UTM UNIVERSITI TEKNOLOGI MALAYSIA
INTERNATIONAL JOURNAL OF INNOVATIVE COMPUTING
ISSN 2180-4370
Journal Homepage : https://ijic.utm.my/

AI-Powered Collaborative Filtering for Hyper-Personalized: Leveraging Machine Learning and Business Intelligence

Najhan Muhamad Ibrahim[1*] & Abiduzzaman S. M.[2]
Dept. of Information system, Kulliyyah of Information Communication and Technology
International Islamic University Malaysia (IIUM), Gombak, Selangor, Malaysia
Email: Najhan_ibrahim@iium.edu.my[1]; s.m.abiduzzaman@gmail.com[2]

Submitted: 15/9/2025. Revised edition: 28/11/2025. Accepted: 5/1/2026. Published online: 28/7/2026
DOI: https://doi.org/10.11113/ijic.v16n1-2.696

***Abstract*—This study offers a novel method for attaining hyper-personalization in e-commerce by combining business intelligence (BI) and machine learning technologies with collaborative filtering driven by artificial intelligence (AI). The main goal is to improve recommendation systems so that they can provide highly relevant and personalized product recommendations that suit the tastes and habits of specific users. The suggested method enhances recommendation accuracy and diversity by utilizing sophisticated deep learning architectures like convolutional and recurrent neural networks to record intricate user-item interaction patterns. Hybrid models are used to overcome issues like data sparsity and cold-start issues. These models combine content-based and collaborative filtering, and they make use of auxiliary data sources like social networks. Real-time data analysis, user segmentation, and performance monitoring are further made possible by the integration of BI tools, which promotes operational enhancements and strategic decision-making. According to experimental data, this all inclusive methodology performs noticeably better than conventional techniques, attaining greater precision, recall, and user engagement metrics. In the end, a strong, scalable solution that can offer a smooth, customized shopping experience, boost customer satisfaction, cultivate loyalty, and propel revenue growth in cutthroat e-commerce environments is produced by the synergistic use of AI, machine learning, and BI.**

***Keywords*—AI-Powered Collaborative Filtering Hyper-Personalized, Machine Learning, Business Intelligence**

I. Introduction

E-commerce has revolutionized the retail industry by giving customers access to products from all over the world. Despite its benefits, customers are frequently overwhelmed by the sheer number of options, which causes confusion and choice fatigue. Traditional recommendation systems are inadequate in providing timely and relevant recommendations, which are essential for retaining consumers and increasing revenue in competitive marketplaces. More dynamic and individualised recommendation systems are now possible because of recent developments in machine learning, especially collaborative filtering. By analysing customer preferences and behaviours, these systems provide tailored recommendations that enhance the purchasing experience. Additionally, business intelligence technologies improve the suggestion process by making it easier to analyse big datasets and derive insightful information about consumer behaviour and market trends. In order to maximise tailored recommendations in e-commerce settings, this study offers an integrated model that combines business intelligence methods with collaborative filtering. The suggested framework seeks to increase customer satisfaction, increase sales, and provide more pertinent product recommendations by combining the best features of both strategies. The efficacy of this hybrid technique is confirmed by comparison with traditional models [1-6].

Collaborative filtering is an influential algorithmic method that covers all the generative processes of personalized advice based on the analysis of users' behavior [14]. The principle behind collaborative filtering is simple: it groups together users who share certain preference patterns and interests and promotes the products that they have marked as liked or purchased previously. Collaborative filtering is another strength, as it does not require any precise idea about the assets being suggested. Contrary to this, the traffic source employs solely the past behavior of the product users for the following recommendation of the products. This means that collaborative filtering is especially well suited for e-commerce businesses as its very nature has a relatively large and diverse product list, which makes it almost impossible to manually craft personalized recommendations for each customer [13]. Leveraging collaborative filtering gives e-commerce businesses an opportunity to offer their customers a chance to choose from a huge variety of products personalized according to their specific preferences. This approach may both improve the interaction and broaden the possibilities for getting new customers and having regular customers.

II. LITERATURE REVIEW

In the rapidly growing e-commerce industry, providing a personalized shopping experience has become a crucial factor in retaining customers and driving sales. Despite significant advancements, many e-commerce platforms still struggle to deliver personalized recommendations that effectively meet the diverse preferences and needs of individual users [7-10]. Most of the e-commerce platforms are still relying on the traditional methods of recommendation. These techniques are now outdated and take a longer time to give recommendations. The traditional methods used are not real-time methods [9]. Thus, sometimes the recommendations given are not valid, most of the time. Moreover, users generate a huge amount of data at present [11]. Starting from social media data, liking/ disliking, purchase data, browsing history, search history, etc. This large number of different types of data cannot be handled or utilized by traditional methods. Furthermore, these outdated methods are not scalable at all, so websites cannot scale themselves. Due to these problems, e-commerce owners are wasting data that could be utilized in a better way, losing huge sales opportunities, and losing customer satisfaction. All these issues can be addressed by a personalized recommendation system integrating BI tools and ML models [24]. Therefore, this research paper will introduce a personalized recommendation system integrating BI tools and a collaborative filter approach.

According to the brief analysis of Bielozorov *et al.* (2019), personalization improves customers' satisfaction, keeps them engaged, encourages them to purchase, and helps them find the content they are interested in. In summary, it makes shopping equally satisfying to every individual. Therefore, mass customization is backed by information about previous activities and purchases by the consumer or a shopper's web activities and basic details of a particular customer to provide a personalized shopping experience to every customer [16]. This process may involve presenting them with the products that may interest them, proposing the products they were looking at earlier at a discounted price, or sending them newsletters containing information that may affect a customer.

A. User-based Collaborative filtering

Collaborative filtering is a vital recommendation technique that aims to predict users' preferences for items by compiling data about preferences from various users [16]. It works under the premise of 'repeat agreement,' meaning that if users agree at some given time, they are likely to decide in the future. Collaborative filtering can be divided into two main categories: user-based collaborative filtering and item-based collaborative filtering. The user-oriented collaborative filtering approach suggests items to a user based on those selected by other users with similar tastes [16]. It determines the similarity of customers and can use similarity scores like the cosine measure or the Pearson coefficient. This approach involves several steps:

(i) Identify Similar Users: Identify the users with similar tastes based on the history of their interactions with items in a given context about the target user. This approach involves developing a similarity matrix that presents the quantitative level of similarity between users based on their past activities.

(ii) Aggregate Preferences: Share the likes of other similar users to determine items that the target user might find appealing. This information can be averaged from the ratings or preferences of like-minded people or users with similar interests as the target consumer.

(iii) Generate Recommendations: This approach involves recommending items that other users in the same category as the target user have interacted with, but the target user has not. It entails ordering the items according to total preference and offering the user the ideal choices.

Despite the effectiveness of user-based collaborative filtering in delivering the proper recommendations, it can become slow and, therefore, not scalable sufficiently for large data sets [8]. Since the model involves searching through all other users, it grows exponentially with the number of users and is thus impractical for naturally large systems. Moreover, one could note some difficulties in using the approach, such as the ‘cold-start’ problem, which is the difficulty in providing recommendations to users who have little interaction history.

