SSRG International Journal of Electronics and Communication Engineering
ISSN: 2348-8549/ https://doi.org/10.14445/23488549/IJECE-V12I4P108

Volume 12 Issue 4, 84-98, April 2025
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Review Article

Survey on Deep Learning-Driven Personalized Recommendation Systems in E-Commerce Websites

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Received: 05 February 2025 Revised: 07 March 2025 Accepted: 08 April 2025 Published: 29 April 2025

***Abstract** - A product recommendation system is essentially a filter that identifies and displays the things a shopper is most likely to purchase. Currently, e-commerce websites are growing as a new market, allowing users to purchase millions of products. Choosing a product from millions of options requires a second tool called a recommendation system. It essentially acts as a filtering mechanism that attempts to anticipate and provide the products a user wants to purchase. Companies can choose which product to launch in the marketplace to gain more benefits by researching user preferences. In order to recommend appropriate customer retention techniques, it is more important to recognize the limitations of existing methods. Therefore, this review article discusses numerous approaches to extracting product recommendation and prediction information from various websites and their advantages and disadvantages for the years 2017 to 2023. This study examines web content capture methods, including machine learning, fuzzy models, deep learning and data mining. This article briefly discusses the difficulties of obtaining information from the internet, possible uses for product recommendations, and helpful future advice to increase effectiveness. The best methods for product recommendation systems can be demonstrated for future use, according to this review article.*

***Keywords** - Product recommendation, Deep learning model, LSTM, E-commerce websites, Principal Component Analysis (PCA), Machine learning method, Gaussian Mixture Model (GMM).*

1. Introduction

Every e-commerce company needs to take into account key elements such as user intent, product recommendations, and client loyalty. E-commerce websites can enhance users' shopping experiences, boost sales, and raise revenue by comprehending user intent, product recommendations, and client retention techniques. [1]. This review discusses the importance of user intent, product recommendation, and customer retention in e-commerce websites, focusing on how these strategies can be used as powerful marketing tools [2]. User intent refers to the purpose and goals of an individual as they interact with a website. A website can track user intent by observing the user's behavior and actions [3-6]. This can be done by analyzing keyword searches, navigation patterns, and items placed in shopping carts. An e-commerce website can better serve its customers by analysing user intent and customizing its user interface, product offerings, and advertisements. This provides the user with a more pleasant experience, resulting in better customer retention and higher conversion rates [7, 8]. Product recommendation is the process of recommending products to customers based on their past purchases or preferences. This can be done by using algorithms that analyze customer data to pinpoint which products they will likely be interested in. This allows an e-commerce company to personalize its product offering for each customer [9]. Additionally, product recommendations can increase customer loyalty by creating a more personalized shopping experience. Customer retention is the process of keeping customers satisfied and returning to the same e-commerce website [10, 11]. This can be done by offering discounts, loyalty programs, or incentives. In addition, engaging content and communication, such as emails, surveys and special offers, can be used to increase customer loyalty. Ultimately, these strategies can help increase customer satisfaction and strengthen relationships, leading to higher customer retention rates and increased sales. Recognizing user intent is a key factor in customer engagement on e-commerce websites [12-14]. ECommerce websites can gain valuable insight into customer needs by understanding user intent.

Furthermore, understanding user intent can aid in providing targeted product suggestions and ensuring customers receive the most relevant products. Gathering and analyzing data on how customers interact with the website can assist in identifying user intent and determining which products are likely to be of interest [15]. Keyword searches

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are a good starting point for determining consumer interests. Also, utilizing customer journey analysis, website heat-maps, and surveys is beneficial [16]. In addition, purchasing behavior analysis helps identify customers' purchasing desires and provides important information about what customers are interested in. With this information, product recommendations can be individually adapted to customer interests and thus increase the chances of purchase. Knowledge of the customer journey and understanding user intent is crucial in driving customer loyalty and making customers feel like they are being addressed on the website [17-19]. Figure 1 shows the basic block diagram of the e-commerce system.

Fig. 1 E-commerce block diagram representation

User intent, product recommendations, and customer loyalty are important strategies for any eCommerce website. By understanding user intentions, e-commerce websites can better recommend product offerings to best fit the customer's needs [20]. In addition, product recommendations and customer loyalty strategies can be used to create a more personalized shopping experience, resulting in higher customer satisfaction and higher sales [21, 22]. By integrating these strategies into an e-commerce website, companies can maximize their success and create a more enjoyable user experience [23].

This review is presented as follows: Section 2 discusses the review objectives. The basics of the e-commerce website and product recommendation system are described in Section 3. Section 4 discusses techniques used for customer engagement from product recommendations on e-commerce websites using deep learning and machine learning methods.

The performance comparison of machine learning methods and deep learning methods used for customer engagement of product recommendations on e-commerce websites is described in Section 5. Section 6 discusses various challenges of product recommendation on e-commerce websites. Section 7 presented the main findings and effective recommendations for the future. Applications of product recommendations in e-commerce websites are presented in Section 8. Finally, Section 9 describes the conclusion of product recommendations in the e-commerce website system.

2. Review Objectives

The goals presented here are to check customer retention of product recommendations in e-commerce using various methods of Machine Learning. These methods will help to evaluate the performance and efficiency of different methods in e-commerce. Previous research used Machine Learning technology to provide users with more accurate product recommendations. According to researchers, this results in more opportunities to provide product recommendations to the user via e-commerce websites. Therefore, the comparison between these techniques is presented here.

- ➢ Comparison with the different techniques for determining product recommendation customer loyalty on e-commerce websites.
- ➢ The performance comparison with various Machine Learning methods for product recommendation on e-commerce websites.
- ➢ The challenges and the possibilities of the techniques were used in e-commerce websites.
- ➢ The applications of product recommendation on e-commerce websites.

3. Basics of E-Commerce Website and Product Recommendation

An e-commerce website is a website that specializes in selling products or services over the internet [24]. It provides companies with a platform to sell their products and services for customers with a platform to purchase products and and services electronically. The growth of E-commerce has been rapid since its development in 1990 [25]. Originally, e-commerce only existed in the form of physical goods; with the advent of the internet, digital services are becoming increasingly popular. E-commerce websites offer a wide range of products and services, including goods and services related to telecommunications, banking and insurance, travel and tourism, media, entertainment, real estate, retailing, auctions, and many more [26]. This has allowed companies to expand their customer base and reach into a global market. One of the main advantages of e-commerce is convenience. Customers can purchase products or services anytime, anywhere and from any device [27].

In addition, the ordering and payment process for goods and services is very simple and secure. Customers can quickly compare prices and providers to select the best deal, making it easier to find the best product or service for their needs [28]. Finally, e-commerce websites promote competition between suppliers, which leads to better prices, discounts and offers. Besides those benefits, there are some risks presented by e-commerce websites. Customers must trust the website as they submit sensitive personal and banking information, which can lead to identity theft and fraud.

Additionally, product safety is a concern as counterfeit products can be sold through these websites [29, 30]. The e-commerce websites have provided businesses and customers with tremendous convenience and growth opportunities. It has enabled suppliers to reach a global market and allowed customers to purchase at the best prices and selection [31]. However, it is important to consider the potential risks when using online commerce websites to ensure personal and banking information security. Figure 2 shows the e-commerce platform.

