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Assessment of recommendation modelling with machine learning

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Abstract

The proliferation of limitless content brought about by the digital age has resulted in an extreme choice paradigm. It is possible for a user who is new to the site or searching for a species to become lost in this vast expanse. As a result, it's essential to create a system that can direct consumers based on their interests. The Recommendation System (RS) was developed as a solution to this issue. RS is a tool that suggests different products according to user's liking. Given the ability to address numerous issues related to over-selection in numerous web applications and widespread use, the advantages of the RS cannot be overstated. Machine learning (ML) has garnered a lot of attention recently in a variety of research fields, including natural language processing (NLP) and pattern recognition etc. This is due in part to ML's remarkable performance as well as its alluring ability to demonstrate learning from scratch. When ML approaches are used to prediction and recommender systems, their impact becomes evident. In order to help future researchers in the field of recommender systems develop an effective system, this paper will conduct a systematic review of various recent contributions made in the field, with a focus on diverse applications such as movies, books, products, etc. We will analyse case studies conducted over the previous thirteen years (2011–2023), with a focus on 58 key studies selected from 2580 research papers found using the CADIMA tool. The goal of this systematic literature review (SLR) is to identify the best evidence-based strategy by evaluating several recommender system approaches applied to

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diverse applications. This review concludes by offering a much-needed summary of the state of the art in this area and highlighting the gaps and difficulties that still need to be filled.

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1. Introduction

Software engines called recommendation systems, sometimes known as RS, are made to make recommendations to users based on their past preferences, interactions with products, and other factors. RS is a programme made to assist users in extracting useful data based on their interests. By assisting each and every customer in identifying and discovering their favourite films, TV series, digital goods, books, articles, services, and more, recommendation engines offer a personalised user experience. These technologies benefit customers and assist businesses in boosting sales. For instance, millions of products are listed on Amazon's website; visitors will probably have trouble navigating and deciding what to buy. Recommendation systems facilitate product discovery, enhance user friendliness, and encourage users to stay on the website rather than leaving.

In the last few decades, RS technology has advanced significantly. RS has reportedly been used in a number of situations to provide recommendation features on popular websites [1]. Research articles, travel, hotels, retail sites, films, and more can all benefit from the use of RS. The suggestion is an additional application domain in which many strategies can be employed to create an effective reinforcement system. These Recommendation systems seek to filter the data in accordance with user preferences. Moreover, the RS has also captured user feedback regarding specific goods or objects. To suggest products to customers based on their interests, these systems are extensively utilised in the e-commerce industry. The products are suggested in accordance with the consumers' past purchases. Predictions about user preferences can also be formed using the analysis. This method assists each consumer in purchasing things that align with their interests; hence it falls under the category of personalisation as shown in figure1. If the recommendation is suitable, this technique can boost sales and build positive relationships with customers.

The business community has taken notice of the RS in the e-commerce space. Amazon, Flipkart etc uses the RS to recommend items based on what customers have bought in the past. Although no system uses all three at once, the majority of RSs on the market today are based on the explicit rating, ownership information, and purchasing history of the user. This enhances the overall quality of the users' shopping experience while also assisting them in making rapid judgements during their transactions via internet. The tourism industry may benefit from the advancement of RS. They help travellers to make proper travel selections by assisting them in managing vast amounts of information. This technology has the ability to recommend a location that fits their profile and offers activities that are appropriate. Spotify, Netflix, YouTube, and other video and music services frequently use RSs as playlist makers. These recommendation systems are one of the best applications of ML technologies in the corporate sector. Recommendation models, which may suggest medical information to both patients and healthcare providers based on their needs, have grown in importance in the healthcare industry.

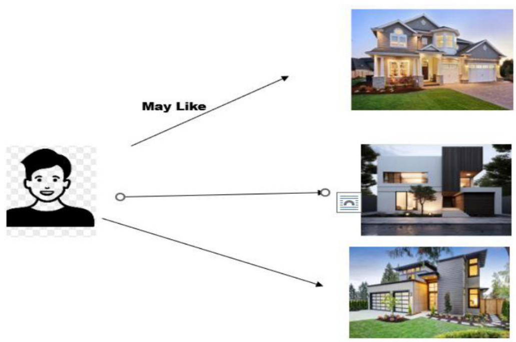

Figure 1

Recommendation of Different homes to a person

There are various sorts of recommender systems, and each has its unique ways of offering customised recommendations. Among them are:

1.1 *Content Based Filtering*

A method for predicting a user's preferences based on the qualities of the products the person has previously liked is called content-based filtering. This method focuses on the characteristics of the products that are being suggested, like the actor, director, genre, or other aspects. It can be used with any kind of thing, such as products, films, music, and literature, that has explicit or implicit qualities. Content-based filtering works on the premise that users are more likely to like goods with comparable attributes in the future if they have previously liked items with those attributes. The algorithm creates a profile of the user's preferences based on the user's previous actions, including ratings and purchases. The items with similar attributes to the ones the user has previously liked are then recommended using this profile. For example, if any user liked action movies, then similar type of movies will be recommended to him, as displayed in the following figure 2.

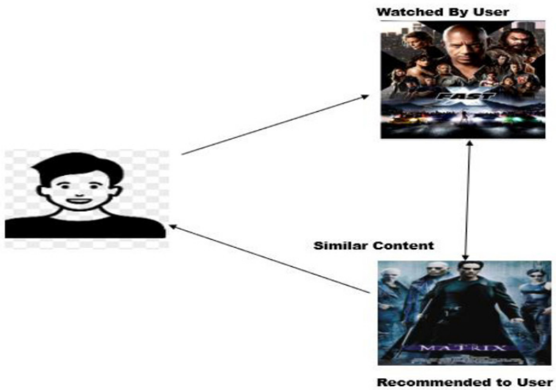

Figure 2

Content-Recommendation Method

1.2 *Collaborative Filtering*

Recommendation systems use a technique called collaborative filtering to infer a user's preferences from those of users who are similar to them. Collaborative filtering operates on the premise that individuals with comparable prior preferences are likely to have similar future preferences. Collaborative filtering algorithms identify comparable end-users and provide recommendations based on information gathered from many end-users' encounters with a specific item, including reviews and purchase histories. Utilising end-user similarity scores, the algorithms determine which items a targeted end-user would seem to be fascinated in based on these scores [2]. For example, if there are two users, as shown in figure 3, who has similar tastes for movies then user1 will be recommended same movie which is liked by user1.

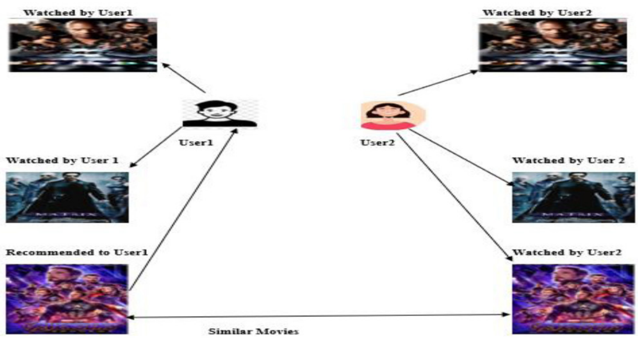

Figure 3

Collaborative Filtering method

1.3 *Hybrid Filtering*

Multiple recommendation approaches are employed by hybrid recommendation systems for generating recommendations that are extra varied and correct. To offer a more thorough and individualised recommendation experience, they integrate the advantages of several recommendation techniques, like collaborative-filtering and content-based filtering.

Netflix is a prime demonstration of a hybrid recommendation model; in order to provide recommendations, it combines content-based filtering as well as collaborative filtering, and other methods. Netflix use content-based filtering to determine the characteristics of the products that a user has previously enjoyed and collaborative filtering to determine the tastes of similar users. Netflix is able to deliver users recommendations that are varied and relevant by combining these two strategies. To provide recommendations that are more accurate, hybrid recommendation systems can additionally use data from external sources, contextual data, and demographic data [3].

Machine Learning algorithms are able to codify increasingly complex abstracts, like higher-level information presentation, and capture nonlinear and unimportant user-material relationships with great effectiveness. Additionally, it gathers intricate relationships within data from publicly accessible information sources, including contextual and visual data.

Various machine learning algorithms can effectively tackle complicated challenges involving unstructured data. The goal of this work is to review the methods utilised for RSs, their application domains, and their advantages and disadvantages. The in-depth explanation of machine learning is presented in Section II of this article. The technique used under this article for choosing the reference papers is presented in Section III. The review of the literature and a thorough analysis of the benefits and drawbacks are found in Section IV. Section V discusses the comparative study of previous work done by different researchers. The paper is finally concluded in Section VI.

2. Machine learning

It is referred to as artificial intelligence (AI) when a system is trained for a certain set of targets in order to classify the categorised data value. AI is classified, and there are various methods for teaching a machine based on learning behaviour. ML is a subfield of AI where statistical techniques are used to train the system. Numerous learning processes are produced by the data distribution architecture. Four categories of learning behaviour are covered here, out of the fourteen different types of learning mechanisms:

2.1 *Supervised*

A type of machine learning algorithm, known as supervised learning, is able to learn from data that has been labelled. Information that has been appropriately answered or categorized is referred to be labelled information. Supervised learning, as the name implies, relies on the presence of a supervisor. Supervised learning is used to guide or educate a machine. This suggests that certain data have already been subjected to the appropriate reaction. After then, a new collection of patterns (information) is provided to the machine, allowing the supervised learning algorithm to assess the training data (set of training instances) and produce an accurate conclusion based on the labelled information.

2.2 *Unsupervised*

Unsupervised learning is the type of machine learning where the knowledge is derived from unlabelled data. This shows that there aren't any tags or categories in the data yet. Unsupervised learning aims to find patterns and relationships in the data without explicit guidance. Unsupervised learning is educating a machine without labelled or classified data and allowing the algorithm to make judgments solely on the data without human supervision. Without the need for prior data training, the machine's task in this scenario is to classify unsorted data based on sequences, similarities and differences.

2.3 *Reinforcement*

The system updates itself using the new, accurate classified items in this learning mechanism.

Additional methods of learning include active learning, online learning, transfer learning, multi-instance learning, inductive learning, deductive inference, transudative learning, multi-task learning, self-supervised learning, and ensemble learning. With ML, users may examine a vast quantity of data. It can take more time and resources to prepare, but it typically yields faster and more precise results for detecting advantageous opportunities or risky hazards. When machine learning is combined with cognitive and artificial intelligence large-scale information processing can be done even more efficiently with the help of technologies. Basically, two different types of machine learning approaches are there: Unsupervised Learning and Supervised Learning. Once more, the supervised method is categorized into two subsections: (a) regression and (b) classification. There are various ways to unsupervised learning, including clustering [4].

3. Methodology

The following stages of a systematic review of the literature are supported by the review work done for this publication. A particular set of procedures used in the administration of this review paper are shown in Fig. 4.

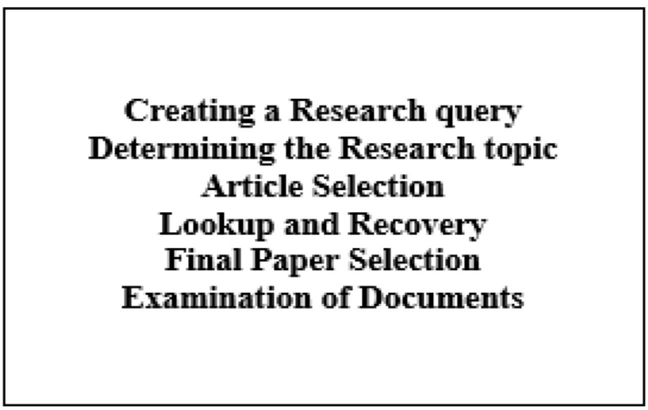

Figure 4

Review Process Structure

3.1 *Questions of Research and its search string*

This literature study aims to understand what problems RSs could effectively solve, how they are designed and assessed, and what areas or elements they may be tested.

In order to do this, we established the following research inquiries:

Q1: Which studies about RS are the most pertinent?

Q2: What methods of machine learning does RS employ?

Q3: What issues and difficulties do RS face?

Q4: How are RS assessed?

Q5: In which particular domains is RS applied?

Q6: Looking ahead, which directions show the most promise for research?

Four digital libraries were selected as the reference of the research articles that were being reviewed. To obtain the research papers, utilized the strings "Review of RSs", "RS Applications" and RSs Techniques. The search yielded a list of 2580 research articles from the specified digital libraries. Papers from two distinct time periods, 2011–2020 and 2021–2023, are included to analyse the beginnings, development, and current state of RSs. For analysis, only English-language journal research papers and conference proceedings are taken into account. As a result, 1050 research papers were chosen. Fig. 5 shows the sources for these research publications.

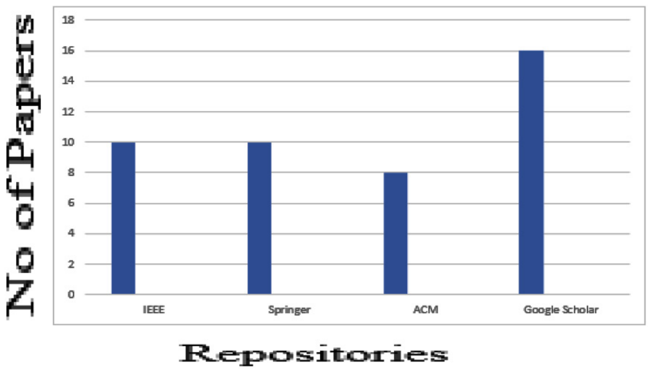

Figure 5

Selected Papers' Resources

Figure 6 shows the percentage of papers that were chosen using RS methods as the selection criteria.

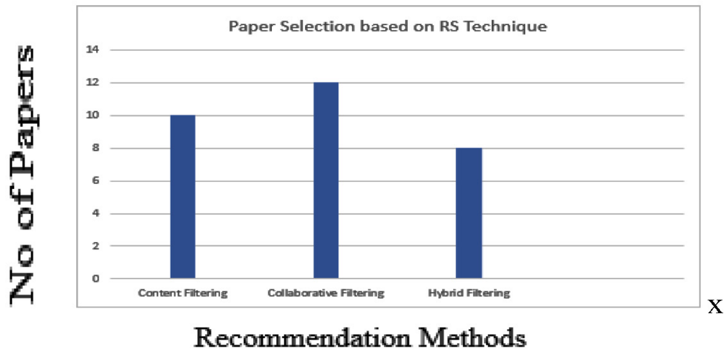

Figure 6

Chosen Papers relied on RS Techniques

Figure 7 shows the total amount of research articles that were discovered according to the Domain area selection criteria.

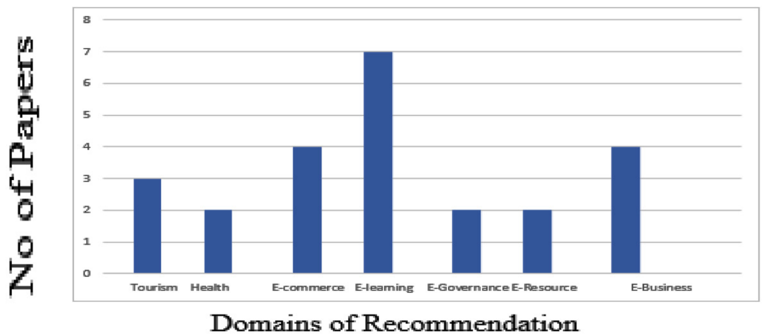

Figure 7

Selected Papers based on Domain Areas

4. Literature survey

A thorough assessment of the literature on various RSs is presented in this work. This section discusses machine learning algorithms, recommendation systems, and frequently used applications. These pieces show how RSs might offer online users tailored recommendations so they can lessen the time and energy invested in choosing goods or services based on their chooices. This segment tackles the initial Research Question and presents the pertinent studies conducted in the field.

In 2011, N. Zheng et al. presented a paper in which they looked into the significance and value of tag and time information in forecasting user preferences and how to use it to create a resource-recommendation algorithm that works well [5].”Neuro-fuzzy-WEb Recommendation (NEWER)” system was created by Castellano et al. [6] to take advantage of the potential to combine human choice and computational intelligence to recommend engaging web pages to users in a dynamic setting. To express the correlations, it took into consideration a set of fuzzy rules between page categories and user relevancy.

In 2012, X Luo et al. gave a work in which they talked about an incremental regularised matrix factorization (RMF)-based Collaborative Filtering recommender. In order to accomplish this goal, they first streamlined the RMF training rule and presented the SI-RMF, which offered a straightforward mathematical form for additional research. From there, they created two different incremental Regularised Matrix Factorization models: the IRMF or Incremental RMF and the IRMF-B or Incremental RMF using linear biases [7]. In order to aggregate appropriate prescriptions for the patients, Chen et al. introduced a diabetic drug prediction model with the help of “SWRL or Semantic Web Rule Language and JESS or Java Expert System Shell”. It sought to identify the most appropriate medications from the specific medication list [8].

In 2013, A technique for recommending e-learning resources was proposed by Salehi and Kmalabadi. It involved “customizing of materials in material’s attribute which is in a multidimensional space.” It made use of both together cooperative-filtering and content- filtering [9]. Aher and Lobo presented a course recommender system which makes usability of data-mining methods including basic K-means clustering and the ARM or Association Rule Mining algorithm. The suggested electronic-learning platform for “MOOCs (Massively Open Online Courses)” was effectively demonstrated [10].

In 2014, for reducing waiting time and traffic at popular tourist destinations, Liu et al. developed a novel route suggestion algorithm and offered personalised, live path recommendations for self-driven traveller. The preferences of the users were taken into consideration when making recommendations [11]. A model for recommendation grounded on unsupervised-learning was provided by Bakshi et al. for handling the problems of scalability of systems that recommend. This approach found the broad neighbour by combining the PSO or Particle Swarm Optimisation technique with transitory similarities [12].

In 2015, F G. Adomavicius et al. presented a work in which they talked about CARS or Context-aware recommender systems tailor recommendations to a unique contextual circumstance of the user in order to produce more relevant results. This paper investigated the use of contextual data to build smart and practical systems which recommends. It offered a summary of complex idea of surroundings and talked about various methods for integrating surroundings into the recommendation system [13]. Thorat et al. gave an overview of recommender-systems which included hybrid filtering, collaborative filtering approaches in their work [14].

In 2016, the current state of research on social recommender systems in general and collaborative filtering in particular is presented by Dou et al. The paper presented the fundamental ideas and equations of two primary methods for collaborative recommendation: collaborative recommendation based on item and collaborative recommendation based on user. The research investigation examined the variations in the user or item resemblance calculation among the revised cosine-based, cosine-based and Pearson-based similarities [15]. Liao et al. presented a preliminary set association rule-based recommender model for online shoppers. The model suggested product categories for e-commerce platforms and calculated the likely behavioural variances of online shoppers [16].

In 2017, the current level of hybrid recommendation systems over past ten years is presented by Çano E et al. in their comprehensive overview of the literature. It was the first quantitative review paper with a hybrid recommender-only focus [17]. A perspective recommender system named "ClickSmart" has been presented by Rawat and Kankanhalli to help mobile users take excellent pictures at well-known tourist locations [18].

In 2018, the SLR or the systematic literature review results on the issue of RS or recommender systems was presented by Murad et al. in their work as a first step towards a future study on the project of LMS or an intelligent learning management system which is used for online learning and it used NLP or Natural Language Processing techniques. This learning concentrated on examining well-known research papers on online learning especially and recommender systems in broad as a basis for a more extensive investigation on smart LMS [19]. Li et al. used Weighted Linear Regression Models (WLRRS) to create a recommendation system. With the help of Movie-Lens-dataset, the provided approach was tried and showed enhanced classification and predicting authenticity [20].

In 2019, Sahoo et al., presented a paper in which they demonstrated how big data analytics can be used to implement an efficient health recommender engine. This paper proposed a HRS or an intelligent health record system with the help of the RBM-CNN or Restricted Boltzmann Machine Convolutional Neural Network using deep learning method. This presented a room for the industry of medical-care to move from a conventional situation to a better personalised prototype in an environment of tele-health [21]. A technique of hybrid-initialization for recommendation of social-network-systems has been proposed by Zhao et al. The methodology made use of attribute mapping, DAE or denoising autoencoder and ANNInit or neural network-based initialization method [22].

In 2020, One IoT or Internet of Things grounded recommendation system utilising the BAS or Beetle Antennae Search algorithm for cancer rehabilitation had been proposed by Han et al. It gave the patients a solution to the issue of an ideal diet programme by taking the recurrence time into account as the objective function [23]. A recommendation system grounded on a tree-model had been presented by Kang et al. for personalised announcement in online- broadcasting. In order to dwindle the preference predictions' overhead, suggestions were originated in real-time by scrutinizing the user-preferences and utilising hash map with combination of the tree's attributes [24].

In 2021, Dhelim et al. employed user's interest-mining and meta-path discovery for generating the personality-based product-recommendation algorithm. In contrast to deep learning and session-based models, this model outperformed the others [25]. For solving the sparseness concern with recommendation machine, Bhalse et al. developed an Internet-based collaborative recommendation system grounded on SVD or Singular Value Decomposition, CS or cosine similarity and collaborative filtering. It provided suggestions based on the movie's thematic information [26].

In 2022, Jayalakshmi et al., executed a thorough evaluation of the literature on a recommender system which was used for movie recommendation. It showed the mechanisms employed in movie recommendation machines, the filtering criteria in recommender machines, the standards for evaluating performance, implementation obstacles, and suggestions for further study [27]. R. C. et al., in order to identifying which deep learning model would perform best given the provided dataset, they were comparing the efficiency of three different models: RBM, Autoencoder, and DNN. they tested the effectiveness of various Deep Learning models using real-world data from sources like MovieLens, which had four csv files [28].

In 2023, Wang et al. conducted a comprehensive investigation of recommendation machines from a viewpoint of data-science. As first step, they showed the many kinds of data that were used to generate recommendations, plus the machine learning methods and models that most accurately represented each kind. Then they provided a brief synopsis of the representative data science and machine learning models that were utilized to build recommender systems.

[29]. S. K. Gupta et al. presented a research under which they provided work on movie recommendation. The suggested approach would leverage a context-rich database that included user, item, and contextual data in addition to other information for improving movie suggestions [30].

5. Comparison of existing recommendation system based on ML

This part included the research articles that many researchers had submitted to build recommendation systems using machine learning techniques. These systems are utilised in a variety of industries, including movie reviews, news, hotel reviews, and several more. The following table 1 will be showing the different work provided by various researchers and also answering the research question2. These are as follows

Table 1

Work provided by different papers

References	Techniques used	System Created for	Features
Lau et al. [31]	Logistic regression and Nave Bayes	News Recommendation	Explained Logistic regression is better than Naïve bayes for news recommendation
Crespo et al. [32]	____	Intelligent electronic books	Attempted to provide an overview of the state of recommendation systems and their use in online distance learning.

Contd...

Kongsakun and Fung [33]	Association rule with ANN and DT	Students' choice	This study presented experimental results and the development of a proposed Intelligent Recommendation System (IRS) framework.
Chang et al. [34]	Cloud computing technology and Hadoop fair scheduler	A cloud-based intelligent TV program	A Hadoop Fair Scheduler is used to enhance processing throughput, and cloud computing technology is employed to create a recommendation engine for digital TV shows.
Lucas et al. [35]	Association Rule	Tourism recommender system	A tourism recommender system's suggestion technique
Chen et al. [36]	Java-Expert-System-Shell and Semantic-Web-Rule-Language	Anti-diabetic drugs selection	This approach can both identify the best medication from a group of related medications and analyse the symptoms of diabetes.
Mohanraj et al. [37]	ODBFA or Ontology driven bee's foraging approach	Web Based recommender system	Determine which navigation profile best fits the current user activity and forecast which navigations online users are most likely to visit.
Aher and Lobo [38]	Clustering and Association Rule Mining	E-learning recommender system	The course recommendation system suggested a course to a student based on what other students had chosen from a certain collection of courses that were gathered from Moodle.
Kardan and Ebrahimi [39]	Association Rule Mining	For asynchronous discussion groups it was a content recommender system	Introduced an innovative method for hybrid recommendation systems that used implicit data gathered from discussion groups to determine the user's similarity neighbourhood.
Adnan et al. [40]	Fuzzy Logic	News	Fuzzy logic is used to identify a group of articles that were connected to one another and could be suggested to a reader.

Contd...

Zahálka et al. [41]	SVM and Convolutional Deep Net	Venue Recommender	A venue explorer that was multimodal and interactive.
Wang et al. [42]	PSO and SVM	Movie	In order to construct an electronic movie personalized recommendation system, this research provided an enhanced PSO (IPSO) and a novel regression model based on the support vector machine (SVM) classification.
Wu et al. [43]	Collaborative Filtering and Problabistic Matrix Facorization	Social media recommender system	The goal of this research was to develop a compound recommendation engine for social media platforms.
Sattar et al. [44]	Nave Bayes	Movie Reviews	To address the issues of sparse ratings, this work presented a novel hybrid recommendation architecture that blended collaborative filtering and content-filtering.
Park et al. [45]	Deep learning	News search	Suggested both a history-based Recurrent Neural Network (RNN) model that encompassed the entirety of the user's prior histories and a modified session-based RNN model designed for news recommendation.
Baskota, and Ng [46]	SVM with KNN	Graduate School	Provided recommendation of courses to graduated students
Zhu et al. [47]	CNN and R-NN	News interest as per click	a deep attention neural network (DAN) was suggested for news suggestion.
Gabriel De Souza et al. [48]	Recurrent Neural Network (RNN)	News	Offered a deep learning-based, contextual hybrid strategy for session-based news recommendation that could make use of a range of information kinds.

Contd...

Da'u et al. [49]	CNN	Restaurant and laptop domain Reviews	The recommendation system shown in this research improved suggestion accuracy by using ABOM or aspect-based opinion mining which was grounded on deep learning techniques.
Dhelim S et al. [50]	_________	Item advocated for internet purchasing	Developed a personality-aware item recommendation system called Meta-Interest that was based on user interest mining and metapath discovery.
Ke et al. [51]	Reinforcement Learning and Edge Computing	Cross-platform dynamic goods recommender system	This research proposed an edge computing and reinforcement learning based cross-platform dynamic commodities recommendation system.
Arpita et al. [52]	Systematic hidden attribute-based recommendation engine (SHARE)	Research paper recommendation	This paper suggested a systematic hidden attribute-based recommendation engine (SHARE). Through the use of numerous hidden features, SHARE uses a feature engineering technique to reveal insightful information about papers.
Wayesa et al. [53]	Content-based Filtering (CBF) and Collaborative Filtering (CF)	Book Recommendation	Proposed use of semantic relationships to inform knowledge-based book suggestions to readers in a digital library by applying Content-based Filtering (CBF) and Collaborative Filtering (CF).

6. Discussion

6.1 *Challenges and Research Gaps of Recommendation System*

Users will receive customised and focused recommendations from RSs. As a result, they deal with the issue of data overload that affects people in the digital age. Recently, several techniques for constructing recommendation systems (RSs) have been created. These techniques can employ collaborative filtering, content-based filtering, or hybrid filtering. The Collaborative filtering is among the largest often used systems and has reached a certain level of maturity. Like collaborative techniques, content-based filtering algorithms ignore user inputs and typically base their predictions on user data. The next section discusses the drawbacks and restrictions of recommendation systems and answer Research Question 3.

i. Over Particularization: When a customer views an item, the system does not recommend items that are similar to what they have already seen. The customer wants to adopt something different, but the model might not let it operate, which could be an issue. Therefore, it is advisable to provide the consumer with a number of options.

ii. Scenario with limited content analysis: In this scenario, two distinct items could be represented with identical qualities, making it impossible to tell them apart.

   Problem with new users: The algorithm weren't able to offer trustworthy advices for new users because they do not yet have enough ratings.

iii. Cold start: Since the model is unfamiliar with the fresh customer's interests, it is challenging to make recommendations to them. Surveys conducted at the moment a user creates their profile can help to resolve this issue. One can ask questions and then propose things based on the user's answers.

iv. Scalability: More resources are required for information processing when a big number of users are present. The resources are used to identify consumers who have similar buying habits. Several kinds of filters can be used to fix this issue.

v. The scarcity: On internet websites, there are a lot of customers and products available. Several recommendation algorithms can be used to generate a neighbourhood of customers based on their profile. The customer will be mapped to the incorrect neighbourhood and it will be challenging to determine their interests if they just rate a small number of products. We refer to this as a data shortage or sparsity problem.

vi. Privacy: Since the RS needs to gather knowledge like as customer's location, information of financial facts, etc., privacy is still another important topic that needs to be covered in this system. Every internet website needs to confirm that the algorithms being utilised are capable of protecting data.

It was discovered throughout this analysis that, despite the outstanding performance of modern recommender systems, there is not any single set of approaches which can be utilised to Analyse each recommender system's efficacy. Comparison of System's efficacy is tough because it is usually measured using a large number of assessment matrices. The degree to which users find these recommender systems satisfying and personalized is a key factor in their performance. It is crucial to develop new assessment criteria that can gauge user satisfaction in real time. Subsequent research endeavours ought to focus on capturing real-time user feedback and leveraging that information to adjust the recommendation mechanism. This will raise the standard of the recommendations.

6.2 *Matrices for Evaluation*

The predictability of the system is gauged by the most widely used assessment metrics in the academic literature. The amount of error that exists between the genuine expected value and the forecasted value is what determines accuracy. The ability of the RS to forecast a consumer's expectations for an item is known as predictive accuracy. The conventional method for determining predictive precision (MAE) is mean absolute error. It is the absolute average of the discrepancies between the user's actual expected value and the estimated values. Research Question4 is the main topic of this section. The following is a list of additional potential evaluation metrics:

i. Uniqueness: A Collaborative Filtering system has the ability to suggest products that the consumer was previously unaware of. One of the most appreciated aspects of the recommendations made by the Collaborative Filtering system is originality for a lot of applications. A novelty-tuned algorithm will deliberately refrain from suggesting new tales that the user is already familiar with.
ii. Randomness: Users receive recommendations for products that they might not have found with their current search methods. A fortuitous plan would involve news articles about topics that readers have never heard of before. Scholars have investigated the ways in which algorithms might be adjusted to promote serendipity and

originality; nevertheless, quantifying novelty is challenging since it requires live user trials in which users identify whether or not a proposal is innovative.

iii. The coverage: It is the percentage of the objects in the Content Filtering system that are known enough for the Content Filtering system to be able to make predictions. It is possible to measure variables like the proportion of products that could be recommended to users, since suggestions with performance optimisations can keep some products from ever being recommended.

iv. Training Rate: This measures the speed at which new information is absorbed by the Recommendation system and turns it into an effective taste signal. These are determined on a per-user basis, indicating how many ratings a user must submit in order to receive customised, high-quality predictions.

v. Positiveness: The capacity of a Recommendation system to assess the probable accuracy of its forecasts is referred to as positiveness or confidence. The majority of Recommendation systems generate ranks according to the most likely predicted rating. Restricting recommendations to high trust can be achieved by a Recommendation system that can measure its forecast confidence properly. This trade-off will result in fewer incorrect predictions, but it will also likely diminish novelty and coverage. In some cases, consumers are shown a measure of prediction trust to assist them in determining whether the risk-return ratio is suitable.

vi. Metrics for measuring user satisfaction: These are only a few examples of possible metrics that might be used for evaluation. In particular, researchers may develop a number of additional measures. These measurements will offer consumers access to a system and compute how they perceive it. Either a customer survey or the computation of usage and retention statistics are usually used to do it.

6.3 *Domains of Applications*

This section answers and summarises Research Question 5. It is possible to obtain the following significant conclusions from the summary of RSs: The three main methods employed in the recommender systems are hybrid, Content Based and Collaborative Filtering methods; of these, hybrid methods are the most widely used. In e-resource RSs, the Collaborative Filtering approaches are commonly applied. Knowledge-based strategies are highly employed by the e-learning RSs. Recent improvements in applications have also been greatly influenced by context awareness-based and social network-based reinforcement learning. The application domains of RSs are as follows:

i. E-Commerce: Recommendation systems were among the first to be widely used in this field. These systems make personalised product recommendations based on customer behaviour analysis, which boosts user satisfaction and sales. An increasing number of e-commerce companies are using one or more RSs technology versions on their websites [54].

ii. E-Government: In e-government, recommendation algorithms are used to give users accurate and trustworthy data. These are programmes that attempt to forecast a user's interest in an item in order to provide the best goods or services to them. Utilising pertinent data about the objects, people, and their interactions allows for this [55].

iii. E-Learning: In e-learning, recommender systems assist students by making relevant learning material recommendations based on their learning objectives and interests. They can also support students in time management and learning process concentration [56].

iv. E-Tourism: In e-tourism, recommendation systems are important because they improve user satisfaction, personalise trip suggestions, and enhance the user experience. Recommendation systems are utilized by e-tourism sites such as Booking.com, Airbnb, and Expedia to provide lodging options based on customer preferences, including price range, location, amenities, and previous booking history. In order to provide recommendations for places that fit a user's interests, travel habits, and demographics, recommendation systems examine user activity, including search queries, browsing history, and previous reservations [55].

v. E-Business: In order to improve user experience, boost revenue, and increase customer engagement, recommendation systems are essential to e-businesses in a variety of industries. These recommendation systems are operated by e-commerce sites for example Amazon, eBay, and Alibaba for generating item recommendations to consumers grounded on their browsing fondness, previous acquisitions, and purchasing nature. These suggestions are frequently found in emails, on product pages, or in the "Customers who ordered this also ordered" sections. Using recommendation systems, e-businesses can target customers with relevant product recommendations via social media adverts, email marketing, or on-site banners, thereby personalising marketing campaigns. Conversion and click-through rates are both raised by this personalisation [57].

vi. E-Resource: Recommendation systems have the potential to greatly enhance e-resource management by facilitating the finding, accessibility, and use of digital resources including books, movies, online courses, and articles. Recommendation systems are used by e-resource platforms to generate relevant content advices based on user's search history, reading habits, interests, and preferences. Users can find new resources that complement their professional or academic interests with the aid of these recommendations [58].

With more people using smartphones to access the Internet, mobile customers can now receive recommendations that are tailored to them and take context into consideration; hence, more mobile RSs are needed. However, mobile data is usually more difficult due to its heterogeneity, noise, need for spatial and temporal auto-correlation, and problems with validation and generalizability. Additional mobile-based analysis in the field of RS may be very beneficial.

7. Conclusion and future scope

Scholars and researchers have become interested in recommender systems. For this publication, we meticulously selected and assessed research publications published from 2011 to 2023 on recommender systems with a range of applications. This article has collected a wide range of knowledge, considering the challenges that different recommender systems face, the strategies employed, the focus on distinct applications, matrices used for evaluation and the many application domains. In addition, gaps in research and problems were presented in order to investigate the recommender systems research viewpoint for the future. There are some restrictions on this research, though. First off, the papers we reviewed were all in English. This study may be expanded by future research to include papers from non-English journals. Second, only a few particular descriptors were searched for in order to do this review. Research papers without those particular keywords were not taken into consideration. Prospective investigations may involve the incorporation of novel wide descriptors and searchable keywords. This will make it possible to expand the study to include a wider range of recommender system articles.

In the final analysis, this work presents a complete understanding of momentous status of the field's research on recommender systems in a novel way and provides directions and advices for future research endeavours.

References

[1] A. Poulose, C. S. Reddy, S. Dash, and B. J. R. Sahu, "Music recommender system via deep learning," *J. Inf. Optim. Sci.*, vol. 43, no. 5, pp. 1081–1088 (2022). [Online]. Available: https://doi.org/10.1080/02522667.2022.2094546.

[2] P. Ajitha, T. Tamilvizhi, K. N. Sowjanya, R. Surendran, and B. Bhoomeshwar, "Consumer product prediction using machine learning," *J. Inf. Optim. Sci.*, vol. 44, no. 3, pp. 565–574 (2023). [Online]. Available: https://doi.org/10.47974/JIOS-1415.

[3] N. Arora, M. Gupta, M. Dharwal, and N. Agarwal, "Luxury adapts to artificial intelligence & digital transformation - A case study of Burberry," *J. Inf. Optim. Sci.*, vol. 44, no. 1, pp. 41–52 (2023). [Online]. Available: https://doi.org/10.47974/JIOS-1294.

[4] P. Malhotra and S. K. Malik, "Fake news detection using supervised machine learning techniques," *J. Inf. Optim. Sci.*, vol. 43, no. 1, pp. 7–15 (2022). [Online]. Available: https://doi.org/10.1080/02522667.2022.2038933.

[5] N. Zheng and Q. Li, "A RS based on tag and time information for social tagging systems," *Expert Syst. Appl.*, vol. 38, pp. 4575–4587 (2011).

[6] G. Castellano, A. M. Fanelli, and M. A. Torsello, "NEWER: A system for neuro-fuzzy web recommendation," *Appl. Soft Comput.*, vol. 11, pp. 793–806 (2011).

[7] X. Luo, Y. Xia, and Q. Zhu, "Incremental collaborative filtering recommender based on regularized matrix factorization," *Knowl.-Based Syst.*, vol. 27, pp. 271–280 (2012).

[8] R. C. Chen, Y. H. Huang, C. T. Bau, and S. M. Chen, "A recommendation system based on domain ontology and SWRL for antidiabetic drugs selection," *Expert Syst. Appl.*, vol. 39, pp. 3995–4006 (2012).

[9] M. Salehi and I. N. Kmalabadi, "A hybrid attribute–based recommender system for e-learning material recommendation," *IERI Procedia,* vol. 2, pp. 565–570 (2012).

[10] S. B. Aher and L. M. R. J. Lobo, "Combination of machine learning algorithms for recommendation of courses in e-learning system based on historical data," *Knowl.-Based Syst.,* vol. 51, pp. 1–14 (2013).

[11] L. Liu, J. Xu, S. S. Liao, and H. Chen, "A real-time personalized route recommendation system for self-drive tourists based on vehicle-to-vehicle communication," *Expert Syst. Appl.,* vol. 41, pp. 3409–3417 (2014).

[12] S. Bakshi, A. K. Jagadev, S. Dehuri, and G. N. Wang, "Enhancing scalability and accuracy of recommendation systems using unsupervised learning and particle swarm optimization," *Appl. Soft Comput.,* vol. 15, pp. 21–29 (2014).

[13] F. G. Adomavicius and A. Tuzhilin, "Context-aware recommender systems," in Recommender Systems Handbook, 2nd ed., pp. 191–226 (2015).

[14] P. B. Thorat, R. M. Goudar, and S. Barve, "Survey on collaborative filtering, content-based filtering and hybrid recommendation system," *Int. J. Comput. Appl.,* vol. 110, no. 4, pp. 31–36 (2015).

[15] Y. Dou, H. Yang, and X. Deng, "A survey of collaborative filtering algorithms for social recommender systems," in Proc. Int. Conf. Semantics, Knowledge Grids (SKG), IEEE, pp. 40–46 (2016).

[16] S. H. Liao and H. K. Chang, "A rough set-based association rule approach for a recommendation system for online consumers," *Inf. Process. Manage.,* vol. 52, pp. 1142–1160 (2016).

[17] E. Çano and M. Morisio, "Hybrid recommender systems: A systematic literature review," *Intelligent Data Analysis,* vol. 21, pp. 1487–1524 (2017).

[18] Y. S. Rawat and M. S. Kankanhalli, "ClickSmart: A context-aware viewpoint recommendation system for mobile photography," *IEEE Trans. Circuits Syst. Video Technol.,* vol. 27, pp. 149–158 (2017).

[19] D. F. Murad, Y. Heryadi, B. D. Wijanarko, S. M. Isa, and B. Budiharto, "Recommendation system for smart LMS using machine learning: A literature review," in Proc. Int. Conf. Computing, Engineering, Design (ICCED), IEEE, pp. 113–118.

[20] C. Li, Z. Wang, S. Cao, and L. He, "WLRRS: A new recommendation system based on weighted linear regression models," *Comput. Electr. Eng.*, vol. 66, pp. 40–47 (2018).

[21] A. K. Sahoo, C. Pradhan, R. K. Barik, and H. Dubey, "DeepReco: deep learning-based health recommender system using collaborative filtering," *Computation*, vol. 7, no. 2, pp. 25 (2019).

[22] J. Zhao, X. Geng, J. Zhou, Q. Sun, Y. Xiao, Z. Zhang, and Z. Fu, "Attribute mapping and autoencoder neural network-based matrix factorization initialization for recommendation systems," *Knowl.-Based Syst.*, vol. 166, pp. 132–139 (2019).

[23] Y. Han, Z. Han, J. Wu, Y. Yu, S. Gao, D. Hua, and A. Yang, "Artificial intelligence recommendation system of cancer rehabilitation scheme based on IoT technology," *IEEE Access*, vol. 8, pp. 44924–44935 (2020).

[24] S. Kang, C. Jeong, and K. Chung, "Tree-based real-time advertisement recommendation system in online broadcasting," *IEEE Access*, vol. 8, pp. 192693–192702 (2020).

[25] S. Dhelim, H. Ning, N. Aung, R. Huang, and J. Ma, "Personality-aware product recommendation system based on user interests mining and metapath discovery," *IEEE Trans. Comput. Soc. Syst.*, vol. 8, pp. 86–98 (2021).

[26] N. Bhalse and R. Thakur, "Algorithm for movie recommendation system using collaborative filtering," Mater. Today Proc. (2021). [Online]. Available: https://doi.org/10.1016/j.matpr.01.235.

[27] S. Jayalakshmi, N. Ganesh, R. Čep, and J. Senthil Murugan, "Movie recommender systems: Concepts, methods, challenges, and future directions," *Sensors*, vol. 22, no. 13, 4904 (2022). [Online]. Available: https://doi.org/10.3390/s22134904.

[28] R. C. K., G. Dhananjaya, L. Ds, P. L. Krishnamurthy, and A. Shreya Pawar, "Recommendation system using deep learning," in IEEE 7th Int. Conf. Recent Adv. Innov. Eng. (ICRAIE), Mangalore, India, pp. 99–103 (2022). [Online]. Available: https://doi.org/10.1109/ICRAIE56454.2022.10054275.

[29] S. Wang, Y. Wang, F. Sivrikaya, H. Chen, J. Li, and W. Zhang, "Data science for next-generation recommender systems," *Int. J. Data Sci. Anal.*, vol. 16, pp. 135–145 (2023). [Online]. Available: https://doi.org/10.1007/s41060-023-00404-w.

[30] S. K. Gupta and A. Suresh, "Movie recommendation system," in 2023 Int. Conf. Comput. Commun. Informatics (ICCCI), Coimbatore, India, pp. 1–7 (2023). [Online]. Available: https://doi.org/10.1109/ICCCI56745.2023.10128220.

[31] C. W. Lau, "News recommendation system using logistic regression and naive Bayes classifiers," (2011).

[32] R. G. Crespo, O. S. Martínez, J. M. C. Lovelle, B. C. P. García-Bustelo, J. E. L. Gayo, and O. P. Pablos, "Recommendation system based on user interaction data applied to intelligent electronic books," *Comput. Hum. Behav.*, vol. 27, pp. 1445–1449 (2011).

[33] K. Kongsakun and C. C. Fung, "Neural network modeling for an intelligent recommendation system supporting SRM for universities in Thailand," *WSEAS Trans. Comput*., vol. 11, pp. 34–44 (2012).

[34] J. H. Chang, C. F. Lai, M. S. Wang, and T. Y. Wu, "A cloud-based intelligent TV program recommendation system," *Comput. Electr. Eng.*, vol. 39, pp. 2379–2399 (2013).

[35] J. P. Lucas, N. Luz, M. N. Moreno, R. Anacleto, A. A. Figueiredo, and C. Martins, "A hybrid recommendation approach for a tourism system," *Expert Syst. Appl.*, vol. 40, pp. 3532–3540 (2013).

[36] R. C. Chen, Y. H. Huang, C. T. Bau, and S. M. Chen, "A recommendation system based on domain ontology and SWRL for antidiabetic drugs selection," *Expert Syst. Appl*., vol. 39, pp. 3995–4006 (2012).

[37] V. Mohanraj, M. Chandrasekaran, J. Senthilkumar, S. Arumugam, and Y. Suresh, "Ontology-driven bee's foraging approach based self-adaptive online recommendation system," *J. Syst. Softw.*, vol. 85, pp. 2439–2450 (2012).

[38] S. B. Aher and L. M. R. J. Lobo, "Combination of machine learning algorithms for recommendation of courses in e-learning system based on historical data," *Knowl.-Based Syst*., vol. 51, pp. 1–14 (2013).

[39] A. A. Kardan and M. Ebrahimi, "A novel approach to hybrid recommendation systems based on association rules mining for content recommendation in asynchronous discussion groups," *Inf. Sci.*, vol. 219, pp. 93–110 (2013).

[40] M. N. M. Adnan, M. R. Taz, I. Ahmed, and R. M. Rahman, "Content-based news recommendation system based on fuzzy logic," in 2014 Int. Conf. Informatics, Electronics & Vision (ICIEV), IEEE, pp. 1–6 (2014).

[41] J. Zahálka, S. Rudinac, and M. Worring, "Interactive multimodal learning for venue recommendation," *IEEE Trans. Multimedia,* vol. 17, pp. 2235–2244 (2015).

[42] X. Wang, F. Luo, Y. Qian, and G. Ranzi, "A personalized electronic movie recommendation system based on support vector machine and improved particle swarm optimization," PLoS One, vol. 11, e0165868 (2016).

[43] H. Wu, K. Yue, Y. Pei, B. Li, Y. Zhao, and F. Dong, "Collaborative topic regression with social trust ensemble for recommendation in social media systems," *Knowl.-Based Syst.,* vol. 97, pp. 75–85 (2016).

[44] A. Sattar, M. A. Ghazanfar, and M. A. Iqbal, "Building accurate and practical recommender system algorithms using machine learning classifier and collaborative filtering," *Arabian J. Sci. Eng.,* vol. 42, pp. 3229–3247 (2017).

[45] K. Park, J. Lee, and J. Choi, "Deep neural networks for news recommendations," in Proc. 2017 ACM Conf. Inf. Knowl. Manage., pp. 2255–2258 (2017).

[46] A. Baskota and Y. K. Ng, "A graduate school recommendation system using the multi-class support vector machine and KNN approaches," in 2018 IEEE Int. Conf. Inf. Reuse Integr. (IRI), pp. 277–284 (2018).

[47] Q. Zhu, X. Zhou, Z. Song, J. Tan, and L. Guo, "Dan: Deep attention neural network for news recommendation," in Proc. AAAI Conf. Artif. Intell., vol. 33, pp. 5973–5980 (2019).

[48] G. De Souza, P. M. Jannach, and A. M. Da Cunha, "Contextual hybrid session-based news recommendation with recurrent neural networks," *IEEE Access,* vol. 7, pp. 169185–169203 (2019).

[49] A. Da'u, N. Salim, I. Rbiu, and A. Osman, "Recommendation system exploiting aspect-based opinion mining with deep learning method," *Inf. Sci.,* vol. 512, pp. 1279–1292 (2020).

[50] S. Dhelim, H. Ning, N. Aung, R. Huang, and J. Ma, "Personality-aware product recommendation system based on user interests mining and metapath discovery," *IEEE Trans. Comput. Soc. Syst.,* vol. 8, pp. 86–98 (2021).

[51] G. Ke, H. L. Du, and Y. C. Chen, "Cross-platform dynamic goods recommendation system based on reinforcement learning and social networks," *Appl. Soft Comput.,* vol. 104, pp. 107213 (2021).

[52] A. Chaudhuri, M. Sarma, and D. Samanta, "SHARE: Designing multiple criteria-based personalized research paper recommendation system," *Inf. Sci.,* vol. 617, pp. 41–64 (2022). [Online]. Available: https://doi.org/10.1016/j.ins.2022.09.064.

[53] F. Wayesa, M. Leranso, G. Asefa, et al., "Pattern-based hybrid book recommendation system using semantic relationships," *Sci. Rep.*, vol. 13, 3693 (2023). [Online]. Available: https://doi.org/10.1038/s41598-023-30987-0.

[54] Y. Feng, "Enhancing e-commerce recommendation systems through approach of buyer's self-construal: Necessity, theoretical ground," *Front. Artif. Intell.,* vol. 6 (2023). [Online]. Available: https://www.frontiersin.org/articles/10.3389/2023.

[55] S. Ilhamsyah, I. Rahmayudha, F. Fakhruzi, A. C. Adi, and V. Gunawan, "Recommendation system for the improvement of e-government services in the tourism sector of Pontianak City," in Int. Conf. ICT Smart Soc. (ICISS), Bandung, Indonesia, pp. 1–4 (2022), doi: 10.1109/ICISS55894.2022.9915103.

[56] K. K. Jena, S. K. Bhoi, T. K. Malik, K. S. Sahoo, N. Z. Jhanjhi, S. Bhatia, and F. Amsaad, "E-learning course recommender system using collaborative filtering models," Electronics, vol. 12, no. 1, 157 (2023). [Online]. Available: https://doi.org/10.3390/electronics12010157.

[57] F. T. Abdul Hussien, A. M. S. Rahma, and H. B. Abdulwahab, "An e-commerce recommendation system based on dynamic analysis of customer behavior," *Sustainability,* vol. 13, no. 19, 10786 (2021). [Online]. Available: https://doi.org/10.3390/su131910786.

[58] L. El Youbi El Idrissi, I. Akharraz, and A. Ahaitouf, "Personalized e-learning recommender system based on autoencoders," Appl. Syst. Innov., vol. 6, no. 6, 102 (2023). [Online]. Available: https://doi.org/10.3390/asi6060102.

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