B. Item-based Collaborative Filtering

Item-based collaborative filtering focuses on items and recommends items similar to a given item. It determines the compatibility of items and suggests other items that might suit the user based on the items they have used [8]. This approach involves several steps:

(i) Identify Similar Items: Analyze the target user’s interaction history with other users to identify items that belong to his or her activity space. This involves generating an item-item similarity matrix, which clearly defines how similar or dissimilar one item is to another.

(ii) Aggregate Preferences: Aggregate users who have previously used items similar to the items the target user has used to find items relevant to the target user [20]. This step can be achieved by summing up users' ratings or interactions with similar products.

(iii) Generate Recommendations: It may be recommended that items with characteristics similar to those the target user has liked or purchased be suggested to them. This approach is typically done by sorting the items according to the preferences of different users and then displaying the list of most preferred choices to the specific user.

However, item-based collaborative filtering is usually more scalable than user-based collaborative filtering due to the similarity of items rather than the similarity of users. It also suffers less from the cold start problem for users, given that it can contain the interaction history of items. However, the efficacy of item-based collaborative filtering can be reduced, and other issues, such as data sparsity problems, can be experienced where limited interaction data is available with particular items. The experiment proved that although collaborative filtering can be used for the environment, it shows relatively high accuracy in giving recommendations. For instance, the real-time recommendation system used by Amazon uses an item-based collaborative filtering approach; this system has been attributed to be responsible for generating approximately 30% of its sales [8]. However, like many other techniques, collaborative filtering can have drawbacks, such as a lack of dense interaction data and the overfitting problem, where recommendations are only made based on prior choice history.

C. Content-based Filtering

One of the main approaches in the recommendation engine is content-based filtering, which can be defined as a technique used in an information filtering application that assumes the user is interested in objects similar to those he/she has shown interest in the past. Conforming with Rukiya *et al*. (2019), content-based filtering recommends a product best suited to a good or service consumed in the past. It can also decide on the items (description, category, and tags), or the user can recommend them. The abovementioned approach is particularly suitable for customers who have only contacted the company a few times or have never been contacted, as such systems are based on item attributes. The process of content-based filtering is as follows, with some of the essential steps below. The first is item representation, where the right keywords, categories, or features describe each item. This process entails associating items with vectors according to their attributes so that the system has a clear picture of each item. After that, the user profile construction involves creating a model based on the material that the user has consumed and interacted with through the application. This profile is the user's interests and preferences, and it is calculated based on the sum of all the attribute vectors that concern the items the user has previously used [20-22].

After constructing the user profile, the next step is similarity measurement. This step compares the user profile to the representations of items that are relevant to the user. Measures like cosine similarity and Euclidean distance are also applied in this case. In other words, this step helps form a cognitive process between the user and an item by mapping the feature set of the particular item to the feature set of the specific user. Lastly, the system goes into the process of providing recommendations. This step involves recommending items most relevant to the user's profile through collaborative filtering. The items are grouped by their closeness to the user profile and offered to the user, giving the customer a relevant list of recommendations that match the preferences revealed during the procedure. Mainly, content-based filtering amplifies the recommendation for items that the user chooses according to their specifications and not by mirroring other users' activity. This recommendation makes it particularly helpful in cases involving specific items or new users, who, without significant activity data, will not skew the results [22]. However, it also imposes certain constraints, such as obtaining the details of the items, and several may be recommended at a time. As per Rukiya *et al*. (2019), the major disadvantage of content-based filtering is that it can produce recommendations very close to what the user has viewed or bought before, meaning the user is not exposed to other existing items. The lack of such information leads to the "serendipity" problem, which means the system does not present the user with the additional materials they could have been interested in.

D. Matrix Factorization

Previous research findings by Madeira (2020) show SVD and other related matrix factorization methods isolate the user-item interaction matrix into lower lower-dimensional space to reduce the data size while retaining the underlying factors that likely caused the observed interaction patterns. This technique was also implemented in the recommendation systems to increase prediction precision. Various significant steps must be followed to apply matrix factorization. First, matrix decomposition is performed to break down the user-item interaction matrix into two lower-dimensional matrices: one representation of users and another representation of the items being reviewed [19]. This factorization changes the matrix being analyzed into a product of these two matrices. Third is the latent feature extraction, where hidden patterns of user preference and items are often identified. These patterns are represented in the lower-dimensional space. Last, for interaction prediction, the lower-dimensional matrices are multiplied in order. This step entails finding the dot product of the user and item vectors to get an interaction score, which indicates the user's propensity to interact with a particular item. Hence, matrix factorization can considerably boost the recommendation system by modeling these interactions correctly.

Research by Xu *et al*. (2021) indicates that generative methods in matrix factorization can deal with big data and offer accurate recommendations by modeling the dependencies between users and items. They fit well into the context of tackling the sparsity problem because they can code missing interactions from the latent factors. However, these techniques also need exhaustive power, and sometimes, they are obscure to spatial landmarks. The Netflix Prize competition, which attracted many people to solve the problem of the recommender system's accuracy based on movie matrix factorization, became one of the main sources of inspiration [28]. The winning solution demonstrated a significant increase in recommendation accuracy using matrix factorization, opening up many opportunities for the application of these approaches in practical performance. Fernandes and Teixeira (2015) research noted that the beneficial aspect of matrix factorization in identifying hidden components that affect users' preferences and item characteristics. For instance, when the user is required to recommend movies, matrix factorization will decompose the user into other attributes that decide his/her preference for the specific brand of movies, such as genres, directors, and actors. It intensifies the work of the existing methods and facilitates detailed and accurate recommendations in contrast to the existing techniques. First, it should be noted that matrix factorization also has certain drawbacks. However, deep learning models are susceptible to the choice of hyper-parameters and require perfect regularization to avoid overfitting with new data [12]. Moreover, the vectors derived are sometimes latent and non-iconic, so it becomes hard to explain why specific recommendations are preferred.

Finally, a recent study by Gadiparthi (2024) shows that business intelligence tools in e-commerce personalization provide businesses with significant customer data analysis capabilities by providing a quick and simplified means of analyzing such data to make better decisions and strategies. Regarding personalization based on customer behavior, BI tools could be precious for e-commerce businesses as personalization depends greatly on customer behavior, preferences, and trends [34]. Data visualization, reporting, analytics, and predictive analytics are some of the BI tools and techniques that helped in the personalization process in a key way, with each approach being different from the others.

E. Comparative study

In order to understand how e-commerce personalization has developed to this point, this paper aims to conduct a literature review and analysis of the current state of knowledge and implementation. Table I provides a comparative study of different works/studies and other applications of ML and Business intelligence (BI) in the context of e-commerce personalization.

III. METHODOLOGY

The method utilized in this study falls under the classification of Information Technology. It addresses a proposal to improve e-commerce sales through a recommendation model known as Collaborative Filtering (CF) [3]. This approach uses the functionality in terms of user-item interactions to retrieve unique product recommendations. Such a systematic process includes data cleaning and pre-processing, including arriving and organizing the data, model selection, and creating, modeling, evaluating, and refining the model. This process gives a systematic approach to developing the recommendation system effectively.