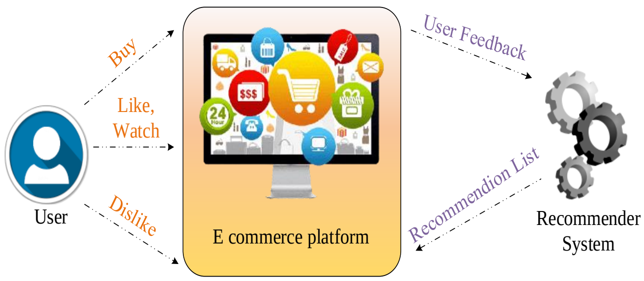

Fig. 2 E-commerce platform

Product recommendation and customer loyalty are two essential components of a successful e-commerce website [32]. Product recommendations help to increase sales by recommending products that are relevant to a customer's purchase history or based on preferences determined through a customer's search and browsing history. It helps personalize the customer experience, resulting in better user engagement and improved customer retention. When customers find relevant and personalized product recommendations in their purchase history, they are more likely to return to the site for further purchases [33]. Customer loyalty is another important factor for a successful e-commerce website. By providing personalized customer service and attractive discount offers, an e-commerce website can maintain the interest and loyalty of existing customers [34, 35]. Understanding consumers' demands promptly, attending to them, and giving them a positive experience are the keys to retaining customers. The combination of product recommendation and customer loyalty can have a huge impact on the success of an e-commerce website. Product recommendations can be tailored to the customer's previous purchases and purchasing habits, and customer loyalty efforts can help build a long-term relationship with the customer [36]. Together, these two components can enable the eCommerce website to maximize its profits through better customer acquisition and higher customer retention.

4. Techniques used for Product Recommendation Customer Retention in E-Commerce Websites with Deep Learning and Machine Learning

The existing analysis of e-commerce websites using Machine Learning and Deep Learning approaches is provided below.

4.1. Machine Learning-based Techniques for E-Commerce Website

E-commerce, commonly referred to as electronic or online commerce, is the act of purchasing and reselling products and services through a public network or the internet. Service providers in an e-commerce system charge different rates for customer website sessions. These tend to favor client web sessions, which are more likely to increase sales by offering higher-quality services. Figure 3 shows several Machine Learning (Machine Learning) algorithms.

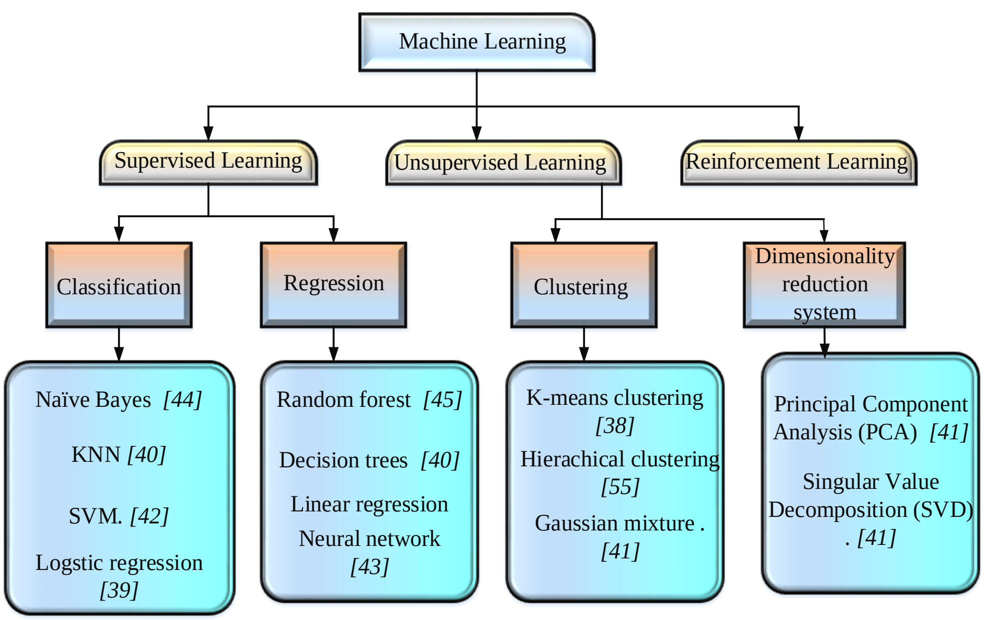

Fig. 3 Machine learning models used product recommendation in e-commerce website

Machine Learning techniques include supervised learning, reinforcement learning, and unsupervised learning. The two primary subtypes of supervised learning are regression and classification. Supervised learning uses labeled datasets to train processors to identify data accurately or estimate results [37]. In addition, unsupervised learning methods use neural networks to determine the features to be analyzed. The study of decision-making is called Reinforcement Learning (RL). This refers to knowing how to respond in a certain circumstance in order to maximize the best advantage. Furthermore, below are some of the most recent machine learning techniques for locating and classifying e-commerce websites presented by different researchers during the previous five years.

The progress of retail marketing has been significantly influenced by the use of data mining tools. This research offers a novel approach to predicting client interest by integrating pattern mining techniques with Multi Variant K-means clustering, which was introduced by Kumar et al. [38]. The method is intended to support E-Commerce systems, and it begins by determining the individual users' purchase histories and making enquiries. Thus, the strategy promotes a greater proportion of client retention. Wen et al. [39] proposed a Machine Learning model for predicting customer purchase behaviors based on Product Popularity (POP) and Multi-Behavioural Trendiness (MBT) (MBT-POP) based on real e-commerce users. The MBT-POP approach shortens the number of days required for an accurate forecast while improving model implementation. The model's ability to retain products was tested using Logistic Regression, XGBoost (XGB), Random Forest (RF), and Histogram-based Gradient Boosting models, all based on Machine Learning techniques.

Demircan et al. [40] presented machine learning techniques to identify the opinions expressed in social media messages. As a result of preliminary research, it was found that e-commerce websites that incorporate product reviews and ratings provided the best example of text-response consistency. An e-commerce website's product ratings and reviews have been organized for use in a machine learning-based opinion analysis approach. Based on the evaluation results, the reviews were divided into three categories: good, negative and neutral. With this statement in mind, Turkish sentiment assessment methods were developed using Support Vector Machines (SVM), Decision Trees (DT), Random Forests (RF), k-Nearest Neighbors and Logistic Regression (LR). The results from cross-validation using test data independently obtained from a similar e-commerce website demonstrate that the sentiment analysis using SVM and RF classification models performs better than the further models. Therefore, the result is lower accuracy and higher computing effort. Image-based search suggestions have increased significantly across many industries, particularly e-commerce sites that provide customers with improved visual search results. Addagarla et al. [41] suggested a machine-learning technique for a comparable image-based recommender system. In order to convert the retrieved characteristics into a lower-dimensional area, a dimensionality reduction system named Principal Component Analysis (PCA) with Singular Value Decomposition (SVD) is used. The K-means++ clustering method was used to identify potential clusters for a collection of related products. Then, compared to the various unsupervised clustering approaches K-Mediod, Mini batch and Gaussian Mixture Model (GMM), 40,000 product image datasets provided by the Kaggle platform were used for the product suggestion process. This resulted in better accuracy, although the amount of the data set was limited.

Due to the importance of Recommendation Systems (RS) in e-commerce, both companies and people are becoming increasingly interested in systems. Anitha et al. [42] presented the Collaborative Filtering approach (CF) as one of the most commonly used RS methods for generating recommendations. However, CF-based RS produces unreliable resemblance data and profits, an unsatisfactory commendation feature. So, the Support vector machine aids in improving CF technique problems. As the SVM model parameter decreases and the classification accuracy decreases, improved ant colony optimization is used in the classifier to optimize the parameter. An SVM classifier is employed in the initial step of the newly proposed system to identify things as positive or negative feedback.

The second step is to create a collaborative filtering method based on SVMIACO. The implementation of the collaborative filtering recommendation only occurs if the entities provide positive input. Due to the previous classification, the actual content used for recommendations is greatly reduced. Therefore, collaborative filtering is less efficient than modern. Ballestar et al. [43] proposed improving the industry's understanding of creating recommendation-based digital marketing initiatives by providing a prediction method for companies. In this way, companies can increase the return on their advertising investments. The machine learning approaches created an estimation method based on a multilayer perceptron (Machine Learning) and an Artificial Neural Network (ANN). This is time-consuming and requires more resources.

