Analysing the Role of AI-powered Recommender Systems in Enhancing Customer Engagement in Online Marketplaces: Developing A Product Recommendation System

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Erdal Ozcelik
Student ID: x22203184

School of Computing
National College of Ireland

Supervisor: VICTOR DEL ROSAL

National College of Ireland
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School of Computing

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Student ID:	x22203184
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Erdal Ozcelik
x22203184

Abstract

The objective of this research project is to examine the influence of AI-driven recommender systems on customer engagement in online marketplaces. The primary focus lies on collaborative filtering methods and hybrid recommender systems, which seamlessly integrate collaborative filtering with natural language processing techniques. Utilizing the Amazon Sales Dataset sourced from Kaggle, the study endeavours to construct and analyse these recommendation systems. The project also conducts a survey to evaluate the effectiveness of these systems, using criteria such as relevance, diversity, satisfaction, and visual appeal. In addition to the technical aspects, delving into the broader implications of AI-powered Recommender Systems on customer engagement. This is achieved through a comprehensive review of related works and literature, exploring their functionality, principles, and impact on customer loyalty. Moreover, the research identifies the key factors contributing to the effectiveness of these systems while also addressing associated ethical issues. In essence, this project provides a comprehensive exploration of AI-driven recommender systems, their construction, evaluation, and broader implications within the context of online marketplaces.

Keywords: *AI-powered recommender systems, Collaborative filtering, Natural language processing (NLP), Customer engagement, Online marketplaces, Personalised recommendations*

1 Introduction

Effective product recommendation systems hold immense importance in the ever-changing world of online marketplaces. These systems play a crucial role in enhancing user experience and engagement by offering personalized and relevant product recommendations. As consumers navigate a wide range of options, an advanced recommender system acts as a helpful guide, assisting users in finding products that align with their preferences. The rise of artificial intelligence has transformed these systems, enabling a deeper understanding of user behaviours and preferences. Major online market platforms like Amazon rely on AI-powered recommendation engines that utilize sophisticated algorithms and predictive analytics to enhance customer customer satisfaction and boost sales.(Rane;

2023). These engines not only enhance the precision of product recommendations but also overcome challenges such as limited data availability for new users who lack historical interaction data. Integrating AI into these systems has strengthened the connection between consumers and the products they seek. By analyzing user-item interactions and employing predictive behavioural models, these AI-enhanced systems refine the shopping experience by providing well-informed recommendations. Continuous advancements in AI technology are revolutionizing personalized shopping across diverse online marketplaces.

The objective of this research project is to gain insights into how AI-powered recommender systems impact customer engagement in marketplaces. The aim is to understand their role in understanding and predicting customer preferences and behaviours to improve the overall customer experience. The research will employ a methodology that involves examining pertinent academic literature and reliable sources in the areas of AI technologies, customer interactions and ethical aspects of e-commerce. As part of this research project, two types of product recommendation systems will be developed: a collaborative filtering system and a hybrid system that combines collaborative filtering with natural language processing (NLP).

These systems will use intelligence techniques to identify users' product preferences and behaviours. The system will generate recommendations tailored to their interests and needs by examining users' past shopping data and product reviews. The system's performance will be evaluated using selected metrics such as relevance, diversity, satisfaction, and visual appeal. The findings from this research project are significant for businesses operating in the e-commerce industry. Understanding how AI-driven recommender systems impact customer engagement, while also addressing concerns related to their use, is crucial for companies aiming to build customer loyalty and enhance interactions in the marketplace. To achieve success, in the evolving world of data-driven and customer-centric e-commerce businesses can position themselves by providing product recommendations while upholding ethical standards. The purpose of this study is to offer insights that can assist businesses in attaining these goals.

This study explores the principles of recommender systems powered by artificial intelligence. It examines the factors that contribute to their effectiveness, in enhancing customer engagement on marketplaces as well as the ethical concerns surrounding these systems. The research methodology will be explained in Section 3 while Section 4 provides an analysis of the design elements of the product recommendation systems developed for this project. The implementation of the study is discussed in Section 5 and Chapter 6 presents the evaluation results and conducts a discussion of these findings. The conclusions drawn from the research are summarized in Chapter 7 and potential areas, for study and research directions are considered as part of concluding this project.

2 Related Work

Recommender systems are software applications that offer personalized suggestions, to users based on their preferences and needs. They find applications in domains like e-commerce, entertainment, education, health, and tourism. By providing tailored recommendations these systems can enhance user experience boost customer satisfaction and loyalty improve business performance and revenue and promote welfare and innovation. However, recommender systems encounter challenges and limitations. These include issues related to the quality and availability of data, the complexity and scalability of algorithms used, the validity and reliability of evaluation methods employed, as well as the ethical responsibilities and accountability associated with their use. AI-powered recommender systems have the advantage of utilizing scale data sets while learning from complex user behaviours to provide more intelligent and interactive recommendations. The purpose of this literature review is to examine existing research on AI-powered recommender systems focusing on aspects such as customer loyalty, effectiveness measures and ethical considerations.

The literature review is organized as follows: Section 2.1 reviews the basic concepts and methodologies of recommender systems, as well as the recent advances and trends in AI-based approaches. Section 2.2 discusses the relationship between recommender systems and customer loyalty, and reviews some of the existing studies and models that measure and improve customer loyalty using recommender systems. Section 2.3 examines the effectiveness of recommender systems, and reviews some of the existing studies and metrics that evaluate the effectiveness of recommender systems, as well as the trade-offs and challenges involved. Section 2.4 explores the ethical challenges and implications of recommender systems, and reviews some of the existing studies and frameworks that address the ethical issues of recommender systems. Section 2.5 wraps up the literature review and provides a summary for the discussion of the literature review.

2.1 Functionality and working principles of AI-powered Recommender Systems

Recommender systems, powered by artificial intelligence have become tools, in various fields providing personalized recommendations based on individual preferences(Burke; 2002). This section offers an overview of the principles of recent advancements and the transformative impact of AI techniques on recommender systems. These systems can be categorized into content-based, collaborative filtering and hybrid approaches all playing a role in delivering relevant content to users(Melville and Sindhwani; 2010). By considering user feedback and distinguishing between implicit feedback systems it can be better to understand the landscape of recommender systems.

