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Deep Reinforcement Learning-Based Personalized Recommendation System for Intelligent and Adaptive E-Commerce Product Recommendation Platforms

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ABSTRACT

The study focused on developing a personalized recommendation system for e-commerce platforms using Deep Reinforcement Learning (DRL) to improve product recommendation quality and user satisfaction. Traditional recommendation methods such as collaborative filtering and content-based filtering often face limitations like cold start, data sparsity, and inability to adapt to changing user preferences. To address these issues, the proposed DRL-based system learned continuously from user interactions such as clicks, purchases, ratings, and cart additions. A synthetic e-commerce dataset containing user, product, and interaction data was used for experimentation. The recommendation process was modelled as a sequential decision-making problem where the system improved recommendations through reward-based learning. Performance evaluation was carried out using metrics such as accuracy, precision, recall, F1-score, MAP, NDCG, hit ratio, and cumulative reward. The findings indicated that while traditional models performed better on smaller datasets, the DRL-based approach demonstrated promising adaptability and long-term personalization potential for future intelligent e-commerce systems.

Keywords: *Deep Reinforcement Learning, Personalized Recommendation System, E-Commerce Platform, Collaborative Filtering.*

I. INTRODUCTION

In the modern age of digital transformation, e-commerce has become one of the most powerful and rapidly expanding sectors of global business. Online shopping platforms have changed the traditional way of buying and selling goods by providing customers with easy access to products, services,

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prices, reviews, offers, and delivery options through digital devices. With the growth of internet connectivity, smartphones, online banking, and digital payment systems, consumers now prefer online shopping because it is convenient, time-saving, and available at any time. Platforms such as Amazon, Flipkart, Alibaba, Myntra, and other online marketplaces offer a large variety of products in categories such as electronics, fashion, groceries, books, home appliances, health products, and many more. This wide availability of products has made e-commerce highly popular among users across urban as well as rural areas.

However, the continuous expansion of e-commerce has also created new challenges for both customers and businesses. One of the most important challenges is the problem of information overload. In an online marketplace, a customer may find thousands of similar products for a single search. For example, when a user searches for a mobile phone, shoes, or laptop, the platform may display a very large number of options with different brands, prices, ratings, specifications, and reviews. Although variety is useful, too many options can confuse the user and make decision-making difficult. Customers may spend more time searching, comparing, and filtering products instead of making a purchase decision. This situation creates the need for intelligent systems that can understand user preferences and suggest the most suitable products automatically. Recommendation systems are developed to solve this problem by helping users discover relevant products based on their interests and behaviour.

A recommendation system is an intelligent software-based technique that provides personalized suggestions to users. It analyses user-related data such as browsing history, purchase records, clicks, ratings, search patterns, wish lists, cart activity, and product preferences. Based on this information, the system predicts what the user may like or purchase in the future. In e-commerce, recommendation systems play a significant role in improving customer experience because they reduce the effort required to search for products. They help users find useful items quickly and make the shopping process easier and more meaningful. For online businesses, recommendation systems are equally important because they increase product visibility, improve sales, enhance customer retention, and support business growth. A well-designed recommendation system can encourage users to explore more products and return to the platform regularly.

Traditional recommendation systems generally use three major approaches: content-based filtering, collaborative filtering, and hybrid filtering. Content-based filtering recommends products similar to the products previously viewed, liked, or purchased by the user. For example, if a user frequently buys sports shoes, the system may recommend similar shoes, sportswear, or fitness accessories. Collaborative filtering works by comparing the behaviour of similar users. If two users have similar purchase patterns, the system may recommend products liked by one user to the other user. Hybrid recommendation systems combine content-based and collaborative filtering methods to improve the quality of recommendations. These traditional methods have been widely used in many e-commerce platforms and have shown good results in different situations.

Despite their usefulness, traditional recommendation techniques also have several limitations. One major limitation is the cold start problem. This occurs when a new user joins the platform or a new product is added to the catalogue. Since there is little or no historical data available, the system finds

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it difficult to generate accurate recommendations. Another limitation is data sparsity, where users interact with only a small portion of the available products. As a result, the system may not have enough information to identify strong patterns. Traditional models also struggle to adjust quickly when user preferences change over time. A customer's interests may change due to seasons, trends, festivals, age, lifestyle, or personal needs. For example, a user who earlier searched for electronic products may later become interested in fashion, travel items, or health products. Conventional recommendation systems may not always respond effectively to such dynamic changes.

To overcome these limitations, modern e-commerce platforms are increasingly using advanced artificial intelligence techniques. Machine learning, deep learning, and reinforcement learning have made recommendation systems more intelligent, adaptive, and accurate. Among these methods, Deep Reinforcement Learning has gained significant attention because it combines the learning capability of deep neural networks with the decision-making ability of reinforcement learning. Deep Reinforcement Learning is different from traditional recommendation methods because it learns through continuous interaction with the user. It does not depend only on fixed historical data; instead, it improves its recommendations by observing user responses and learning from them over time.