As e-commerce systems evolve, online reviews are widely viewed as important for building and maintaining a good reputation. Elmogy et al. [44] proposed machine learning techniques to classify fake reviews. This research uses numerous feature techniques in addition to the feature extraction method of reviews to extract different behaviors of the reviewers. The study compares the performance of various tests conducted on a real Yelp data set of reviews for restaurants that do and do not use customer behavior features. The performance is compared with the different classifiers such as Naive Bayes, KNN, Random Forest, SVM and logistic regression. The evaluations also consider several N-gram language models, particularly bi-grams and tri-grams. According to the results, KNN outperforms the other classifiers in terms of F-score and produces better results. Large companies report significant product quality and sales increases due to machine learning methods that categorize customer feedback about online products.

Alotaibi et al. [45] suggested that accurate suggestions in online e-commerce stores depend on machine learning strategies incorporated into social media and online customer reviews. In Natural Language Processing (NLP), opinion extraction is used to locate and extract opinions from text input. A number of research investigations to examine the various opinion extraction methods and strategies, with Machine Learning being a prominent option due to the ability to recognize patterns and categorize data. The classification methods KNN, Random Forest and SVM achieved better results. For product recommendations on e-commerce websites, the accuracy value achieved by various Machine Learning techniques is presented in Table 1.

4.2. Deep Learning Technique for Product Recommendation Customer Retention in E-Commerce Website

Deep learning is an advanced machine learning technique that has paved the way for revolutionary advances in various industries, including customer engagement through product recommendations on e-commerce sites. By implementing deep learning-based models, companies can analyze large amounts of data to gain insights and build more personalization systems to meet customer needs. Using customer profiles, purchase histories, page views, and other available data points, businesses can create intelligent recommendations that increase customer loyalty and provide a more engaging shopping experience. Improved customer engagement through personalization can increase sales and reduce marketing costs. Deep learning algorithms can boost customer engagement and retention by providing relevant product recommendations, accurate search results, dynamic pricing models, proactive customer engagement, and faster response times. Figure 4 shows deep learning techniques.

Table 1. Summary of machine learning models for product recommendation in e-commerce website

Author	Machine Learning Method	Limitations	Advantages
Kumar et al. [38]	K-means clustering	Hard to compare with various amounts of clusters.	It is fast and easy to understand.
Wen et al. [39]	Logistic Regression (LR), Random Forest (RF)	It is only applicable to estimating discrete functions and is unable to resolve non-linear issues.	It operates faster with comparable precision.
Demircan et al. [40]	SVM, Decision Trees (DT), Random Forests (RF), k-Nearest Neighbors and Logistic Regression (LR)	This approach is utilized when missing values may be difficult to predict.	Both classification and regression issues can be solved using it.
Addagarla et al. [41]	K-Mediod, Gaussian Mixture Model (GMM),	The algorithm can be slow and extremely complicated.	It contains more contextual information.
Anitha et al. [42]	SVM	Due to the enormous volume of elementary data, modern collaborative filtering typically faces difficulties such as poor suggestion prediction accuracy and effectiveness.	In high-dimensional spaces, it performs well.
Ballestar et al. [43]	Multilayer perceptron (Machine LearningP) and Artificial Neural Network (ANN)	The training period is long when utilizing huge datasets. Simulations require a lot of time and effort.	It effectively manages vast volumes of input data.
Elmogy et al. [44]	KNN, Random forest, SVM and logistic regression	It can be modified to multiple classes using a variety of applications but cannot automatically classify multi-class data.	It is significantly simpler to set up and train.
Alotaibi et al. [45]	KNN, random forest, and SVM	Training sample size and unbalanced data have a greater impact on classification accuracy.	It can hanDeepLearninge more number of data.

Zho et al. [46] introduced the e-commerce recommendation based on the deep learning technique. Window RNN creates an automated data-driven environment to improve user experience through better predictions and recommendations. The system can be customized with different settings and parameters to suit the needs of different companies. With advanced algorithms, Window RNN can understand users' needs and preferences and offer personalized recommendations. In addition, historical data is used to analyze individuals' past behaviour and recommend the most suitable products to them. With the help of Window RNN, e-commerce websites can increase user engagement, website visits, and conversions and improve customer loyalty. In the actual database of an e-commerce website, traditional algorithms are used instead of traditional recommendation algorithms. Window RNN (W-RNN) is used for feature extraction. 30 windows are used in the method. A decent gradient algorithm from Adagrad is used. The accuracy rate is 38.52%.

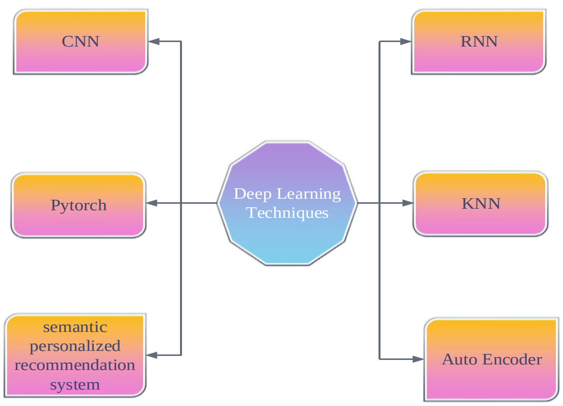

Fig. 4 Deep learning techniques

Gopal et al. [47] implemented a hybrid action-related KNN for recommendation system (HAR-KNN) on e-commerce websites. The HAR-KNN is a hybrid action-related KNN-based recommendation system on an e-commerce website, popularly used to suggest relevant products, services or customized content to customers. It is founded on the idea of giving customers personalized recommendations based on their past activities and purchasing behavior. It also includes knowledge of users' past activities, such as which websites they visited, which products they browsed and what they bought. The HAR-KNN system uses the collaborative filtering technique to create a list of recommended items based on the interactions and purchasing patterns of similar customers. The system compares the similarity between customers based on their previous purchasing behavior and other activities. The nearest neighbor of the customer request and retrieves the recommended products from these customers. To select the most appropriate product recommendations, the hybridity of actions such as browsing and purchasing and the relationship between different clients in the system must be considered. The HAR-KNN system is extremely helpful as it provides customers with more accurate recommendations and increases their satisfaction with the online e-commerce platform. It uses breed classifiers to categorize the traits by both number and quality aspects. The method evaluates consumers' product choices while balancing functional analysis. The traits are the breed classifiers from both quality and quantity aspects. Sunny et al. [48] introduced a semantic personalized recommendation system (SPRS) based on deep learning techniques. The deep learning-based semantic personalized recommendation system can be used to solve the problem in the recommendation system in e-commerce. By leveraging natural language processing techniques, this type of system can be trained to recognize customer preferences and suggest items of interest. Deep learning techniques are used to analyze customer feedback and account data to train a model of customer preferences. This model is then used to classify new customer preferences as current or future interests. These classifications can then be used by the recommendation system to make better product suggestions tailored to the individual customer. The videos are recommended to the system by users based on past activity on the e-commerce website. The candidate recommendation module is used to assess the user's history. The system uses the film lens data set for the semantic personal recommendation system.

Rostami et al. [49] implemented the recommended food system based on the deep learning technique. The system involves two steps. In the initial phase, graph clustering techniques are used, and in the second phase, a deep learning approach is used to group the user and the foods. The data set used here comes exclusively from Recipes.com. The deep embedded clustering uses the auto-encoder to decrease the sizes of data and improve the representation of the embedding vector. The AE consists of two phases, which are fine-tuning and pre-training. The vanishing gradient problem is solved by unsupervised learning for every layer in the neural network. This helps to improve the capability of input data. All layers consist of a nonlinear SeLU (Scaled Exponential Linear Units) function. The algorithm reduces the chance of overfitting by a dropout algorithm.

