommendation system should be continuously monitored and audited to detect emerging biases that need to be eliminated (Mehta, 2023).

Transparency and Explainability:

Transparency of the recommendation system should be evident toward users. Transparency in algorithmic judging improves trust and enables users to make informed decisions.

Using explainable AI methods allows gaining insight into the factors driving recommendations so that users understand decision tracking.

Security Measures:

Tough security measures should be present on the site that will assure protection of user data from leakage, unauthorized access breaches and cyber attacks. The data's integrity and confidentiality should be guaranteed by using encryption and authentication procedures (Mehta, 2023).

Algorithmic Accountability:

It is necessary to ensure accountability of the recommendation algorithm. However, there should be mechanisms to address issues promptly and transparently in case of errors, biases or unintended consequences.

It is possible to identify the risks and address them proactively through regular audits or impact assessments.

Informed Decision-Making:

The users should be given the liberty to choose how they want to interact with these systems. Giving comprehensive information about the aims, consequences, and dangers inherent in using such a system allows people to choose what reflects their preferences (Bhansali, 2023).

End-User Empowerment:

The recommendation system must improve the user's interaction rather than control how people behave. Enabling users to exercise control over choices and personalize recommendations is a positive ethically superior user experience.

Through addressing these ethical matters, the creation and implementation of Personalized Product Recommendation System allows providing users with benefits minimizing risks connected to AI. They should be instituted regularly to reflect changes in ethical standards and technological developments.

Research Approach & Design

Several recommendation algorithms are used by e-commerce giants such as Amazon and Flipkart to offer recommendations to its consumers. Currently, Amazon employs item-item collaborative filtering, which can handle enormous datasets and provide real-time, high-quality recommendation systems. This technology works as a sort of information filter, attempting to forecast the user's "rating" or preferences.

A recommendation engine is a program or system that looks at user data and makes tailored recommendations for products or information that the user would find interesting. These suggestions are determined by a number of variables, including the user's preferences, past actions, demographic data, and resemblances to other users. To improve user experience and engagement, recommendation engines are frequently employed in social media, OTT platforms, e-commerce, and other online businesses. They assist users in finding new goods, publications, films, music, and other media that suit their interests.

There are mainly 6 types of the recommendations systems (Tchlabs, 2021):-

1. Popularity based systems: - It functions by suggesting highly rated products that are seen and bought by most users. It is not advice tailored to you specifically .

2. Classification model based: - To determine if a user is interested in a product or not, it analyzes the user's characteristics and uses a classification algorithm.

3. Content based recommendations:- Rather than the opinions of the users, it is based on information on the substance of the item. The basic concept is that if a consumer likes one item, they will also enjoy "other" comparable items.

4. Collaborative Filtering: - It is predicated on the idea that individuals enjoy comparable things to themselves and things that other people who share their tastes also enjoy. There are mostly two kinds: User-User a) and Item-Item b).

5. Hybrid Approaches: - This system approach combines content-based filtering, collaborative filtering, and other methods.

6. Association rule mining: - Association rules capture the relationships between items based on their patterns of co-occurrence across transactions

Findings, Conclusion, Reflection and Recommendations

Findings:

An analysis of the code presented above shows some important findings. The first point is that the data set has many user-product interactions; there are more than 2 million ratings, and over one million unique users. The collaborative filtering recommendation system in implementation involves data preprocessing such as dealing with missing values, duplicates, and product –filter based on minimum ratings. EDA also allows users to analyze the distribution of ratings and consumer preference towards different products. Correlation analysis shows that there is a positive relationship seen between average ratings and the number of ratings given to a product. The addition of the Surprise library enables collaborative filtering algortithms such as KNNWithMeans. Matrix factorization using TSVD reduces the dimensionality to enable efficient operation.

Conclusion:

Finally, the personalized recommendation system shows a process to improve user experience through e-commerce. The deployment of collaborative filtering methods, EDA and matrix factorization terms yields in producing most relevant product suggestions that are personalized. The correlation analysis emphasis importance of the average rating and number ratings when making recommendations. The Surprise library integration gives a flexible toolset for executing collaborative filtering algorithms.

Reflection:

It becomes clear from the development process that there is a careful approach to data accuracy, algorithm selection and evaluation metrics. The iterative approach for algorithm optimization and continuous improvement follows the principles of best practices when designing recommendation systems. The modular design of the code and use of external libraries helps in making it readable as well easy to maintain. On the other hand, reflections initiate for further improvements like scalability tests on large datasets and integrating more evaluation metrics for full analysis.

Recommendations:

Going forward, tests of scalability are recommended to evaluate and ensure the system's use for real-world wide traffic e-commerce platforms. Additional evaluation measures, besides MSE alone may provide a more detailed view of the quality of recommendations. Further, the incorporation of user feedback mechanisms and observation regarding system performance to adaptive changes in terms of **user's** tastes can also promote continuous adjustments. Documents and comments within the code are also going to need improvement for easier understanding among programmers. Lastly, the implementation plan of integrating recommendation systems for live e-commerce platforms needs to be investigated and improved.

Project Management

For the approach and methodology, I choose Agile and Prince2. An approach centered on processes and products is called PRINCE2. It provides "Principles," "Processes," and "Themes," which together make up the "How," "Why," and "What" of project management. Although PRINCE2 has many competitors, its emphasis on sound planning and strategic governance has made it a widely used framework. Those who even have a rudimentary understanding of PRINCE2 may contribute to project teams far more effectively so prince 2 is very effective in many companies as well (goodelearning, 2022).

PRINCE2 is a process and product-based methodology that offers an extremely strong foundation for efficient project management. Its main parts are 'Processes' (How), 'Principles'(Why) and Themes (What), which provide a structured approach. In the 'PRINCE2 vs. In this debate between Agile' both approaches have benefits, with PRINCE2 being strong in its strategic-level management and continued business justification. On the other hand, agile focuses on adaptability, small actionable steps, and timely value delivery.

The benefits of adopting PRINCE2 in the creation of a Personalized Recommendation System are several. Strategic planning is a necessity when generating recommendation algorithms, and the fact that PRINCE2 emphasizes solid plans aligns well with this need. The framework's business justification makes sure that the project is directed by its objectives and goals.

As a hybrid approach, PRINCE2 Agile integrates the detailed governance level of project management offered by PRINCE. In terms of the provided code, PRINCE2 can be implemented to enable thorough planning and management throughout various development phases. The 'Hexagon Model' in PRINCE2 Agile and includes elements such as Time, Cost. Benefits Risk Quality and Scope offers an integrated viewpoint. Time and Cost are inflexible, which is in line with the necessity for a rigid project timetable; Benefits and Risk encourage flexibility critical to moving recommendation systems.

The structured and phased approach in management of developing recommendation systems is greatly assisted by PRINCE. The defined processes and principles serve as the foundation for each predevelopment stage, which guarantees that every step is consistent with project goals. Essentially, PRINCE2 provides clarity in the chaotic characteristic of building a recommendation system; it creates control and imposes discipline over this dynamic process. This integration helps ensure that the project stays focused on business objectives, responds to environmental changes, and delivers effective personalized recommendations.

