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CRM ENHANCEMENT USING RECOMMENDER SYSTEMS – A REVIEW

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Abstract

As the prominent role of the internet in life generally increased, commerce and financial businesses had to be affected as well. CRM has changed from a system of record to a system of recommendation and random ads are no longer accepted. Nowadays, most of the famous applications and websites use recommendation systems, and the applications or websites that have the better recommender systems are the most popular, they have the ability to attract and retain customers because users like to have a personalized and customized experience. And marketers who use AI in their engines are making a noticeable increase in their revenue. However, there are problems in some of the recommender systems' algorithms. In this review paper, we present a study about the recommender systems and related works and algorithms proposed to solve the problems and enhance their performance. We made a comparison among previously proposed systems. Moreover, we compare systems' experimental results which use different technique on customer behavior including statistical methods, and purchase behavior and comparison behavior in calculating users' similarity. The performance of the algorithms was evaluated by precision and recall values. The comparison shows that the statistical method may show a better performance in some cases.

Keywords: artificial intelligence; e-commerce; big data; data mining; customer service; recommender system, similarity

1. INTRODUCTION

To improve business relationships and grow the business, CRM or Customer Relationship Management has been released in the 1980s by Pat Sullivan and Mike Muhney (Leubitz, 2016). At that time, many of the features that exist today were not found. With time, and by developing and innovating, many technologies like artificial intelligence, data science, data mining, cloud computing, natural language recognition, and others, many features have been added to CRM software that can help to acquire and retain customers. At the same time, customer service has been enhanced and the cost has been decreased, revenue has been increased and other benefits. Some of these features are known as recommendation systems. According to Gartner (an information technology (IT) research and consultancy company), by 2023, most organizations that use A.I. in their electronic commerce operating systems will achieve a noticeable increase in customer satisfaction, besides increasing revenue and reducing costs (Moore, 2019). Artificial Intelligence marketing strategies helped organizations to have long-term relationships with customers by attracting and retaining them. It helped in personalizing and customizing marketing that fits every potential customer (Muhammad Anshari, 2018). That's why the marketers who use A.I. somewhere in their acquisition and retention engines have increased to reach 84% of marketers in 2020, approximately three times over their percent in 2018 (KIHN, 2022).

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Besides the recommendation systems, artificial intelligence can help provide many functions in E-commerce including chatbots, which is a service that's available in most E-commerce websites to improve customer service and increase customers' satisfactions. With chatbots there is no need for human employers to work 24/7 and that will reduce the cost and save time. These chatbots have the ability to learn from previous inputs and requests, and then provide the best recommendations to customers (Harikumar Pallathadka, 2021).

Other intelligent services include:

- Customer segmentation, which can be demographic segmentation (dividing the customers according to their age, gender, marital status, etc.) and geographic segmentation (based on the country of residence),
- Intelligent demand forecasting to accurately predict the change in consumer demand, customer churn prediction to detect which customer may leave a service, intelligent pricing for putting dynamic prices according to the change in market conditions,
- Personalized product recommendations for showing a selection of product recommendations to every user according to their behavior and profile,
- Competitor price monitoring, which helps to place the product at an advantage in relation to the market,
- Predict customer lifetime value CLV, which helps to predict future profits based on past transactions, Automated content generation, and Product image analytics. All these services help to increase efficiency, save time and reduce the cost. (AISmartz) (Kian, 2021)

A. Artificial Intelligence in Customer Service

Artificial Intelligence is a term coined in the 1950s at The Dartmouth Conference by John McCarthy, a professor emeritus of computer science at Stanford. In (MYERS, 2011), A.I. is a branch of computer science that deals with simulating the intelligent behavior in machines and computers (Ipsos Encyclopedia - Artificial Intelligence, 2017). With the development of AI, machine learning ML came out and was popularized by Arthur Samuel (Education, Machine Learning, 2020), ML can be defined as a subfield of artificial intelligence where the machine can be trained to learn from data like a human without being explicitly programmed (Mohannad A. M. Abu Daqar, 2019). When Machine learning blossomed, Deep learning appeared and the E-commerce industry increased exponentially, and the customers moved to a new level of experience in a new form. Artificial neural networks, a branch of machine learning, are algorithms that were motivated by the structure and operation of the brain (Brownlee, 2019).