In recent times, AI has led to progress in enhancing recommender systems. Deep learning is an AI technique that utilizes networks to extract meaningful features and model intricate relationships between users and items(Mu; 2018). Various architectures such, as autoencoders, convolutional neural networks (CNNs) recurrent neural networks (RNNs) attention networks and generative adversarial networks (GANs) have further improved the capabilities of recommender systems(Wu et al.; 2020). Reinforcement learning has given these systems the ability to improve long-term objectives by adapting to user feedback and effectively navigating unpredictable user item environments (Zhao et al.; 2018).

While AI-powered recommender systems show promising results in various fields, they also bring about challenges and potential risks. Essential factors to consider include data privacy and security, transparency and explainability of algorithms, user autonomy and agency social bias and manipulation, ethical content, and responsibility. Giving thought to the implications of AI-powered recommender systems is crucial. It calls for an examination of how they impact customer loyalty, effectiveness, and ethical considerations.

2.2 Impact of AI-powered Recommender Systems on Customer Loyalty

Customer loyalty, an aspect, in the world of e-commerce refers to the willingness of users to consistently support a brand(Keller; 1993). In this section, it investigates the relationship between recommender systems and customer loyalty by analysing the factors affecting user loyalty. By reviewing existing studies and models, it explores efforts to measure and strengthen customer loyalty through the use of recommender systems.

One key focus of this exploration is trust and personalization as elements that shape customer loyalty within recommender systems(Ebrahimi et al.; 2019). Trust is defined as users' confidence in the reliability and competence of the system(O'Donovan and Smyth; 2005). It plays a role in determining customer satisfaction and retention. Therefore, it becomes essential for recommender systems to strike a balance between providing recommendations and respecting the user's autonomy, in decision-making. This ensures that trust is fostered rather than compromised. Trust plays a role, in building customer loyalty especially when it comes to recommender systems. Users' trust in the reliability, honesty and competence of these systems greatly affects their satisfaction, acceptance, and willingness to share information. Privacy concerns are significant. Highlight the importance of recommender systems to provide explanations about how recommendations are generated and give users control over their preferences and profiles.

One crucial aspect of this discussion is personalization – how recommender systems tailor suggestions based on user needs, interests, and preferences. Given the changing nature of customer preferences, it is essential for recommender systems to offer personalization that adapts to evolving user needs over time(Adomavicius et al.; 2008). Striking this balance is key to securing and enhancing customer loyalty.

Ultimately recommender systems have an impact on cultivating customer loyalty by providing relevant product suggestions. Customer loyalty serves as an indicator of user satisfaction and retention while also influencing the relationship, between users and brands. However, the ethical aspects of recommendation systems as discussed in sections call for an examination of methods to ensure that fostering customer loyalty is, in line, with empowering users and considering ethical factors.

2.3 Key Factors Contributing to the Effectiveness of AI-powered Recommender Systems

The main goal of recommender systems is to be effective, in helping users make decisions when faced with a range of choices. Evaluating this effectiveness involves studying research and metrics that measure how well recommender systems perform. Metrics like accuracy, precision, recall, F1 score, mean absolute error, root mean square error, normalized discounted gain and diversity are used to assess aspects of quality and performance(Sinha and Dhanalakshmi; 2022). These metrics highlight the need for evaluation criteria when assessing recommender systems.

However, measuring the effectiveness of recommender systems is complex. Requires dealing with trade-offs and challenges(Adomavicius and Kwon; 2008). Systems that prioritize accuracy may unintentionally recommend similar items. On the other hand, systems that focus on diversity may compromise accuracy or user satisfaction. Another balance to consider is, between personalization and generalization.

Customized systems designed to meet the requirements of each user might face difficulties due to either overfitting or inadequate data. On the other hand, relying on average user behaviour may not be able to account for the distinct contexts of individual users. The effectiveness of recommender systems is influenced by challenges such as data sparsity, cold start and popularity bias. Data sparsity refers to the lack or incompleteness of data, which can hinder reliable recommendations. Cold start scenarios occur when recommendations are needed for users or items with data posing another challenge(Sinha and Dhanalakshmi; 2022). Popularity bias adds complexity by favouring items over valuable but less recognized ones due to skewed distributions of user interactions among items.

In conclusion, the effectiveness of recommender systems is a concept that depends on factors such as employed metrics, trade-offs made during development and challenges faced. To truly improve and maximize effectiveness it is crucial to take a holistic approach that considers the needs, preferences, behaviours, feedback, and context of users. The research and measurements mentioned in this section highlight how recommender systems are constantly evolving and the continuous endeavours to enhance their effectiveness across applications.

2.4 Ethical Concerns in AI-powered Recommender Systems

Recommender systems, which are deeply integrated into domains bring up concerns that require careful examination. Privacy, being of importance revolves around users having control, over their data and protection against unauthorized access(Ohm; 2009). Recommender systems often rely on user data, which poses privacy risks. Transparency and explainability are crucial for building user trust; however, recommender systems sometimes fall short in these areas, which may affect user autonomy. As recommender systems influence user decisions, concerns about autonomy arise due to biases and the creation of filter bubbles that limit exposure to diverse perspectives (Pariser; 2011).

Furthermore, recommender systems must address issues of bias where existing prejudices in data or algorithms can perpetuate discrimination(Barocas and Selbst; 2016). The fairness and inclusivity of recommendations play a role as biases could marginalize user groups(Bostrom and Yudkowsky; 2014). Additionally, there is a need for recommender systems to strike a balance between personalization and ethical content. The challenge lies in ensuring that recommendations align, with user preferences while upholding principles—especially when dealing with sensitive content.

Recommender systems have a responsibility to consider issues related to manipulation, where intentional or unintentional tactics can influence how users behave(Acquisti et al.; 2015). While aiming for user engagement these systems may unknowingly compromise user autonomy and critical thinking. It is important to recognize the impact of manipulations, on user well-being and satisfaction emphasizing the need for ethical content. The moral aspect of recommendations becomes crucial when dealing with items or information.

In summary, ethical considerations in recommender systems cover challenges ranging from privacy concerns to bias issues and content ethics. As these systems continue to evolve it is vital to address these dimensions to ensure user-centered deployment. Research and interdisciplinary collaboration play a role in developing guidelines that strike the right balance between personalization and ethical factors, within recommender systems.