In a Deep Reinforcement Learning-based recommendation system, the recommendation engine acts like an intelligent agent. The user's profile, browsing activity, previous purchases, interests, and current context are considered the state. The product recommended to the user is considered the action. The user's response, such as clicking on the product, purchasing it, ignoring it, adding it to the cart, or giving a rating, is considered the reward. Based on this reward, the system updates its learning process and tries to make better recommendations in the future. This continuous learning process makes DRL highly suitable for e-commerce environments were user behaviour changes frequently.

The main strength of Deep Reinforcement Learning is that it focuses not only on immediate results but also on long-term benefits. Traditional recommendation systems often aim to increase instant clicks or purchases. However, Deep Reinforcement Learning attempts to maximize long-term user satisfaction, engagement, and loyalty. This means that the system learns to recommend products that may create better customer experiences over time. For example, instead of repeatedly showing similar products, the system can learn to balance relevance, diversity, and user interest. This helps in improving customer trust and long-term business value. As mentioned in the provided study material, DRL treats user interaction as a continuous learning process where user behaviour, product recommendation, and user response are used to improve future suggestions.

The topic "Personalised Recommendation System for E-Commerce Platforms Using Deep Reinforcement Learning" is therefore highly relevant in the present digital business environment. Personalization has become an essential feature of modern e-commerce because every user has different needs, preferences, budgets, and shopping habits. A personalized recommendation system can make online shopping more user-friendly by displaying products that match individual interests. It can also help businesses understand customer behaviour and design better marketing strategies. By using Deep Reinforcement Learning, the recommendation system can become more flexible, dynamic, and capable of learning from real-time user interactions.

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This study focuses on developing an intelligent recommendation approach that improves product suggestion accuracy and enhances user satisfaction. The proposed system aims to reduce information overload, increase personalization, improve decision-making, and support better business performance. It also highlights the importance of adaptive learning in recommendation systems. Since e-commerce platforms operate in a fast-changing environment, a recommendation system must be able to learn continuously and update its suggestions according to user behaviour and market trends. Deep Reinforcement Learning provides a strong framework for achieving this goal.

Thus, the introduction of Deep Reinforcement Learning into e-commerce recommendation systems represents an important step toward smarter and more personalized digital shopping platforms. It provides a solution to the weaknesses of traditional models and supports the development of future-ready recommendation systems. Such systems can improve customer experience, increase user engagement, and help online businesses remain competitive in the digital marketplace. Therefore, this research is significant because it connects artificial intelligence with e-commerce personalization and presents a modern approach for improving recommendation quality in online shopping environments.

II. REVIEW OF LITERATURE

Zhang (2025) discussed the challenges posed by rapid Internet development, which led to information overload for users, and highlighted how recommendation systems have been used to offer personalized services as a solution. The study noted that traditional recommendation systems struggled with issues such as concept drift and data sparsity. To address these problems, Zhang proposed a personalized recommendation framework based on deep reinforcement learning, which improved diversity, accuracy, and scalability. The approach involved acquiring user preferences through profiles and a deep learning model that combined rating matrices with sentiment analysis. Additionally, the algorithm was optimized using attention mechanisms, Actor-Critic methods, and Transformer architectures. The results reportedly demonstrated significant advantages over existing methods. Zhang also indicated that future research would explore social networks, user feedback integration, and real-time updates of user interest models, ultimately contributing to the advancement of recommendation models and supporting e-commerce applications.

Ibrahim et al. (2025) argued that buying had become a prevalent aspect of consumer behaviour, which necessitated the development of highly personalized recommendation systems. Their study critically analysed a collaborative filtering technique that incorporated machine learning and business intelligence (BI) to enhance e-commerce recommendation systems. Through a review of existing literature, they identified significant gaps in current research, particularly regarding the effective utilization of large datasets and advanced artificial intelligence methods. Their findings suggested that integrating deep learning with reinforcement learning notably improved the reliability of suggestions and responsiveness to user preferences. Additionally, they proposed a comprehensive framework for analyzing large datasets using collaborative filtering and BI tools, which yielded actionable insights into customer behaviour, market trends, and product performance. This integration was reported to not only enhance the recommendation process but also to create a more engaging and enjoyable shopping experience. The study emphasized the need for ongoing research in

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personalized recommendation systems to fully exploit future e-commerce technologies. It was also demonstrated that traditional recommendation approaches often failed to provide meaningful suggestions, with user satisfaction rates as low as 60% in some cases. Conversely, their proposed architecture, combining collaborative filtering and BI technologies, showed a substantial increase in recommendation accuracy specifically, a 35% improvement in reliability and a 25% boost in user engagement. The inclusion of BI tools further enhanced data visualization and predictive analytics, enabling e-commerce firms to better comprehend customer behaviour and market dynamics. Ultimately, the study underscored the importance of continuous innovation in personalized recommendation systems to meet consumers' rising expectations in the competitive e-commerce environment.