The word "**deep**" in Deep Learning refers to the number of hidden layers (Gala, 2022). The more layers in the system (besides using activation functions), the more efficient and accurate prediction (Mesquita).

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A service that does not use deep learning can only analyze the customers' preferences according to the products and services that bought or watched. While with deep learning, artificial intelligence can predict customer behavior and intentions based on previous data. Then, it can help personalize and customize the marketing to target customers who are likely concerned with the product or service (Schroeder, 2022).

Artificial Intelligence has passed through many developing stages to reach this level. The development of A.I. is referred to two crucial factors, big data, as well as hardware accelerators (graphics processing units GPUs and tensor processing units TPUs) (Neha Sonia, 2019).

B. Big data

"Big Data" is a term used to describe any large or complex dataset or data *that cannot be managed by traditional data management approaches* (Davy Cielen, 2016). In the recommendation systems, specific types of data should be collected from customers to offer them the products and services they are interested in more.

According to (Pratt, 2022) the data can be categorized as:

- Structured data has a clear structure and is available in established forms like GPS coordinates and credit card information.
- Unstructured data is present in the format in which it was produced, such as social media posts.
- Semi-structured data is a combination of text and structured data, such as email addresses. In addition, in (Itay Goldstein, 2021), the following common sources of data are discussed:
- Geo-location or geographic data and movement pattern those data collected by capturing GPS data, which is frequently included in the "digital exhaust" of mobile and other services. This might be considered a specific type of behavioral data.
- Purchases made with a credit card, at retail locations, or online
- Social listening enables previously unheard-of 'listening in' on genuine exchanges arising from online conversation, such as tweets, Facebook updates, blogs, vlogs, and debates.
- Unstructured sources are those that cannot be easily summarized and analyzed because they are not included in conventional data formats. Usually, this will include specific people's images, videos, and texts. For example, Natural language processing (NLP), a branch of A.I., allow researchers to discern tone information from voice and audio. *Chatbots can* use (*NLP*) with speech recognition to provide a better user experience. Also, as an example of an unstructured source, semantic information can be extracted from photos and videos to identify geographic or facial information using a computer vision CV.

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- Logistical - the arrangement of resources and aggregated data, which may be created automatically and frequently provides contextual information, such as the amount of power used by national networks or the amount of air traffic in major cities. It might be helpful on its own or as background information to comprehend the person's conduct.
- Behavioral – Here, the data is collected by tracking customers individually, to customize and personalize the service to every customer and give him the best experience through the Internet of Things (IoT), where data is collected by sensors on TVs, refrigerators, vehicles, and other devices, online habits, mobile activity, and software use are just a few examples.

The term "intent" is crucial because it helps us create relevant experiences. The more precisely and rapidly we can predict our clients' intentions, the better. And the more frequently we provide a user with a pertinent customer journey, the more probable it is that they will convert. Long-term client loyalty is also more likely when customers have a fantastic experience. (Gill, 2021)

According to Gartner three elements of "Three Vs" should be in the data to be considered as “big data”, and those elements are:

Volume: The core characteristic of data to be considered “Big Data” is its volume, the data should be so large that it is unsuitable to use traditional processing tools and techniques.

Variety: The data that are produced every day are more than two exabytes. As mentioned above, this data comes in many different forms like pictures, natural text, video, data collected from sensors, etc.

Velocity: Modern data flows swiftly and is quickly consumed, so its speed is not merely a function of how quickly it is produced. On Twitter, there are more than 500 million tweets posted every day, and over a million client transactions are handled by Walmart per hour. Therefore, there is a significant need to consider providing information in almost real-time.

According to IPSOS, two other “Vs” should be in data to be considered as “Big Data”,

Veracity and its value, “Unlike the three original Vs (volume, variety, and velocity), they do not describe what Big Data is, but we believe they are critical to consider when moving a discussion about Big Data from theory to actionable insight.” [IPSOS, 2016]

Veracity: Whether analyzing a single data source or integrating or fusing various sources, the accuracy of Big Data is crucial.