2.5 Summative Insights

The literature review has thoroughly evaluated the current state of and difficulties faced by AI-powered recommender systems. It has focused on aspects such as customer loyalty, effectiveness measures and ethical considerations. The relationship, between recommender systems and customer loyalty has been discussed, highlighting its significance as an indicator of customer satisfaction and retention. Various studies and models that measure and enhance customer loyalty using recommender systems have also been reviewed, along with factors like trust, transparency and personalization that influence it. Additionally, the review delves into the effectiveness of recommender systems in aiding users in making informed decisions to achieve their goals. It covers existing studies and metrics used to assess effectiveness while acknowledging challenges such as data sparsity, cold start issues and popularity bias. Furthermore, the ethical implications of recommender systems are explored in depth. In general, the literature review not only enhances our comprehension of recommender systems but also highlights potential areas for further investigation and the importance of interdisciplinary cooperation to tackle the intricate challenges and ethical aspects in this developing field.

3 Methodology

In this section, the methodology employed for the research project is discussed. The project aims to explore the influence of AI-driven recommender systems on customer engagement in online marketplaces. The study primarily focuses on collaborative filtering methods and hybrid recommender systems that integrate collaborative filtering with natural language processing techniques. The "Amazon Sales Dataset" obtained from Kaggle has been extensively utilized to build the recommendation systems[1].

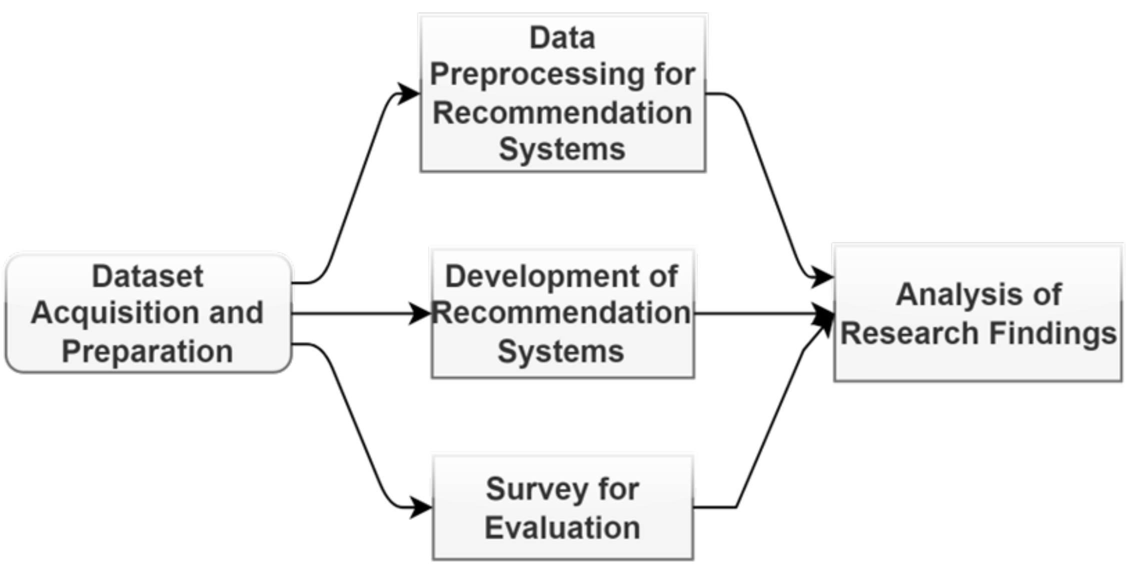

Figure 1: Research Methodology

[1] https://www.kaggle.com/datasets/karkavelrajaj/amazon-sales-dataset

The research has begun with the acquisition and preparation of the "Amazon Sales Dataset" from Kaggle. This dataset contains various information regarding Amazon electronic product sales, user interactions and detailed product data. During the data pre-processing stage, missing values have been addressed, duplicates have been handled, redundant information has been eliminated, and the dataset has been formatted appropriately for collaborative filtering and the hybrid recommender systems. To make the dataset suitable for the product recommendation systems, the user-item interactions data, including ratings and reviews, have been organized into a well-structured user-product matrix.

The development of the recommendation systems proceeded using systematic filtering techniques. Combined models have been built based on both user behaviours and item characteristics to generate personalized product recommendations. Additionally, a hybrid recommender system has been created that utilizes collaborative filtering as well as natural language processing methods to make use of both user-item ratings and textual descriptions of products.

A thorough survey has been conducted to evaluate the effectiveness of these models. Participants have been asked to share their opinions on each product recommendation system. The evaluation process has included different types of questions, such as demographic inquiries, Likert scale assessments and scenario-based queries. By diligently analyzing the gathered data, meaningful conclusions have been derived about the performance of the recommender systems. The research findings have been carefully examined, considering both the strengths and weaknesses of each recommendation system. Insights have been provided into how collaborative filtering and hybrid recommender systems impact customer engagement in the e-commerce industry.

4 Design Specification

This research project introduces and assesses two innovative recommendation system models that aim to address the challenges associated with user experience and customer engagement in online marketplaces. The study discusses the factors taken into account during the design of these systems, as well as their underlying principles and outcomes, highlighting the strengths and limitations of each model.