Zhu et al. (2024) were reported to have introduced DRL-PricePro, a novel deep reinforcement learning framework designed for personalized dynamic pricing on e-commerce platforms that explicitly accounted for supply constraints. It was noted that traditional pricing optimization methods often neglected inventory limitations, which led to suboptimal pricing strategies when product availability was a significant factor. Their proposed framework formulated the dynamic pricing challenge as a constrained Markov Decision Process (CMDP) and employed a modified Soft Actor-Critic algorithm tailored for e-commerce settings. DRL-PricePro was described as integrating multi-level constraint handling that combined strict inventory limits with softer constraints informed by learned inventory patterns. Additionally, the framework incorporated a personalization engine that segmented customers based on behavioral data and adjusted pricing strategies accordingly, all while respecting supply constraints. Experimental evaluation on a large dataset of 2.7 million transactions reportedly showed that DRL-PricePro achieved a 12.3% revenue increase compared to static pricing baselines and outperformed rule-based dynamic pricing by 7.6%. It maintained a 98.7% rate of constraint satisfaction, markedly higher than the 76.4% observed in unconstrained reinforcement learning approaches. Case studies involving seasonal products, limited-stock premium items, and flash sales were said to provide practical business insights on the interplay between supply constraints and optimal pricing, highlighting the framework's effectiveness in real-world e-commerce scenarios.

Deepa et al. (2024) were reported to have highlighted that the exponential expansion of e-learning had significantly broadened educational opportunities worldwide, enabling students to engage in learning from any location. However, they pointed out that the sheer volume of online courses created challenges in customization, often leading to reduced learning outcomes as learners found it difficult to select courses suited to their individual needs. Their study suggested that personalized learning could address these issues by adapting activities to learners' unique requirements, thereby promoting capability and personality development. They proposed a system combining Markov Decision Processes (MDPs) and Reinforcement Learning (RL), using deep Q-learning for sequential recommendations and the adaptability of MDPs to customize learning paths. This integrated approach was viewed as having the potential to transform e-learning by providing personalized and adaptive experiences. According to their findings, learners were able to benefit from tailored courses and learning paths that optimized their educational journeys, while continuous adaptation through the MDP framework and user feedback was said to further improve the system's effectiveness in e-learning contexts.

Necula (2023) aimed to investigate the influence of time spent reading product information on consumer behavior in e-commerce. Acknowledging the rapid growth of online shopping and the necessity of understanding consumer behavior in digital environments, the study focused on how customer navigation affected purchasing decisions. Given the complex and dynamic nature of consumer behavior, machine learning techniques were employed to manage intricate data structures and uncover latent behavioral patterns. Through analyzing clickstream data through ML algorithms, the study offered novel insights into the structure of customer clusters and introduced a methodology for examining non-linear relationships within the data. The findings indicated that time spent engaging with product-related content, alongside variables such as bounce rates, exit rates, and customer type, significantly shaped purchase decisions. The study was said to enrich e-commerce literature and provide actionable guidance for website design and marketing strategies.

El Youbi El Idrissi, Akharraz, and Ahaitouf (2023) had explored the role of recommender systems in addressing the challenge of information overload on e-learning platforms, where learners often struggled to identify content that matched their specific needs. They had highlighted collaborative filtering (CF) as a commonly used technique, though it faced issues related to high dimensionality and data sparsity. Recognizing the growing relevance of deep learning, the authors had proposed the use of an autoencoder to enhance collaborative filtering by enabling more effective data dimension reduction, feature extraction, and reconstruction. Their model had been designed to predict student preferences within an e-learning recommendation system. Based on experimental results using Kulkarni et al.'s dataset, the autoencoder-based approach had demonstrated superior accuracy and had outperformed traditional models such as K-nearest neighbour (KNN), singular value decomposition (SVD), SVD++, and non-negative matrix factorization (NMF), as measured by root-mean-square error (RMSE) and mean absolute error (MAE).

Liu (2022) examined the growing complexity of e-commerce platforms due to the increasing volume of user choices, which had led to significant issues of information overload. To address this, the study explored personalized recommendation systems powered by machine learning technologies. It was noted that users often struggled to identify key information amid the data deluge. The paper had analyzed various recommendation technologies and algorithms, and had proposed a new architecture tailored to modern e-commerce demands, emphasizing accuracy and real-time performance. The system had been structured into offline mining and online recommendation modules, with an in-depth discussion on their respective functionalities. Different types of recommender systems—user-based, collaborative filtering, and content-based—had been evaluated. Liu had argued that personalized recommendations not only facilitated quicker discovery of relevant products but also enabled users to make more informed comparisons. However, limitations such as lack of personalization, reduced relevance, and poor timeliness were identified in existing systems. Consequently, the author had designed a hybrid recommendation model combining three algorithms and conducted comparative experiments to assess its performance. Additionally, the paper had integrated theoretical insights and practical analyses, employing surveys to investigate factors influencing consumers' personalized purchasing behavior. The findings had indicated that variables like income level, shopping experience, product price and quality, recommendation relevance, credit evaluation, and service quality significantly affected consumers' willingness to shop, suggesting that e-commerce platforms could leverage these factors to enhance personalized recommendation services.