Value: Any data collected should be meaningful and useful.

C. Data mining

Data mining's beginnings can be identified in the late 1980s. The phrase "data mining" refers to a wide range of mathematical modeling strategies and software tools that are employed to identify patterns in data and then utilize them to create models (Schafer,

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2009). Or it can be defined as the techniques and strategies that are performed to extract hidden information with the importance of the word “hidden” and generalizing the word “information” (COENEN, 2004). In recommender systems, the collection of analysis methods used to derive recommendation guidelines or create recommendation models from big data sets is referred to as data mining (Vaishnavi.S, 2013).

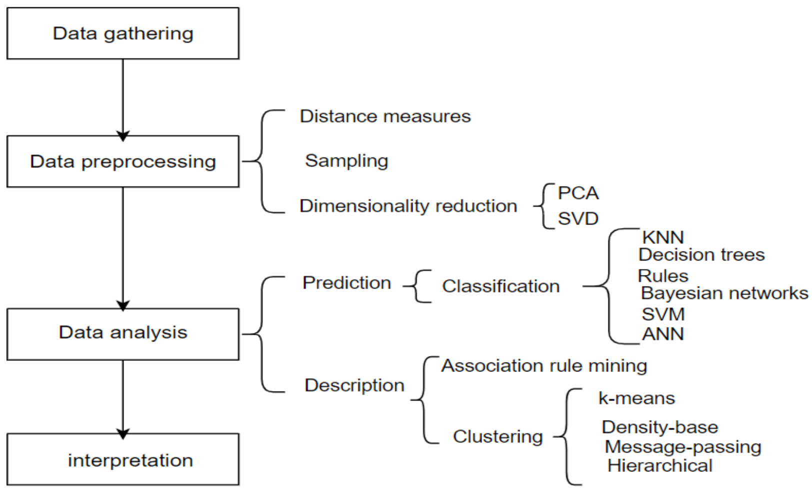

Figure 1: Steps and methods in data mining

2. RECOMMENDER SYSTEMS

“The Web, they say, is leaving the era of search and entering one of discovery. What's the difference? Search is what you do when you're looking for something. Discovery is when something wonderful that you didn't know existed, or didn't know how to ask for, finds you.” Jeffrey M. O'Brien, Fortune Magazine writer wrote in an article published in CNN Money.

Getting the right people to see relevant adverts is crucial for marketing to be effective, for that reason, the recommender systems have found. A recommendation system's fundamental objective is to make a suggestion for something new that satisfies the user's needs or preferences for goods or information services (Farah Tawfiq Abdul Hussien, 2021). And thus, it increases user retention and customer satisfaction, which will significantly boost the business's profits. For example, 80% of Netflix viewer activity is driven by individualized recommendations from the engine, demonstrating how accurate the recommendation system is. According to estimates, Netflix saves over $1 billion annually thanks to the NRE, Netflix Recommendation Engines, (McAlone, 2016) and (Meltzer, 2020). A recommendation system is a filtering method used to access online content. Based on the user profile or past behavior, these filtering algorithms learn from users' selections and then propose their preferences for a certain item (Sneha Bohra, 2022). A recommender system is a type of information filtering system that aims to anticipate the "rating" or "preferred" a user would assign to a certain item. They are mostly applied in commercial settings (Shi, 2020). The goal of recommendation systems is to increase the effectiveness of e-commerce systems by making it easier for customers to locate the right goods and services based on their interests (Farah Tawfiq Abdul Hussien, 2021).