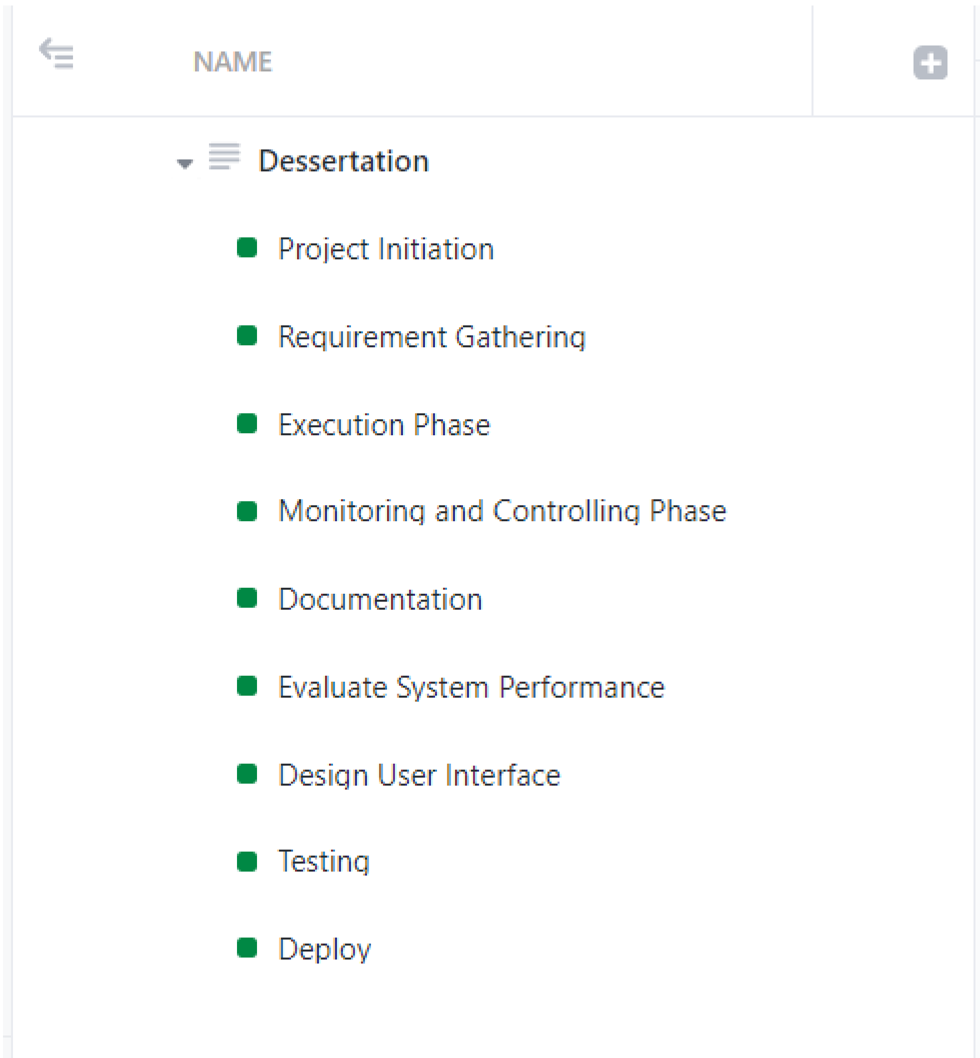


Figure 42 Project TimeLine Parameters

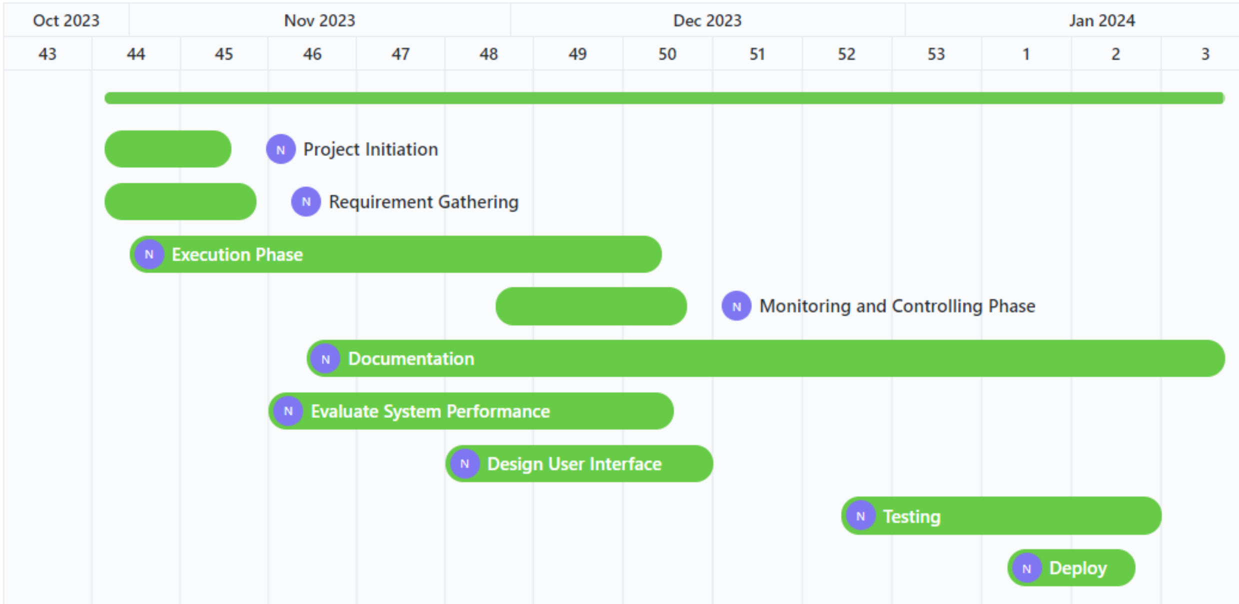


Figure 43 Product timeline from clickup

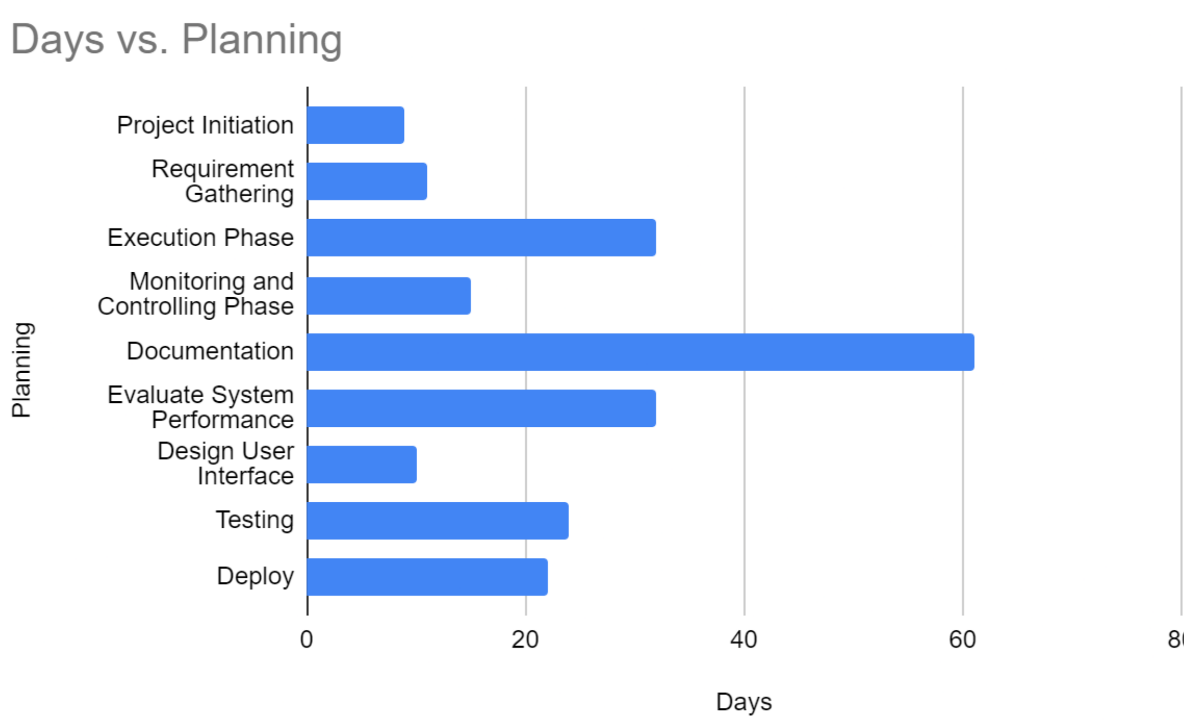


Figure 44 Days vs Planning Chart

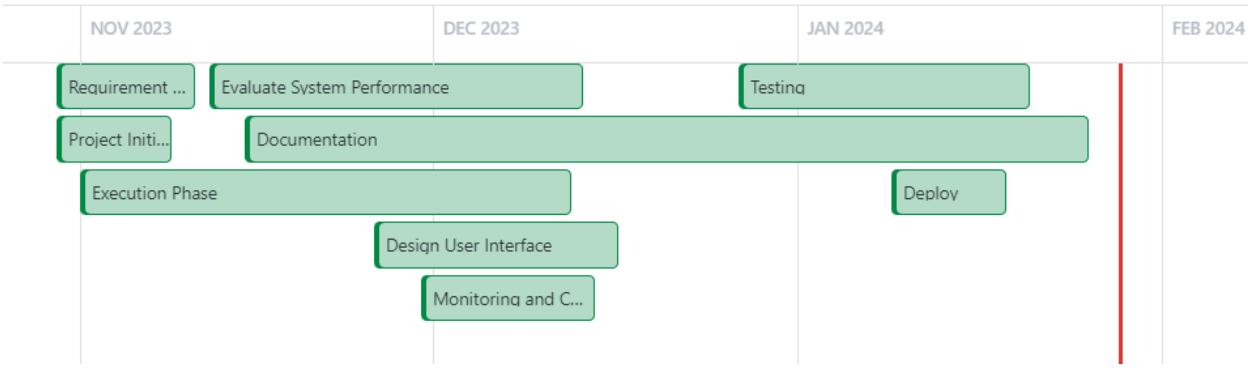


Figure 45 Month Long Planning Chart

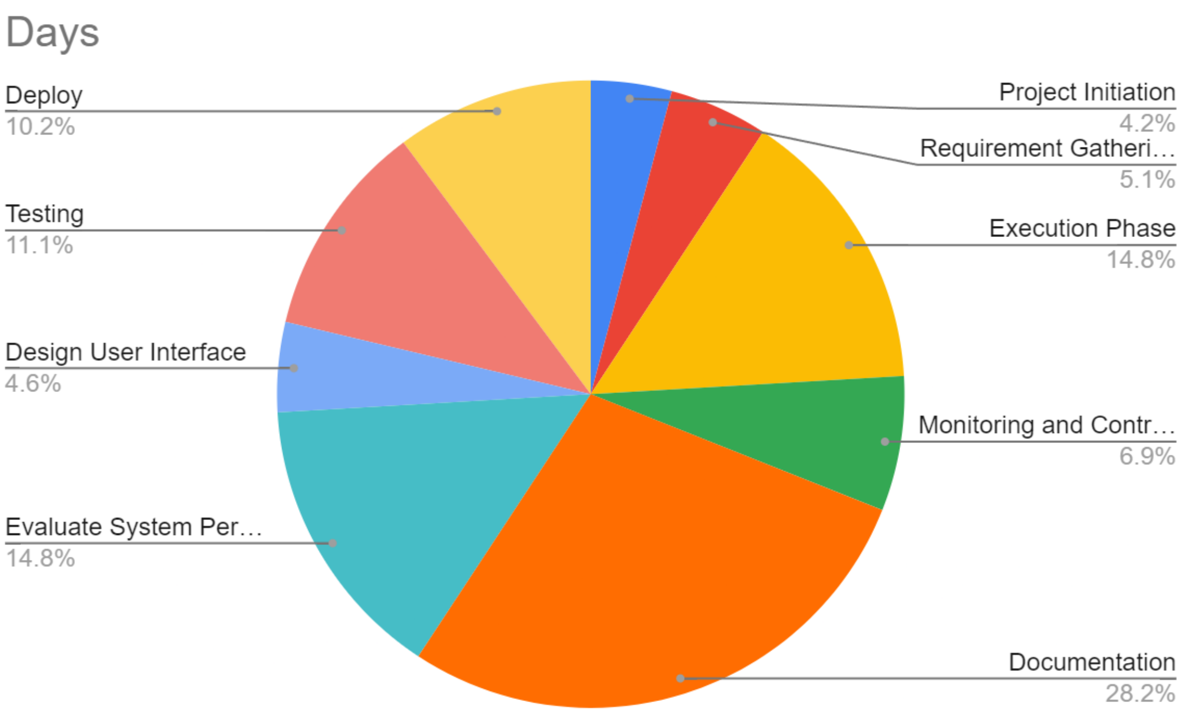


Figure 46 Pie Chart of Days Distribution of the project

Initiation Phase (10/30/23 - 11/8/23):

- *Define Project Objectives and Scope: Clearly state what the recommendation system is supposed to achieve and where it should end.*

- *Identify Stakeholders:* Identify and engage with stakeholders, including end-users and development team members.

Planning Phase (10/30/23 - 11/10/23):

- *Develop Project Plan:* Craft a comprehensive project plan that will include the tasks, dependencies, timelines, and resources involved.
- *Conduct Risk Assessment:* First, identify potential risks and determine mitigation strategies
- *Define Quality Metrics:* Set quality parameters for the recommendation system.

Execution Phase (11/1/23 - 12/12/23):

- *Data Collection and Preprocessing (11/1/23 - 12/5/23):* Collect and clean e-commerce dataset, work with missing values and make sure of good data quality.
- *Exploratory Data Analysis (12/6/23 - 12/19/23):* Perform EDA to learn about the user and product distributions, identify patterns, discover correlations.
- *User and Product Filtering (12/20/23 - 1/2/24):* Enable product filtration based on the ratings and establish a trustworthy recommendation engine.
- *Collaborative Filtering Integration (1/3/24 - 1/23/24):* Connect Surprise library, choose and implement collaborative filtering algorithms.
- *Matrix Factorization with Truncated SVD (1/24/24 - 2/13/24):* Use truncated SVD as a method of matrix factorization for dimensionality reduction that preserves necessary characteristics.

Monitoring and Controlling Phase (11/30/23 - 12/14/23):

- *Evaluation Metrics Implementation (11/30/23 - 12/13/23):* Then use evaluation metrics such as MSE for measuring the recommendation system accuracy.
- *Output Analysis and Interpretation (12/14/23 - 12/27/23):* Analyze recommendation outputs and determine how relevant they are to those of the user.

Closing Phase (11/15/23 - 1/15/24):

- *Documentation and Reporting:* Record the project process, results and make a detailed report.

- *User Interface Development (11/26/23 - 12/16/23):* Create the UI for presenting recommendations, considering diversity considerations, novelty and explain ability.