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Almahmood and Tekerek (2022) had reviewed the growing challenges of shopping in recent years, particularly during the COVID-19 pandemic, which had led to a surge in online shopping and a corresponding increase in web-based information. They had noted that E-commerce recommendation systems aimed to address these challenges by helping users discover or select suitable products based on personalization trends, employing techniques like rating, ranking, and reviewing. The study had emphasized that intelligent agents, including personal agents and specialized interfaces, were commonly used to model these systems, often integrating Artificial Intelligence algorithms. The researchers had described recommendation systems as predictive tools designed to minimize users' search efforts and enhance product selection through advanced methods such as deep learning. They had conducted a systematic review of existing literature, assessing data collection and retrieval approaches, and evaluating each system's accuracy, interpretability, and practical implications. Their findings had indicated that deep learning algorithms including CNNs, RNNs, and sentiment analysis had been particularly effective in addressing common challenges like the cold start and data sparsity problems.

III. RESEARCH METHODOLOGY

3.1 Introduction

Research methodology is an important part of any research work because it explains the complete procedure followed to conduct the study in a systematic and scientific manner. In the present study, the methodology was designed to develop and evaluate a Personalised Recommendation System for E-Commerce Platforms Using Deep Reinforcement Learning. The main purpose of this chapter is to describe the research design, data collection process, dataset preparation, preprocessing methods, model development, system architecture, tools used, and performance evaluation techniques.

In e-commerce platforms, users perform different types of activities such as searching products, viewing items, clicking recommendations, adding items to cart, purchasing products, and giving ratings. These activities generate valuable behavioural data. This data can be used to understand customer preferences and provide suitable product suggestions. However, user behaviour is not always fixed. It changes according to time, trends, needs, budget, season, and personal interests. Therefore, a recommendation system must be capable of learning from continuous user interaction and improving its suggestions over time.

Traditional recommendation methods such as collaborative filtering and content-based filtering are useful, but they have certain limitations. They often depend heavily on historical data and may not work effectively when new users or new products are added. They also face difficulty in capturing the changing behaviour of customers. To overcome these problems, this study uses Deep Reinforcement Learning, which considers product recommendation as a continuous decision-making process. In this approach, the system learns by interacting with users and receiving feedback from their responses. The uploaded chapter also explains that Deep Reinforcement Learning treats recommendation as a sequential decision-making problem where user feedback helps the model improve its recommendation strategy over time.

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3.2 Research Design

The present study follows an experimental and analytical research design. The experimental design was used to build and test the proposed recommendation model, while the analytical design was used to examine data patterns, compare results, and evaluate the performance of the system. This research design is suitable because the study involves both technical implementation and result analysis.

The experimental phase began with the preparation of an e-commerce dataset. Since real customer data is often private and difficult to access, a synthetic dataset was created for this research. This dataset was prepared in such a way that it represents real online shopping behaviour. It included details of users, products, and user-product interactions. User interaction data included events such as product views, clicks, cart additions, purchases, ratings, session details, and timestamps. These data points were used to train the proposed model and evaluate its recommendation ability.

The study also considered traditional recommendation models as baseline methods. These baseline models included content-based filtering, collaborative filtering, and matrix factorization. These models were used for comparison with the proposed Deep Reinforcement Learning-based recommendation system. By comparing the results, the effectiveness of the proposed model could be measured more clearly.

In the proposed system, the recommendation process was designed as an interaction between an agent and an environment. The agent represents the recommendation system, while the e-commerce platform represents the environment. The user's profile, browsing history, preferences, and current session activity were considered as the state. The product recommended by the system was considered as the action. The user's reaction, such as clicking, purchasing, ignoring, or adding a product to cart, was considered as the reward. Through this process, the model learned which recommendations were more useful and which were less effective.

3.3 Dataset Collection and Preparation

Dataset collection is a major step in developing any recommendation system. In this study, a structured synthetic dataset was prepared to represent the behaviour of online shoppers. The dataset was divided into three main parts: user data, product data, and interaction data.

The user data contained information such as user ID, age, gender, location, device type, membership category, preferred product category, and average monthly spending. These details helped the model understand the background and shopping pattern of different users. The product data contained information such as product ID, product name, category, brand, price, rating, stock status, and product popularity. These features helped the system identify product characteristics and match them with user interests.