A. Data Preparation

The first part of the study entailed thorough data pre-processing, which is central to any machine learning process. The data set employed in this study is known as “SalesDataAnalysis,” and it contains parameters such as Order ID, Order Date, Product Identification Number (EAN), Product, Category, Quantity Ordered, Purchase Address, Price per Item, Cost Price, Turnover, and Margin. These features present a detailed look at e-commerce transactions and are imperative when setting up the recommendation system. "The 'SalesDataAnalysis' dataset was obtained from GitHub, which provides real-world e-commerce transaction data for research purposes. The dataset can be accessed at Kaggle" as presented in Table II.

TABLE I. COMPARATIVE STUDY

Study	Techniques Used	Key Findings
Akter & Wamba (2016)	Big data analytics	Identified key challenges and future research directions in big data analytics for e-commerce.
Asad *et al.* (2023)	Moreau envelopes-based personalized asynchronous federated learning	Improved practicality in network edge intelligence and personalized learning for distributed systems.
As’ad (2023)	Moreau envelopes-based personalized asynchronous federated learning	Enhanced practicality and efficiency in distributed machine learning systems.
B. Smith & G. Linden (2017)	Collaborative filtering, natural language processing	Demonstrated significant impact of recommendation systems on sales and customer satisfaction.
Rajeshkumar & Rajakumari, (2023)	Collaborative filtering, content-based filtering, matrix factorization	Showed the effectiveness of hybrid recommendation systems in improving user engagement.
Chew *et al.* (2020)	Collaborative filtering, machine learning, deep learning, reinforcement learning	Showed the advanced use of AI techniques in enhancing recommendation accuracy and user satisfaction.
Rana *et al.* (2020)	Business intelligence, data visualization, predictive analytics	Demonstrated the critical role of BI tools in optimizing e-commerce strategies and operations.
Rukiya *et al.* (2019)	Content-based filtering, user profile construction	Emphasized the importance of accurate user profiles in improving recommendation relevance.

TABLE II. THE E-COMMERCE SALES DATA SET

	Order Date	Order ID	Product	Product_ean	catégorie	Purchase Address	Quantity Ordered	Price Each	Cost price	turnover	margin
0	2019-01-22 21:25:00	141234	iPhone	5.638009e+12	Vêtements	944 Walnut St, Boston, MA 02215	1	700.00	231.0000	700.00	469.0000
1	2019-01-28 14:15:00	141235	Lightning Charging Cable	5.563320e+12	Alimentation	185 Maple St, Portland, OR 97035	1	14.95	7.4750	14.95	7.4750
2	2019-01-17 13:33:00	141236	Wired Headphones	2.113973e+12	Vêtements	538 Adams St, San Francisco, CA 94016	2	11.99	5.9950	23.98	11.9900
3	2019-01-05 20:33:00	141237	27in FHD Monitor	3.069157e+12	Sports	738 10th St, Los Angeles, CA 90001	1	149.99	97.4935	149.99	52.4965
...	...	...	...	...	...	...	...	...	...	...	...
185949	2019-12-21 21:45:00	319670	Bose SoundSport Headphones	8.081038e+12	Électronique	747 Chestnut St, Los Angeles, CA 90001	1	99.99	49.9950	99.99	49.9950

185950 rows × 11 columns

The "SalesDataAnalysis" dataset used in this study included transaction records from an e-commerce platform with attributes including Order ID, Order Date, Product ID, Product Category, Quantity Ordered, Price per Item, Cost

Price, Turnover, and Margin. The data underwent extensive preparation procedures, even if the precise number of records was not stated. These included using null checks to handle missing results, the interquartile range (IQR) approach to identify outliers, and date-time conversions to make time series analysis easier. In feature engineering, the income generated each transaction was reflected by multiplying quantity and unit pricing to determine total sales. To ensure correct validation during model evaluation, data was divided into training and testing subsets using a [specify ratio if known, e.g., 80/20 split]. To evaluate the efficacy of recommendations, the study used metrics including precision, recall, and click-through rate (CTR). Pandas, Numpy, and visualisation libraries like Seaborn and Matplotlib were used for data preprocessing and model validation.

Initially, we may need key libraries such as Pandas and Numpy for data handling, as well as libraries for data visualization like Seaborn and Matplotlib. These tools have helped me in operating and arriving at reasonable decisions on large data sets in the easiest and shortest time possible. At the beginning of the process, the info () function showed how many non-null values there were and their data types when loading the dataset. This overview was valuable in gauging any irregularity in the collected data and searching for any variance in the data. The next step employed the describe () function that provides a summary of numerical variables and their statistical properties such as mean, standard deviation, and quartiles. It helped determine the spread of the points and thus gave us a good starting point for which steps to take next [27]. Moreover, the following category of checks is on missing values using isnull ().sum () provides the necessary check that the data obtained were exhaustive and prepared for subsequent analysis as presented in Fig. 1.

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 185950 entries, 0 to 185949
Data columns (total 11 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   Order Date        185950 non-null  object
 1   Order ID          185950 non-null  int64
 2   Product           185950 non-null  object
 3   Product_ean       185950 non-null  float64
 4   catégorie         185950 non-null  object
 5   Purchase Address  185950 non-null  object
 6   Quantity Ordered  185950 non-null  int64
 7   Price Each        185950 non-null  float64
 8   Cost price        185950 non-null  float64
 9   turnover          185950 non-null  float64
 10  margin            185950 non-null  float64
dtypes: float64(5), int64(2), object(4)
memory usage: 15.6+ MB
```