Post-Implementation Review (11/12/23 - 12/13/23):

- *Evaluate System Performance: Evaluate the performance of the recommendation system, collect user feedback for further development*.

The proposed PRINCE2 approach to project management allows for a controlled implementation of the personalized recommendation system within agreed deadlines thus facilitating its development and application.

Conclusions & Future Work

Conclusions:

In order to work towards developing a personalized product recommendation system for an e-commerce platform, several major criteria were addressed and implemented. With collaborative filtering where we used KNNWithMeans from the Surprise library, it became possible to make recommendations according to user behavior and preferences. The system managed to generate recommendations for a given product using the dataset from Amazon reviews.

The recommendation system proved useful in identifying products closely related to a given input by recommending possible items that the users might find interesting. Moreover, the collaborative filtering algorithm along with matrix factorization via Truncated Singular Value Decomposition (SVD) helped to discover latent features and patterns through user-product interactions.

Limitations:

However, it's crucial to acknowledge the limitations encountered during the project. The dataset used was a subset of the entire dataset, consisting of 7.2 million records, due to hardware limitations. This subsampling may impact the overall accuracy and generalization of the recommendation system. As a result, the system might not capture the full spectrum of user behaviors and preferences.

Future Work:

1. **Optimizing for Larger Datasets:**

- In the future, improving the system's ability to manage bigger datasets is one of the main goals. This might entail using distributed computing frameworks, parallel processing, or algorithm optimization.

2. **Scalability:**

- Scalability is needed for the recommendation system to handle an increasing volume of customers and items. We could investigate techniques like distributed databases and sharding.

3. **Real-time Recommendations:**

- Adding real-time recommendations will make the system more valuable. Stream processing may make use of technologies such as Apache Kafka or Apache Flink..

4. **Advanced Machine Learning Models:**

- Investing in more sophisticated machine learning models, including neural collaborative filtering or deep learning-based recommendation systems, may result in increased accuracy.

5. **User Engagement Metrics:**

- Including feedback systems and analytics for measuring user involvement to keep improving the recommendation algorithms based on user satisfaction and preferences.

6. **A/B Testing:**

- Using A/B testing to assess how well various recommendation algorithms work and adjust their settings for improved outcomes.

7. **Security and Privacy:**

- Addressing privacy and security issues, particularly when managing sensitive user data, to maintain legal compliance and foster user confidence..

8. **Cross-Platform Integration:**

- For a consistent user experience, the recommendation system should be smoothly integrated across all platforms (web, mobile applications).

9. **User Interface Enhancements:**

- Enhancing the recommendation system's user interface, adding user-friendly features, and giving suggestions more concise justifications.

10. **Benchmarking and Evaluation:**

- Comparing the results to the most advanced recommendation systems through extensive benchmarking, assessment, and testing using a variety of datasets..

In summary, although the existing system shows that tailored product suggestions are feasible, more work on optimization, scalability, and sophisticated algorithmic improvements will be necessary to guarantee the system's efficacy and applicability in a changing and growing e-commerce landscape.

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Appendix:

Ethical Form Stage 1:

LEEDS BECKETT UNIVERSITY

STAGE 1 - RESEARCH ETHICS APPROVAL FORM

Research by students and staff at the University must receive ethical approval before any data collection commences. Applications may be made on the Research Ethics Online system or via approval forms.

If using the approval forms, applicants complete this Stage 1 - Research Ethics Approval Form which includes the Risk Checklist.

For student projects classified as Risk Category 1 (e.g., many literature reviews), these can be approved on this Stage 1 – Research Ethics Approval Form by the Research Supervisor.

Applicants whose research studies are classified as Risk Category 2 or 3 must also complete and submit the separate Stage 2 - Research Ethics Approval Form.

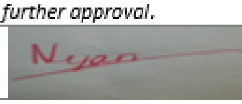
Guidance for completion of this form and the application process is provided on pages 3 and 4.

APPLICANT DETAILS	
Your name (if a group project, include all names)	Nujan Shrestha
School	The British College
STATUS	
• Undergraduate student	☐
• Taught Postgraduate student	☐
• Research Postgraduate student	☒
• Staff member	☐
• Other (give details)	
IF THIS IS A STUDENT PROJECT	
• Student ID	77359492
• Course title (eg, BA (Hons) History)	Msc IT
• Student email	snujan22@tbc.edu.np
• Research Supervisor's name Or Director of Studies' name	Dr.Mahesh Maharjan
THE PROJECT/STUDY	
Project /study title	Personalized Product Recommendation System for E-commerce using Artificial Intelligence
Start date of project	09/25/2023
Expected completion date of project	01/15/2024
Project summary – please give a brief summary of your study (maximum 100 words)	
The project aims to create a reliable stress management system using physiological data like body temperature, ECG, and EDA. The study include the use of machine learning techniques, such as SVM and Decision Trees for stress detection and a CNN-LSTM model for stress categorization. The system's goal is to give categorized stress management techniques by evaluating these signals. The initiative uses a variety of stress-reduction strategies, assesses their efficacy, and customizes recommendations based on user reactions. Users get immediate feedback on their stress levels, encouraging proactive stress management and enhancing general wellbeing.	

CONFIRMATION STATEMENTS	
The results of research should benefit society directly or by generally improving knowledge and understanding. Please tick this box to confirm that your research study has a potential benefit. *If you cannot identify a benefit you must discuss your project with your Research Supervisor to help identify one or adapt your proposal so the study will have an identifiable benefit.*	☒
Please tick this box to confirm you have read the Research Ethics Policy and the relevant sections of the Research Ethics Procedures and will adhere to these in the conduct of this project.	☒

RISK CHECKLIST - Please answer ALL the questions in each of the sections below – tick YES or NO **WILL YOUR RESEARCH STUDY……..?**		YES	NO
1	Involve direct and/or indirect contact with human participants?	☐	☒
2	Involve analysis of pre-existing data which contains personal or sensitive information not in the public domain?	☐	☒
3	Require permission or consent to conduct?	☐	☒
4	Require permission or consent to publish?	☐	☒
5	Have a risk of compromising confidentiality?	☐	☒
6	Have a risk of compromising anonymity?	☐	☒
7	Collect / contain sensitive personal data?	☐	☒
8	Contain elements which you OR your supervisor are NOT trained to conduct?	☐	☒
9	Use any information OTHER than that which is freely available in the public domain?	☐	☒
10	Involve respondents to the internet or other visual/vocal methods where participants may be identified?	☐	☒
11	Include a financial incentive to participate in the research?	☐	☒
12	Involve your own students, colleagues or employees?	☐	☒
13	Take place outside of the country where you are enrolled as a student, or for staff, outside of the UK?	☒	☐
14	Involve participants who are particularly vulnerable or at risk?	☐	☒
15	Involve any participants who are unable to give informed consent?	☐	☒
16	Involve data collection taking place BEFORE informed consent is given?	☐	☒
17	Involve any deliberate deception or covert data collection?	☐	☒
18	Involve a risk to the researcher or participants beyond that experienced in everyday life?	☐	☒
19	Cause (or could cause) physical or psychological harm or negative consequences?	☐	☒
20	Use intrusive or invasive procedures?	☐	☒
21	Involve a clinical trial?	☐	☒
22	Involve the possibility of incidental findings related to health status?	☐	☒
23	Fit into any of the following security-sensitive categories: concerns terrorist or extreme groups; commissioned by the military; commissioned under an EU security call; involves the acquisition of security clearances? If yes, see the guidance.	☐	☒