The interaction data was the most important part of the dataset because it represented actual user behaviour on the e-commerce platform. It included information such as user ID, product ID, event type, click status, purchase status, rating, timestamp, session ID, and session step. These interaction records helped the model understand how users responded to different products. For example, if a user viewed a product but did not click it, the response was weak. If the user added the product to the

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cart or purchased it, the response was considered strong and positive. Before training the model, data preprocessing was performed to improve the quality of the dataset. Missing values were handled using suitable replacement techniques. Duplicate records were removed to avoid repeated information. Invalid entries, such as incorrect product IDs or incomplete timestamps, were filtered out. Categorical variables such as product category, user type, and interaction type were converted into numerical form through encoding techniques. Numerical values such as price, rating, age, and spending amount were normalized so that all features could remain within a similar range. This helped improve the stability and accuracy of model training.

3.4 Development of the Proposed Model

The proposed recommendation system was developed using a Deep Reinforcement Learning approach. In this model, the recommendation process was treated as a Markov Decision Process. The system learned by observing the current user state, selecting an action in the form of product recommendation, receiving feedback from the user, and then updating its recommendation strategy.

The state representation included different types of information related to the user and product. User-related features included demographic details, previous purchases, browsing history, preferred categories, and session behaviour. Product-related features included product category, price, rating, brand, and availability. Session history was also included because it helped the system understand the sequence of user actions during shopping. The action space consisted of products or product categories that could be recommended to the user. The model selected an action by choosing a product that was most likely to match the user's current interest. After the recommendation was shown, the user's response was recorded as a reward. A high reward was given when the user purchased the product or added it to the cart. A medium reward was given when the user clicked or viewed the product. A low or negative reward was given when the user ignored or skipped the recommendation. The purpose of the model was to learn a policy that could maximize the total reward over time. This means the system did not focus only on immediate clicks but also aimed to improve long-term customer satisfaction and engagement. During training, the model explored different recommendation options and gradually learned which products were more suitable for different types of users. Techniques such as exploration and exploitation were used to maintain balance between trying new recommendations and using already learned successful recommendations.

3.5 System Architecture

The proposed system architecture was divided into four major layers. The first layer was the **User** Interaction Layer. This layer collected user activities from the e-commerce platform, such as product views, clicks, cart additions, purchases, searches, and ratings. These activities formed the basic input for the recommendation system.

The second layer was the Data Processing Layer. In this layer, collected data was cleaned, encoded, normalized, and transformed into useful features. The purpose of this layer was to prepare high-quality data for training the model. Clean and properly processed data helped the system generate better recommendations.

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The third layer was the Deep Reinforcement Learning Model Layer. This was the core part of the proposed system. It included state representation, action selection, reward calculation, and policy learning. The model analysed user behaviour and selected suitable product recommendations based on the learned policy.

The fourth layer was the Recommendation Output Layer. This layer generated personalized product suggestions for users. The output could be in the form of Top-N product recommendations, next-item suggestions, or category-based recommendations. This layer helped users discover products that matched their interests and improved their shopping experience.

3.6 Tools and Technologies Used

Different software tools and technologies were used for the development and analysis of the proposed recommendation system. Python was used as the main programming language because it provides strong support for data analysis, machine learning, deep learning, and reinforcement learning. Jupyter Notebook was used for coding, experimentation, visualization, and result interpretation.

Pandas was used for data handling and preprocessing, while NumPy was used for numerical operations. Scikit-learn was used for baseline recommendation models and evaluation metrics. TensorFlow or PyTorch was used for developing the deep learning model. Reinforcement learning libraries such as OpenAI Gym and Stable-Baselines3 could be used to create the learning environment and implement DRL algorithms. Matplotlib and Seaborn were used to create graphs and visual representations of results.

The hardware requirements for this study included a computer system with a suitable processor, at least 8 GB RAM, and sufficient storage capacity. A GPU could be used for faster training, especially when working with large datasets or complex neural networks.

3.7 Performance Evaluation

Performance evaluation was carried out to measure the effectiveness of the proposed recommendation system. The trained model was tested using unseen user interaction data. The performance of the proposed Deep Reinforcement Learning model was compared with traditional recommendation techniques such as collaborative filtering, content-based filtering, and matrix factorization. Different evaluation metrics were used to analyse the model performance. Accuracy was used to measure the overall correctness of recommendations. Precision measured how many recommended products were actually relevant to the user. Recall measured how many relevant products were successfully recommended by the system. F1-score provided a balanced value between precision and recall. Ranking-based metrics such as Mean Average Precision and Normalized Discounted Cumulative Gain were used to evaluate the order and quality of recommendations. Hit Ratio was used to check whether the recommended list contained useful products for the user. Cumulative reward was used to measure the long-term learning ability of the Deep Reinforcement Learning model. These metrics helped determine whether the proposed system improved personalization, recommendation accuracy, and user engagement.