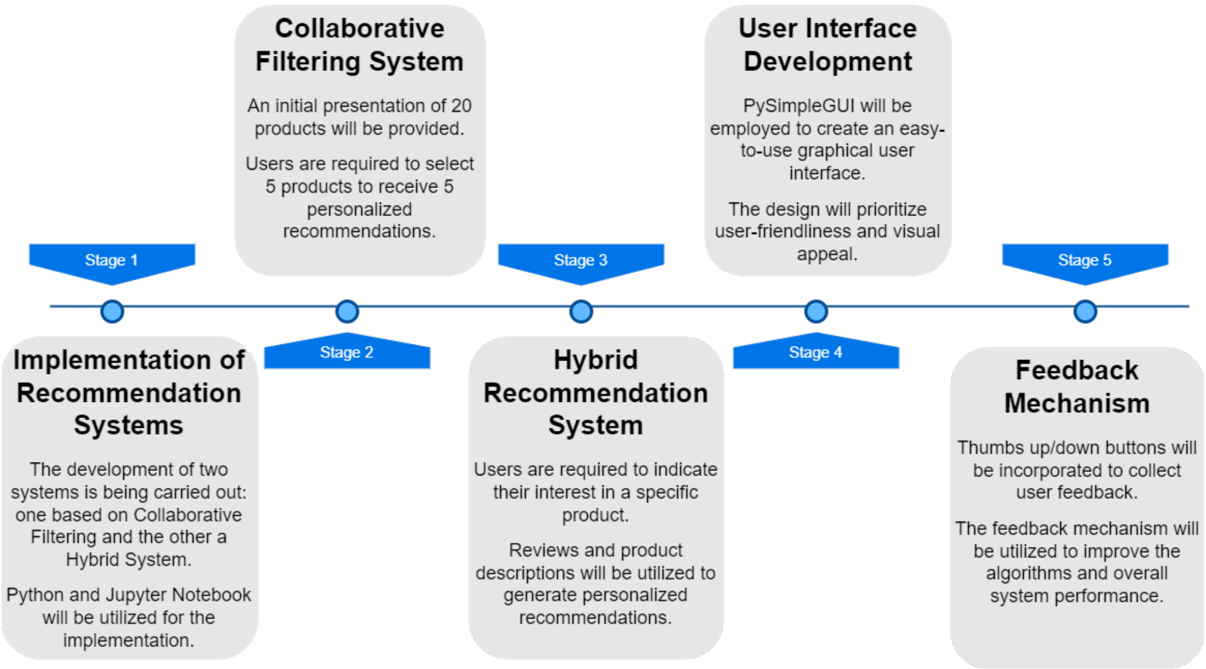

Figure 2: Product Recommender System Framework Architecture

The project involves the implementation of two distinct recommendation systems for electronic products sold on Amazon. One is a collaborative filtering recommendation system that suggests products to users based on their ratings for those products. The other is a hybrid recommendation system that combines collaborative filtering with natural language processing techniques. It is assumed that this hybrid system provides more personalized and realistic recommendations by analyzing the user's product reviews and descriptions. Both recommendation systems are developed within the Jupyter Notebook environment using Python programming language, along with libraries and frameworks like Surprise and PySimpleGUI. The project utilizes the PySimpleGUI library to create user interfaces, making it easy and straightforward to develop graphical user interfaces (GUIs) in Python. With just a few lines of code, PySimpleGUI enables the creation of windows, buttons, text boxes, images, and other GUI elements. The goal is to design user-friendly and visually appealing interfaces for the project.

In the first model approach, users are introduced to a randomly offered selection of 20 products for initial exploration. They are then encouraged to express their preferences by selecting 5 products, which forms the basis for generating 5 personalized recommendations. This approach aims to actively involve users in shaping their preferences and ultimately provides more tailored recommendations. The second model takes a targeted approach by prompting users to articulate their interest in a specific product. Through a concise description provided by the users, relevant keywords and product characteristics are extracted. This information is then used to generate 5 recommendations that closely align with the user's specified preferences. This method enhances precision and caters specifically to users with distinct product needs, resulting in more refined and personalized recommendation options.

Both models incorporate a robust feedback mechanism, enabling users to actively participate in the recommendation process with a simplified approach. Users can provide feedback by using intuitive thumbs-up and thumbs-down buttons associated with the products shown. This direct method empowers users to express their positive or negative sentiments, directly influencing the system's understanding of their preferences. The iterative feedback loop not only increases user involvement but also serves as a valuable source of data for improving recommendation algorithms, leading to continuous enhancement in system performance. The design principles underlying these recommendation systems revolve around putting the user at the centre, keeping things simple, offering personalization and being adaptable. By prioritizing user needs and expectations, designing intuitive interfaces, and delivering personalized recommendations, systems have been created that enhance user experience and engagement.

To summarize, the recommendation systems successfully combine user-friendliness, personalization, and adaptability in a harmonious way. This design philosophy has not only resulted in positive user experiences but has also encouraged increased customer engagement and satisfaction. Through ongoing refinement based on user feedback, these systems demonstrate the effectiveness of a well-executed design approach that focuses on putting users first in the realm of recommendation systems.

5 Implementation

In this research project, two different recommendation systems for electronic products being sold on Amazon have been implemented in the Jupyter Notebook environment in Python programming language. These recommendation systems are designed to accelerate sales of these electronic products and enhance customer engagement in online marketplaces. The first recommendation system utilises the collaborative filtering method and recommends products to users with similar preferences based on the ratings given by the users to the products. The second recommendation system combines the collaborative filtering method with natural language processing techniques to provide more personalised and realistic recommendations based on users' product reviews and product descriptions.

The dataset used in the project is the Amazon Sales Dataset obtained from Kaggle. This dataset consists of 16 attributes and 1465 observations. In the pre-processing phase of the dataset, missing and duplicate data have been cleaned, user IDs have been replaced with random names and product names have been shortened. Thus, a revised dataset consisting of 16 attributes and 1463 observations has been created and uploaded to the local drive for use in recommendation systems.

The first recommendation system is created by converting the score attribute into numerical data and creating a dataset compatible with the Surprise library. This data set has been divided into 80% training and 20% testing, and the RMSE score has been calculated by applying the SVD model on the training data set. While creating the recommendation set, the recommendation rate has been increased by prioritising products with a score above 3.5. In the second recommendation system, product reviews and product descriptions have been analysed with text mining techniques and similarity scores between products have been calculated. These scores have been integrated with the collaborative filtering recommendation system and the five products closest to the product that the user is interested in are recommended according to the hybrid algorithm. Both recommendation systems are presented with a user-friendly interface using PySimpleGUI library. An interactive experience is provided by allowing users to give positive or negative feedback about the products offered by the system.