Vali et al. [50] introduced the program recommendation system CNN (Convolutional Neural Network) for smart TV users. The CNN algorithm trains datasets such as Labeled Faces and CelebFaces Attribute Dataset in the Wild-People for the extracted feature and human face recognition. The user image is recognized using the camera module. The hybrid filtering method is used for single or multiple users. CelebA and LFW-People are used as facial recognition datasets. Preprocessing includes morphological transformation, magnification, image resizing to the same size and normalization. The hidden layer and the output layer consist of active functions such as ReLU and Softmax. The biggest limitation of the method is recognizing people with similar faces.

Table 2. Deep learning methods comparison

Author	Deep Learning Method	Limitations	Advantages
Zho et al. [46]	RNN	Difficult to train, and it cannot process very long data sequences.	The weights are shared across the time steps and can be processed at any input length.
Gopal et al. [47]	KNN	Slow speed, cannot use large datasets and lack of storage.	Better classification and intuitive.
Sunny et al. [48]	SPRS	Lack of work in low-quality data and large quantities of data is required.	Improved accuracy and less time is required.
Rostami et al. [49]	Autoencoder	High complexity and difficult to manage.	Extract the required features easily and clearly remove the noise.
Vali et al. [50]	CNN	High complexity with less dataset.	Automatic and accurate feature extraction.
Huang et al. [51]	Pytorch	It requires more time for processing and lacks stability.	High performance and easy to handle.

Huang et al. [51] implemented the recommendation of a travel route system model of an intelligence robot using Deep Learning techniques. The website data provides basic information and services for tourist locations necessary for the user. The neural network method is based on the self-attention technique. Gaussian kernel function and Node2vec model are used to retrieve the data. The self-attention mechanism is used to capture users' long-term and short-term preferences. The Pytorch deep learning model is implemented in the travel recommendation system model. The comparison of the deep models is clearly shown in Table 2.

5. Performance Comparison of Machine Learning Methods and Deep Learning Methods Used for Product Recommendation Customer Retention in E-Commerce Website

In today's society, e-commerce has made enormous progress in making items accessible to everyone. This is extremely convenient for consumers as they are not even forced to leave the safety of their homes to make purchases. Reviews are becoming increasingly valuable as consumers increasingly rely on Internet shopping sites. Gondhi et al. [52] introduced the performance, which was improved by combining word2vec representation and long short-term memory using the 2018 Amazon Review dataset. Four performance metrics are precision, recall, F1 score, and precision. The highest precision of the four parameters is 97%. The F1 score, which results in a score of 93%, is the best indicator of the model's effectiveness. The accuracy and recall performance are 89% and 90%, respectively. The main goal of this research was to use a lot of data to estimate the model's functionality. This strategy produces good results even with such a large dataset of around 938,261 reviews.

Yin et al. [53] introduced that in order to establish customer preferences by understanding what information is perfect for the firm, several Machine Learning and data mining techniques are mandatory. This study develops a sales forecasting method suited for online products and assesses the model's adaptability to various categories of online products. The research phase shows that the CNN model is accurate and generalizable by contrasting the whole connection system with the CNN training outcomes. By comparing the CNN model to a non-deep learning approach, the advantages of the CNN model are shown in terms of performance across numerous product categories. Models are collected using a system of influencing factors, then use an automatic noise reduction encoder to pre-train the network and build a deep convolutional network-based Deep Learning product sales forecast model. The results of the experiment demonstrate the high accuracy of the model, which can exceed 97%.

Liu et al. [54] presented the Deep Learning method of Bert-BiGRU-Softmax with review extraction, hybrid coverage and attention mechanism. It uses the sentiment Bert method as the input layer to remove multi-dimensional product attributes from online customer reviews. The bidirectional GRU method is the secreted layer used to obtain semantic encryption and estimate the sentiment weights of analysis. A softmax function through the attention device is the output layer used to categorize the positive or negative hue. The Python 3.5 and TensorFlow framework at PyCharm IDE is used in this research tests on multi-source datasets with different domains. First, the IMDB dataset has been used as a benchmark dataset for a long time. The dataset consists of 25,000 tweets about the film reviews, of which 12,500 are good, and 12,500 are negative. The Chinese emotional corpus ChnSentiCorp is the second dataset that includes a variety of sentiment corpora, such as ChnSentiCorpHtl and ChnSentiCorpMov. Gulzar et al. [55] introduced the Ordered Clustering-based Algorithm (OCA), a novel clustering technique, which is the subject of this work to mitigate the impact of cold start and information sparsity problems in e-commerce recommendation schemes. The OCA strives to group users based on shared perceptions by leveraging the collaborative filtering approach to e-commerce recommendation systems.

Real-world e-commerce data collection was used in a series of experiments to evaluate the effectiveness and efficiency of the proposed solution. Using actual e-commerce Amazon datasets, the performance of the proposed method was evaluated with clustering methods, including K-means clustering and Hierarchical Clustering Algorithm (HCA) in terms of Precision (P), F-measure (F), and Recall (R) compared.

The results show that the OC technique outperforms together the Hierarchical Clustering Algorithm and the K-Means technique in precision and recall, with improvements of 16.23% in precision, 12.89% in recall, and 14 .44% for F-measure. These commendations are based on 42 clusters created using the Hierarchical Clustering Algorithm (HCA), 42 clusters created using the OC algorithm, and only 14 clusters created using the K-Means method.

Geetha et al. [56] Sentiment analysis is used to classify consumers' evaluation information into positive and negative emotions. Classification of multiple model scores was done using Naive Bayes, Support Vector Machine and LSTM. The Amazon Product Dataset, which uses performance evaluation measures and comparisons for Bidirectional Encoder Representations of Transformers (BERT), outperforms traditional feature extraction and machine learning methods in accuracy prediction.

Applying Machine Learning methods such as SVM, Naive Bayes, and LSTM enables the evaluation of performance metrics, including 88.09% precision, 89.41% F1-measure, and 86.22% recall.

A comparative analysis of these algorithms is carried out using the BERT model. The BERT model is evaluated, and a comparative performance similarity analysis is performed by changing the hyperparameter values. Table 3 shows the performance comparison of Machine Learning and Deep Learning models.

6. Challenges of Product Recommendation Customer Retention in E-Commerce Website

Because of the organization's requirements for using and implementing Recommendation Systems (RSs) change, it isn't easy to assess their performance [57]. User satisfaction is typically the most representative measure.

Users' satisfaction cannot be determined through a heuristic method, but the effectiveness of RSs can still be evaluated based on the way in which they manage common problems.

Mishra et al. [58] introduced the measures employed to assess how effectively RSs perform when compared to the significant issues of habitat effect, data sparsity, cold-start, diversity, and scalability. Figure 5 shows the architecture of challenges in the product recommendation system.

6.1. Habituation Effect

Recommendation interfaces are regarded as an essential component of advertising strategies and can be used to distribute advertising content. Marketers typically employ strategies centered on enhancing the graphic intensity of given objects by utilizing animations and flickering effects. The most effective way to lessen the habituation effect is to use Multi-Criteria Decision Analysis (MCDA) features.