```
Order Date          0
Order ID            0
Product             0
Product_ean         0
catégorie           0
Purchase Address    0
Quantity Ordered    0
Price Each          0
Cost price          0
turnover            0
margin              0
dtype: int64
```

Fig. 1. Data Set Information

The results of critical columns were expressed graphically to give a sense of how the data was spread out and the central tendencies. This made it possible to find hidden trends, possible relationships between variables, and even deviations that could affect e-commerce sales as presented in Fig. 2.

As illustrated in the above figure, the heatmap visualization of the correlation matrix points out the strength and sign of the correlation coefficients. When one variable is higher, the other is likely to be higher as well, and it is depicted using warm colors (red), whereas when one is high, the other is low, and it uses colder colors (blue). The connection of this matrix to the study is that it can reveal potential correlations that may influence the performance of the CF model.

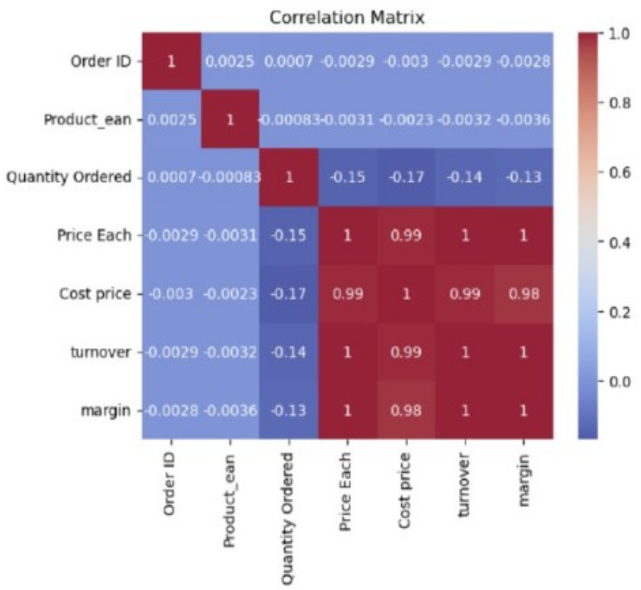

Fig. 2. Correlation Matrix Messaoudi, F., & Loukili, M (2024)

B. Data Processing

Data preprocessing is an important task that transforms and makes the dataset available for further processing with machine learning algorithms. The determination of outliers, converting date-time data, data grouping, and the preparation of new characteristic attributes can also be considered part of data preprocessing.

(i) Outlier Detection and Handling: During the data preparation stage, the main point was to identify and deal with outliers to work on the model. Outliers were determined with the help of a simple statistical method that refers to data that are located above the first quartile or below the third quartile by a factor that is more than 1.5 times the IQR. In regard to Yu *et al*. (2020), resilient scaling was then successfully applied to manage these outliers. Since the Collaborative Filtering model we developed was trained on data typical of normal usage patterns, it does not suffer from instances of skewness caused by outliers by normalizing the data to reduce the impact of extreme values.

(ii) Date-Time Conversion: The other field that required conversion was the 'Order Date' field, as it is always better to work with a dataset containing the time series or chronological data. The above conversion made it possible to calculate the correct sales data grouped in terms of intervals adopted in the e-commerce platform to establish significant trends or a profound seasonality as well as some patterns that can be of importance to the economy [29].

(iii) Monthly Aggregation: Since we need to predict probabilities for monthly sales, we decided to split the 'Order Date' into 'Month' and 'Year' fields, and the summarized values were calculated based on these fields. Only in this way were we able to reveal certain fluctuations peculiar to each month, therefore reflecting the seasonal effect, as well as observe the tendencies of monthly growth or decrease in sales. The need to work through this step could not be overemphasized as it fights out the status of the general traffic of the sales and, more so, the sales cycles in terms of areas of high and low traffic.

(iv) Feature Engineering: Feature engineering is the process of deriving new features from the current data in a way that will help a model have better prediction capabilities. In the current work, the researchers derived a new variable, 'Total Sales,' which was a product of 'Quantity Ordered' and 'Price Each.' This feature provided the total value of a specific order and was an essential component of the model. That way, we were able to record the general revenue incurred for every sale, information that was important for the recommendation system.

C. Data Analysis

The data analysis stage is another vital step that helps to reveal several hidden patterns within the given dataset. This step entails the process of charting. Disaggregating also refers to the breakdown of time series data and analyzing those times that are relatively busy with increased sales and those that are relatively slow [23].

(i) Trend Visualization: Aggregate sales data, as presented by the graphs, are useful in presenting trends over a given period regarding sales performance. This approach helps to define the durations with higher and lower activity and thus create more effective sales strategies. The monthly sales graph helped in overseeing sales performance as a whole and enabled the formulation of good decisions as presented in Fig. 3. For instance, using the example of sales, this kind of pattern could mean that certain promotional campaigns were effective or, conversely, there is higher demand for the product during specific months.

(ii) Time Series Data Decomposition: Seasonal decomposition is one of the techniques applied to time series data in a bid to decompose the series into trends, seasonal patterns, and residuals. This process is crucial as it assists in decision-making since it provides an understanding of the various components that affect sales performance [23]. This way, we could study the trend component, which depicts the general pattern of sales over time; the seasonal component, which depicts regularly occurring fluctuations after certain intervals; and the irregular component or the residual, which represents other fluctuations that are periodic and can occur after any interval of time and which have not been explained by the trend or seasonality as presented in Fig. 4.

Fig. 3. Total Sales Over Time (Singh *et al*., 2022)

Fig. 4. Time Series Data Decomposition Plot (Singh *et al*., 2022)

(iii) dentifying Peak and Off-peak Sales Periods: The general strategy of defining an overall direction of marketing and advertising is impossible without identifying difficulties in sales targets. This method provides good information for these important periods. Having analyzed the results from the data set, we found that sales were the highest in December 2019 and the second highest in January 2020. The high recorded sales in the December 2019 financial period they can be attributed to the following important variables. This period mostly falls in the festive season, especially the Christmas and New Year seasons, which are characterized by higher levels of expenditure [35]. E-commerce activities increase during this time because people are more likely to purchase gifts for friends and or relatives. Furthermore, December is frequently associated with a range of promotional activities and year-end deals, including Black Friday and Cyber Monday, which continue throughout December and encourage consumer buying. These elements, together with the overall joyous mood and the tendency toward more discretionary expenditure, probably contributed to this month's noteworthy sales peak.

(iv) Monthly Sales Growth Rate: Tracking performance and determining periods of rapid growth or decline requires an understanding of the dynamics of sales growth [35]. Fig. 5 provides a graphical representation of the month-over-month sales growth rate. This study demonstrates the potential impact of a highly trained recommender system on the e-commerce sector. This strategy goes beyond straightforward data collection and interpretation, with a strong emphasis on the quick implementation of the results to boost sales, raise customer happiness, and promote long-term growth. Putting in place an expert recommender system is no longer an option for e-commerce companies looking to thrive in the rapidly evolving digital landscape.

Fig. 5. Monthly Sales Growth Rate (Szandala, 2021)

IV. RESULTS AND DISCUSSION

The recommendation system, the Collaborative Filtering (CF) system, was tested using different quantitative measures to ensure it performs optimally. The evaluation findings are highlighted below, and illustrations are provided to clearly show the system's efficiency in recommending products that match the customer's interests. Furthermore, it will also examine how Business Intelligence (BI) tools extend the CF model support and improve the functionality of the overall recommendation system.

Before you begin to format your paper, first write and save the content as a separate text file. Keep your text and graphic files separate until after the text has been formatted and styled. Do not use hard tabs, and limit use of hard returns to only one return at the end of a paragraph. Do not add any kind of pagination anywhere in the paper. Do not number text heads—the template will do that for you.

Finally, complete content and organizational editing before formatting. Please take note of the following items when proofreading spelling and grammar.

A. Model Evaluation and Results