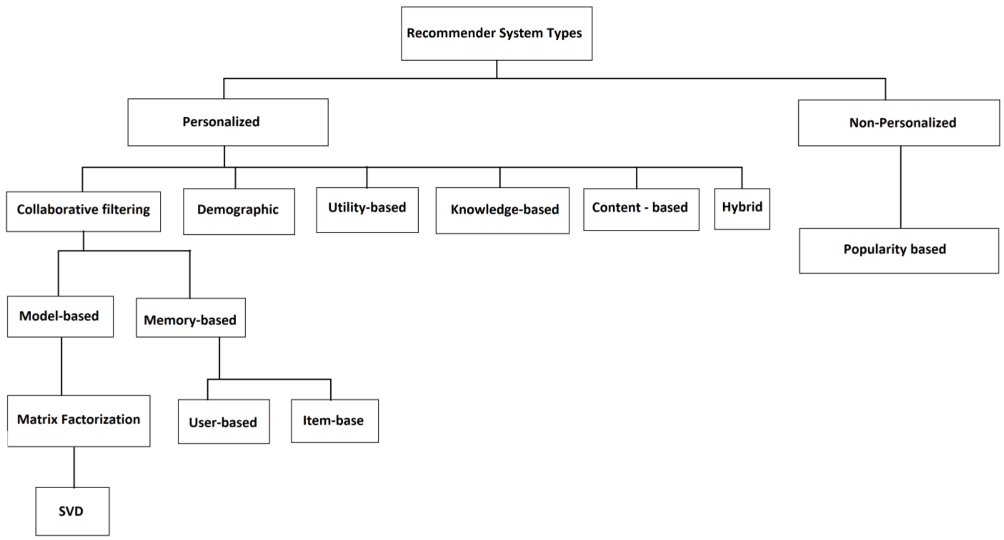

Figure 2: The recommender systems types

According to the filtering technique used by the system to recommend, recommender systems can be classified into many types. These kinds of systems originate from the early 1990s, when news filtering services first appeared in newsgroups, allowing its user base to view only content that would be of significance to them (E. Peis, 2008).

A. Non-personalized recommendation systems

These kinds of recommender systems do not pay attention to the users' individual tastes, as the name would imply. These systems generate the same recommendations for every customer. The recommendations on e-commerce websites can either be chosen manually by the online merchant based on the popularity of the products or they can be the top N new products. For instance, if we visit amazon.com as an anonymous user, it displays products that other users are currently viewing. These systems suggest products to customers based on reviews or average ratings provided by previous customers. As was already said, recommendations are just lists of possible goods that the user could enjoy. They are not based on the preferences of the user. Two types of algorithms are primarily employed by non-personalized recommender systems: Basic product association recommender and aggregated opinion recommender (Anil Poriya, 2014).

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B. Personalized recommendation systems: This classified mainly into:

Content-Based Filtering

Including recommendations for specialized items, can be highly tailored to the user's preferences because the method focuses on comparing the qualities or attributes of a database object with the user's profile. For instance, it will identify a user's preferences and interests, such as the title of a specific movie, and provide helpful recommendations with features that are comparable. Companies that have enormous product libraries of a single type, like cellphones, and need to provide suggestions based on a range of qualities would find content-based filtering to be very helpful (Rithwik Ramesh, 2022).

The advantages of this type are:

- It doesn't require information about different users to make suggestions (Ekta Sharma, 2022).
- No cold start, new items can be easily incorporated.
- Transparency, explanations, and understandable.
- While disadvantages are:
- Does not take into account other people's evaluation of the product, therefore a poor-quality product may be recommended.
- Overspecialization (more of the same), too similar items.
- Ratings or information about new user has to be collected.

Collaborative filter (CF)

One of the most well-known and commonly used recommender systems is the collaborative filter (CF), which is recognized as one of the most crucial elements of effective E-commerce systems (Vincenzo Moscato, 2020).

Collaborative filtering can be classified into Model-based and Memory based which can be sub-classified into User-based collaborative filtering and Item-based collaborative filtering (Garima Gupta, 2019). Darko Marjanovic et al. (Darko Marjanovic) Explain the user-based and the item-based simply on their website:

- User-based “Users who are similar to you also liked…”
- Item-based “Users who liked this item also liked…”

CF has a number of drawbacks, such as a lack of cold-start capability, scalability, sparsity of the user-item matrix, and the evolution of consumer preferences over time (Deuk Hee Park, 2012). One of the biggest issues with CF is a cold start, which occurs when the system lacks sufficient data to produce reliable recommendations (Farah Tawfiq Abdul Hussien, 2021).