Table 3. Performance comparison of machine learning methods and deep learning methods

SL. No	Author's Name	Methods	Accuracy	F1 Score	Recall	Precision
1.	Gondhi et al. [52]	LSTM	89%	93%	90%	97%
2.	Yin et al. [53]	CNN	97%	-	-	-
3.	Liu et al. [54]	RNN, Bert-BiLSTM, and BiGRU	89.03%	88.57%	-	-
4.	Gulzar et al. [55]	Clustering-based Algorithm	-	14.44%	12.89%	16.23%
5.	Geetha et al. [56]	Naive Bayes, SVM and LSTM	-	89.41%	86.22%	88.09%

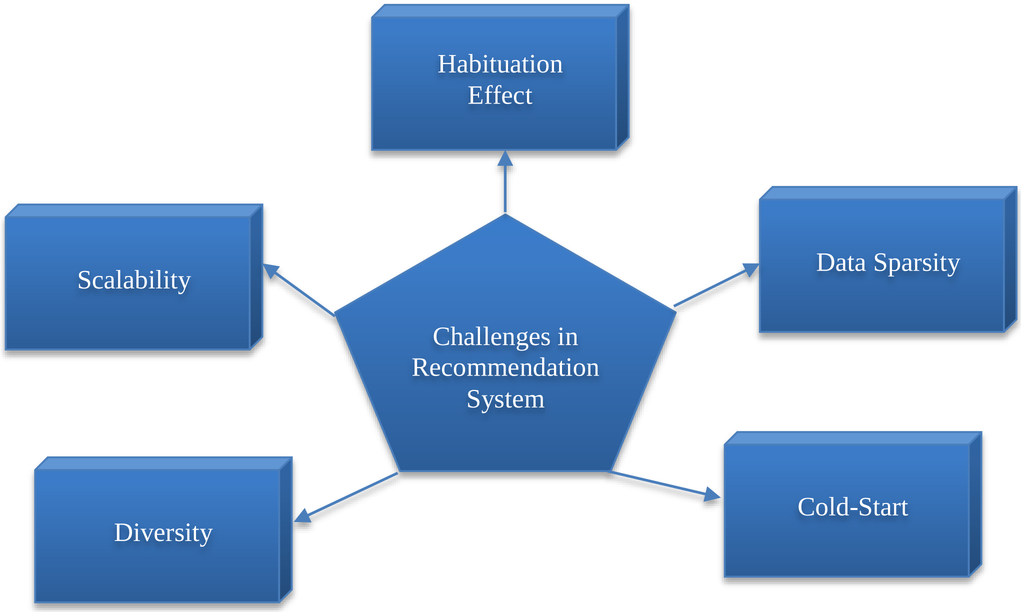

Fig. 5 Architecture of challenges in product recommendation system

6.2. Data Sparsity

When there are insufficient or absent user interactions or ratings for an item, this is referred to as data sparsity. Due to a lack of incentives or user awareness to rate items, the reported user-item matrix typically groups the ratings of comparable users. As a result, RSs may make unreasonable suggestions to people who offer no comments or ratings. Assume that a digital bookshop has X users and publishes 2 million different books. Each customer is represented by a 2 million-element integer feature matrix, where each element's value represents the customer's rating of a particular book. So this matrix is referred to as the "consumer-product interaction matrix". Both the consumer and product populations are massive in the majority of large-scale applications. By modeling users' needs based on their activities and reliable social relationships, many strategies effort to address the data sparsity problem. The adaptability of RSs has greatly benefited from the extensive use of trust. Trust is defined as confidence in another person's capacity to offer reliable ratings. By calculating the number of arcs that connect each user, the trust value can be determined. Users and trust declarations can be represented as directed and node edges in a trusted network, respectively. The median error of predicted accuracy has greatly decreased because of these techniques.

6.3. Cold-Start

Automobiles are the source of the phrase "cold start." They have trouble starting while the engine is cool, but once they reach their ideal temperature, they have no trouble running. The RSs are subject to the same issue. An RS does not operate at its peak efficiency when inadequate data or metadata are available. Cold starts can be divided into two separate subsets: user and product cold starts. An e-commerce site goes through a process known as "product cold start", whenever a new item is on sale. As a result, there will be no reviews because there is no customer engagement. When an individual establishes a without any existing product preferences or purchase histories, creates a new account. This performance is known as "cold start." When measuring and analyzing cold-start recommendations, the Bayes classification is most frequently utilized. Graphical replicas known as Bayesian models are utilized in Artificial Intelligence and probability. No matter if a model-based RS was cooperative or content-based, Bayesian reasoning will probably be used in a certain way. The naive Bayes approach is the most common way to use Bayesian models. Heuristics and the projection in Weighted Alternating Least Squares (WALS) are sometimes employed for the cold-start issue.

$$min_{o_{j_0} \in S^e} \left\| B_{j0} - o_{j0} U^R \right\| \tag{1}$$

The above equation represents one iteration of the WALS algorithm. If the scheme has no connections, the embeddings produced by heuristic approaches for fresh items can be approached. The next step is to average the item's embeddings within the same category.

6.4. Diversity

Depending on the situation, recommendation systems make choices for more unique or comparable things. Commendations based on user or item similarities get the most accurate results at similar times. The diversity problem occurs when recommendations focus on similarities rather than differences. The variety of references enables consumers to discover items they might not find on their own. Surprisal and personalisation are two metrics that can be used to assess an RS's diversity. Measures of surprisal or self-information are used to assess the RS's capacity to produce unexpected results.

Personalization, also known as inter-user diversity, is the distinctiveness of various users' recommendation lists, and the inter-list distance is a simple tool for calculating this. In order to handle diversity problems while preserving item recommendations, the accuracy level must be maintained. The Linear Time Closed Item-set Miner (LCM) may improve diversity by discovering efficient frequent item sets.

6.5. Scalability

Scalability problems have been substantially exacerbated by the e-commerce websites' explosive growth. Modern RS techniques are required for complex applications in order to get results fast. RSs can search for a vast array of potential neighbors in real time, but the demands of contemporary e-commerce sites push them to look for additional neighbors. When dealing with people with a lot of information, algorithms likewise struggle with efficiency issues. The massive increase in users or products makes nearest-neighbour filtering techniques more computationally intensive. Scalability issues are frequently addressed through one-dimensionality reduction. Clustering techniques can be used to lessen scalability issues. Their primary responsibility is to segment the user population into neighborhoods using a clustering technique. Utilizing clustering.

The scalability issue has also been minimized using singular value decomposition. For the reduction of dimensionality, SVD is employed. A set of unrelated eigenvectors are produced by SVD. Using this method, the same eigenvectors can map customers who have rated products that are similar but not identical. Measuring the cosine similarity among n-pseudo customers and n-pseudo products might be used to make predictions.

7. Significant Findings and Effective Future Recommendations

E-commerce personalized recommendations have become an increasingly important part of making purchases online. Every ecommerce platform must stay on top of the growing trends and technologies in this space in order to stay competitive and ensure they're offering the best services to their customers. For this reason, it's important for ecommerce platforms to make future recommendations in their personalized recommendation that are needed.

A larger range of universal models in new domain languages: The Machine Learning and Deep Learning models are suitable only in English. The increased availability and use of data that comes with digitalization have enabled the development of powerful ecommerce personalized recommendation systems. Palomares et al. [59] introduced these sophisticated models, allowing for an automated and personalized approach to advertising products. The services to potential customers result in a higher rate of conversion and increased customer satisfaction. However, the success of these systems is highly dependent on the models used to describe the input data or domain languages. In order to effectively utilize such models, domain experts must ensure their adaptability to the specific needs of the application domain. Recent advancements in Artificial Intelligence and natural language processing have allowed for the development of more universal models that can be easily adapted to any application domain. The development of universal models in new domain languages facilitates faster and more efficient adaption of recommendation systems to the vast array of needs among ecommerce providers. Additionally, deeper insights can be gained from customer data as the models can represent more complex domain-specific characteristics. Ultimately, using universal models in new domain languages improves the effectiveness. The efficiency of ecommerce recommendation systems, delivering more accurate recommendations while decreasing development and implementation costs.