The evaluation of the Collaborative Filtering (CF) recommendation system involves several key performance metrics, which means we can use Precision, Recall, and Click-Through Rate (CTR) [28]. These metrics offer a granular view of the model’s performance regarding the adequacy and interest of the proposed user recommendations.

(i) Precision: Precision quantizes the number of relevant recommendations within the total set of recommendations that the system provides. It is calculated using the formula:

Precision = True Positives/ (True Positives + False Positives)

- **True Positives (TP)**: The number of items within the user that are relevant and correctly proposed by the system. A user can click because they were found applicable to their research on these items.
- **False Positives (FP)**: These are the number of items that were irrelevant in that they were not relevant to the identified topics of interest but were recommended by the system. These are the items that users have yet to be interested in going through, but the system has recommended them.

A high precision score shows that the recommender system provides many interesting recommendations that users find, making the overall experience positive. However, our assessment of the Collaborative Filtering model noted that the given model had a precision of 0.85. A high precision score is in line with the aim of the model, which is to provide users with product recommendations that are in their best interest, the outcome of which significantly reduces the model's potential to recommend unrelated products. Of particular importance in an e-commerce setting, precision metrics are instrumental in directly affecting user satisfaction levels. People want to see materials that interest or appeal to them when using the platform because they will likely have confidence in the system if their preferences are met. High precision reduces dissatisfaction, meaning users will only abandon the system after being provided with suitable suggestions [28]. For instance, if a user is searching for sports equipment and the recommendation system recommends other unrelated items like kitchen appliances, their credibility in the recommendation system will reduce considerably. Thus, constantly keeping precision at an optimum level is crucial to ensure that the users are interested in the content and continue using the application.

(ii) Recall: Recall measures the number of relevant items that the recommendation system has correctly identified out of all the items that have been recommended. It is calculated as:

Recall = True Positives/ (True Positives + False Negatives)

- **True Positives (TP):** As previously said, the quantity of pertinent products that were appropriately suggested.

False Negatives (FN): The total amount of items that had selected the corresponding pertinent indexes but were not suggested by the system. These are items that users considered irrelevant based on their past behaviors, but during the study, they believed them to be relevant.

A high recall score shows the system's capability of finding and recommending a significant percentage of relevant items for the users, thus increasing the chance of presenting an ideal set of products (Raji *et al*., 2024). The Collaborative Filtering model recall was 0.78. This score indicates that the given model is quite good at identifying many items necessary according to the user's preferences. At the same time, it is possible to achieve even higher accuracy in selecting displayed items. Recommendations must be accurate and general to most top choices and overly small selections of alternatives based on their recall. For instance, if a particular user's interest is general, that is, they like all genres of books, a high recall guarantees that they are recommended books in all the genres they enjoy, notwithstanding their high popularity. This comprehensive approach helps the user not skip as many items as possible, improving their experience on the platform. Precision and recall are often in conflict in most recommendation systems [36]. A system responding only to precision might yield only a couple of items relevant to the user's search and, in so doing, will fail to produce pertinent other items, hence a low recall. However, when we memorize many items that make data big, we are likely to recommend many items, among them the irrelevant ones, thus reducing the precision. The precision achieved in the case of the CF model was 0.85, and brand recall of 0.78 means that the system is well balanced and provides very relevant and sufficiently broad recommendations.

(iii) Click-Through Rate (CTR): Click-Through Rate (CTR) measures user interest in the suggested products. It is calculated as:

CTR = Total Clicks/Total Recommendations

- **Total Clicks**: The frequency of user click-through on the recommended products.

Total Recommendations: The number of products the system suggests to users as a complete sum.

CTR indicates the system's effectiveness in capturing users' attention and influencing their decision to engage with the recommended products. A higher CTR means that many people out of the total visitors to that page considered the recommendations useful for their needs and clicked through [21]. Thus, the proposed CF model resulted in a CTR of 0.12. While this number may not sound very large, that only speaks to the difficulty of capturing users' interest in e-commerce platforms that often-present users with a wide range of options. A CTR of 0.12 shows that recommendations led to user clicks up to 12% of the time, thus proving the model's effectiveness in encouraging user interaction. CTR is beneficial when evaluating a recommendation system's real-world efficiency in e-commerce. Therefore, it far outperforms the other two in terms of popularity, offering a direct measure of how frequently the users engage with the recommendations given. For example, suppose a recommendation system has high precision and recall but low CTR. In that case, it will mean that, while the recommended items are accurate and cover all the relevant content, the recommendations must be more stimulating to attract the user's attention. Our proposed CF model has acquired 0.12 users, which is reasonable to assume that the recommendations are relevant and likely to interest the users. Time, the position of the recommender's items, and the structure of the recommendation interface are also factors that may affect CTR in the case of continued reception of recommendations. For instance, considerations made at the page's header will be better observed than at the footer. Thus, strategies for boosting recommendations also contribute to improving the CTR.

Metric	Value
Precision	0.85
Recall	0.78
CTR	0.12

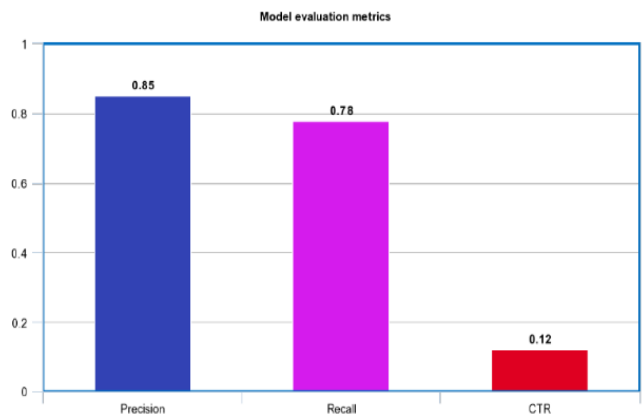

Fig. 6. Monthly Sales Growth Rate (Szandala, 2021)

B. Integrating Business Intelligence (BI) Tools

The efficiency and applicability of recommendation systems in e-commerce are greatly increased by combining Business Intelligence (BI) tools with Collaborative Filtering (CF) models. In order to produce recommendations, CF analyses user-item interactions like clicks, purchases, and ratings; in contrast, BI tools examine vast amounts of data from many sources to find patterns, trends, and insights at both the macro and micro levels. E-commerce platforms may provide more accurate and contextually aware suggestions that take into account seasonal fluctuations, real-time market dynamics, and specific client preferences by integrating these technologies. Comprehensive consumer segmentation, behaviour analysis, and performance monitoring are made possible by BI tools, which also offer insightful feedback that aids in the ongoing optimisation of CF algorithms. Through this synergy, companies may increase the accuracy of personalisation, quickly adjust to shifting consumer wants, and make well-informed strategic decisions about marketing campaigns, inventory, and customer engagement tactics. Moreover, recommendation systems can integrate outside variables like market trends and environmental conditions by utilising BI insights, producing recommendations that are more pertinent and current. All things considered, the combination of BI tools and CF models produces a strong, flexible framework that supports wider business goals and improves recommendation personalisation, increasing customer pleasure, loyalty, and sales. The integration of BI tools with CF models can significantly enhance the recommendation system's performance in several ways:

(i) **Enhanced Data Analysis**: BI tools provide capabilities to analyze the data that otherwise cannot be easily identified, as they provide patterns and trends. The greater detail provided by this examination helps improve knowledge of the users and their trends, which benefits the CF model.