CLASSIFICATION **The following guidance will help classify the risk level of your study**	**Tick the box which applies to your project**
If you answered NO to all the above questions, your study is provisionally classified as **Risk Category 1** (literature reviews will be Risk Category 1).	☒
If you answered **YES** to any question from 1-13 and **NO** to all questions 14-22, your study is provisionally classified as **Risk Category 2.**	☐
If you answered **YES** to any question from 14-22, your study is provisionally classified as **Risk Category 3.**	☐
If question 23 has been answered **YES**, your application will be reviewed by the Chair of the University Research Ethics Sub-committee	☐

DECLARATION AND SIGNATURE/S			
I confirm that I will undertake this project as detailed above. I understand that I must abide by the terms of the approval and that I may not make any substantial amendments to the project without further approval.			
Signed		*Date*	11/04/2023

FOR RISK CATEGORY 1 STUDENT PROJECTS					
Approval from the Research Supervisor or Director of Studies for a student project: *I have discussed the ethical issues arising from the project with the student. I approve this project.*					
Name	Dr. Mahesh Maharjan	*Signed*		*Date*	11/05/2023

NEXT STEP
RISK CATEGORY 1 PROJECTS: IF YOUR PROJECT HAS BEEN CLASSIFIED AS RISK CATEGORY 1: • Students: The Research Supervisor should return the signed form to the student and send a copy to the Local Research Ethics Co-ordinator and where relevant, the Research Module Leader, for information. • Staff: Submit this form to your Local Research Ethics Co-ordinator. **RISK CATEGORY 2 OR 3 PROJECTS:** IF YOUR PROJECT HAS BEEN CLASSIFIED AS RISK CATEGORY 2 OR 3 please complete the Stage 2 - Research Ethics Approval form and submit both forms together with supporting documentation. **QUESTION 23:** If this question has been answered **YES**, your application will be reviewed by the Chair of the University Research Ethics Sub-committee, and the forms should be submitted directly to Professor Karl Spracklen, k.spracklen@leedsbeckett.ac.uk. You will need to submit the Security-sensitive research form available from the Research Ethics web page. *Research ethics application forms will be retained in the School for the purposes of quality assurance of compliance and audit for THREE years*

NOTES FOR COMPLETION

University Research Ethics Policy and Procedures: The University Research Ethics Policy and Research Ethics Procedures should be read prior to commencing this application. Consideration of the application by the reviewer/s will be undertaken in accordance with the Policy and Procedures.

External requirements for the project: Applicants should consider if there are requirements by any relevant professional, statutory or regulatory body, or learned society, which may be relevant to the project or if the project also requires external approval.

Submission

- Student applicants: email the typed form/s to your Research Supervisor or Director of Studies.
- Staff applicants: email the typed form/s to your Local Research Ethics Co-ordinator.

How to complete the form

You can navigate through the form by using the tab keys. If you prefer to complete a normal Word document, you can unlock the form by selecting the 'Restrict Editing' button on the Developer tab, then click on 'Stop Protection'. The boxes should expand to allow space for your text.

Signatures
Electronic/typed signatures are acceptable for emailed forms, as the emails provide the audit trail for all parties' agreement and approval of the forms (e.g., student applicant →Research Supervisor →Local Research Ethics Co-ordinator).

Outcome
Applicants will be advised of the outcome of the application by receipt of the signed form fromm:

- The Research Supervisor or Director of Studies for Risk Category 1 student projects;
- The Local Research Ethics Co-ordinator or the School level group for Risk Category 2 and 3 projects.

YOU MAY ONLY BEGIN ANY DATA COLLECTION ONCE YOU RECEIVE NOTIFICATION THAT THE PROJECT HAS ETHICAL APPROVAL. If the circumstances of your research study change after approval it is your responsibility to revisit the Risk Checklist and complete a further application.

Advice
When completing the Stage 1 - Research Ethics Approval Form., if you are uncertain about the answer to any question, read the relevant section of the Research Ethics Procedures document, and if you are still unsure:

- if you are student, seek guidance from your Research Supervisor or Director of Studies;
- if you are a staff member, contact your Local Research Ethics Co-ordinator.

APPROVAL PROCESS

- Local Research Ethics Co-ordinator = LREC
- School level group (if your School uses a different review process, please follow your School guidance)
- University Research Ethics Sub-Committee = URESC

Category	Student applicants	Staff applicants
Risk Category 1	If your study has been provisionally classified as Risk Category 1, your Research Supervisor (or Director of Studies) can normally give approval for the project. You must complete this form and submit it to your Research Supervisor for consideration. A copy of the signed form if approved must be given or emailed to the LREC and, where relevant, the Research Module Leader, for information.	If your study has been classified as Risk Category 1, you do not need ethical approval for the project. You must complete the remainder of this form so that your research project is registered with the University. Please submit this form to your LREC.
Risk Category 2	If your study has been provisionally classified as Risk Category 2, your Supervisor (or Director of Studies) can recommend approval for your study by the LREC. You must complete this application form and also the separate Stage 2 - Research Ethics Approval form. Once you have completed the forms please submit both forms and supporting documentation to your Research Supervisor for consideration. Your Supervisor may disagree with your assessment and ask you to make revisions or reject your application. When the Research Supervisor is happy to recommend the application for approval, they will send the forms to the LREC. The LREC will review your project and then decide to approve it, ask for revisions, reject it or pass it on for review by the School level group.	If your study has been provisionally classified as Risk Category 2, your project will be considered for ethical approval by the LREC. You must complete this application form and also the separate Stage 2 - Research Ethics Approval form. Please submit both forms and supporting documentation to your LREC for consideration. The LREC will review your project and then decide to approve it, ask for revisions or pass it on for review by the School level group.
Risk Category 3	**Postgraduate Research Students** If your study has been provisionally classified as Risk Category 3, your Supervisor or Director of Studies can recommend approval for your study by the LREC. You must complete this application form and also the separate Stage 2 - Research Ethics Approval form and submit both forms to your Director of Studies. If your Director of Studies recommends approval of your project they will refer it to the LREC who will review your project and decide whether to grant ethical approval, request revisions, reject the application or refer it to the School level group for review. **Undergraduate and Taught Postgraduate Students** If your study has been provisionally classified as Risk Category 3, you should consult with your Research Supervisor immediately as it is unlikely you will be able to proceed and you should negotiate a project that is of lower risk. However, if you have already discussed the project with your Supervisor and they have agreed that a case for approval is warranted, proceed in line with the details above for Research Students.	If your study has been provisionally classified as Risk Category 3, your project will be considered for ethical approval by an appropriate LREC. You must complete this application form and also the separate Stage 2 - Research Ethics Approval form and submit both forms with supporting documentation to your LREC. The LREC will review your project and then decide to approve it, ask for revisions or pass it on for review by the School level group.

Q23	If question 23 has been answered ´yes´, your application will be reviewed by the Chair of the University Research Ethics Sub-committee. The answer does not affect the Risk Category.

Ethical Form Stage 2:

LEEDS BECKETT UNIVERSITY

STAGE 2 - RESEARCH ETHICS APPROVAL FORM

All research carried out by students and staff at the University must receive ethical approval before any data collection commences.