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Knowledge-Based Recommendation System (KBRS)

A recommender system is said to be knowledge-based when it provides recommendations based on specific queries rather than a user's rating history. It could request that the user supply a list of requirements or specifications for how the output should look, along with an illustration of an item. The system then looks for related products in its item database and returns them (Rithwik Ramesh, 2022). The recommendations here are more reliable and this approach can solve the limitation and weaknesses of other recommendation techniques like cold-start, and grey sheep problem (The term "grey-sheep" refers to users who have distinctive interests and likes, making it challenging to create precise profiles (Rabaa Alabdulrahman, 2021)). The knowledge base's construction, which is typically a challenging task requiring substantial domain knowledge and knowledge representation expertise, is the only restriction that the KBRS faces (Sarah Bouraga, 2014).

The ontology-based recommender is a type of knowledge-based recommender that uses an ontology to represent knowledge about the user and items (John K. Tarus, 2017). Knowledge of the user, the products, and their relationships is represented by ontology. (Márcio Guia, 2019). Recent studies show that the ontology-based approach enhances recommendation systems by addressing the most prevalent shortcomings of conventional systems. But creating an ontology-based recommendation system is a difficult and time-consuming undertaking that requires knowledge of engineering expertise (John K. Tarus, 2017), (Gina George, 2019) and (Márcio Guia, 2019).

Some researchers have explained the difference between those three approaches in a simple way:

- Collaborative filtering: “what is popular among my peers”
- Content-based: “more of the same”
- Knowledge-based: “what fits my needs”

In order to address the drawbacks and restrictions of utilizing only one strategy, a hybrid recommender system integrates two or more ways of recommendations. Numerous studies have found that hybrid systems perform better than other pure techniques and offer intriguing recommendations (Sneha Bohra, 2022).

For instance, the recommended approach in social networks like Facebook typically suggests user profiles based on their preferences or interests. The algorithm then adopts user profiles as things and accesses its content to look for additional profiles with comparable characteristics. Finally, a recommendation is returned with the two profile groups (Leandro Miranda, 2020).

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Table 1: Some famous social media recommender systems.

Social Media	Recommender System
YouTube	Two neural networks make up the technology in YouTube: one for candidate generation that offers extensive customization through collaborative filtering. And one for ranking. Then a small group of videos is retrieved from a larger corpus (Paul Covington, 2016). Youtube also uses Watchtime and Survey Responses to know for how long the user watched the video and indicate if he liked it and want to see more similar videos (Goodrow, 2021).
Netflix	**Netflix uses Netflix Recommendation Engine (**NRE**)**, which is composed of algorithms that filter material according to each user's unique profile. On the basis of user choices, the engine screens over 3,000 titles at once utilizing 1,300 suggestion clusters (Meltzer, HOW NETFLIX UTILIZES DATA SCIENCE, 2020)**.** To solve the cold start problem, they invite the new user to select a few titles he or she enjoys when registering the Netflix account or add a new profile to the account. They use these titles to jump-start the user's recommendations. But it's not mandatory to choose titles. If the user decides not to take this action, they will provide him with a varied and well-liked selection of titles to get started (Netflix).
Facebook	Facebook uses "open-sourcing a state-of-the-art deep learning recommendation model DLRM" which facilitates dealing with such kind of sparse data. By integrating the principles of collaborative filtering and predictive analytics-based techniques, DLRM improves on existing models and is able to operate effectively with production-scale data and deliver cutting-edge outcomes (Maxim Naumov, 2019).
Instagram	Instagram's engineering team created IGQL, a domain-specific language designed for recommender system candidate retrieval. With IGQL, handling various responses (follow, like, remark, etc.) and media kinds became simpler. They developed a retrieval process that prioritizes account-level data above media-level data. The same distance metric that is used in embedding training is defined between two accounts, and it is often cosine distance or dot product. To locate thematically comparable accounts for any account in the embedding, they use a KNN lookup based on this information. The Explore recommendation systems in Instagram can be divided into two primary stages: a three-stage ranking infrastructure and the candidate creation stage (also known as the sourcing stage) (Ivan Medvedev, 2019).