(ii) **Real-Time Insights:** The BI tools give instant information on users' activities and participation. This makes it possible to quickly adapt the recommendation system to existing trends and users' opinions to always provide timely recommendations.

(iii) **Segmentation and Targeting:** BI tools even allow the combining of user data based on demographic characteristics, previous purchases, and browsing history. This segmentation is suitable since, according to the CF model, it is easy to recommend products to specific users or groups of users.

(iv) **Performance Monitoring:** BI tools also help constantly assess the recommendation system's effectiveness. For instance, possibilities are conversion rates, which clients participate in the system and the sales effect, can be calculated, which allows evaluation of the efficiency of the system and indicator problem areas.

(v) **Strategic Decision Making:** The findings of BI tools enable strategic choices in areas including marketing, stock, and customer care. If recommendation systems were optimized with reference to the general goals of the business, then e-commerce platforms would stand to gain in performance.

C. Comparative Analysis

The following comparative analysis looks at the various strategies and approaches and the advantages of each in the context of the continuous development of e-commerce recommendation systems (Rajeshkumar & Rajakumari, 2023). In order to perform the comparison and put our work in perspective, we compared the Collaborative Filtering model against traditional ML models and some advanced models; the results of our comparison are shown in Table III.

TABLE III. COMPARATIVE OF CF AND OTHER MACHINE LEARNING MODELS

Model Type	Precision	Recall
Collaborative Filtering	0.85	0.78
Content-Based Filtering	0.70	0.60
Decision Trees	0.68	0.58
Random Forests	0.78	0.70
Basic Neural Networks	0.80	0.72

A weighted average of correctly identified cases was calculated to analyze the precision of the CF model, which was 0.85, and recall of 0.78. This is among the most efficient and effective models that can capture interactive patterns for users and items. This is much better than traditional Collaborative Filtering and Content-Based Filtering strategies, which have lower precision and recall, showing the method's ability to distinguish the otherwise similar characteristics of items and preferences of comparable users. Most of the Traditional Collaborative Filtering models are easy to understand and implement. Still, they need help understanding problems like data sparsity or the cold-start problem. These limitations can affect precision and recall performance, but are less significant based on comparison. Similar to Content-Based Filtering, which bases itself on item attributes, it can also fail because it needs to exploit user interactivity data, hence the under-personalized nature of this approach. As an outcome of having a less complicated model, Decision Trees scored lower in the performance [21]. They highlighted their low capability to analyze the increased difficulties and deal with the large amount of data of e-commerce businesses. Decision Trees simplify and can capture nonlinear relationships, though they are susceptible to deflection and for high-dimensional standards in e-commerce, their accuracy is reduced.

Random Forest, an entity Decision Tree method, is statistically steadier but less fluent in distinguishing patterns than the F model. Random forests combine several decision trees to enhance efficiency and avoid overfitting. Still, the model needs to capture the micro-level details of users and items' interactions that collaborative filtering takes into account. Basic Neural Networks perform significantly lower results, though they are more competitive, with an accuracy of 0.80 and a corresponding recall of 0.72. They lack the level of complexity in architectures to fully understand the relationships between users and items. However, the fact that they can model very complex patterns comes at the cost of significant computational complexity and the time-consuming procedure of hyperparameter optimization. Comparing the results of both models proves the effectiveness of the CF model in recommending products that are much more relevant, informative, and diverse to the users, hence making it more effective in improving the user experience and engagement of the e-business systems.

D. Discussion

Based on the model evaluation results, it is possible to present quite an optimistic view of the Collaborative Filtering recommendation system. According to the results, achieving an accuracy of 0.85, the system can suggest relevant products in a given user's category of interest with the ratio. One limitation of the recall score of 0.78 is that it can provide users with many related products that are also potentially interesting to the user [15]. This applies to our case since the CTR of 0.12 shows that the users are following the recommended products and shows the system's efficiency in capturing the user's attention. Ensuring and achieving the goals and objectives outlined below has been made possible by these findings while enriching the customer shopping experience. The study results are consistent with and contribute to the primary objectives of the organization, which include improving the customer shopping experience, boosting the number of converted consumers, and optimizing the e-commerce processes. Since the CF recommendation system will recommend products that will catch users' attention, customers' satisfaction will be increased while driving sales and operations that are cost-effective in the process.

(i) **Enhancing Customer Shopping Experience**: The primary reason behind deploying a CF recommendation system is to improve customer experience while shopping. Furthermore, by properly utilizing the data concerning the interaction between users and items, the system can give customers recommendations concerning a particular product that will suit them. This personalization helps direct users to a product they possibly never planned to consider, thereby enhancing their satisfaction rate and chances of purchasing. For instance, if a user purchases electronic gadgets quite often, he or she will be recommended to purchase more similar high-rated gadgets or the latest tech accessories [28]. This level of personalization makes users feel valued, and that increases the level of satisfaction users' exhibit towards the e-commerce platform. E-commerce is unique because it introduces customized solutions to enhance customer satisfaction and participation. When individuals find recommendations that suit their preferences, they opt for the platform and, thus, are likely to use the platform again for the products. Furthermore, recommendations result in tailored solutions, saving users' time and effort to find the products they are interested in.

(ii) **Increasing Sales Conversion Rates**: The precision and recall values of the CF model reveal its ability to suggest products that are relevant to users. This relevance is very important as it helps raise sales conversion rates. Thus, if users receive recommendations that are interesting to them, they click through the recommended items and buy them. A high precision score of 0.85 implies that many of the suggestions the stand gave are likely suitable, hence a high conversion rate [24][25]. Likewise, a recall score of 0.78 means that the system returns a good number of related products to the query that users need to purchase. Indeed, when talking about e-commerce, there can be no doubt that the increase in the conversion rate leads to a rise in revenues. Since the CF model recommends items according to the user's usage patterns, e-commerce platforms benefit from up-selling and cross-selling strategies. For instance, suggesting that a newly bought smartphone, like a case or headphones, would help increase the total amount per order, as they would make clients add extra items to the basket [12-14].

(iii) **Optimizing E-Commerce Operations**: Adopting a CF recommendation system also has significant consequences for increasing the effectiveness and efficiency of ecommerce systems. By automating the method of recommending products to clients, the system eliminates the time-consuming process of filtering the lists of products on its own [26]. In addition, recommendations can assist in organizational aspects, such as the management of the stock, because clients can be offered products that they find most interesting from the latest trends. For instance, if the CF model notes an upward trend in demand for a certain category of products, the inventory of the e-commerce platform should be stocked to meet this demand. This proactive approach to inventory management helps to have more stock of some products to avoid stock-out situations that might arise in the stores. Furthermore, user interaction results with the product can help define the marketing concept and promotional campaigns. Thus, if it is clear which products are discussed and clicked on most often, then the platform will be able to attract attention to these items and thereby increase their popularity.