Notes

- Applicants complete the Risk Checklist and Stage 1 - Research Ethics Approval Form prior to completing this Stage 2 - Research Ethics Approval Form. Following completion of the Risk Checklist and Stage 1 - Research Ethics Approval Form, if your research study was provisionally classified as Risk Category 2 or 3, you need to complete this form.
- Full details of the project are to be provided in this Stage 2. Where a question in the Risk Checklist was answered YES, please ensure that specific details are included in the appropriate box below.
- If a question does not apply to your project, insert 'Not applicable' or N/A.
- Help is provided for each question. Further help can be found in the Research Ethics Procedures document.
- You navigate through the form by using the tab keys. If you prefer to complete a normal Word document, you can unlock the form by selecting the 'Restrict Editing' button on the Developer tab, then click on 'Stop Protection'. The boxes should expand to allow space for your text.
- Spellchecking is not available in Word forms, so you may find it helpful to prepare your responses in a Word document and then copy these to this form.
- Ensure the form is completed in sufficient detail to allow the reviewer to judge the ethical issues raised by the study. Remember that the reviewer will be considering the following questions when reviewing your application in order to be able to give ethical approval:
  - is it ethical to conduct the research project and is the proposed method of investigation appropriate, thorough and ethical?
  - does the research project meet the requirements of the relevant Research Ethics Principles (Research Ethics Policy A2.4)?

TO BE COMPLETED FOR PROJECTS IN RISK CATEGORY 2 AND 3	
Your name	Nujan Shrestha
Project title	Personalized Product Recommendation System for E-commerce using Artificial Intelligence

1	**Project Overview**
Please give a brief overview of your study, including a summary of your aims and objectives. Help: Describe the purpose of the research and what question(s) the project should answer.	
Imagine a revolutionary solution called the "Personalized Product Recommendation System for E-commerce using Artificial Intelligence" changing the game of online shopping. Through cutting-edge AI algorithms, this system has the ability to tailor product recommendations to each user's unique preferences. By incorporating popular trends and collaborative filtering techniques, including both memory-based and model-based approaches, the system guarantees a wide range of accurate suggestions. The addition of advanced machine learning elevates prediction accuracy. Ethical considerations, such as user privacy and fairness, are highly valued in the system while it remains flexible and adaptable to cater to a diverse user base. Ultimately, users can enjoy a highly personalized and trend-savvy shopping experience, eliminating decision fatigue and ensuring complete satisfaction, less fatigue and ensuring data privacy. As we delve into this innovative solution, consider these questions: 1. How does the system balance personalization and staying up-to-date with market trends?	

2. What are the key features of the collaborative filtering techniques employed in the recommendation system?
3. How does the integration of advanced machine learning techniques contribute to the accuracy of product predictions?
4. What ethical considerations and measures have been implemented to ensure user privacy and fair recommendations?

2	Methodology

Please give a description of your methodology, including any data collection and analysis methods.
Help: Give an outline of your study here. If the project is complex, you can also submit your research proposal/protocol (no more than 2-3 A4 sides) if this would help the reviewer's understanding of the project. Include details of your (or your Research Supervisor's) appropriate skills and qualifications to carry out this research.

At the core of our strategy for developing the "Personalized Product Recommendation System for E-commerce using Artificial Intelligence" is a comprehensive approach that focuses on both data collection and analysis. During the data collection phase, we carefully gather extensive user interaction data, including details such as product views, searches, purchases, and feedback, along with valuable demographic information and in-depth product metadata. Rest assured, we take stringent measures to uphold ethical standards and protect user privacy. Moving to data analysis, our methodology involves conducting exploratory studies to grasp user patterns and behaviors. Leveraging both memory-based and model-based collaborative filtering techniques, we analyze the complex user-item interactions. In addition, we utilize popularity trends and machine learning algorithms to boost predictive accuracy. To gauge our system's effectiveness, we utilize precision as one of our primary evaluation metrics.

3	Main Ethical Considerations

Please give a brief description of the main ethical considerations involved in the study.
Help: All research projects will have ethical issues, and you will be asked later in the process on recruitment, voluntary participation and the right to withdraw, but highlight here the main ethical considerations for your study (which may concern, e.g., the type of participants, the sensitive nature of the study, the data collection process, a lone researcher carrying out research off-campus, security-sensitive research) and advise how you will address the main issues. If the project is funded, give details here, and whether there are any potential conflicts of interest involved in the study.

Ensuring the highest standards of ethical conduct is paramount in the development of our "Personalized Product Recommendation System for E-commerce using Artificial Intelligence." We are committed to safeguarding user privacy by implementing robust measures to anonymize and secure personal data. Transparency in data practices is maintained, providing users with clear insights into how their information is utilized. To mitigate biases, our system undergoes continuous scrutiny to ensure fairness and equity in recommendations. Users have the autonomy to control their privacy settings, fostering a sense of trust and transparency. Additionally, our adherence to ethical guidelines extends to the responsible collection and use of user feedback, allowing for an ongoing dialogue that shapes the system's ethical framework. This unwavering commitment to ethical considerations forms the foundation of a recommendation system that prioritizes user trust, privacy, and fairness.

4	Human Participants

If your study includes Human Participants (or their data), please give a description of who will be included.

Help:

- Please note this should include sample size/number of participants, whether the project will focus on any particular groups/individuals, if it will include any at risk or vulnerable participants, participants aged 16 years or under, etc. Please also specify your rationale for including / excluding groups of participants.
- If the research involves secondary data not in the public domain, give details in this section.

5	Recruitment, Voluntary Participation, Consent and Right to Withdraw

If your study includes Human Participants, please give a brief description of the recruitment process, how you will ensure voluntary participation, if (and how) informed consent will be obtained prior to participants taking part in the study, and the right of withdrawal from the research process.

Help:

- This should include clear information on how participants will be identified, approached and recruited; whether the study will include any covert research or deliberate deception; whether help is required from a third party/ gatekeeper to access participants; what information you will give participants, etc.
- If expenses or any incentives are to be offered to participants, give full details.
- If your research involves students, colleagues and/or other employees then you must specify the rationale for this and how you will address issues of coercion or feelings of obligation.
- Regarding withdrawal from the study, discuss the different stages/dates a participant could withdraw or withdraw their data, and how they could do this.

6	Risks and Benefits
Please give a brief description of how, when and where the research will take place and whether there are any risks and/or benefits involved. Help: • This should include information on what participants will be required to do, the rationale for this and the level of risk involved. • When considering risks, please refer to risks to the participants (e.g., for research in sensitive areas), the researcher, any other parties to the research; and also any health and safety issues for anyone involved (e.g., for lone researchers carrying out fieldwork). • If participants will be exposed to ionising radiation, separate approval documentation must be submitted with this application.	

7	Personal Data, Anonymity and Confidentiality
Please specify what type of information/data will be collected/analysed and the source(s). In addition, specify if and how you will ensure the anonymity of participants and keep information confidential. Help: This should include information on whether you are collecting new information/data or using that that is already in the public domain; whether the data you are using includes personal details; how the data will be processed and stored; who will have access to it; how and when it will be destroyed; the Data Protection requirements for any sensitive personal data, etc. In addition, include whether there may be any requirements for disclosure of information to other parties due to professional practice or legal reasons. If there are limits to confidentiality, explain clearly how the participants would be advised about these limits and possible outcomes.	

8	Reporting and Dissemination
Please give details of the planned dissemination and specify if the findings from the research will be published and whether any permission is required for this. Help: This should include information on the methods of dissemination (e.g., dissertation/thesis) and/or what will be published and where (research papers, conference presentations). Specify if any permission is needed (e.g., from participants, clients, gatekeepers, etc.) prior to publication, and whether there are any potential issues relating to Intellectual Property Rights when creating or using materials.	