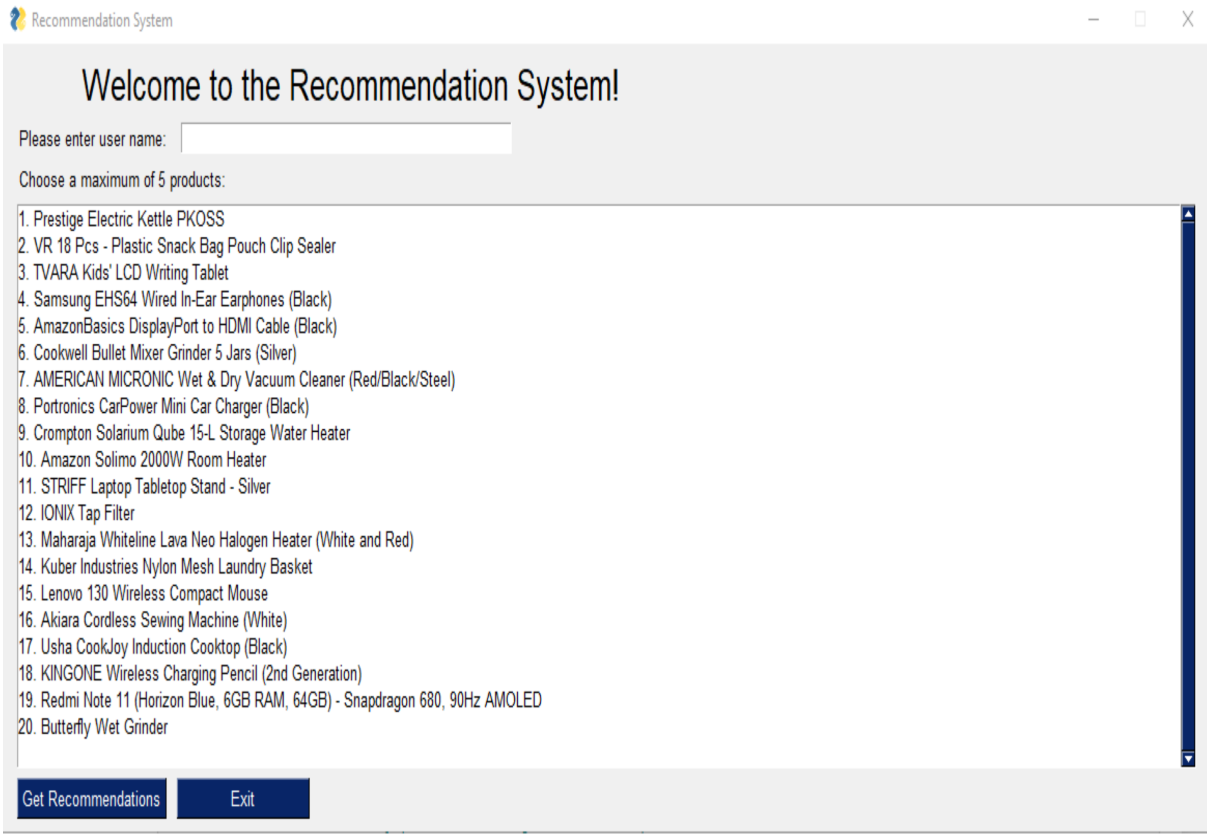

Figure 3: Interactive Collaborative Filtering Display

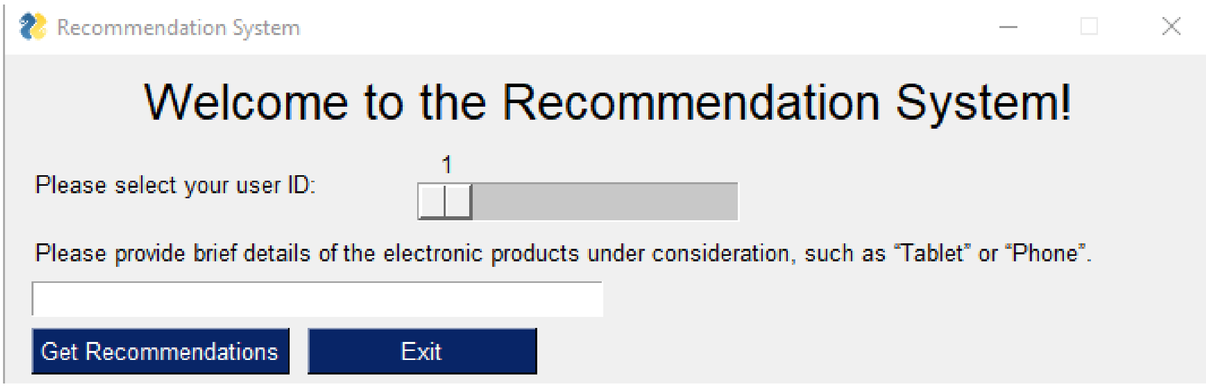

Figure 4: Hybrid Recommender System Interface

In the first recommendation system model, the system first displays 20 randomly selected products to the user. Then, the user is asked to select 5 of these products and based on these preferences, 5 recommendations are presented by the system. In the second recommendation system model, the user is prompted to briefly write the product they are interested in and 5 recommendations are presented to the user according to the information entered.

This research project introduces and implements two distinct recommendation systems: collaborative filtering and collaborative filtering integrated with natural language processing techniques. These systems are accompanied by intuitive and user-friendly interfaces. The inclusion of a robust feedback mechanism empowers users to actively engage with and respond to the system's recommendations. This holistic approach is designed to deliver an elevated level of personalization, ultimately enhancing user satisfaction within recommender systems.

6 Evaluation

For the evaluation part of this research project, the product recommendation systems are being assessed. Google Forms are used to distribute a survey consisting of 19 questions[2]. The survey is divided into three sections. The first section includes general personal questions, the second section focuses on evaluating the collaborative filtering model-based product recommendation system, and the third section assesses the product recommendation system based on collaborative filtering and NLP.

The purpose of this survey is to compare randomly generated products with the product recommendation system based on a collaborative filtering model and the product recommendation system based on both the collaborative filtering and NLP model. The survey also aims to explore the preferences of users of product recommendation systems with user profiles such as age, occupation, gender, education level, shopping method preference and frequency. The evaluation criteria encompass relevance, inclination to purchase additional recommended products, a diverse range of recommendations, and satisfaction level, as well as assessing how visually appealing and user-friendly each system is.

To conduct this survey online, Google Forms have been utilized, and a snowball sampling technique has been employed. A total of 57 participants with verified accounts have taken part in this study. To ensure accurate data analysis across different languages and spelling variations for occupational categories, English standardization has been applied. For Likert scale questions, a value of 3 is assigned when only a small amount of data is missing or when participants give neutral responses.