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IV. RESULT ANALYSIS AND DISCUSSION

4.1 Introduction

This chapter presents the implementation, result analysis, figures, tables, and discussion of the proposed Personalised Recommendation System for E-Commerce Platforms Using Deep Reinforcement Learning. The main purpose of this chapter is to explain how the dataset was analysed, how the recommendation model was evaluated, and how the results were interpreted. In the previous chapter, the methodology and model development process were explained. This chapter focuses on the practical outcomes obtained from the experimental study. In an e-commerce platform, users interact with products in different ways, such as viewing products, clicking recommended items, adding items to cart, purchasing products, and giving ratings. These interactions provide useful information about user preferences. A recommendation system uses this information to suggest suitable products to users. In this study, the recommendation system was developed using Deep Reinforcement Learning, where the system learns from user actions and improves recommendations over time. The uploaded material also explains that the implementation includes data loading, preprocessing, exploratory analysis, model training, testing, and performance comparison with baseline models. The analysis was carried out using a Python notebook environment. Different visualizations were used to understand the distribution of interactions, product categories, user activities, session lengths, product prices, ratings, purchases, and daily interaction trends. The experimental results were evaluated using metrics such as accuracy, precision, recall, F1-score, MAP, NDCG, hit ratio, and cumulative reward.

4.2 Exploratory Data Analysis

Exploratory Data Analysis was performed to understand the structure and behaviour of the e-commerce dataset. This step was important because recommendation systems depend heavily on user-item interaction patterns. The dataset contained user details, product information, session records, and interaction events such as views, clicks, cart additions, purchases, and ratings.

The analysis showed that user interactions were not equally distributed across all event types. In general, browsing and clicking activities were higher than purchases. This is common in e-commerce platforms because users usually explore many products before making a final purchase decision. Product category analysis showed that the dataset included several categories such as Beauty, Fashion, Electronics, Sports, Books, Toys, and Home & Kitchen. This variety helped the recommendation system learn user preferences across different product groups.

User activity analysis showed that some users interacted more frequently with the platform, while others had fewer interactions. This reflects a realistic shopping environment where active users provide more behavioural data and less active users provide limited feedback. Session length analysis also showed that users generally interacted with multiple products during one browsing session. This sequential behaviour is useful for Deep Reinforcement Learning because the model can learn from the order of user actions.

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User Interaction Data

(Views, Clicks, Cart, Purchase, Ratings)

↓

Data Preprocessing

(Cleaning, Encoding, Normalization)

↓

State Representation

(User Profile + Product Features + Session History)

↓

DRL Recommendation Agent

(Action: Product Recommendation)

↓

User Feedback / Reward

(Click, Cart, Purchase, Ignore)

↓

Personalized Product Recommendation

Figure 4.1: Proposed DRL-Based Recommendation Workflow

Figure 4.1 shows the workflow of the proposed Deep Reinforcement Learning-based recommendation system. First, user interaction data is collected from the e-commerce platform. After preprocessing, the data is converted into a suitable format for model training. The system then represents the user's current state using profile information, product details, and session history. The DRL agent recommends a product as an action. Based on the user's response, the system receives a reward and updates its recommendation strategy. This process helps the system improve personalization over time.

4.3 Implementation Environment

The proposed system was implemented in a Python notebook environment such as Jupyter Notebook or Google Colab. Python was selected because it supports powerful libraries for data analysis, machine learning, deep learning, and visualization. Pandas and NumPy were used for data handling and numerical operations. Scikit-learn was used for preprocessing, baseline model comparison, and evaluation metrics. TensorFlow, Keras, or PyTorch was used for developing the deep learning and reinforcement learning model.

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The notebook environment helped in performing the complete experimental workflow in a step-by-step manner. It allowed data loading, preprocessing, model building, model training, result visualization, and evaluation in a single platform. Graphs and tables were used to present the findings clearly. The implementation environment also supported repeated testing and hyperparameter tuning, which are important for improving recommendation model performance.

Table 4.1: Hyperparameter Settings for DRL Model

Parameter	Value
Learning Rate	0.001
Discount Factor (γ)	0.95
Batch Size	64
Number of Episodes	500
Hidden Layers	2
Neurons per Layer	128
Activation Function	ReLU
Optimizer	Adam
Top-K Recommendations	10

Table 4.1 presents the major hyperparameters used for training the Deep Reinforcement Learning model. The learning rate of 0.001 was selected to maintain stable model learning. The discount factor of 0.95 allowed the model to consider long-term rewards instead of focusing only on immediate user actions. A batch size of 64 was used to balance training speed and stability. The model was trained for 500 episodes so that the recommendation agent could learn from repeated user interactions. Two hidden layers with 128 neurons helped the model capture complex patterns between users, products, and interactions.