9	Location of research
Will the research take place outside of the country where you are enrolled as a student, or for staff, outside of the UK?	
YES ☐ NO ☒ **If yes, give details below.** Help: If yes, please specify where the research will take place and what will be involved. Research must comply with the laws of the country where it is taking place and also comply with local Data Protection and Intellectual Property legislation: you must confirm that your research is compliant with local requirements and how you have ascertained this. Advise if the project requires ethical approval in-country and how this has been ascertained. If approval is required, a copy of this should be included in the application or details of the process of how it will be obtained. Please make reference to insurance and indemnity cover for the project where relevant.	

10	Collaborative Projects
Is the research is a collaborative project (i.e., it involves more than one institution)?	
YES ☐ NO ☒ **If yes, give details below.** Help: If yes, please specify the other institutions involved and if ethical approval needs to be / has been given by them. Please also specify what procedures have been put in place to ensure ethical compliance from all partners.	

11	Any other permission or external ethical approval required to undertake the project

Please specify if the project requires any other ethical approval or permissions not mentioned previously in this application and how and when these will be obtained.

Help:

- Other permissions: ethical approval does not give the right of access to the University's students, staff or the use of University premises to carry out research, and you may need to contact an appropriate University gatekeeper for agreement to approach potential participants or for the use of premises, so please give details.
- Gatekeepers: permission of a gatekeeper for initial access to participants may be required or to carry out data collection on their premises.
- If your project requires approval from an external ethics committee, this should normally be obtained prior to submitting this application.
- If a Disclosure and Barring Service check is required due to the specific participant group, give details.
- Regarding insurance and indemnity cover, some projects will require individual confirmation of cover. See the Research Ethics Procedures document for more details.

FOR PROJECTS INVOLVING RISK CATEGORY 2 AND 3: DECLARATION AND SIGNATURE/S			
APPLICANT (STUDENT/STAFF MEMBER/RESEARCHER)			
I confirm that I will undertake this project as detailed in stage one and stage two of the application. I understand that I must abide by the terms of this approval and that I may not make any substantial amendments to the project without further approval. I understand that research with human participants or their data must not commence without ethical approval.			
I have read an appropriate professional or learned society code of ethical practice:		Yes ☐ N/A☐	
Where applicable, give the name of the professional or learned society:			
Signed		*Date*	

RESEARCH SUPERVISOR/DIRECTOR OF STUDIES RECOMMENDATION FOR STUDENT PROJECTS					
I confirm that I have read stage one and stage two of the application. The project is viable and the student has appropriate skills to undertake the project. Where applicable, the Participant Information Sheet and recruitment procedures for obtaining informed consent are appropriate and the ethical issues arising from the project have been addressed in the application. I understand that research with human participants must not commence without ethical approval. I recommend this project for approval.					
Name		*Signed*		*Date*	

Local Research Ethics Co-ordinators

Please complete *EITHER* **A** *(giving ethical approval for the project)* *OR* **B** *(recommending the project to the School level group for approval)*

A	**LOCAL RESEARCH ETHICS CO-ORDINATOR APPROVAL** *For projects approved by the Local Research Ethics Co-ordinator*				
I confirm ethical approval for this project					
LREC Name		*Signed*		*Date*	

OR

B	**LOCAL RESEARCH ETHICS CO-ORDINATOR'S RECOMMENDATION FOR SCHOOL APPROVAL** *For projects that require School level approval*				
I recommend this project for consideration at school level. It cannot be approved at local level due to the following reason(s)					
LREC Name		*Signed*		*Date*	

School level group

For projects approved at School level please complete the box below.

PROJECTS APPROVED BY THE SCHOOL LEVEL GROUP					
I confirm that this project was considered by the School level group and has received ethical approval					
Group Lead		*Signed*		*Date*	

OR

University Research Ethics Sub-Committee

For projects approved by URESC please complete the box below.

Projects involving security-sensitive research do not need supervisor/LREC approval prior to being considered by the Chair of URESC.

PROJECTS APPROVED BY THE RESEARCH ETHICS SUB-COMMITTEE					
I confirm that this project was considered by the Research Ethics Sub-committee and has received ethical approval					
Chair		*Signed*		*Date*	

This form will be retained for the purposes of quality assurance of compliance and audit for THREE years

SUPPORTING DOCUMENTATION: what to submit with the application

For projects involving human participants, you must submit, where appropriate, the Participant Information Sheet/s and consent form/s. You must also submit every communication a participant will see or receive. Failure to do so will cause delays to the application.

Below is a checklist reminder of what could be submitted, depending on the research project. Please tick the appropriate boxes for each attachment or give details of the document at the end of the checklist.

SUBMISSION CHECKLIST	Tick box
RISK CHECKLIST AND STAGE 1 – RESEARCH ETHICS APPROVAL FORM	☐
STAGE 2 – RESEARCH ETHICS APPROVAL FORM	☐
Participant Information Sheet(s)	☐
Consent Form(s)	☐
Assent Form (usually for children participants)	☐
Recruitment documents *eg, posters, flyers, advertisements, email invitations, letters, web pages if online research*	☐
Measures to be used *eg, questionnaires, surveys, interview schedules, psychological tests*	☐
Screening questionnaire	☐
Letters/communications to and from gatekeepers/third parties	☐
Evidence of any other approvals or permissions *eg, NHS research ethics approval, in-country approval*	☐
Research proposal/protocol (no more than 2-3 A4 pages) *It is not a requirement that this is included, however, if this would help the understanding of a complex project by the reviewer(s), please include*	☐
Risk assessment form *Some projects may require a risk assessment form: see the Procedures document for details (eg, projects involving a physical intervention, collecting data off-campus)*	☐
Approval documentation for projects involving ionising radiation	☐
Confirmation of insurance and indemnity cover where relevant *Some projects need to be referred to the Insurance & Risk Officer: see the Procedures document*	☐
Security-sensitive research form	☐
Other: give details here:	☐
	☐

SUBMITTING YOUR FORMS

- Students: email the typed forms (stage one and stage two) and supporting documentation to your Research Supervisor or Director of Studies.
- Staff: email the typed forms (stage one and stage two) and supporting documentation to your Local Research Ethics Co-ordinator.
- Security-sensitive research: the stage one form (and stage two form if applicable) should be submitted directly to the URESC Chair, Professor Karl Spracklen, k.spracklen@leedsbeckett.ac.uk and include the Security-sensitive research form, available from the Research Ethics web page.