Furthermore, some of the missing data has been modified to null to explicitly indicate nonresponse. This is done without making any assumptions, to include all participants in the analysis. For the upcoming data analysis, IBM SPSS will be used, and the necessary steps have been taken to ensure compatibility with the program. The analysis process will start with data preparation and cleansing, followed by examining descriptive statistics, frequency distribution analysis, correlation assessment, and comparative tests.

[2] `https://forms.gle/ihRnLSUqjKxx7fKr7`

Figure 5: Participant Demographics

Out of the 57 individuals who have taken part in the study, 51% are male, 44% are female, and 3% have chosen not to reveal their gender. The participants have represented a range of professions with 84% having completed university-level education. Additionally, 93% of the participants have stated that they are familiar with recommendation systems.

6.1 Visual Appeal and User-Friendliness

The product recommendation system's overall visual appeal has received a thumbs up from 81% of the participants. Likewise, 83% of the participants have found the system to be user-friendly, considering its ease of use.

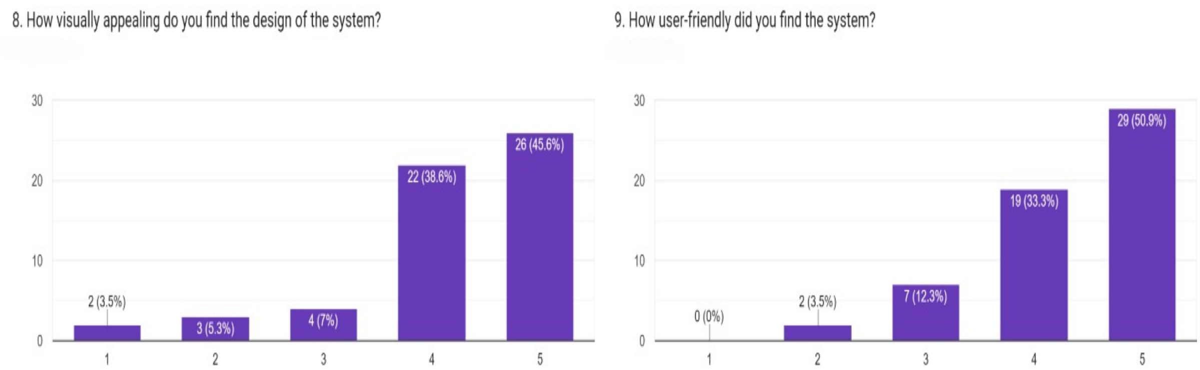

Figure 6: Visual Appeal and User-Friendliness Ratings

It is worth mentioning that there is a strong positive correlation of 0.780 between the visual appeal and user-friendliness of the system. This suggests that an improvement in one aspect leads to an improvement in the other.

6.2 Collaborative Filtering Results

Concerning the 10th question in the survey, participants are asked to choose 5 out of 20 products that are randomly suggested by the product recommendation system based on collaborative filtering. Afterwards, participants are required to assess the relevance of these selected items compared to another set of 5 products generated randomly.

	Mean	Std. Deviation
Recommendation_Suitability_Set1	4.23	.926
Relevance_of_Mobile_Phone_Recommendations_CF	4.25	.830
Inclination_to_Purchase_Additional_Recommended_Products_CF	4.14	.934
Satisfaction_with_System_Performance_CF	4.33	.831

Figure 7: Frequencies of Collaborative Filtering based on Recommendation System

The average rating of 4.23, with a standard deviation of 0.926, indicates that, on average, the ratings given by participants for the system's recommendations are closely grouped around the mean. This suggests a consistent and similar perception among participants that the suggestions made by the system are more relevant than randomly generated products.

Moving on to the 11th question, participants are asked to evaluate how relevant they found 5 product recommendations provided by the product recommendation system based on collaborative filtering for someone considering purchasing a mobile phone. The participants have given the system's recommendations a high rating of 4.25, indicating that they have found them to be highly relevant to the user's interests. Afterwards, the participants are asked about how the system impacted their willingness to buy a product from the recommended options.

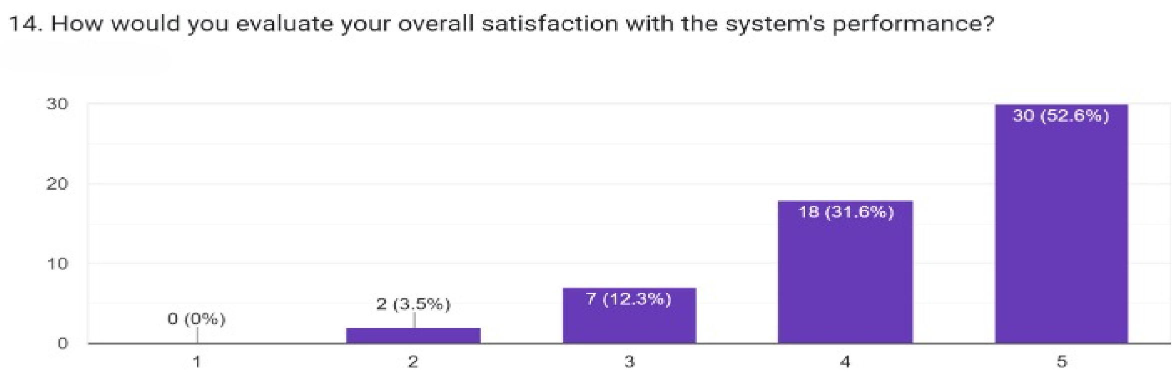

Figure 8: Collaborative Filtering based on Recommendation System‘s Performance

The participants have shown a strong inclination, with an average rating of 4.14 and a significant standard deviation of 0.934, indicating that most participants had a strong tendency to consider purchasing at least one product from the suggested options. Furthermore, the participants have acknowledged that the product recommendation system based on collaborative filtering offers a diverse range of recommendations, with 84% expressing positive feelings about it. This indicates that the system introduces variety in its suggestions and enhances user satisfaction.

6.3 Collaborative Filtering and NLP System Results

In the third section, a hybrid product recommendation system that combines collaborative filtering and natural language processing (NLP) is evaluated. Participants are given a selection of 5 mobile phone-related products and asked to share their opinions on relevance, inclination of purchasing the second product, diversity, and overall satisfaction.