Techniques for aspect-level sentiment analysis: Businesses can better understand client preferences by using aspect-level sentiment analysis to create personalized recommendation systems based on customer's needs. This deeper understanding can be very beneficial in increasing the satisfaction of each customer, leading to a higher overall customer retention rate. When using aspect-level sentiment analysis for ecommerce personalization, companies should assess the sentiment towards various aspects of products and services. By focusing on the different aspects expressed in customer views or reviews, companies can better understand the customer's tastes and preferences. In addition, sentiment exploration can gauge the sentiment towards specific brands, companies, or products. For instance, understanding the customer's sentiment towards a company or brand can allow ecommerce companies to tailor product recommendations to the customer's preferences and needs.

Aspect-based sentiment analysis: implicit aspect recognition and extraction: Aspect-based sentiment analysis is an effective technique used to assess customer reviews and opinions, thus making it a vital component of the ecommerce personalization recommender system. It aims to study customers' opinions about products or services and the sentiment associated with each specific aspect. In traditional sentiment analysis models, a single overall sentiment is assigned to the reviews, derived by taking a weighted average of sentiments expressed about each aspect. However, such techniques do not reflect important implicit aspects that may exist in the reviews.

Shokeen et al. [60] introduced aspect-based sentiment analysis, which allows us to go beyond a single overall sentiment and gain more detailed insights into specific aspects of products or services. Once the aspects are recognized, techniques such as sentiment scores, coaster values or numerical scale ratings can be used to quantify the sentiment associated with each aspect to make an educated and comprehensive recommendation to the customers. These scores and ratings are then used to personalize the ecommerce experiences better and provide customers with accurate recommendations. By providing the customer with a detailed assessment of products and services, the ecommerce personalization recommender system can also deliver more meaningful insights and help create a better customer experience to increase customer loyalty and satisfaction.

Detecting Sarcasm: Sarcasm can impact the online customer experience, especially regarding personalized ecommerce recommendations. If customers are being recommended items with a sarcastic tone, they may not find them amusing, and this could reduce their willingness to shop on that website. Therefore, it is important to consider the possibility of sarcasm when developing a personalized recommendation system for an ecommerce website. One way to detect sarcasm in a personalized recommendation system is to integrate natural language processing into the system. Thaokar et al. [61] presented identifying sarcasm used in ecommerce.

Artificial Intelligence and machine learning can also be used in such a system to determine the user's sentiment by analyzing text for certain keywords and phrases that would indicate a sarcastic comment. By investing in natural language processing, deep learning and machine learning, the system can be designed to identify and react appropriately to sarcasm while still providing helpful, personalized recommendations to customers. This ensures that customers have a positive experience on the website.

8. Applications of Product Recommendation Customer Retention in E-Commerce Website

The use of recommender systems is extensive, with businesses utilizing them to suggest films, music, television programming, books, learning materials, documents, etc. Some of the benefits of the recommendation system are utilized in this work, such as increased sales/conversion, increased user satisfaction, reduced churn, and increased loyalty and share of mind. Figure 6 shows the application of the recommendation system.

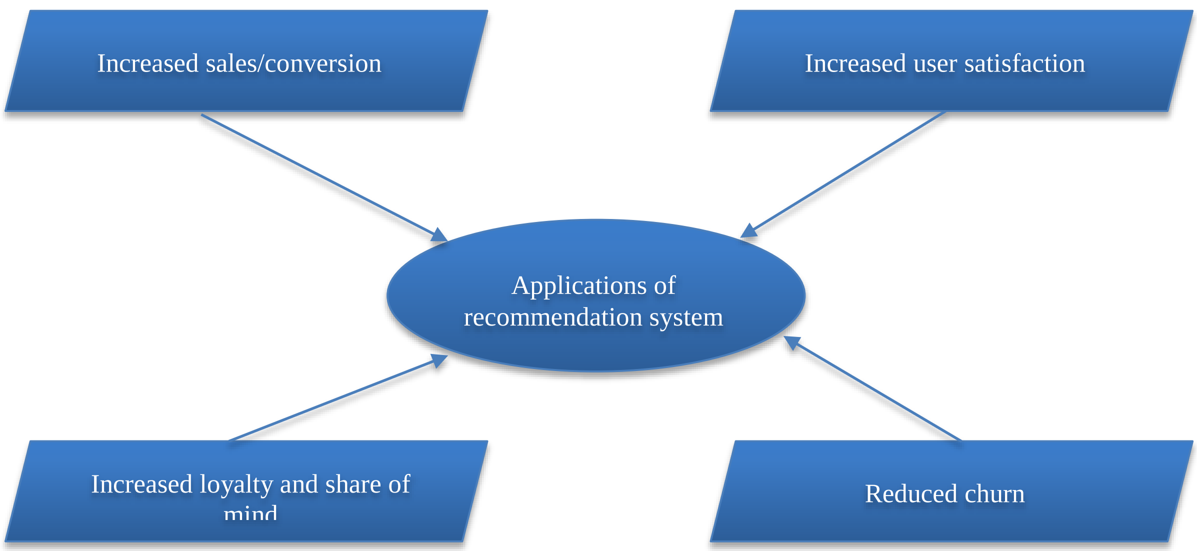

Fig. 6 Applications of recommendation system

8.1. Sales Conversion

Sales conversion is the process or outcome of a marketing campaign. A potential customer or website visitor becomes a real customer by purchasing a good or service through the business.

Sales conversion remains one of the primary objectives that e-commerce enterprises or other online businesses desire to accomplish in the framework of digital marketing methods.

Depending on the type of organization and the established marketing objectives, there are many techniques to measure sales conversion. The usual methods for evaluating sales conversion include:

8.1.1. Product Purchase

When a prospective consumer purchases a good or service the business provides. This conversion shows that the sales process successfully convinced the client to take the desired action.

8.1.2. Newsletter Sign-up

When someone visits a website and signs up for a company's email list or newsletter. This conversion demonstrates a higher level of involvement and interest on the visitor's part in the company or product.

8.1.3. App Download

Conversions for mobile app companies can be tracked when users download the app.

8.1.4. Subscription Services

Conversions are typically calculated whenever a customer subscribes and pays for a company's subscription service. Understanding the effectiveness of a digital marketing campaign depends on measuring sales conversion. Additionally, conversion data helps the development of future marketing plans and more effective resource allocation to achieve the best possible business outcomes.

8.2. User Satisfaction

User satisfaction is generally considered a key factor in the success of information systems. To help customers choose the best products from the huge range of products available, recommenders collectively try to make recommendations. Therefore, consumers should be more satisfied and more likely to purchase compared to situations without recommenders. Previous studies that assessed the effect of recommenders on user happiness used various definitions and dimensions as satisfaction indicators.

8.3. Reduced Churn

In order to reduce customer turnover, a Customer Attrition Management Framework (CAM) was designed and created that can identify customers who have a significant chance of attrition. There are two stages in the customer attrition management system.

- Stage I involves using the early churn signal to spot possible departing clients.
- Stage II involves developing a recommender system offering decision-makers practical and quantifiable methods for lowering client attrition.

8.4. Loyalty and Share of Mind

For businesses to increase their competitive power, customer loyalty is a crucial component. Customers devoted to a brand are more likely to buy more items, pay a lower price to product prices, and recommend the company to their family and friends. How to measure and calculate client loyalty is a crucial topic.

9. Conclusion

While traditional machine learning techniques have been extensively employed in recommendation systems, they come with inherent limitations, such as reliance on feature engineering, difficulties capturing complex patterns, and challenges adapting to diverse and dynamic user preferences. To overcome these limitations and deliver more personalized and context-aware recommendations, deep learning techniques and Large Language Models (LLMs) offer a transformative solution. With their ability to understand intricate relationships in data, leverage vast amounts of information, and adapt to changing user needs, LLMs provide a powerful framework for building next-generation recommendation systems. As these models continue to evolve, they pave the way for more accurate, scalable, and personalized recommendation experiences.

References

[1] Lei Cui et al., “SuperAgent: A Customer Service Chatbot for E-Commerce Websites,” *Proceedings of ACL 2017, System Demonstrations*, Vancouver, Canada, pp. 97-102, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[2] Albérico Rosário, and Ricardo Raimundo, “Consumer Marketing Strategy and E-Commerce in the Last Decade: A Literature Review,” *Journal of Theoretical and Applied Electronic Commerce Research*, vol. 16, no. 7, pp. 3003-3024, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[3] Sebastián Molinillo, Francisco Liébana-Cabanillas, and Rafael Anaya-Sánchez, “A Social Commerce Intention Model for Traditional E-Commerce Sites,” *Journal of Theoretical and Applied Electronic Commerce Research*, vol. 13, no. 2, pp. 80-93, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[4] Octavian Dospinescu, and Percă-Robu, “The Analysis of E-Commerce Sites with Eye-Tracking Technologies,” *Broad Research in Artificial Intelligence and Neuroscience*, vol. 8, no. 3, pp. 85-100, 2017. [Google Scholar] [Publisher Link]

[5] Borja Requena et al., “Shopper Intent Prediction from Clickstream E-Commerce Data with Minimal Browsing Information,” *Scientific Reports*, vol. 10, no. 1, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[6] Yulia W. Sullivan, and Dan J. Kim, “Assessing the Effects of Consumers’ Product Evaluations and Trust on Repurchase Intention in E-Commerce Environments,” *International Journal of Information Management*, vol. 39, pp. 199-219, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[7] Hussain Saleem et al., “Strategic Data Driven Approach to Improve Conversion Rates and Sales Performance of E-Commerce Websites,” *International Journal of Scientific & Engineering Research*, vol. 10, no. 4, pp. 588-593, 2019. [Google Scholar]

[8] Davide Di Fatta, Dean Patton, and Giampaolo Viglia, “The Determinants of Conversion Rates in SME E-Commerce Websites,” *Journal of Retailing and Consumer Services*, vol. 41, pp. 161-168, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[9] Artem Bielozorov, Marija Bezbradica, and Markus Helfert, “The Role of User Emotions for Content Personalization in E-Commerce: Literature Review,” *HCI in Business, Government and Organizations, Ecommerce and Consumer Behavior*, pp. 177-193, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[10] Mounika Veeragandham et al., “Consumer Buying Behaviour towards ECommerce during COVID-19,” *International Journal of Research in Engineering, Science and Management*, vol. 3, no. 9, pp. 78-82, 2020. [Google Scholar]

[11] Zhongqiang Zhang et al., “An Optimization Model for Logistics Distribution Network of Cross-Border E-Commerce Based on Personalized Recommendation Algorithm,” *Security and Communication Networks*, vol. 2021, no. 1, pp. 1-12, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[12] Taqwa Hariguna, and Berlilana, “Understanding of Antecedents to Achieve Customer Trust and Customer Intention to Purchase E-Commerce in Social Media, an Empirical Assessment,” *International Journal of Electrical and Computer Engineering*, vol. 7, no. 3, pp. 1240-1245, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[13] Xiaolin Lin, Xuequn Wang, and Nick Hajli, “Building E-Commerce Satisfaction and Boosting Sales: The Role of Social Commerce Trust and Its Antecedents,” *International Journal of Electronic Commerce*, vol. 23, no. 3, pp. 328-363, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[14] Ajay Kaushik Noronha, and Potti Srinivas Rao, “Effect of Website Quality on Customer Satisfaction and Purchase Intention in Online Travel Ticket Booking Websites,” *Management*, vol. 7, no. 5, pp. 168-173, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[15] Thi Mai Le, and Shu-Yi Liaw, “Effects of Pros and Cons of Applying Big Data Analytics to Consumers’ Responses in an E-Commerce Context,” *Sustainability*, vol. 9, no. 5, pp. 1-19, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[16] Christian Märtin, Bärbel Christine Bissinger, and Pietro Asta, “Optimizing the Digital Customer Journey-Improving User Experience by Exploiting Emotions, Personas and Situations for Individualized User Interface Adaptations,” *Journal of Consumer Behavior*, vol. 22, no. 5, pp. 1050-1061, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[17] Monika Januszkiewicz et al., “Online Virtual Fit Is Not Yet Fit For Purpose: An Analysis of Fashion E-Commerce Interfaces,” *8th International Conference and Exhibition on 3D Body Scanning and Processing Technologies*, Montreal, Canada, pp. 210-217, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[18] Hamzah Mohammed Kadhim Al-Gburi, “*Investigating Website Features Quality Using Three Online Techniques on the Lead Generation Website - A Case Study*,” PhD Thesis, University of Southern Queensland, pp. 1-312, 2020. [Google Scholar] [Publisher Link]

[19] Patrik Forsström, “*An Analysis of Online Attraction and User Experience on an E-Commerce Website*,” Master’s Thesis, International Business Management, pp. 1-110, 2019. [Google Scholar] [Publisher Link]

[20] Lifang Peng et al., “Moderating Effects of Time Pressure on the Relationship between Perceived Value and Purchase Intention in Social E-Commerce Sales Promotion: Considering the Impact of Product Involvement,” *Information & Management*, vol. 56, no. 2, pp. 317-328, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[21] Yingxia Cao, Haya Ajjan, and Paul Hong, “Post-Purchase Shipping and Customer Service Experiences in Online Shopping and their Impact on Customer Satisfaction: An Empirical Study with Comparison,” *Asia Pacific Journal of Marketing and Logistics*, vol. 30, no. 2, pp. 400-416, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[22] Nebojša Vasić, Milorad Kilibarda, and Tanja Kaurin, “The Influence of Online Shopping Determinants on Customer Satisfaction in the Serbian Market,” *Journal of Theoretical and Applied Electronic Commerce Research*, vol. 14, no. 2, pp. 70-89, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[23] Vipin Jain, Bindoo Malviya, and Satyendra Arya, “An Overview of Electronic Commerce (E-Commerce),” *Journal of Contemporary Issues in Business and Government*, vol. 27, no. 3, pp. 665-670, 2021. [Google Scholar] [Publisher Link]

[24] Aleksy Kwilinski, et al., “E-Commerce: Concept and Legal Regulation in Modern Economic Conditions,” *Journal of Legal, Ethical and Regulatory Issues*, vol. 22, no. 2S, 2019. [Google Scholar] [Publisher Link]

[25] George Saridakis et al., “Industry Characteristics, Stages of E-Commerce Communications, and Entrepreneurs and SMEs Revenue Growth,” *Technological Forecasting and Social Change*, vol. 128, pp. 56-66, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[26] Mark Anthony Camilleri, “E-Commerce Websites, Consumer Order Fulfillment and After-Sales Service Satisfaction: The Customer is Always Right, Even after the Shopping Cart Check-Out,” *Journal of Strategy and Management*, vol. 15, no. 3, pp. 377-396, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[27] Bhavna Taneja, “The Digital Edge for M-Commerce to Replace E-Commerce,” *Emerging Challenges, Solutions, and Best Practices for Digital Enterprise Transformation*, pp. 299-318, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[28] Ghada Taher, “E-Commerce: Advantages and Limitations,” *International Journal of Academic Research in Accounting Finance and Management Sciences*, vol. 11, no. 1, pp. 153-165, 2021. [Google Scholar] [Publisher Link]