Meeting Logs:

School of Computing, Creative Technologies and Engineering 2022/23 **Level 7 Dissertation**			
MEETING RECORD SHEET:			**Meeting Number:1**
Student: Nujan Shrestha		**Student I.D.: 77359492**	
Date of Meeting: 3rd November,2023		**Supervisor: Dr. Mahesh Maharjan**	
Actions agreed at previous meeting (completed or comment):			
1	**NA** ☐		
Comments of student (if any): **First Meeting Topic Discussion. And Ethical Form Discussion.**			
ABOVE here *– student to complete before Meeting with supervisor.* ***BELOW here*** *– complete at the Meeting.*			
Next meeting (date/time):**3rd Nov 2023 7:30 pm to 9:00 pm**			
Agreed Actions to complete before next meeting:			
1	**Prepare to submit Ethical Consideration form**		
2	**Select a dataset to work on and methods to use**		
Comments of supervisor (if any):			

School of Computing, Creative Technologies and Engineering 2022/23 **Level 7 Dissertation**		
MEETING RECORD SHEET:		**Meeting Number:2**
Student: Nujan Shrestha	**Student I.D.: 77359492**	
Date of Meeting: 21st Nov, 2023	**Supervisor: Dr. Mahesh Maharjan**	
Actions agreed at previous meeting (completed or comment):		
1	**Submit Ethical Consideration form**	
2	**Select a dataset to work on and methods to use**	
Comments of student (if any):		
ABOVE here *– student to complete before Meeting with supervisor.* ***BELOW here*** *– complete at the Meeting.*		
Next meeting (date/time):**28th Nov 2023 7:30 pm to 9:00 pm**		
Agreed Actions to complete before next meeting:		
1	**Prepare the literature review.**	
2		
Comments of supervisor (if any):		

School of Computing, Creative Technologies and Engineering 2022/23 **Level 7 Dissertation**		
MEETING RECORD SHEET:		**Meeting Number:3**
Student: Nujan Shrestha	**Student I.D.: 77359492**	
Date of Meeting: 4th Nov, 2023	**Supervisor: Dr. Mahesh Maharjan**	
Actions agreed at previous meeting (completed or comment):		
1	**Prepared the literature review on major topics.**	
Comments of student (if any): **I started reading researching on more articles for literature review.**		
ABOVE here *– student to complete before Meeting with supervisor.* ***BELOW here*** *– complete at the Meeting.*		
Next meeting (date/time)**:21st Nov 2023 7:30 pm to 9:00 pm**		
Agreed Actions to complete before next meeting:		
1	**Start reading papers for literature review.**	
2		
Comments of supervisor (if any):		

School of Computing, Creative Technologies and Engineering 2022/23 **Level 7 Dissertation**		
MEETING RECORD SHEET:		**Meeting Number:4**
Student: Prabun Koirala	**Student I.D.: 77359492**	
Date of Meeting: 21st Nov, 2023	**Supervisor: Dr. Mahesh Maharjan**	
Actions agreed at previous meeting (completed or comment):		
1	**Start reading different literatures for review.**	
Comments of student (if any): **Literature review for research topic was discussed and details required to add on were discussed.**		
ABOVE here *– student to complete before Meeting with supervisor.* ***BELOW here*** *– complete at the Meeting.*		
Next meeting (date/time)**:10th Dec 2023 7:30 pm to 9:00 pm**		
Agreed Actions to complete before next meeting:		
1	**Decided on the Methods to use**	
2		
Comments of supervisor (if any):		

School of Computing, Creative Technologies and Engineering 2022/23 **Level 7 Dissertation**		
MEETING RECORD SHEET:		**Meeting Number:5**
Student: Nujan Shrestha	**Student I.D.: 77359492**	
Date of Meeting: 14th Dec, 2023	**Supervisor: Dr. Mahesh Maharjan**	
Actions agreed at previous meeting (completed or comment):		
1	**Decided on the Methods to use**	
2		
Comments of student (if any): **Different literatures reviews were discussed.**		
ABOVE here *– student to complete before Meeting with supervisor.* ***BELOW here*** *– complete at the Meeting.*		
Next meeting (date/time)**:5th January 2023 7:30 pm to 9:00 pm**		
Agreed Actions to complete before next meeting:		
1	**Complete Literature Review**	
2		
Comments of supervisor (if any):		

School of Computing, Creative Technologies and Engineering 2022/23 **Level 7 Dissertation**	
MEETING RECORD SHEET:	**Meeting Number:6**
Student: Nujan Shrestha	**Student I.D.: 77359492**
Date of Meeting: 12th Dec, 2023	**Supervisor: Dr. Mahesh Maharjan**
Actions agreed at previous meeting (completed or comment):	
1	**Complete Literature Review**
Comments of student (if any): **Started working on Methodology.**	
ABOVE here *– student to complete before Meeting with supervisor.* ***BELOW here*** *– complete at the Meeting.*	
Next meeting (date/time)**:14th Dec 2023 7:30 pm to 9:00 pm**	
Agreed Actions to complete before next meeting:	
1	**Continue with the technical Implementation of the project**
2	
Comments of supervisor (if any):	

School of Computing, Creative Technologies and Engineering 2022/23 **Level 7 Dissertation**		
MEETING RECORD SHEET:		**Meeting Number:7**
Student: Nujan Shrestha	**Student I.D.: 77359492**	
Date of Meeting: 14th Dec, 2023	**Supervisor: Dr. Mahesh Maharjan**	
Actions agreed at previous meeting (completed or comment):		
1	**Continue the technical Implementation for the project**	
2		
Comments of student (if any): **Technical Implementation for the project and coding began.**		
ABOVE here *– student to complete before Meeting with supervisor.* ***BELOW here*** *– complete at the Meeting.*		
Next meeting (date/time)**:31st Dec 2023 7:30 pm to 9:00 pm**		
Agreed Actions to complete before next meeting:		
1	**Continue with the technical Implementation of the project**	
2		
Comments of supervisor (if any):		

School of Computing, Creative Technologies and Engineering 2022/23 **Level 7 Dissertation**		
MEETING RECORD SHEET:		**Meeting Number:8**
Student: Nujan Shrestha	**Student I.D.: 77359492**	
Date of Meeting: 31st Dec, 2023	**Supervisor: Dr. Mahesh Maharjan**	
Actions agreed at previous meeting (completed or comment):		
1	**Continue the technical Implementation for the project**	
2		
Comments of student (if any): **The technical implementation was completed.**		
ABOVE here *– student to complete before Meeting with supervisor.* ***BELOW here*** *– complete at the Meeting.*		
Next meeting (date/time)**:7th Jan 2024 7:30 pm to 9:00 pm**		
Agreed Actions to complete before next meeting:		
1	**Prepare poster and documentation for thesis**	
2		
Comments of supervisor (if any):		

School of Computing, Creative Technologies and Engineering 2022/23 **Level 7 Dissertation**		
MEETING RECORD SHEET:		**Meeting Number:9**
Student: Nujan Shrestha	**Student I.D.: 77359492**	
Date of Meeting: 7th Jan, 2024	**Supervisor: Dr. Mahesh Maharjan**	
Actions agreed at previous meeting (completed or comment):		
1	**Prepare Poster and documentation for thesis**	
2		
Comments of student (if any): **Research Outcome was discussed.**		
ABOVE here *– student to complete before Meeting with supervisor.* ***BELOW here*** *– complete at the Meeting.*		
Next meeting (date/time)**:16th Jan 2024 7:30 pm to 9:00 pm**		
Agreed Actions to complete before next meeting:		
1	**Complete Conclusion**	
2	**Start preparing for Poster Presentation**	
Comments of supervisor (if any):		

School of Computing, Creative Technologies and Engineering 2022/23 **Level 7 Dissertation**		
MEETING RECORD SHEET:		**Meeting Number:10**
Student: Nujan Shrestha	**Student I.D.: 77359492**	
Date of Meeting: 16th Jan, 2024	**Supervisor: Dr. Mahesh Maharjan**	
Actions agreed at previous meeting (completed or comment):		
1	**Complete Conclusion**	
2	**Start preparing for Poster Presentation**	
Comments of student (if any): **Conclusion was completed and poster sample was discussed.**		
ABOVE here *– student to complete before Meeting with supervisor.* ***BELOW here*** *– complete at the Meeting.*		
Next meeting (date/time)**:23rd Jan 2024 7:30 pm to 9:00 pm**		
Agreed Actions to complete before next meeting:		
Comments of supervisor (if any):		

Product Link:

GitHub Link: