IJFANS INTERNATIONAL JOURNAL OF FOOD AND NUTRITIONAL SCIENCES
ISSN PRINT 2319 1775 Online 2320 7876
Research paper UGC CARE Listed (Group-I) Journal Volume 11 , Iss2, Aug 2022

Machine Learning Applications in E-commerce Using Recommendation Algorithms

Viral Balvantray Pansiniya[1]

[1]Assistant Professor, Computer Science & Engineering Department, Government Engineering College, Patan, 384265, India, Email: vbpansiniya@gmail.com

Pinesh Arvindbhai Darji[2*]

[2*]Assistant Professor, Computer Science & Engineering Department, Government Engineering College, Patan, 384265, India, *Email: darji_pinesh@gtu.edu.in

Prof. Ketan Sarvakar[3]

[3]Assistant Professor, Information Technology Department, U V Patel College Of Engineering, 384012, India, Email: ksarvakar@gmail.com

Rathod Hiral Yashwantbhai[4]

[4]Assistant Professor, Computer Science & Engineering Department, Government Engineering College, Patan, 384265, India, Email: rathod.hiral26@gmail.com

Payal Prajapati[5]

[5]Assistant Professor, Computer Engineering Department, L.D. College of Engineering, Ahmedabad, 380015, India, Email: payalprajapati2808@gmail.com

Archana Gondalia[6]

[6]Assistant Professor, Computer Engineering Department, L.D. College of Engineering, Ahmedabad, 380015, India, Email: archana.gondalia@gmail.com

Abstract

A new time in e-commerce has arrived due to the integration of machine learning and Recommendation algorithms, an important element of machine learning's connection with online commerce, which is changing this industry. These algorithms make use of data analytics to provide users with customized purchasing experiences that improve user retention, satisfaction, and conversion rates. In an era of information overload, customization is the key to making the process of finding products faster. Systems for recommendation make product suggestions by studying user actions and choices, increasing engagement, and increasing the number of sales.These algorithms additionally improve the management of stocks by accurately projecting consumption and reducing oversupply and understock issues. Also, they're important in the security of transactions, confidence among customers, and scam prevention and detection. The systems for recommendations boost loyalty to brands and repeat economics by continuously providing personalized suggestions and offers. Artificial machine learning and recommendation algorithms will continue to be crucial tools for companies aiming to stay competitive and deliver outstanding customer service as e-commerce grows.

IJFANS
International Journal of
Food And Nutritional Sciences
Official Publication of International Association of Food and Nutrition Scientists

This article thoroughly examines these uses these uses in-depth, highlighting their importance and practical usefulness.

Keywords: E-commerce, Recommendation Algorithms, Machine Learning

1 Introduction

The addition of recommendation algorithms and machine (Fayyaz et al., 2020) e-learning signifies a turning point in e-commerce. These algorithms are important to machine learning's function in online commerce and are transforming the sector. They offer users customized shopping experiences with the use of data data analysis, which increases retention of users, satisfaction, and rate of conversion. Modification speeds up and improves the rate of product finding in an era of information overload. This is carried out by recommendation systems by evaluation of user behavior and preferences, greater involvement, and higher sales.

These mathematical models and algorithms are crucial for managing inventories, precisely predicting consumption, and solving issues with excess and understock. They are also vital in promoting confidence among customers, defendingagainst fraud, and transaction security. By consistently making individualized suggestions and offers, recommendation systems foster brand loyalty and encourage repeat business. Artificial machine learning and recommendation algorithms are still crucial for businesses looking to stay competitive and provide outstanding customer service as e-commerce grows. The research paper in this article looks into different uses, highlighting their significance and relevance.

1.1 E-Commerce

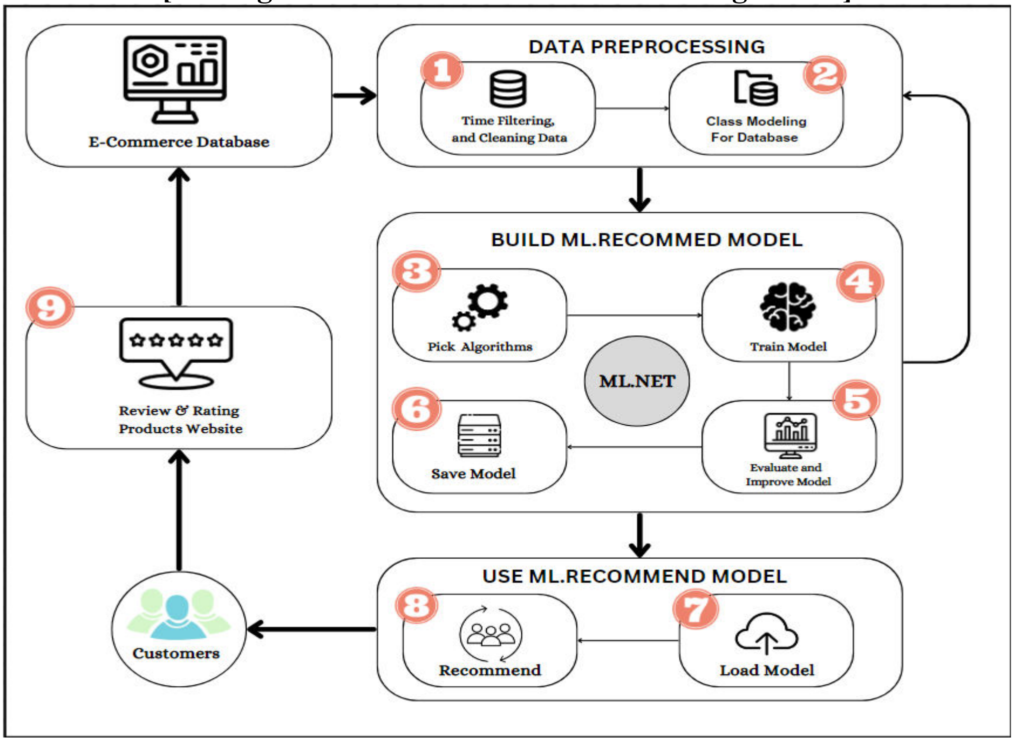
E-commercein a research paper describes Internet business activities, such as buying and selling goods or services, receiving payments online, and conducting interactions with consumers through the Internet or other digital networks. It is a significant and active sector that has an impact on companies, customers, and the world economy. E-commerce studies examine its technology, trends, effects, and challenges, as well as how to improve online buying operations through the use of technologies like machine learning and recommendation algorithms.

1.2 Recommendation Algorithms

Recommendation Algorithms are systems based on computers that use database analytics as well as machine learning techniques to provide customized recommendations and suggestions to users in an article of research. By recommending relevant products, services, or content based on user preferences and actions such algorithms are commonly used in a range of areas, such as e-commerce, for bettering user experiences. The techniques applications and success rate of recommendation algorithms are discussed in research articles on how they can increase retention of customers, engagement, and satisfaction with online platforms and services.

IJFANS INTERNATIONAL JOURNAL OF FOOD AND NUTRITIONAL SCIENCES
ISSN PRINT 2319 1775 Online 2320 7876
Research paper UGC CARE Listed (Group-I) Journal Volume 11 , Iss2, Aug 2022

[1.2. Figure: Flowchart of Recommend Algorithm]



1.3 Machine Learning

The online buying procedure is being transformed by the use of Machine Learning with Recommendation Algorithms in e-commerce investigation. By using data analytics to make customized product recommendations, these modern algorithms boost customer satisfaction and increase the rate of conversion. By accurately predicting demand from customers, they additionally help to improve the control of stocks by reducing stock-related problems. These methods are essential to improving transaction security, helping increase trust between customers, and reducing fraud. By regularly offering users customized suggestions and promotions, they promote loyalty to the brand.Machine Learning describes the research and use of techniques that make machines identify patterns in data, learn from them, and make decisions without having to be explicitly programmed. It has an array of uses, covering e-commerce, recommendation systems, natural language processing, picture verification, and more, and offers considerable advantages for work automation and improving decision-making processes.

[1.3.Table: Comparison of Machine learning approaches]

No.	Machine Learning Approaches	Description
1	Supervised learning	On the basis of the relationships found from previous information sets, it suggests the most expected output value for new data using previous information as a variable of input. (i) Regression is a type of prediction method that looks at how a variable that is dependent and an independent variable is connected. (ii) The classification is a technique in which the algorithm identifies and produces new findings by learning from the data input that is supplied to it.
2	Unsupervised learning	The algorithm is developed on unlabeled information with lacking labels, and its goal is to investigate the data to find any structure. (i) Clustering organizes a collection of objects into groups in which mem-

		bers of the same group overlap more characteristics than individuals of other categories. Before evaluation, unneeded information is reduced by reduction of dimensionality. (ii) It's used for removing unnecessary data as well as oddities.
3	Reinforcement learning	With that approach, (i) the algorithm knows by means of experimentation to determine which sessions produce the best payouts. (ii) It is often used in robotics, gaming, and navigation.
4	Deep learning	(i) The use of deep learning helps teach algorithms how to deal with poorly mentioned issues. (ii) Systems for speech and image recognition frequently employ the use of deep learning and neural networks for learning.

2 Literature survey

2.1 Mobile e-Commerce Recommendation System Based on Multi-Source Information Fusion for Sustainable e-Business

This research paper discusses forecasting e-commerce site usability using features like sorting and effectiveness.[1] It mentions a 6% accuracy improvement with a specific technique in cart scenarios and the use of supervised learning methods like Random Forest and Logistic Regression. [1] Various risk evaluation techniques are used, and visualization methods are employed. The integration of web analytics is encouraged, and the importance of conversion evaluation is highlighted. Future work includes advanced algorithms, real-time analytics, improved personalization, ethics, emerging tech integration, globalization considerations, sustainability, collaboration, and adaptive models.

2.2 E-Commerce Personalized Recommendation Based on Machine Learning Technology

This research paper discusses the importance of customized information and products to attract and keep customers on websites for e-commerce. [2] To evaluate its feasibility, it proposes an updated structural equation model (SEM) that incorporatesAircraft Maintenance and Engineering Operating System (AMOS) indicators. [2] There are tests and verification of hypotheses related to things like income levels, online shopping experiences, product prices, and more. [2] The investigation demonstrates that variables including motivation to shop, income, shopping experience, and product prices all favorably impact consumers' buying behavior. However, the customer evaluation computations and recommendation system's versatility may use some work. [2] Future work will focus on improving recommendation systems, increasing the fusion of recommendation lists, and improving feedback from consumers.

2.3 Probabilistic Unsupervised Machine Learning Approach for a Similar Image Recommender System for E-Commerce

The research focuses on a model developed for e-commerce platforms that enables users to select an item's image and retrieve related product photos. Unsupervised statistical machine learning methods are used. [3] In the beginning, the main Singular Value Decomposition (PSVD) is used to reduce the number of dimensions. This method keeps 144 main components while reducing the variance by 90.01% from 14,400 dimensions. On the PSVD-transformed photos, K-means++ clustering is used, and it is contrasted with various clustering algorithms. [3] In terms of similarity and variance metrics, the PSVD-K-means++ technique performs better than others, but not as well on average similarity.[3] The paragraph makes recommendations for further research, including using deep learning and image augmentation techniques for more precise image feature extraction and recommendations.

2.4 RecommendationSystems For E-commerce Systems An Overview

This study highlights the importance of recommendation systems (RS), which successfully rank and supply clients with modified material, in reducing information overload on the internet. [4] According to the desired recommended outcomes, several RS algorithms may be used. It also provides suggestions for addressing drawbacks in each category of RS techniques.[4] The essay also emphasizes the importance of RS in contemporary e-commerce, where they improve the effectiveness of commercial websites by showcasing well-liked products, hence raising customer happiness and enhancing business revenues.

2.5 The Recommending Agricultural Product Sales Promotion Mode in E-Commerce Using Reinforcement Learning with Contextual Multiarmed Bandit Algorithms.

The current research studies the LinUCB algorithm's success in cases with linear user-product relationships and suggests applying the Hybrid-LinUCB algorithm in instances in which the products are changing. [5] It also investigates how contextual Multiarmed Bandit algorithms can be used to generate recommendations based on preferences.[5] To improve the performance of product sales, future work includes data collection, factor analysis, and practical testing.

2.6 Improving E-Commerce Sales Using Machine Learning.

The research paper discusses of e-commerce, the research research points out the importance of knowing and optimizing customer journeys.[6] It highlights the non-linearity of modern purchase journeys and the importance of anticipating and impacting customers' behavior at many points.[6] Machine learning (ML) has been recognized as a useful technique for reviewing historical data and modifying customer journeys to reduce barriers and exposure to comparable companies. The short-term nature of consumer data, fragmented journey data across domains, and disjointed data processing in the marketing ecosystem are all problems.[6] Future work involves using ML to complete customer journeys, fix journeys that have broken in multi-channel contexts, use real-time data, build complex prediction techniques, enhance data integration, and reduce mindless remarketing in e-commerce.

2.7 Recommendation Systems: Algorithms, Challenges, Metrics, and Business Opportunities

This paper provides a survey of recommendation systems (RSs) used in various domains. [7] It discusses different types of RSs and their combination strategies. Challenges like data sparsity and scalability are highlighted. [7] The paper also explores RS applications in fields like e-commerce and health.[7] Future work includes incorporating new technologies like blockchain and handling large datasets from deep learning-based RSs.

2.8 Comprehensive Empirical Evaluation of Deep Learning Approaches for Session-Based Recommendation in E-Commerce.

Multiple neural-based models and baseline algorithms are examined for session-based recommendation in the e-commerce area in this research paper. [8] The results highlighted how well the VSKNN algorithm, recurrent models, and neural-based models with attention mechanisms expect the needs of users.[8] Handling changes in item attributes, including dynamic item embedded data, modeling other user interactions, optimizing hyperparameters, extending evaluations to many domains, and investigating alternative evaluation metrics are among the challenges and future work.[8] The next study should also look into the effect of varying training-test divides on the performance of models.

2.9 An Intelligent Data Analysis for Recommendation Systems Using Machine Learning.

In a big-data Cluster context with a Cassandra database, this study of research provides an original shared filtering recommendation system that can deal with a range of data types, such as textual reviews, ranks, votes, and video views.[9] The system applies sentiment analysis to extract hotel characteristics from textual evaluations, and it makes accurate recommendations to various guest types using fuzzy rules and Euclidean distance. [9]With a response rate of just 2.65 milliseconds, the system provides high-quality recommendations.[9] With bigger data sets, its performance may significantly decline, but it still produces good results. For more growth, future work will incorporate dynamic, real-time data and user feedback.

2.10 Exploring the Impact of Time Spent Reading Product Information on E-Commerce Websites: A Machine Learning Approach to Analyze Consumer Behavior

Applying traffic data analysis, the research paper studies characteristics influencing e-commerce customers' planned purchases. Time spent on paperwork and product information are important issues.[10] The ability to predict client goals using a variety of algorithms—including logistic regression, decision trees, random forests, and support vector classifiers (SVC)—has generally been successful.[10] Future research should focus on bettering learner predictions and improving the identification of sites that require more information, particularly for users who are about to leave pages.

3 Evaluation Metrics

3.1 Recall and Precision

Similar to how RS suggests intriguing and helpful objects from a collection of materials, information retrieval, or IR, is focused on gathering relevant records from a collection. For RSs, the field of IR is considered an accurate provider of tools including evaluation metrics. 'Precision and recollection' are two significant metrics. Recall is the proportion between the number of important items suggested to the total quantity of products that should be suggested and precision is a percentage of appropriate items among all the items that are suggested to a user. The item that the consumer finds attractive is one that is relevant. A confusion matrix, such as the one in Table 1, is computed to determine precision and recall measures. The confusion matrix depicts the four consequences that any recommendation could have, andthe recommendation works out if the user considers it relevant; otherwise, it is useless.

[3.1 Table Confusion matrix for a recommender system]

	Successful Recommendation	Not a Successful Recommendation
Recommended	A	B
Not Recommended	C	D

Where "a" denotes the total amount of authentic beneficial information that the RS successfully collected and recommended for recommendations. The number of things that the RS refused to successfully suggest while identifying them as recommended, is represented by the value of "b". The number of items suggested by the RS to be excluded is denoted by the value "c". The number of things that are marked and retrieved as "not recommended" is the genuine negative value, "d."

A decent RS aims to simultaneously optimize both metrics. For instance, it can give the consumer recommendations for many different kinds of goods to get the most press. The Precision would remain at the same low level as the pool's useful product/item proportions.

$$\text{Precision} = \frac{a}{a + b}$$

$$\text{Recall} = \frac{a}{a + c}$$

3.2 Accuracy

The needs of the company must be taken into consideration while selecting an RS based on an evaluation metric. Predicted ratings are typically employed as a system evaluation metric.Due to the lack of a specific technique for judging whether or not a recommendation is accurate, determining the correctness of RS is not simple. By applying split-validation of data for offline comparisons, one must look for minimal prediction errors in order to evaluate an RS's correctness. Consider the scenario where we give an RS 80% of a customer purchase history dataset and ask it to forecast the remaining 20%. In that situation, Equation can be used to determine the system's accuracy based on genuine recommendations.

$$\text{Accuracy} = \frac{\text{Number of success ful recomendations}}{\text{Total number o f recommendations}}$$

Particularizing the measure to RS, accuracy is usually used for analysis; for example, the root of the mean square error (RMSE) is used to assess an algorithm. The mean average error, the normalized mean average error, and the mean square error are additional RMSE substitutes. Since RMSE measures both positive and negative rating inaccuracies, it is the most suitable method.When the errors cannot be distinguished, the use of RMSE is advised. Predicting, for instance, a rating difference between 1 and 2 stars could not be as significant as one between 2 and 3 stars.

3.3 ROC Curve

Precision and recall can be replaced by an ROC analysis (receiver operating characteristic) study. Figure in displays a precision versus recall curve. The recall values decrease as the precision increases. The ROC curve shows the relationship between fallout and recall. The goal of ROC analysis is to retrieve the pertinent items while avoiding retrieving the unimportant ones. This is accomplished via maximizing recall. with the fallout minimum, also known as the true positive rate, and the false positive rate, also known as the true positive rate. We can categorize an item as "to be recommended" or "not to be recommended" by using ROC curves to clearly depict the trade-off between recall and precision when the threshold is modified The ROC, accuracy, and Recall curves can all be optimized similarly. By directing the peak of the curves toward the points Precision = 1 and Recall = 1 it is possible to maximize the recall and precision values. A ROC curve that eventually reaches all of the pertinent things encountered and then moves on to the remaining items is the result of a perfect prediction system. Similar to precision and recall measures, ROC curves also presuppose binary relevance. A recommendation is either successful or unsuccessful depending on how it is classified. The ROC measure is unaffected by the relevant elements' order when this is taken into account. An optimal ROC curve is produced when all relevant items appear before irrelevant items.Studying the region under that curve allows us to use the ROC curve as an indicator of success The chance of the system being able to correctly choose two distinct items, where one item is selected at random from the set of acceptable items and the second item is selected from the set of defective items, is expressed by the area under the ROC curve.

3.4 F- Measure

An additional statistic produced by recall and accuracy is the F-measure, which performs similarly to both of those metrics. F-measures may be a more useful statistic than precision and recall since

IJFANS INTERNATIONAL JOURNAL OF FOOD AND NUTRITIONAL SCIENCES
ISSN PRINT 2319 1775 Online 2320 7876
Research paper UGC CARE Listed (Group-I) Journal Volume 11 , Iss2, Aug 2022

they provide different information that, when combined, can complete each other. The metric that performs better than the other will be reflected in the F-measure. The F-measure is the number of tests that must be run in order to identify the first failure from a statistical viewpoint. By varying β, the value of Fβ gives more weight to one metric over the other. Yet, the most common F-measure is known as the consistent mean of precision and recall (F1), where β = ½. Note that the maximum value F-measure can be 1, which means that all predictions are accurate recommendations. Understanding ranked retrieval is helpful. Here, Precision@K and Recall@K represent the ratio of the top k relevant things and the top k relevant items, respectively. The basis for ranked retrieval is the user's belief that they will only look at the top k results. Knowing this demonstrates that the rising tendency of the recall value will lead the F-measure to rise as the value of k rises. Equations explain how to calculate F1 and Fβ.

$$\mathrm{F}\beta = \frac{precision \ \times recall}{(1\times \ \beta) \times \ precision + \ \beta \ \times recall}$$

$$F1 = \frac{2 \ \times \mathrm{precision} \times \ \mathrm{recall}}{precision + \ recall}$$

4 Business Adoption and Applications

[4.Table: Business adoption of Recommendation Systems (RSs) in five application areas]

Area	**Application**	**Reference**
E-commerce	- Items recommendations to buyers.	[22,23]
	- recommendations on videos or films.	[24]
Transportation	- Path Recommendation for transporting individuals as well as items.	[25,26,27]
	- Travel suggestions for improvement.	[28,29,30]
	- Recommended area.	[31,32,33]
E-health	- Medical guide or a recommendation for a course of action to take	[34,35,36,37]
	- Recommending customers for customized treatments	[38]
	- Specialists hired to suggestions	[39]
	- Mobile systems' guidance for healthcare	[40]
	- Suggested healthy behaviors	[41]
	- Suggestions concerning nutrition	[42]
Agriculture	- Workers receive instructions to apply fertilizer as well	[43]
	- Crop cultivation suggestion	[44]
	- Assisting farmer's inquiries	[45]
	- Agricultural products recommendation	[46]
	- Crop cultivation suggestion	[47,48,49,50]
Media	- Event recommendations	[51]
	- Museum recommendations	[52,53]
	- Multimedia recommendations	[54,55,56]
	- Open Social Networks recommendations	[57,58,59,60,61]

IJFANS International Journal of Food And Nutritional Sciences
Official Publication of International Association of Food and Nutrition Scientists

ISSN PRINT 2319 1775 Online 2320 7876
Research paper ©2012 IJFANS. All Rights Reserved, UGC CARE Listed (Group-I) Journal Volume 11 , Iss2, Aug 2022

5 Methodology

5.1 Association rule mining

A method based on machine learning termed association rule mining is applied to analyze E-commerce log data to find patterns and connections between different products or user actions. It aids in making sense of connections between various activities or things that are commonly seen together in log data. By offering insights into user behavior and product connections, this strategy is useful for comprehending customer preferences, optimizing recommendations, and enhancing the overall E-commerce experience.

To discover association rules in e-commerce log data using association rule mining:

- Data Preparation: Accept and preprocess log data from online stores, making sure it is in a transactional format.
- Identify frequent itemsets (combinations of items that occur frequently) by using algorithms like Apriori or FP-Growth.
- Create association rules that illustrate the relationships between items based on frequently occurring itemsets.
- Rule Assessment: Measure the strength and importance of rules using metrics like support, confidence, and lift.
- Filtering and Interpretation: To better understand user behavior and develop e-commerce strategies, filter rules and interpret them.

5.2 Machine learning

By applying data analysis and algorithms, machine learning approaches can be used to enhance a variety of grocery-related operations, including customer segmentation, product recommendations, and fraud detection. To improve supermarket operations and customer experiences, this process entails data collection, preprocessing, feature engineering, algorithm selection, model training, evaluation, deployment, and continual improvement.

on using machine learning methods on a dataset of groceries :

-Data gathering and preparation: Obtain a dataset that includes details on products, customers' transactions, and past purchases that are relevant to groceries. Clean up the data, handle missing values, and prepare it for analysis.
- Engineering features that are pertinent, such as product classifications, customer demographics, and frequency of purchases. These features should be transformed and encoded for machine learning techniques.
- Model Education: Create training and testing sets from the dataset. Train the chosen machine learning models on the training data, modifying the hyperparameters as necessary to achieve the best performance.
- Evaluation: Depending on the particular job, assess the model's performance using pertinent metrics like accuracy, precision, recall, or F1-score.
- Deploy a model for usage in a real-world grocery scenario, such as an online store or a physical retail location, if you are satisfied with its performance.
- Monitoring and Improvement: Constantly keep an eye on the model's output and collect fresh data for retraining. Models should be adjusted to reflect shifting consumer preferences and grocery industry developments.

5.3 Collaborative filtering

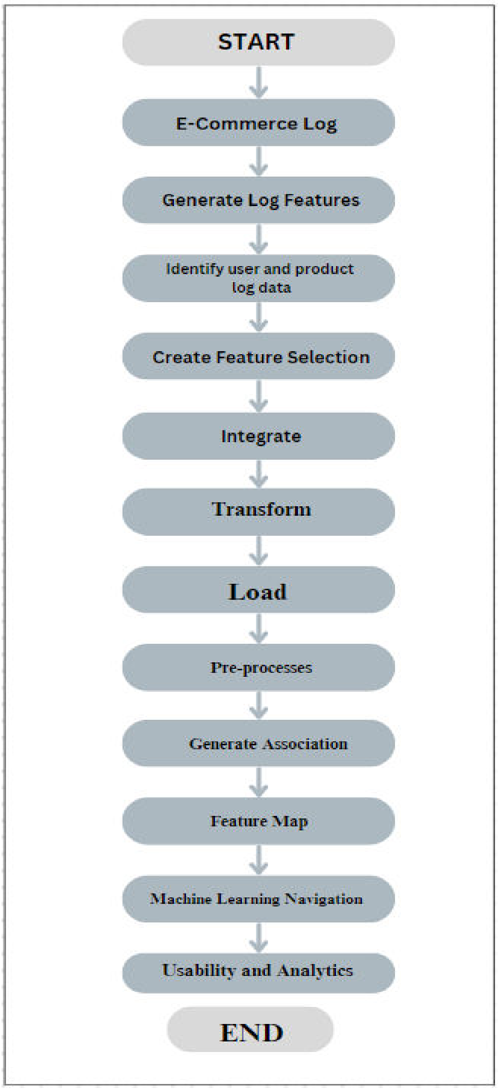
In machine learning, collaborative filtering uses information including shipping data, emotional data, and purchasing rates to provide customized suggestions. Utilizing user interactions and behavior to identify patterns and preferences, this technique aids in recommending goods and services that suit certain tastes. By examining user-item interactions and using algorithms like matrix factorization or closest-neighborapproaches to produce recommendations, collaborative filtering can be discovered. This method improves user experiences by offering individualized ideas that are in line with their past actions and preferences. Examples include e-commerce and content recommendations.

In general, use the following actions to apply machine learning algorithms to a dataset that includes shipping, sentiment, and purchasing rate data:

- Data collection: Compile the dataset including the purchasing rates, sentiment scores, and delivery information. Make sure the dataset is organized and clean.
- Data Preprocessing: Preparing the data involves addressing missing values, encoding categorical variables, and, if necessary, normalizing or scaling numerical features.
- Engineering Features: Make pertinent attributes that will help machine learning models when they are making predictions or suggestions. For users or products, you may compute average sentiment scores.
- Split Data: To assess the effectiveness of your machine learning models, split the dataset into training and testing sets.
- Choose ML Models: Based on the requirements of your assignment, pick the best machine learning models. Collaborative filtering, matrix factorization, or deep learning models like neural collaborative filtering (NCF) are popular options for recommendation systems.
- Model Training: Use the training data to run your chosen machine learning models. Hyperparameters should be tuned to enhance model performance.
- Evaluation of the Model: Use appropriate evaluation measures, such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), or precision and recall for recommendation systems, to assess the models.
- Model Deployment: Use the trained model to provide forecasts or suggestions based on fresh data.
- Monitoring & Upkeep: Keep an eye on the model's performance at all times, and occasionally retrain it to take into account new trends or patterns in the data.
- Implementing a feedback loop: would allow you to update your recommendations and enhance the model based on user interactions and input.

ISSN PRINT 2319 1775 Online 2320 7876
 UGC CARE Listed (Group-I) Journal Volume 11 , Iss2, Aug 2022

5.4 Proposed Method



[5.4. Figure: Flowchart of proposed method]

[5.Table: Performance evaluation of state-of-the research]

Author	Methods Used						
	Association Rule Mining	**Bagging**	**MLP**	**Stacking**	**Web Mining**	**Collaborative Filtering**	Accuracy
Moorthi, K.[11]	YES	NO	NO	✓	-	-	91.9%
Drivas, I.C[12]	✓	NO	NO	✓	-	-	93.9%
Nurcahyo, R[13]	✓	✓	✓	✓	-	-	89.9%
Matuszela ´nski, K[14]	✓	✓	YES	✓	-	-	78%
Gerrikagoitia, J.K[15]	✓	NO	✓	-	-	-	89%
Nadikattu[16]	✓	✓	NO	✓	-	✓	86%
Sutinen, U[17]	NO	NO	-	✓	-	✓	76%
Lahkani,	YES	YES	-	-	✓	✓	87.6%

M.J[18]							
Hassani, H[19]	NO	✓	-	✓	-	✓	78.88%
Hasan, L[20]	✓	-	-	✓	✓	✓	91.5%
Li, Y.; Zhong[21]	-	-	-	✓	-	-	82.6%

6 Conclusion

The Summary of Research Paper Through the use of individualized product suggestions, the fusion of machine learning and recommendation algorithms has revolutionized e-commerce, improving user experiences and boosting customer retention and happiness. Additionally, these algorithms enhance transaction security, foster brand loyalty, and optimize inventory management. Machine learning is a strong tool because of its adaptability, which includes supervised, unsupervised, reinforcement, and deep learning. A review of the literature identified several e-commerce-related research fields, including image-based systems and tailored suggestions. The performance of recommendation systems depends on key evaluation criteria like recall, precision, accuracy, ROC curves, and F-measure. Throughout as well as e-commerce, machine learning and recommendation algorithms are used in a wide range of industries, including media, healthcare, agriculture, and transportation. A combination strategy incorporating association rule mining, machine learning, and collaborative filtering is highlighted in the methodology section, which details the procedures from data collection to model deployment. In the end, this connection has transformed e-commerce and has potential in many different fields. These algorithms are still essential for competitive businesses offering top-notch customer service as technology advances.

References

1. Author, Kumar, B., Roy, S., Sinha, A., Iwendi, C., &Strážovská, Ľ. (2022). E-commerce website usability analysis using the association rule mining and machine learning algorithm. Mathematics, 11(1), 25.[https://doi.org/10.3390/su10010147]
2. Author, Liu, L. (2022). e-commerce personalized recommendation based on machine learning technology. Mobile Information Systems, 2022.[https://doi.org/10.1155/2022/1761579]
3. Author, Addagarla, S. K., &Amalanathan, A. (2020). Probabilistic unsupervised machine learning approach for a similar image recommender system for E-commerce. Symmetry, 12(11), 1783.[https://doi.org/10.3390/sym12111783]
4. Author, Hussien, F. T. A., Rahma, A. M. S., & Wahab, H. B. A. (2021, May). Recommendation systems for e-commerce systems an overview. In Journal of Physics: Conference Series (Vol. 1897, No. 1, p. 012024). IOP Publishing.[10.1088/1742-6596/1897/1/012024]
5. Author, Hsu, J. Y., Tseng, W. K., Hsieh, J. Y., Chang, C. J., & Chen, H. (2020). The recommending agricultural product sales promotion mode in e-commerce using reinforcement learning with contextual multiarmed bandit algorithms. Mathematical Problems in Engineering, 2020, 1-10.[https://doi.org/10.1155/2020/8836000]
6. Author, Thobani, Shaheen. "Improving e-Commerce sales using machine learning." PhD diss., Massachusetts Institute of Technology, 2018.[http://hdl.handle.net/1721.1/118511]
7. Author, Fayyaz, Zeshan, Mahsa Ebrahimian, Dina Nawara, Ahmed Ibrahim, and Rasha Kashef. "Recommendation systems: Algorithms, challenges, metrics, and business opportunities." Applied Sciences 10, no. 21 (2020): 7748[https://doi.org/10.3390/app10217748]
8. Author, Maher, M., Ngoy, P. M., Rebriks, A., Ozcinar, C., Cuevas, J., Sanagavarapu, R., &Anbarjafari, G. (2022). Comprehensive empirical evaluation of deep learning approaches for session-based recommendation in e-commerce. Entropy, 24(11), 1575 [https://doi.org/10.3390/e24111575]

Author, Ramzan, Bushra, Imran Sarwar Bajwa, Noreen Jamil, Riaz Ul Amin, Shabana Ramzan, Farhan Mirza, and Nadeem Sarwar. "An intelligent data analysis for recommendation systems using machine learning." Scientific Programming 2019 (2019): 1-20.[https://doi.org/10.1155/2019/5941096]

9. Author, Necula, Sabina-Cristiana. "Exploring the Impact of Time Spent Reading Product Information on E-commerce Websites: A Machine Learning Approach to Analyze Consumer Behavior." Behavioral Sciences 13, no. 6 (2023): 439. [https://doi.org/10.3390/bs13060439]
10. Author, Moorthi, K., Gaurav Dhiman, P. Arulprakash, C. Suresh, and K. Srihari. "WITHDRAWN: A survey on impact of data analytics techniques in E-commerce." (2021).[https://doi.org/10.1016/j.matpr.2020.10.867]
11. Author, Drivas, Ioannis C., Damianos P. Sakas, Georgios A. Giannakopoulos, and Daphne Kyriaki-Manessi. "Big data analytics for search engine optimization." *Big Data and Cognitive Computing* 4, no. 2 (2020): 5.[https://doi.org/10.3390/bdcc4020005]
12. Author, Nurcahyo, Rahmat, and Prawira Adi Putra. "Critical factors in indonesia's e-commerce collaboration." *Journal of Theoretical and Applied Electronic Commerce Research* 16, no. 6 (2021): 2458-2469.[https://doi.org/10.3390/jtaer16060135]
13. Author, Matuszelański, K., &Kopczewska, K. (2022). Customer Churn in Retail E-Commerce Business: Spatial and Machine Learning Approach. Journal of Theoretical and Applied Electronic Commerce Research, 17(1), 165-198. [https://doi.org/10.3390/jtaer17010009]
14. Author, Gerrikagoitia, Jon Kepa, Iñigo Castander, Fidel Rebón, and Aurkene Alzua-Sorzabal. "New trends of Intelligent E-Marketing based on Web Mining for e-shops." Procedia-Social and Behavioral Sciences 175 (2015): 75-83. [https://doi.org/10.1016/j.sbspro.2015.01.1176]
15. Author, Nadikattu, Rahul Reddy. "Research on data science, data analytics and big data." INTERNATIONAL JOURNAL OF ENGINEERING, SCIENCE AND 9, no. 5 (2020): 99-105.[http://dx.doi.org/10.2139/ssrn.3622844]
16. Author, Sutinen, Ulla-Maija, Hannu Saarijärvi, and Mika Yrjölä. "Shop at your own risk? Consumer activities in fashion e-commerce." International Journal of Consumer Studies 46, no. 4 (2022): 1299-1318. [https://doi.org/10.1111/ijcs.12759]
17. Author, Marjaneh Jahangiri, Shouyang Wang, Mariusz Urbański, and Mariya Egorova. "Sustainable B2B E-commerce and blockchain-based supply chain finance." Sustainability 12, no. 10 (2020): 3968[https://doi.org/10.3390/su12103968]
18. Author, Hassani, Hossein, Christina Beneki, Stephan Unger, Maedeh Taj Mazinani, and Mohammad Reza Yeganegi. "Text mining in big data analytics." Big Data and Cognitive Computing 4, no. 1 (2020): 1.[https://doi.org/10.3390/bdcc4010001]
19. Author, Hasan, Layla, Anne Morris, and Steve Probets. "Using Google Analytics to evaluate the usability of e-commerce sites." In Human Centered Design: First International Conference, HCD 2009, Held as Part of HCI International 2009, San Diego, CA, USA, July19-24, 2009 Proceedings 1, pp. 697-706. Springer Berlin Heidelberg, 2009. [Using Google Analytics to Evaluate the Usability of E-Commerce Sites | SpringerLink]
20. Author, Li, Yuefeng, and Ning Zhong. "Web mining model and its applications for information gathering." Knowledge-Based Systems 17, no. 5-6 (2004): 207-217.[https://doi.org/10.1016/j.knosys.2004.05.002]
21. Author, Schafer, J.B.; Konstan, J.A.; Riedl, J. E-commerce recommendation applications. Data Min. Knowl. Discov. 2001, 5, 115–153. [https://link.springer.com/article/10.1023/A:1009804230409]

22. Author, Smith, B.; Linden, G. Two decades of recommender systems at Amazon.com. IEEE Internet Comput. 2017, 21, 12–18. [DOI: 10.1109/MIC.2017.72]
23. Author, Ge, M.; Delgado-Battenfeld, C.; Jannach, D. Beyond accuracy: Evaluating recommender systems by coverage and serendipity. In Proceedings of the Fourth ACM Conference on Recommender Systems, Barcelona, Spain, 26–30 September 2010; Association for Computing Machinery: New York, NY, USA, 2010; pp. 257–260.[https://dl.acm.org/doi/abs/10.1145/1864708.1864761]
24. Author, Gheraibia, M.Y.; Gouin-Vallerand, C. Intelligent mobile-based recommender system framework for smart freight transport. In Proceedings of the 5th EAI International Conference on Smart Objects and Technologies for Social Good, Valencia, Spain, 25–27 September 2019; pp. 219–222. [https://doi.org/10.1145/3342428.3342697]
25. Author, Hu, R.; Pu, P. Enhancing recommendation diversity with organization interfaces. In Proceedings of the 16th International Conferenceon Intelligent User Interfaces, Palo Alto, CA, USA, 13–16 February 2011; pp. 347–350. [https://doi.org/10.1145/1943403.1943462]
26. Author, Rodriguez-Carrion, A.; Garcia-Rubio, C.; Campo, C.; Cortés-Martín, A.; Garcia-Lozano, E.; Noriega-Vivas, P. Study of LZ-based location prediction and its application to transportation recommender systems. Sensors 2012, 12, 7496–7517. [https://doi.org/10.3390/s120607496]
27. Author, Madhusree, K.; Rath, B.K.; Mohanty, S.N. Crop Recommender System for the Farmers using Mamdani Fuzzy Inference Model. Int. J. Eng. Technol. 2018, 7, 277–280.[https://www.drsachinandan.com/publication/17%20ACFrOgCg2usVBT5ead-RpoQJQsAQX7LHUGqa7iMosdjK8w57PjbzCPAgnBJ2HhqWySWxiGUzeIavy9NHwieXuDCK2NjsmFAoOLbFd1fre9jef_DWF3Dv6_Y9obDbh8RWasHvHBJvhz2mpTRlKr.pdf]
28. Author, Sezgin, E.; Sevgi, Ö. A systematic literature review on Health Recommender Systems. In Proceedings of the 2013 E-Health and Bioengineering Conference (EHB), Iasi, Romania, 21–23 November 2013; IEEE: Piscataway, NJ, USA, 2013; pp. 1–4. [https://ieeexplore.ieee.org/abstract/document/6707249]
29. Author, Zhang, M.; Yi, C.; Xiaohong, Z.; Junyong, L. Study on the recommendation technology for tourism information service. In Proceedings of the 2009 Second International Symposium on Computational Intelligence and Design, Changsha, China, 12–14 December 2009; IEEE: Piscataway, NJ, USA, 2009; Volume 1, pp. 410–415.[https://doi.org/10.3390/app10217748]
30. Author, Panagiotis, S.; Nanopoulos, A.; Manolopoulos, Y. MoviExplain: A recommender system with explanations. In Proceedings of the Third ACM Conference on Recommender Systems, New York, NY, USA, 22–25 October 2009; pp. 317–320. [https://doi.org/10.1145/1639714.1639777]
31. Author, Geuens, S.; Coussement, K.; De Bock, K.W. A framework for configuring collaborative filtering-based recommendations derived from purchase data. Eur. J. Oper. Res. 2017, 265, 208–218. [https://doi.org/10.1016/j.ejor.2017.07.005]
32. Author, Sulikowski, P.; Zdziebko, T. Deep Learning-Enhanced Framework for Performance Evaluation of a Recommending Interface with Varied Recommendation Position and Intensity Based on Eye-Tracking Equipment Data Processing. Electronics 2020, 9, 266. [https://doi.org/10.3390/electronics9020266]
33. Author, Mustaqeem, A.; Anwar, S.M.; Majid, M. A modular cluster-based collaborative recommender system for cardiac patients. Artif. Intell. Med. 2019, 102. [https://doi.org/10.1016/j.artmed.2019.101761]
34. Author, Cremonesi, P.; Turrin, R.; Lentini, E.; Matteucci, M. An evaluation methodology for collaborative recommender systems. In Proceedings of the 2008 International Conference on Au-

tomated Solutions for Cross Media Content and Multi-Channel Distribution, Florence, Italy, 17–19 November 2008; IEEE: Piscataway, NJ, USA, 2008; pp. 224–231.[https://www.diva-portal.org/smash/record.jsf?pid=diva2%3A1414472&dswid=-1222]

35. Author, Gao, H.; Tang, J.; Liu, H. Exploring temporal effects for location recommendation on location based social networks. In Proceedings of the 7th ACM Conference on Recommender Systems, Hong Kong, China, 12–16 October 2013; Association for Computing Machinery: New York, NY, USA, 2013; pp. 93–100.[https://doi.org/10.1145/2507157.2507182]
36. Author, Yuan, Q.; Cong, G.; Ma, Z.; Sun, A.; Magnenat-Thalmann, N. Time-aware point-of-interest recommendation. In Proceedings of the 36th International ACM SIGIR Conference on Research and Development in Information Retrieval, Dublin, Ireland, 28 July–1 August 2013; pp. 363–372. [https://doi.org/10.1145/2484028.2484030]
37. Author, Gunawardana, A.; Shani, G. A survey of accuracy evaluation metrics of recommendation tasks. J. Mach. Learn. Res. 2009, 10,2935-2962.[https://www.jmlr.org/papers/volume10/gunawardana09a/gunawardana09a.pdf]
38. Author, del Olmo, F.H.; Gaudioso, E. Evaluation of recommender systems: A new approach. Expert Syst. Appl. 2008, 35, 790–804.[https://doi.org/10.1016/j.eswa.2007.07.047]
39. Author, Park, M.H.; Hong, J.; Cho, S. Location-based recommendation system using bayesian user's preference model in mobile devices. In Proceedings of the 4th International Conference on Ubiquitous Intelligence and Computing, Hong Kong, China, 11–13 July 2007; Springer: Berlin/Heidelberg, Germany, 2007; pp. 1130–1139.[https://link.springer.com/chapter/10.1007/978-3-540-73549-6_110]
40. Author, Yin, H.; Sun, Y.; Cui, B.; Hu, Z.; Chen, L. LCARS: A location-content-aware recommender system. In Proceedings of the 19th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, Chicago, IL, USA, 11–13 August 2013; pp. 221–229. [https://doi.org/10.1145/2487575.2487608]
41. Author, Horozov, T.; Narasimhan, N.; Vasudevan, V. Using location for personalized POI recommendations in mobile environments. In Proceedings of the International Symposium on Applications and the Internet (SAINT'06), Phoenix, AZ, USA, 23–27 January 2006; IEEE: Piscataway, NJ, USA, 2006; p. 6. [https://ieeexplore.ieee.org/abstract/document/1581323]
42. Author, Archana, K.; Saranya, K.G. Crop Yield Prediction, Forecasting and Fertilizer Recommendation using Voting Based Ensemble Classifier. SSRG Int. J. Comput. Sci. Eng. 2020, 7.[https://d1wqtxts1xzle7.cloudfront.net/63354060/IJCSE-V7I5P101_120200518-129172-1avb6kf-libre.pdf?1589851992=&response-content disposition=inline%3B+filename%3DCrop_Yield_Prediction_Forecasting_and_Fe.pdf&Expires=1700598994&Signature=HqrCkVbsv6O3~yTnngbI2-TtnJXZ1C2UCHXwcoeBtWVrKKsDEX~flJ7bXZ~69K~BO-RTPaiA0REYygKRuY0jkoSEtcIweHZHTwajXOCGzOVo7AZU1qvyXL8IFWH-tnaA74M4x0Z5tnNU87pnweWTDLPbnxB~pyYjexKavnU5ITLbu-vKC57RShfEnrZsahJMMVOQyNa39UpuulY-YjWE99NlpAXteOsOmFLziadfnipi-4QuO1YYt7NSUCUwtnj0RQBW0KCmESxB1jtiq8v105UrwrI4LMt22gNtkW53DxPthmiVAeuhqNqwGd~nnmmeOXVx0n-8LSi0Km8~np1hHw__&Key-Pair-Id=APKAJLOHF5GGSLRBV4ZA]
43. Author, Hanley, J.A.; McNeil, B.J. The meaning and use of the area under a receiver operating characteristic (roc) curve. Radiology 1982, 143, 29–36 [https://doi.org/10.1148/radiology.143.1.7063747]
44. Author, Chen, T.Y.; Kuo, F.-C.; Merkel, R. On the statistical properties of testing effectiveness measures. J. Syst. Softw. 2006, 79, 591–601.[https://doi.org/10.1016/j.jss.2005.05.029]

45. Author, Hamid, K. Personalized Healthcare System Based on Ontologies. In Proceedings of the International Conference on Advanced Intelligent Systems for Sustainable Development (AI2SD '2018), Tangiers, Morocco, 12–14 July 2018; Volume 4, p. 185. [https://doi.org/10.3390/app10217748]
46. Author, Lee, J.; Ahn, J.H.; Park, B. The effect of repetition in internet banner ads and the moderating role of animation. Comput. Hum. Behav. 2015, 46, 202–209. [https://doi.org/10.1016/j.chb.2015.01.008]
47. Author, Sung, Y.-S.; Dravenstott, R.W.; Darer, J.D.; Devapriya, P.D.; Kumara, S. SuperOrder: Provider order recommendation system for outpatient clinics. Health Inform. J. 2019, 26, 999–1016.[https://doi.org/10.1177/1460458219857383]
48. Author, Frittelli, D.M.V. An Architecture for e-Health Recommender Systems Based on Similarity of Patients' Symptoms. In Blockchain Technology for Smart Cities; Springer: Singapore, 2020. [https://link.springer.com/chapter/10.1007/978-981-15-2205-5_8]
49. Author, Mezei, J.; Nikou, S. Fuzzy optimization to improve mobile health and wellness recommendation systems. Knowl. Based Syst. 2018, 142, 108–116.[https://doi.org/10.1016/j.knosys.2017.11.030]
50. Author, Hong, M.; Jung, J.J.; Piccialli, F.; Chianese, A. Social recommendation service for cultural heritage. Pers. Ubiquitous Comput. 2017, 21, 191–201.[https://link.springer.com/article/10.1007/s00779-016-0985-x]
51. Author, Pavlidis, G. Recommender systems, cultural heritage applications, and the way forward. J. Cult. Herit. 2019, 35, 183–196.[https://doi.org/10.1016/j.culher.2018.06.003]
52. Author, Su, X.; Sperlì, G.; Moscato, V.; Picariello, A.; Esposito, C.; Choi, C. An edge intelligence empowered recommender system enabling cultural heritage applications. IEEE Trans. Ind. Inform. 2019, 15, 4266–4275. [https://ieeexplore.ieee.org/abstract/document/8675979]
53. Author, Yang, J.; Wang, H.; Lv, Z.; Wei, W.; Song, H.; Erol-Kantarci, M.; Kantarci, B.; He, S. Multimedia recommendation and transmission system based on cloud platform. Future Gener. Comput. Syst. 2017, 70, 94–103.[https://doi.org/10.1016/j.future.2016.06.015]
54. Author, Mwinyi, I.H.; Narman, H.S.; Fang, K.; Yoo, W. Predictive self-learning content recommendation system for multimedia contents. In Proceedings of the 2018 Wireless Telecommunications Symposium (WTS), Phoenix, AZ, USA, 18–20 April 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 1–6. [https://ieeexplore.ieee.org/abstract/document/8363949]
55. Author, Baek, J.-W.; Chung, K.-Y. Multimedia recommendation using Word2Vec-based social relationship mining. Multimed. Tools Appl. 2020, 1–17. [https://link.springer.com/article/10.1007/s11042-019-08607-9]
56. Author, Aysha, K.; Ali, R. Recommender System Based on OSN Data Analytics. In Information and Communication Technology for Intelligent Systems, Proceedings of ICTIS 2018, Padang, Indonesia, 25–26 July 2018; Springer: Singapore, 2018; Volume 2, p. 2. [https://link.springer.com/chapter/10.1007/978-981-13-1747-7_19]
57. Author, Moscato, V.; Picariello, A.; Sperli, G. An Emotional Recommender System for music. IEEE Intell. Syst. 2020, 1. [https://ieeexplore.ieee.org/abstract/document/9204829]
58. Author, Yang, X.; Dong, M.; Chen, X.; Ota, K. Recommender System-Based Diffusion Inferring for Open Social Networks. IEEE Trans. Comput. Soc. Syst. 2020, 7, 24–34.[https://ieeexplore.ieee.org/abstract/document/8913686]
59. Author, Sperlì, G.; Amato, F.; Mercorio, F.; Mezzanzanica, M. A Social Media Recommender System. Int. J. Multimed. Data Eng. Manag. 2018, 9, 36–50.[https://www.igi-global.com/article/a-social-media-recommender-system/196248]

60. Author, Ma, X.; Jianfeng, M.; Li, H.; Jiang, Q.; Gao, S. ARMOR: A trust-based privacy-preserving framework for decentralized friend recommendation in online social networks. Future Gener. Comput. Syst. 2017, 79, 82–94.[https://doi.org/10.1016/j.future.2017.09.060]