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TikTok	The video is examined using three criteria: computer vision, natural language processing (NLP), and metadata as the first stage in TikTok's recommendation technique. The user will then see more pertinent videos using content-based filtering implemented by TikTok's algorithm (Mage, 2022). Each user has a customized "For You" feed. The algorithm ranks movies according to a variety of criteria, starting with the interests you declare as a new user and correcting for items you say you're not interested in. Users who don't choose categories will initially be presented with a broad feed of trending videos to get things started. • User interactions, video information, device settings, and account settings are all given different weights depending on how valuable they are to the user. A powerful sign of interest, such as whether a person watches a lengthier video all the way through or if the producer and watcher of the video are from the same nation (TikTok, 2020).

3. PREVIOUS WORKS

Here, we present a summary of previous research papers in the last few years that focus on the recommendation system that's related to user behavior in the E-commerce field.

Bo Wang et al. (Bo Wang, 2018) proposed a personalized recommendation algorithm based on a user's implicit feedback (BUIF). In addition to the user's purchase behavior, BUIF takes the user's comparison behavior and item sequences into account when they computed the user's similarity. Then, they extended word-embedding to item-embedding to determine the item's similarity. They developed a secondary reordering model based on the aforementioned technique to produce the user recommendation results. The experiment's findings on the JData dataset demonstrate that their algorithm outperforms existing CF algorithms in terms of suggestion accuracy. Precision and recall were better with the BUIF approach than with the others (user-based traditional CF and item-based traditional CF) as a result of the fact that they select the nearest neighbors based on the entire user set and item set, treating all behaviors as one type.

T.T.S. Nguyen et al. (T.T.S. Nguyen, 2018) Used Item2Item model to improve predicting customer behavior. Utilizing the Item2Item model to increase the prediction accuracy and integrating a number of conventional strategies to lessen the limitations of each individual methodology. This work uses a publicly available dataset that includes user sessions and restaurant information as a case study to examine user behavior prediction in restaurant recommender systems. In this dataset, restaurant information is retrieved for content-based filtering and user behavior may be found for collaborative filtering. The item-based collaborative filtering, which compares eateries based on user sessions, makes use of the pre-trained word embedding concept from natural language processing. According to experimental findings, the combination of these strategies resulted in useful recommendations.

Ting Yuan et al. (Ting Yuan, 2018) showed how the subjective nature of the user's emotions interferes with the objectivity of the scoring; as a result, the scores are not an accurate representation of the user's preferences. Then, in order to increase the dependability of the recommendations, they suggested a system built on the combination of mood sensitivity (MS) and better user-based collaborative filtering (UCF). By analyzing the wording of user comments, MS determines how sensitive each user is to their mood. The preference of the target consumers is then predicted using this method in combination with UCF. User credit is also taken into account to thwart bogus users and ensure the advice is trustworthy.

In Márcio Guia et al. paper (Márcio Guia, 2019), the K-Nearest Neighbor algorithm (KNN), the most popular method in collaborative filtering, has been combined with the effectiveness of ontology-based recommenders to create a hybrid recommendation system. And that's to compensate for the ontology-based systems' high cost and complexity, which call for knowledge engineering skills. The results of their experimental research demonstrate that the recommended technique yields recommendations of higher quality when compared to collaborative filtering. Results about the items that, although belonging to categories that customers are ignorant of, nevertheless meet their likes and are recommended, as well as the scalability, support the considerable improvement.

Leandro Miranda et al. (Leandro Miranda, 2020) made a study to find out the answers to three inquiries: What clustering methods are employed in RSs? Which dataset domains were utilized for the experimental analysis? Which methods of recommendation are most popular? For answering the first question they made a study on 49 research papers and they found out that five different kinds were used in them. The majority of papers employed partitional methods, with 1 article using K-medoids and the remaining 18 using K-means. Due to its efficiency and ease of operation, K-means dominates RS. Typically, this approach leads to a workable answer. All clustering algorithms utilized in the publications were agglomerative hierarchical algorithms in terms of hierarchy. For the second question, the domain of the dataset that is commonly used in recommendation system research is the movies domain. Simple data access is one factor that led to this outcome. And for the third question, the most commonly used recommendation approach, this finding indicates that collaborative filtering is a topic of extensive study on clustering algorithms-based recommendation systems. Another finding is that collaborative filtering is used in all studies that employ content-based filtering.