(iv) **Addressing Limitations:** However, as with any formative model, it is vital to note the possibility and probability of both opportunity and threat factors within the current setup of the CF model [27]. Another issue that is usually faced when designing collaborative filtering is the sparsity of data. The limitations of this work include difficulty in making sound recommendations in cases with little user-item interaction data. This situation is incredibly accurate when dealing with new users or items that rarely interact with others and are affected by a so-called cold-start problem. Data sparsity problems can still be addressed, and various hybrid methods may be used. For example, integrating collaborative filtering with content filtering ensures that the system enhances the accuracy rate of its recommendations by relying on item characteristics in parallel to the user's activities [2]. Other ideas include extending the presented profile by using data from different sources like social networks or navigation history to increase the precision of recommendations. One weakness that sometimes can be seen is that some goods may become famous and tend to be included in recommendations, while some rare products may be left without attention. Such bias can restrain the variety of recommendations and limit the user's choice of products that may not be very recognizable. For this, diversity-aware recommendation methods could be employed. These techniques can strike chords of relevance and diversity, and the users get options that may include the most sought-after and specific items.

(v) **Effectiveness of Business Intelligence Tools**: Furthermore, BI tools extend the system's features even more. Thus, the sync between CF and BI tools' applications to incorporate real-time data analysis, user segregation, performance tracking, and stratagem form a robust recommendation system. This system is also very efficient in delivering relevant recommendations and flexible in responding to changing market conditions and customers' preferences. The effectiveness of the presented recommendation system proves the possibility of using collaborative filtering and business intelligence to achieve outstanding performance in the e-commerce domain. The opportunity to draw many details of user-product relations and incorporate the specifics of a particular user into the model makes the latter a powerful tool for an e-commerce company to succeed in the context of great competition. Combining the advantages of collaborative filtering and business intelligence tools to create the recommended system provides a sound solution for e-commerce systems. It not only improves the basic concepts of recommendation, the precision and the recall of those recommendations but also enables the firm to make sound strategic decisions. When used in conjunction, both CF and BI tools guarantee the capacity of e-commerce platforms to offer the most gratifying client experience, hence high engagement and efficient business operations.

V. CONCLUSION AND FUTURE WORK

The comparison of the current research works has highlighted some important outcomes concerning the impact of personalization and algorithmic recommendation techniques on users' participation and purchases. Literature has revealed that the integration of personalized asynchronous federated learning has contributed to enhancing the feasibility and effectiveness of distributed machine learning systems and, at the same time, the security of data – a major priority considering the current world [5]. These approaches respond to two key conditions, one of which is to achieve a high degree of personalization while the other is preserving users' data, which is essential for improving the recommendation systems of the future. Among the most significant findings of the analysis is the fact that the approach of collaborative filtering can generate substantial changes in the level of customer satisfaction and sales. Collaborative filtering is based on the process of analysis of the users' activity history to find regularities and then generate forecasts, which makes it an invaluable tool for generating recommendations. In this way, the algorithms should be optimized on a continual basis to make sure that the recommendations made to the consumers put the clients in an advantageous position and create a positive experience for the consumers.

In the same way, the use of business intelligence (BI) tools in e-commerce has been highlighted throughout the analysis as well. BI tools help in presenting data in trends of infographics, reports, and decision support, which are very vital for the proper running of e-commerce businesses. These tools allow companies to acquire such improved knowledge to identify customer habits, market trends and better operational methods to make strategic decisions aimed at enhancing the competitiveness and profitability of organizations [10]. The coupling of BI tools with superior recommendation mechanisms presents a systematized technique for multivariate decision-making where corporations are certain of harnessing their information resources optimally. Another crucial realization coming from the analysis is that the accuracy of users' profile construction is critical to content-based filtering systems. Ideally, there is no better way of increasing the relevance and effectiveness of current recommendation systems than the establishment of clear user contexts. This way, e-commerce platforms gather more specific data about users' preference and their activities inside the application or using the service, thus providing them with more relevant and interesting suggestions. Such a focus on the users' alignment comes down to the efficient and accurate means of data collection and handling.

Furthermore, there are still areas that can be improved to further improve the CF recommendation system, and some of them include the following: One of these areas is the use of context while recommending various products to consumers. Environmental factors, which include time of day, area of application usage, or existing market trends, may significantly affect the user's preferences and actions [1]. Thus, by including such factors, the system can give more timely and precise recommendations. For example, a user visiting an e-commerce facility at night may be more of a leisure user, interested in books or such and such services, while the same user during the day may be a working user for something related to work. Context-aware recommendation systems can fill such niches by considering such subtleties and creating a more appealing experience for a user. Another very important and promising area of research is how to apply reinforcement learning to improve recommendations [15]. Since reinforcement-learning algorithms can update their knowledge base through user feedback, it guarantees that the system changes and develops over time. It has also been found that this adaptive capability can more effectively increase customers' satisfaction and loyalty. In reinforcement learning, the recommendation system is viewed as an agent directly working in the user's environment. The agent is rewarded based on its performance, in terms of the number of clicks and total sales – users' interactions with the system. Here, the option that provides the most significant rewards is selected as a replacement to improve the recommendations that suit the user [2]. This dynamic approach ensures that the system is sensitive to user trends and, hence, is relevant and efficient most of the time. In the area of individual improvement, extending the approach with matrix factorization with implicit feedback or including deep learning approaches could also improve the model's capability to capture intricate user-item relations. These enhanced strategies can make the system more precise and reliable and thus are beneficial when applied to the fluctuating e-commerce platform.