	Mean	Std. Deviation
Relevance_of_Mobile_Phone_Recommendations_CF_NLP	4.26	.856
Inclination_to_Purchase_Additional_Recommended_Products_CF_NLP	4.18	.966
Relevance_of_Mobile_Phone_Recommendations_CF_vs_CF_NLP	4.23	.926
Satisfaction_with_System_Performance_CF_NLP	4.37	.957

Figure 9: Frequencies of collaborative filtering and natural language processing (NLP) based on Recommendation System

The participants found the recommendations from the hybrid system to be relevant, with an average rating of 4.26 and a standard deviation of 0.856. This indicates that their perceptions are consistent and stable across the board. Moreover, participants have expressed interest in considering purchasing products based on the system's recommendations, as reflected by an average rating of 4.18. Regarding diversity in the recommendations, 86% of participants have acknowledged it positively, while 14% have felt that it can be improved further.

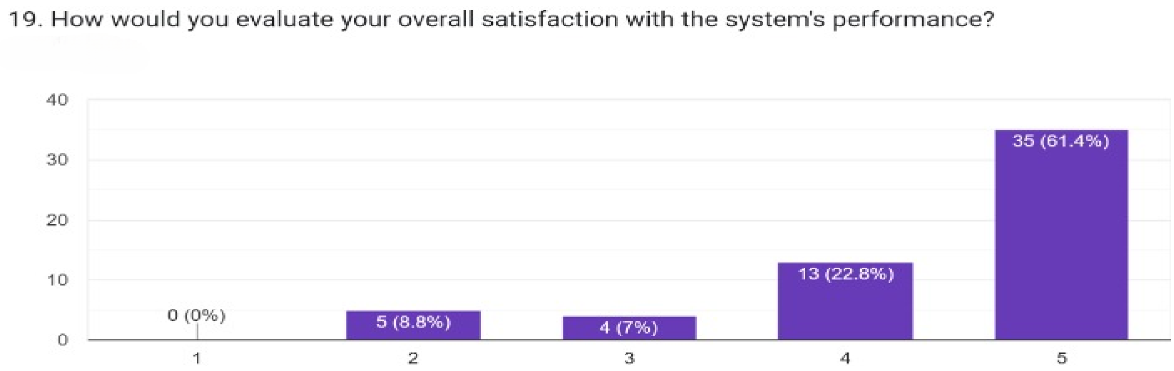

Figure 10: Collaborative Filtering and Natural Language Processing (NLP) based on Recommendation System‘s Performance

Overall, participants evaluated the hybrid system’s performance positively, giving it an average rating of 4.37. This suggests a high level of satisfaction among participants.

6.4 Correlation Analysis of Attributes

In this phase of the analysis, the IBM SPSS program is utilized to investigate correlations among 10 attributes. The statistical significance of these correlations is also assessed. In the correlation table generated, a correlation coefficient of -1 indicates a strong negative correlation, 1 indicates a strong positive correlation, and 0 signifies no correlation relationship.

Upon examining the correlations between the attributes, several statistically significant relationships have been identified. Notably, a robust correlation coefficient of 0.780 is observed between the Visual Appeal of the System and User Friendliness of the System. This suggests that as the visual appeal increases, the user-friendliness tends to increase as well.

		Visual_Appeal_of_System	User_Friendliness_of_System	Recommendation_Suitability_Set1	Relevance_of_Mobile_Phone_Recommendations_CF	Inclination_to_Purchase_Additional_Recommended_Products_CF	Satisfaction_with_System_Performance_CF	Relevance_of_Mobile_Phone_Recommendations_CF_NLP	Inclination_to_Purchase_Additional_Recommended_Products_CF_NLP	Relevance_of_Mobile_Phone_Recommendations_CF_vs_CF_NLP	Satisfaction_with_System_Performance_CF_NLP
Visual_Appeal_of_System	Pearson Correlation	1	.780	.789	.750	.723	.794	.805	.675	.770	.738
User_Friendliness_of_System	Pearson Correlation	.780	1	.813	.691	.774	.805	.687	.533	.720	.708
Recommendation_Suitability_Set1	Pearson Correlation	.789	.813	1	.623	.829	.804	.621	.513	.667	.710
Relevance_of_Mobile_Phone_Recommendations_CF	Pearson Correlation	.750	.691	.623	1	.600	.708	.712	.658	.716	.739
Inclination_to_Purchase_Additional_Recommended_Products_CF	Pearson Correlation	.723	.774	.829	.600	1	.767	.578	.447	.581	.680
Satisfaction_with_System_Performance_CF	Pearson Correlation	.794	.805	.804	.708	.767	1	.703	.571	.804	.764
Relevance_of_Mobile_Phone_Recommendations_CF_NLP	Pearson Correlation	.805	.687	.621	.712	.578	.703	1	.634	.734	.708
Inclination_to_Purchase_Additional_Recommended_Products_CF_NLP	Pearson Correlation	.675	.533	.513	.658	.447	.571	.634	1	.593	.663
Relevance_of_Mobile_Phone_Recommendations_CF_vs_CF_NLP	Pearson Correlation	.770	.720	.667	.716	.581	.804	.734	.593	1	.810
Satisfaction_with_System_Performance_CF_NLP	Pearson Correlation	.738	.708	.710	.739	.680	.764	.708	.663	.810	1

Figure 11: Correlation Coefficients Map among the 10 attributes

The correlation coefficient between Recommendation Suitability Set1 and Inclination to Purchase Additional Recommended Products CF is 0.829, indicating a strong and statistically significant relationship. Similarly, Recommendation Suitability Set1 exhibits a significant correlation of 0.813 with the User Friendliness of the System. Additionally, the correlation coefficient of 0.804 between Recommendation Suitability Set1 and Satisfaction with System Performance CF further emphasizes its statistical significance. These findings suggest that as participants perceive an increase in the relevance of the recommendation set, there is also an associated inclination to purchase additional recommended products, an improvement in overall system satisfaction, and an increased perception of system user-friendliness.