R.V. Karthik et al. (R.V. Karthik, 2021) Proposed predicting the customers' interests using sentiment analysis and ontology. They suggested a fuzzy logic-based product RS, which dynamically forecasts the most pertinent goods for clients buying online based on their current preferences. Seven primary components make up the RS: the client (an online shopper), the user interface module, the decision manager, the fuzzy recommendation system, the ontological database, the rule base, and the fuzzy rule manager. The

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suggested fuzzy rules and ontology-based recommendation systems make recommendations more accurately and predictably depending on the search context by using ontology alignment. The suggested RS performs better than the current product recommendation systems in terms of prediction accuracy of the pertinent goods for target consumers and in the time required to deliver such suggestions, according to testing data.

Shiuann-Shuoh Chen et al. (Shiuann-Shuoh Chen, 2021) proposed predicting customer choices based on price effect using a neural network-based price-sensitive recommender. A price-aware two-pathway matrix factorization (2way-MF) model that aims to memorize the implicit feedback of the customer-product interaction. The suggested models outperform the industry-standard Matrix Factorization models in terms of model performance. The method was revalidated using information from a Taiwanese retail chain. The suggested methodology for predicting customer demands based on price sensitivity is adaptable to other sectors. In order to accurately estimate the product's personalized price sensitivity level, the suggested technique used a new hybrid method that infers the SHOPPERS model for capturing customer and product purchase information as well as the price at the time of purchase and merges it with Deep Learning. By randomly selecting from their negative implicit feedback, we can infer customers' preferences based on the costs of the things they purchased as well as some other products they chose not to buy. The framework for predicting customer preferences based on price sensitivity is offered for adoption by other sectors.

Farah Tawfiq Abdul Hussien et al. (Farah Tawfiq Abdul Hussien, 2021) Built a system based on customers' behavior to solve the problems of traditional recommendation systems like the cold start. They applied statistical analysis to an e-commerce site in order to improve its performance and enhance decision-making. The experiment findings demonstrated that employing statistical methods enhances decision-making to boost the precision of recommendation lists offered to clients.

Aleksandra Baczkiewicz et al., (Aleksandra Baczkiewicz, 2021) made research and suggested a strategy that uses multi-criteria decision-making (MCDM) techniques, which could be useful as a tool in consumer choice support systems for purchases made on e-commerce websites. A solution based on four MCDM methods is being used in the research to solve a multi-criteria monitor selection problem. According to the results, the suggested strategy appears to be a viable option for consumer decision assistance systems. As future work, they suggest involving investigating techniques that offer a consensus solution and including other MCDM methods in the comparison analysis. Additionally, it is advised to do a sensitivity analysis to exactly evaluate the significance of each criterion in the topic under study due to the varied influences of criteria on final rankings.

Ilona Pawełoszek (Pawełoszek, 2021), based on the idea that understanding consumer behavior has always been crucial for businesses since it aids in market share acquisition, product success, and customer loyalty, proposed to integrate standard recommendation algorithms with information on consumers' physical activity. The guidelines were geared for those who actively jog or run. The 210 active joggers and runners who participated in

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the study (and who use various sport-tracking software) are prospective buyers of athletic wear and certain kinds of running shoes. The user groups were determined based on the most important exercise factors. With the use of the Orange program, clustering and several classification models were evaluated, and fundamental divisional principles were established. This study demonstrates that user segmentation can be done rather accurately and suggests ways to enhance it. Putting together diverse knowledge models that describe consumer behavior and attributes from numerous angles may help one develop insightful and distinctive marketing knowledge.

Sneha Bohra and Mahip M. Bartere (Sneha Bohra, 2022) stated the issues in the recommendation system and its corresponding solution and subsequently suggested combining the models of the item-based and domain-specific recommendation systems. Every user is identified uniquely through the combination of the two algorithms depending on his or her area of interest. By offering fresh predictions, this user categorization into domain-specific clusters will increase system performance. They employed Matrix factorization as the Rating Prediction Module and a bi-clustering model as the Domain Detection Module, Regression Regularization Module, and Recommendation Module to systematically comprehend how to find user-item domains. Through their experiment result, they found that the Pearson Correlation is the best similarity measure, and hybrid filtering methods give a better result when compared to individual memory or model-based collaborative techniques.