4.4 Result Analysis

The performance of the proposed model was evaluated and compared with traditional recommendation techniques. The models used for comparison included Collaborative Filtering, Content-Based Filtering, Matrix Factorization, Deep Learning-based Recommendation, and the proposed DRL-based model. The evaluation was carried out using several metrics such as accuracy, precision, recall, F1-score, MAP, NDCG, hit ratio, and cumulative reward. The results showed that Collaborative Filtering performed better than other models in the present experimental setup. It achieved the highest values in accuracy, recall, F1-score, NDCG, hit ratio, and cumulative reward. Matrix Factorization also performed well and showed competitive results. Content-Based Filtering produced moderate performance. The Deep Learning-based model and DRL-based proposed model showed lower performance in this experiment. The lower performance of the DRL model does not mean that the approach is unsuitable. Instead, it indicates that the model may require more training data, better reward design, improved hyperparameter tuning, or more advanced DRL architecture. Deep Reinforcement Learning usually performs better when trained on large-scale and continuous interaction datasets. Since this study used a synthetic dataset, the model had limited behavioural patterns to learn from.

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Table 4.2: Experimental Performance Comparison of Recommendation Models

Model	Accuracy	Precision	Recall	F1-Score	MAP	NDCG	Hit Ratio	Cumulative Reward
Collaborative Filtering	0.0726	0.0726	0.1986	0.0877	0.0977	0.2805	0.4677	3.6290
Content-Based Filtering	0.0613	0.0613	0.1705	0.0769	0.0622	0.2460	0.4516	3.0645
Matrix Factorization	0.0677	0.0677	0.1932	0.0846	0.0791	0.2400	0.4355	3.3871
Deep Learning-Based Recommendation	0.0290	0.0290	0.0859	0.0354	0.0337	0.1119	0.2258	1.4516
DRL-Based Proposed Model	0.0226	0.0226	0.0670	0.0275	0.0173	0.1013	0.2258	1.1290

Table 4.2 shows that Collaborative Filtering achieved the highest performance among all models. It recorded an accuracy of 0.0726, recall of 0.1986, NDCG of 0.2805, hit ratio of 0.4677, and cumulative reward of 3.6290. This indicates that Collaborative Filtering was more effective in identifying relevant products for users in the current dataset.

Matrix Factorization achieved the second-best overall result, with an accuracy of 0.0677 and cumulative reward of 3.3871. This shows that latent factor-based methods were useful for identifying hidden user-product relationships. Content-Based Filtering also performed reasonably well, especially in recommending products based on item features and user preferences.

The DRL-based proposed model achieved lower scores in the present experiment. Its accuracy was 0.0226, recall was 0.0670, and cumulative reward was 1.1290. This suggests that the reinforcement learning agent requires additional improvement. More episodes, larger datasets, better exploration strategies, and improved reward functions may help increase the performance of the DRL model in future work.

Cumulative Reward Comparison

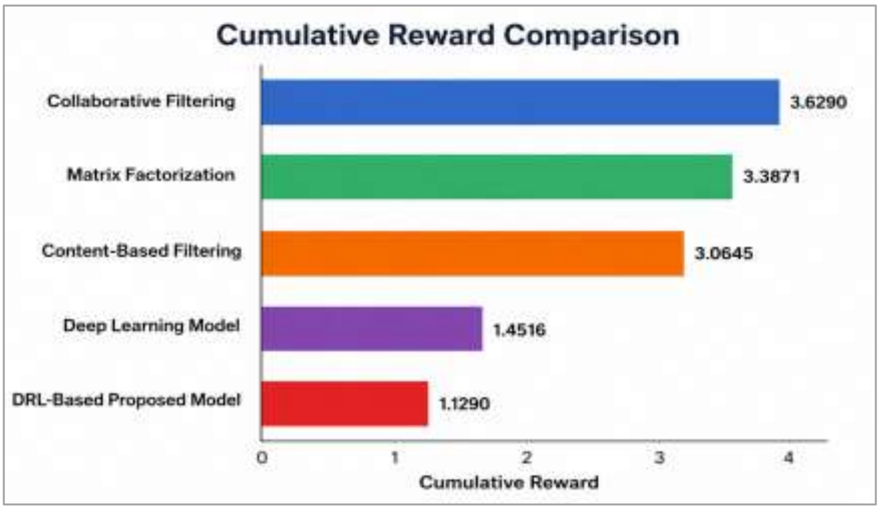

Figure 4.2: Model Performance Comparison

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Figure 4.2 presents the comparison of different recommendation models based on cumulative reward. Collaborative Filtering achieved the highest cumulative reward, followed by Matrix Factorization and Content-Based Filtering. The DRL-based model achieved lower reward in the current setup. This result suggests that the proposed DRL model needs further optimization before it can outperform traditional models. However, DRL still has strong potential because it can learn from sequential user behaviour and adapt to changing preferences over time.