On the other hand, upon analyzing the connections within the hybrid product recommendation system that combines collaborative filtering and NLP techniques, it is observed that these connections generally fall within a moderate range. For instance, a moderate correlation coefficient of 0.578 exists between "Relevance of Mobile Phone Recommendations CF NLP" and "Inclination to Purchase Additional Recommended Products CF

NLP.” This indicates a moderate relationship between the recommendations provided by the system and the inclination to purchase additional recommended products. Furthermore, there is a relatively stronger correlation coefficient of 0.708 between “Relevance of Mobile Phone Recommendations CF NLP” and “Satisfaction with System Performance CF NLP”, suggesting a more pronounced relationship. This implies that the perceived relevance of mobile phone recommendations from the collaborative filtering and NLP hybrid system is moderately associated with purchase inclination and even more strongly linked to overall satisfaction with the system.

6.5 Paired Samples t-test Analysis

In the final stage of the evaluation, a Paired Samples t-test is utilized to analyze the relationships between different attributes.

Paired Samples Test

		Paired Differences							Significance	
					95% Confidence Interval of the Difference					
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper	t	df	One-Sided p	Two-Sided p
Pair 1	Relevance_of_Mobile_Phone_Recommendations_CF - Relevance_of_Mobile_Phone_Recommendations_CF_NLP	-.018	.641	.085	-.188	.152	-.207	56	.418	.837

Figure 12: Paired Samples t-test Results for Relevance

The initial comparison is conducted between “Relevance of Mobile Phone Recommendations CF” and “Relevance of Mobile Phone Recommendations CF NLP.” The resulting p-value is 0.844, which exceeds the usual significance level of 0.05. Consequently, the null hypothesis cannot be rejected. This suggests that there is insufficient statistical evidence to assert that one system outperforms the other in terms of relevance in mobile phone recommendations.

Paired Samples Test

		Paired Differences							Significance	
					95% Confidence Interval of the Difference					
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper	t	df	One-Sided p	Two-Sided p
Pair 1	Inclination_to_Purchase_Additional_Recommended_Products_CF - Inclination_to_Purchase_Additional_Recommended_Products_CF_NLP	-.035	.999	.132	-.300	.230	-.265	56	.396	.792

Figure 13: Paired Samples t-test Results for Inclination

Subsequently, the Paired Samples t-test is employed to assess the relationship between “Inclination to Purchase Additional Recommended Products CF” and “Inclination to Purchase Additional Recommended Products CF NLP.” The p-value is 0.792, surpassing the significance threshold of 0.05, indicating that the null hypothesis cannot be rejected. Despite the absence of statistical significance, a moderate practical difference appears to exist in participants' inclination to purchase additional recommended products between these two conditions.

Paired Samples Test

		Paired Differences							Significance	
					95% Confidence Interval of the Difference					
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper	t	df	One-Sided p	Two-Sided p
Pair 1	Satisfaction_with_System_Performance_CF - Satisfaction_with_System_Performance_CF_NLP	-.035	.626	.083	-.201	.131	-.423	56	.337	.674

Figure 14: Paired Samples t-test Results for Satisfaction with System Performance

A Paired Samples t-test is performed to explore the connection between "Satisfaction with System Performance CF" and "Satisfaction with System Performance CF NLP." The obtained p-value of 0.674, which is higher than the significance level of 0.05, suggests that the null hypothesis cannot be rejected. Thus, no significant difference is observed in terms of satisfaction with system performance between these two variables. In summary, the analysis indicates that there is not a statistically significant difference in satisfaction with system performance between the two conditions.

6.6 Discussion

The participants had a positive response to the overall visual appeal and user-friendliness of the product recommendation systems. This indicates that the system is easy to use, navigate and visually appealing. Moreover, there is a clear positive relationship between the visual appeal and user-friendliness of the system. This suggests that improving one aspect leads to an improvement in the other. The collaborative filtering-based product recommendation system effectively recommended relevant products to users. The participants found these recommendations more relevant than randomly generated products and were more inclined to make a purchase from the recommended options. Additionally, they recognized that the collaborative filtering-based product recommendation system offers a diverse range of recommendations. Furthermore, the hybrid product recommendation system that combines collaborative filtering and natural language processing (NLP) was also effective in suggesting relevant products based on users' interests as rated by the participants. Furthermore, the participants expressed their interest in considering purchasing products based on the recommendations provided by the system. In addition, they acknowledged that the hybrid system offers a wide variety of recommendations.

Overall, the participants positively evaluated the performance of the hybrid system. The correlation analysis revealed several significant relationships between different attributes. Notably, there is a strong positive correlation between the relevance of the recommendations and the inclination to purchase additional recommended products. This implies that as participants perceive an increase in relevance within the recommended set, their inclination to buy additional recommended products also increases. Despite high ratings given to the relevance of recommendations from the hybrid system, statistical analysis using paired samples t-test did not find any significant differences between them regarding relevance, inclination to purchase more products or satisfaction with system performance. This suggests that both systems effectively recommend relevant products to users. The findings of this study indicate that both collaborative filtering-based product recommendation systems and hybrid systems combining collaborative filtering and NLP are successful in recommending relevant products to users. Moreover, both systems are user-friendly and visually appealing. However, it is important to note that this study has a limitation in terms of sample size being relatively small. To obtain results that can be applied more broadly, it would be beneficial to have a larger sample size. In the future, researchers could explore how these two systems perform in various domains like suggesting music or recommending books.

7 Conclusion and Future Work

The research delves deeply into the vast world of AI-based recommender systems and their crucial role in shaping customer engagement on online marketplaces. The study meticulously explores the collaborative filtering system and the hybrid system that combines collaborative filtering with natural language processing (NLP) to uncover the complexities of personalized product recommendations. By utilizing the extensive Amazon Sales Dataset, it comprehensively evaluates the implementation of these systems, considering important factors such as relevance, diversity, user satisfaction and visual appeal.

Throughout the research journey, an extensive analysis of existing literature and related studies has been conducted to gain profound insights into the ever-evolving landscape of recommender systems. The synthesis of this information enriches the understanding of how these systems significantly impact customer loyalty, effectiveness, and ethical considerations.

The results of the study vividly demonstrate the success of collaborative filtering and hybrid recommender systems in enhancing the user experience and providing compelling recommendations. The survey findings provide a user-centric perspective that highlights the tangible impact and value these systems bring to users. This research contributes to an ongoing discussion about recommender systems by shedding light on their multifaceted implications and reinforcing their importance in shaping contemporary e-commerce environments.

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