[29] Johanes Fernandes Andry, Kevin Christianto, and Fuji Rahayu Wilujeng, “Using Webqual 4.0 and Importance Performance Analysis to Evaluate E-Commerce Website,” *Journal of Information Systems Engineering and Business Intelligence*, vol. 5, no. 1, pp. 23-31, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[30] Yudiyanto Joko Purnomo, “Digital Marketing Strategy to Increase Sales Conversion on E-commerce Platforms,” *Journal of Contemporary Administration and Management*, vol. 1, no. 2, pp. 54-62, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[31] Agus Purwanto, “What is the Role of Customer Behavior for Electronic E-Commerce and Modern Market Visit Intention?,” *Journal of Information Systems and Management*, vol. 1, no. 6, pp. 46-57, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[32] Abdul Kadir Othman et al., "Factors that Influence Customer Loyalty in Using E-Commerce," *Journal of Islamic Management Studies*, vol. 2, no. 2, pp. 43-58, 2020. [Google Scholar]

[33] Soma Bandyopadhyay, S.S. Thakur, and J.K. Mandal, "Product Recommendation for E-Commerce Business by Applying Principal Component Analysis (PCA) and K-Means Clustering: Benefit for the Society," *Innovations in Systems and Software Engineering*, vol. 17, pp. 45-52, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[34] Waqas Sadiq et al., "*Engagement Marketing: the Innovative Perspective to Enhance the Viewer's Loyalty in Social Media and Blogging E-Commerce Websites*," Sumy State University, 2020. [Google Scholar] [Publisher Link]

[35] Jacinda Sukendi et al., "The Impact of E-Service Quality On Customer Engagement, Customer Experience and Customer Loyalty in B2c E-Commerce," *Turkish Journal of Computer and Mathematics Education*, vol. 12, no. 3, pp. 3170-3184, 2021. [Google Scholar] [Publisher Link]

[36] Adnan Veysel Ertemel et al., "The Role of Customer Experience in the Effect of Online Flow State on Customer Loyalty," *PloS One*, vol. 16, no. 7, pp. 1-15, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[37] Harikumar Pallathadka et al., "Applications of Artificial Intelligence in Business Management, E-Commerce and Finance," *Materials Today: Proceedings*, vol. 80, no. 3, pp. 2610-2613, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[38] M. Rajesh Kumar, J. Venkatesh, and A.M.J. Md Zubair Rahman, "Data Mining and Machine Learning in Retail Business: Developing Efficiencies for Better Customer Retention," *Journal of Ambient Intelligence and Humanized Computing*, pp. 1-13, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[39] Zhanming Wen, Weizhen Lin, and Hongwei Liu, "Machine-Learning-Based Approach for Anonymous Online Customer Purchase Intentions Using Clickstream Data," *Systems*, vol. 11, no. 5, pp. 1-14, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[40] Murat Demircan et al., "Developing Turkish Sentiment Analysis Models Using Machine Learning and E-Commerce Data," *International Journal of Cognitive Computing in Engineering*, vol. 2, pp. 202-207, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[41] Ssvr Kumar Addagarla, and Anthoniraj Amalanathan, "Probabilistic Unsupervised Machine Learning Approach for a Similar Image Recommender System for E-Commerce," *Symmetry*, vol. 12, no. 11, pp. 1-18, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[42] J. Anitha, and M. Kalaiarasu, "Optimized Machine Learning Based Collaborative Filtering (OMLCF) Recommendation System in E-Commerce," *Journal of Ambient Intelligence and Humanized Computing*, vol. 12, pp. 6387-6398, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[43] María Teresa Ballestar, Pilar Grau-Carles, and Jorge Sainz, "Predicting Customer Quality in E-Commerce Social Networks: A Machine Learning Approach," *Review of Managerial Science*, vol. 13, pp. 589-603, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[44] Ahmed M. Elmogy et al., "Fake Reviews Detection Using Supervised Machine Learning," *International Journal of Advanced Computer Science and Applications*, vol. 12, no. 1, pp. 601-606, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[45] Fahad M. Alotaibi, "A Machine-Learning-Inspired Opinion Extraction Mechanism for Classifying Customer Reviews on Social Media," *Applied Sciences*, vol. 13, no. 12, pp. 1-12, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[46] Lichun Zhou, "Product Advertising Recommendation in E-Commerce Based on Deep Learning and Distributed Expression," *Electronic Commerce Research*, vol. 20, pp. 321-342, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[47] Sunkuru Gopal Krishna Patro et al., "A Hybrid Action-Related K-Nearest Neighbour (HAR-KNN) Approach for Recommendation Systems," *IEEE Access*, vol. 8, pp. 90978-90991, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[48] Sunny Sharma, Vijay Rana, and Vivek Kumar, "Deep Learning Based Semantic Personalized Recommendation System," *International Journal of Information Management Data Insights*, vol. 1, no. 2, pp. 1-7, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[49] Mehrdad Rostami, Mourad Oussalah, and Vahid Farrahi, "A Novel Time-Aware Food Recommender-System Based on Deep Learning and Graph Clustering," *IEEE Access*, vol. 10, pp. 52508-52524, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[50] Khasim Vali Dudekula et al., "Convolutional Neural Network-Based Personalized Program Recommendation System for Smart Television Users," *Sustainability*, vol. 15, no. 3, pp. 1-18, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[51] Xiang Huang, "Personalized Travel Route Recommendation Model of Intelligent Service Robot Using Deep Learning in Big Data Environment," *Journal of Robotics*, vol. 2022, no. 1, pp. 1-8, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[52] Naveen Kumar Gondhi et al., "Efficient Long Short-Term Memory-Based Sentiment Analysis of E-Commerce Reviews," *Computational Intelligence and Neuroscience*, vol. 2022, no. 1, pp. 1-9, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[53] Xiaoting Yin, and Xiaosha Tao, "Prediction of Merchandise Sales on E-Commerce Platforms Based on Data Mining and Deep Learning," *Scientific Programming*, vol. 2021, no. 1, pp. 1-9, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[54] Yi Liu et al., "Sentiment Analysis for E-Commerce Product Reviews by Deep Learning Model of Bert-BiGRU-Softmax," *Mathematical Biosciences and Engineering*, vol. 17, no. 6, pp. 7819-7837, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[55] Yonis Gulzar et al., "OCA: Ordered Clustering-Based Algorithm for E-Commerce Recommendation System," *Sustainability*, vol. 15, no. 4, pp. 1-22, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[56] M.P. Geetha, and D. Karthika Renuka, "Improving the Performance of Aspect Based Sentiment Analysis Using Fine-Tuned Bert Base Uncased Model," *International Journal of Intelligent Networks*, vol. 2, pp. 64-69, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[57] Anurag Mishra et al., "The Drivers and Challenges for Customer Satisfaction in E-Commerce Industry for Urban and Rural India: A Key Stakeholders' Perspectives," *Applications of Operational Research in Business and Industries: Proceedings of 54th Annual Conference of ORSI*, pp. 429-452, 2023. [CrossRef] [Google Scholar] [Publisher Link]
[58] Zeshan Fayyaz et al., "Recommendation Systems: Algorithms, Challenges, Metrics, and Business Opportunities," *Applied Sciences*, vol. 10, no. 21, pp. 1-20, 2020. [CrossRef] [Google Scholar] [Publisher Link]
[59] Iván Palomares et al., "Reciprocal Recommender Systems: Analysis of State-of-Art Literature, Challenges and Opportunities towards Social Recommendation," *Information Fusion*, vol. 69, pp. 103-127, 2021. [CrossRef] [Google Scholar] [Publisher Link]
[60] Jyoti Shokeen, and Chhavi Rana, "Social Recommender Systems: Techniques, Domains, Metrics, Datasets and Future Scope," *Journal of Intelligent Information Systems*, vol. 54, pp. 633-667, 2019. [CrossRef] [Google Scholar] [Publisher Link]
[61] Rahul Tilokani et al., "Recommendation System: Overview, Current Applications and Future Scope," *International Journal of Next-Generation Computing*, vol. 12, no. 5, 2021. [CrossRef] [Google Scholar] [Publisher Link]