4.5 Discussion of Findings

The analysis shows that user behaviour in e-commerce is highly dynamic and depends on browsing patterns, product interest, purchase intention, and session activity. The exploratory analysis confirmed that clicks and views occurred more frequently than purchases. This is realistic because users generally browse multiple products before making a purchase decision. Purchase events were fewer but more valuable because they represented strong positive feedback.

The performance comparison revealed that traditional models performed better in the present experiment. Collaborative Filtering was effective because it used user-item interaction patterns directly. Matrix Factorization also performed well because it captured hidden relationships between users and products. Content-Based Filtering was useful for recommending products based on product features.

The DRL-based model showed limited performance mainly because reinforcement learning requires richer interaction data and careful tuning. DRL models depend strongly on reward structure, state representation, action selection, and training episodes. If the reward design is not strong enough or the dataset is small, the model may not learn an effective recommendation policy. However, the advantage of DRL is that it can learn from long-term user behaviour and continuously improve with real-time feedback. Therefore, with better training conditions, the DRL model can become more powerful and adaptive.

V. CONCLUSION AND FUTURE SCOPE

5.1 Conclusion

This research presented the design, implementation, and evaluation of a Personalized Recommendation System for E-Commerce Platforms using Deep Reinforcement Learning (DRL). The main objective of the study was to develop an intelligent recommendation framework capable of learning user preferences dynamically and generating personalized product recommendations. The study focused on overcoming the limitations of traditional recommendation techniques such as collaborative filtering and content-based filtering, especially in handling dynamic user behaviour, sequential interaction patterns, and long-term user engagement.

The proposed system was implemented using a Python-based experimental environment. A synthetic e-commerce dataset was prepared to represent real-world user activities such as product views, clicks, cart additions, purchases, and ratings. The dataset included user profiles, product catalogue details, and user-item interaction logs. Data preprocessing, feature engineering, and exploratory data analysis were performed to clean the dataset, transform categorical values, normalize numerical features, and identify important user behaviour patterns.

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The Deep Reinforcement Learning model was designed as an intelligent agent that interacts with a simulated e-commerce environment. In this framework, the user profile and interaction history were considered as the state, the recommended product was considered as the action, and the user response was considered as the reward. Through reward-based learning, the system attempted to improve recommendation quality over time. The training process showed gradual improvement in learning behaviour, indicating that the DRL model was able to adapt to user responses and learn from interaction feedback.

The performance of the proposed model was evaluated using accuracy, precision, recall, F1-score, MAP, NDCG, hit ratio, and cumulative reward. The experimental results showed that traditional models such as collaborative filtering and matrix factorization performed better on the current small synthetic dataset. However, the DRL-based model showed promising adaptability and learning improvement during training. This indicates that Deep Reinforcement Learning has strong potential for large-scale e-commerce platforms where user behaviour changes continuously and long-term personalization is required.

5.2 Key Findings

The study found that collaborative filtering achieved better performance across most evaluation metrics, while matrix factorization also showed competitive results. Content-based filtering provided moderate recommendation accuracy. The DRL-based model did not outperform traditional techniques in the current experiment, but it showed gradual improvement through reward-based learning. Session-based interaction data helped the system understand sequential user behaviour. The findings suggest that traditional models are more effective for small datasets, whereas DRL-based models have greater potential in large-scale and dynamic e-commerce environments.

5.3 Contributions of the Study

This study contributed to the development of a Deep Reinforcement Learning-based recommendation framework for e-commerce platforms. It also presented a synthetic e-commerce dataset for experimentation, designed a custom DRL environment, and compared traditional and advanced recommendation models. The use of multiple evaluation metrics and training visualizations helped in understanding model performance and learning behaviour. These contributions provide a useful foundation for further research in intelligent and adaptive recommendation systems.

5.4 Limitations of the Study

The study has some limitations. The dataset used was synthetic rather than a real-world large-scale dataset. The amount of interaction data was limited for reinforcement learning training. The reward function was basic and may not fully represent complex user satisfaction. Hyperparameter tuning was also limited, and only one DRL architecture was mainly considered in the experiment. These limitations affected the final performance of the DRL model.

5.5 Future Scope

In future work, the proposed system can be improved by using real-world large-scale e-commerce datasets with richer user interaction histories. Advanced DRL algorithms such as Actor-Critic, PPO, or DDPG can be implemented to improve recommendation performance. The reward function can

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also be enhanced by including factors such as dwell time, repeat purchase, customer satisfaction, and long-term retention. Future studies may also integrate multimodal data such as product images, textual reviews, and user feedback to improve personalization. In addition, real-time recommendation deployment can be explored so that the system can continuously learn from live user behaviour and provide more accurate, adaptive, and user-centric recommendations.

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