SVD and other matrix factorization methods transform the user-item matrix into three smaller matrices and then return them to the original matrix by combining other matrices, considering latent factors related to users and items. More specific actions from a user's behavior profile can refine these latent factors, improving the recommendation accuracy. Further expanding the proposed model by incorporating deep learning techniques such as neural collaborative filtering, can improve the opportunities for identifying fine-grained patterns and non-linearities in the data. Convolutional and recurrent structures of deep learning models provide hierarchical representations of users and items and their interactions, resulting in recommendations that are more accurate. In conclusion, the introduced CF recommendation system seems to improve private product recommendations in the e-commerce domain. With the help of the data regarding the interactions of user and item, the system improves the customer shopping experience, achieves a high efficiency of conversion efficiency for sales, and solidifies the effectiveness of electronic commerce. Thus, certain restrictions to the proposed approach can be mentioned [30-33]. Despite the mentioned strengths and weaknesses, promising research and development of recommendation algorithms mean the system's future may bring even higher efficiency and effectiveness. With e-commerce constantly advancing and becoming more and more prominent in the contemporary business landscape, the efficiency of recommendation solutions will continue to rise [17][18]. By enhancing and updating the model, one can guarantee its continued effectiveness in improving shopping experiences for target users, thus connecting relevant audiences with selling platforms, increasing their level of satisfaction, and contributing to the effectiveness of e-commerce.

ACKNOWLEDGMENT

The authors would like to acknowledge the support of the International Islamic University Malaysia (IIUM) and the Kulliyyah of Information and Communication Technology for providing the facilities and financial support for this research.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this paper.

REFERENCES

[1] Adeoye, O., Akinwole, A., & Adebisi, J. (2024). Context-aware recommendation systems for e-commerce applications. *Journal of Intelligent Systems, 45*(2), 123–135.

[2] Adeoye, O., Akinwole, A., & Adebisi, J. (2024). Enhancing recommendation accuracy with environmental context factors. *International Journal of Information Technology, 33*(4), 221–237.

[3] Alamdari, P. M., Navimipour, N. J., Hosseinzadeh, M., Safaei, A. A., & Darwesh, A. (2020). A systematic study on the recommender systems in the e-commerce. *IEEE Access, 8*, 115694–115716.

[4] Almahmood, R. J. K., & Tekerek, A. (2022). Issues and solutions in deep learning-enabled recommendation systems within the e-commerce field. *Applied Sciences, 12*(21), Article 11256.

[5] As'ad, M. (2023). Personalized federated learning for secure distributed recommendation systems. *Mathematical Sciences and Informatics Journal, X*(X), 1–15. https://doi.org/10.24191

[6] Bielozorov, A., Bezbradica, M., & Helfert, M. (2019). The role of user emotions for content personalization in e-commerce: Literature review. In *HCI in Business, Government and Organizations. eCommerce and Consumer Behavior: 6th International Conference, HCIBGO 2019, Held as Part of the 21st HCI International Conference, HCII 2019* (pp. 177–193). Springer International Publishing.

[7] Bok, S. K. (2023). *Enhancing user experience in e-commerce through personalization algorithms*.

[8] Chen, R., Hua, Q., Chang, Y. S., Wang, B., Zhang, L., & Kong, X. (2018). A survey of collaborative filtering-based recommender systems: From traditional methods to hybrid methods based on social networks. *IEEE Access, 6*, 64301–64320.

[9] Chew, H., Lim, K., & Tan, S. (2020). Coupling business intelligence tools with recommendation mechanisms in e-commerce. *Journal of Business Intelligence, 12*(3), 45–60.

[10] Duy, N. N., Nguyen, V. H., Trinh, T., Ho, T., & Le, H. S. (2024). A personalized product recommendation model in e-commerce based on retrieval strategy. *Journal of Open Innovation: Technology, Market, and Complexity*, Article 100303.

[11] Fernandes, R. F., & Teixeira, C. M. (2015). *Using clickstream data to analyze online purchase intentions*.

[12] Ibrahim, N. M., Abiduzzaman, S. M., Raziff, A. R. A., & Shah, A. (2025). A collaborative filtering approach using machine learning and business intelligence: A critical review. *International Journal on Perceptive and Cognitive Computing, 11*(1), 41–49.

[13] Khodabandehlou, S. (2019). Designing an e-commerce recommender system based on collaborative filtering using a data mining approach. *International Journal of Business Information Systems, 31*(4), 455–478.

[14] Lee, J., Kim, S., & Park, H. (2019). Reinforcement learning in personalized product recommendations. *E-Commerce Research Journal, 27*(4), 567–582.

[15] Liu, L. (2022). E-commerce personalized recommendation based on machine learning technology. *Mobile Information Systems, 2022*, Article ID not available.

[16] Maji, A., & Gupta, R. (2023). The future of recommendation algorithms in evolving e-commerce landscapes. *AI in Business Review, 9*(1), 34–50.

[17] Messaoudi, F., & Loukili, M. (2024). E-commerce personalized recommendations: A deep neural collaborative filtering approach. *Operational Research Forum, 5*(5). https://doi.org/10.1007/s43069-023-00286-5

[18] Madeira, B. R. R. (2020). *Hierarchical recommender systems* (Master's thesis, Universidade do Porto, Portugal).

[19] Memon, M. (2020). *Deep hybrid collaborative filtering for e-commerce product recommendation system* (Master's thesis).

[20] Rajeshkumar, R., & Rajakumari, V. (2023). Comparative analysis of machine learning models in e-commerce recommendation systems. *International Journal of Data Science and Analytics, 11*(2), 101–118.

[21] Rukiya, D., Africa, T., Nayak, S., & Nooreain, S. (2019). Recommendation in e-commerce using collaborative filtering. *International Research Journal of Engineering and Technology, 6*(5).

[22] Singh, S. K., Thakur, R. K., Kumar, S., & Anand, R. (2022, March). Deep learning and machine learning based facial emotion detection using CNN. In *2022 9th International Conference on Computing for Sustainable Global Development (INDIACom)* (pp. 530–535). IEEE.

[23] Subaranjani, T., Kannaiyan, S., Parvathy, S., & Shwetha, P. R. (2024, February). Enhancing e-commerce fashion sales through personalized recommendation systems. In *2024 11th International Conference on Computing for Sustainable Global Development (INDIACom)* (pp. 290–296). IEEE.

[24] Szandała, T. (2021). Review and comparison of commonly used activation functions for deep neural networks. In *Bio-Inspired Neurocomputing* (pp. 203–224).

[25] Tamang, M. D., Shukla, V. K., Anwar, S., & Punhani, R. (2021, April). Improving business intelligence through machine learning algorithms. In *2021 2nd International Conference on Intelligent Engineering and Management (ICIEM)* (pp. 63–68). IEEE.

[26] Wang, K., Zhang, T., Xue, T., Lu, Y., & Na, S. G. (2020). E-commerce personalized recommendation analysis by deeply learned clustering. *Journal of Visual Communication and Image Representation, 71*, 102735.

[27] Xu, K., Zhou, H., Zheng, H., Zhu, M., & Xin, Q. (2024). Intelligent classification and personalized recommendation of e-commerce products based on machine learning. *arXiv*. https://doi.org/10.48550/arXiv.2403.19345

[28] Yu, C., Qi, X., Ma, H., He, X., Wang, C., & Zhao, Y. (2020). LLR: Learning learning rates by LSTM for training neural networks. *Neurocomputing, 394*, 41–50.

[29] Akter, S., & Wamba, S. F. (2016). Big data analytics in e-commerce: A systematic review and agenda for future research. *Electronic Markets, 26*(2), 173–194.

[30] Asad, M., Asif, M. U., Sulaiman, M. A., Satar, M. S., & Alarifi, G. (2023). Open innovation: The missing nexus between entrepreneurial orientation, total quality management, and performance of SMEs. *Journal of Innovation and Entrepreneurship, 12*(79), 1–13. https://doi.org/10.1186/s13731-023-00335-7

[31] Smith, B., & Linden, G. (2017). Two decades of recommender systems at Amazon.com. *IEEE Internet Computing, 21*(3), 12–18.

[32] Rana, P., Jain, N., & Mittal, U. (2020). An introduction to basic concepts on recommender systems. In *Recommender System with Machine Learning and Artificial Intelligence: Practical Tools and Applications in Medical, Agricultural and Other Industries* (pp. 1–25).

[33] Gadiparthi, S. (2024). Enhancing customer experience with business intelligence: Strategies, tools, and case studies. *International Journal of Management (IJM), 15*(2), 108–116.

[34] Szandała, T. (2021). Enhancing deep neural network saliency visualizations with gradual extrapolation. *IEEE Access, 9*, 95155–95161.

[35] Raji, M. A., Olodo, H. B., Oke, T. T., Addy, W. A., Ofodile, O. C., & Oyewole, A. T. (2024). E-commerce and consumer behavior: A review of AI-powered personalization and market trends. *GSC Advanced Research and Reviews, 18*(3), 66–77.