Rasha Kashef and Hubert Pun (Rasha Kashef, 2022) noticed that the quality and accuracy of recommenders have become a core issue for e-commerce companies due to dynamic changes in customer behavior patterns. They suggested a clustering-based RS that can efficiently find the best cross-selling chances based on past customer purchases and preferences, including product contexts. This RS uses the concept of the cross-sold score and is known as “I CrossSold.” The use of clustering lessens the issue of data sparsity that most RSs experience and increases their scalability. To provide a more useful set of tailored recommendations, they suggest and test this method. Comparing the proposed approach to the most advanced collaborative filtering RSs, clustering-based collaborative filtering RSs, and rule-based RSs reveals a considerable increase in both prediction accuracy and speedup.

4. METHODOLOGY

Here, we made a comparison among previously proposed systems in their similarity technique, dataset, and what the systems are based on.

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Table 2: A comparison among previously proposed systems.

Paper	Based on	Dataset	Similarity
(Bo Wang, 2018)	Based on user's purchase behavior and the comparison behavior	JD (a large Chinese e-commerce platform), the dataset contains different items and is not specialist in a specific type.	They calculated the user's similarity by the Pearson correlation coefficient with the user's purchase behavior and comparison behavior. And in calculating the Item's Similarity they use the CBOW model and Skip-gram model to map items to low-latitude vector space, and they used cosine to calculate the item's similarity
(Ting Yuan, 2018)	Based on Mood-Sensitivity Identification and User Credit	Real-world movie datasets collected from douban	The similarity of interest preference among users is calculated by Pearson correlation coefficient. Calculate the similarity of score and interest between the target user and other users by K Nearest Neighbour
(T.T.S. Nguyen, 2018)	Item-based collaborative filtering	A public dataset including restaurant information and user sessions	They used the cosine similarity in the content-based filtering process to calculate distance between restaurant profiles to find the NN for each restaurant visited by an active user. Secondly, in the user-based filtering process, user-to-user similarity is represented by Euclidean distance. Users who are the most similar to the target user are selected.
(Márcio Guia, 2019)	Ontology-Based	MongoDB	Considers not only the users with similar preferences to the active user but also obtains knowledge about the user. KNN algorithm applies to find the nearest ones
(Pawełoszek, 2021)	Activity-based segmentation (based on activity monitoring applications)	Dataset acquired from 210 active joggers and runners who use different sport-tracking applications.	Customer segmentation is carried out, dividing them into groups having in mind similar preferences, needs, and behavior
(Aleksandra Baczkiewicz, 2021)	Based on MCDM methods (multi-criteria decision-making)	Were collected from various websites.	Two coefficients established rankings' similarity: symmetrical rw and asymmetrical W S.
(Shiuann-Shuoh Chen, 2021)	Neural network based model	They consider a dataset of transactions in a unit of a large supermarket chain in Germany.	They used Euclidean proximity as it was better suited than cosine similarity due to good sensitivities towards vectors, and the results were not biased. (Dr. Vinay Singh)
(R.V. Karthik, 2021)	Fuzzy logic-based system	Amazon review dataset which is available as a	The similarity score is calculated for the recommended list of products

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		standard benchmark dataset.	based on product category and the item purchased. Similarity computed by using the cosine similarity.
(Farah Tawfiq Abdul Hussien, 2021)	The customers' behavior and cooperation with the statistical analysis	The dataset was taken from a website specialist in computers and their peripherals.	Not mentioned
(Rasha Kashef, 2022)	Clustering-based RS using the notion of the cross-sold score—namely, "I − CrossSold"	They used four datasets, the Global Super Store 2016 (GSS2016), the Global Super Store 2018 (GSS2018), and OnlineRetail I and OnlineRetail II	They developed a novel similarity measure that captures the product's context as selling price, purchasing price, and the association factor between products.

Among those previously proposed systems, we compared the experimental results of: A recommender system based on the User's Implicit Feedback (BUIF), a system proposed by Bo Wang et al. that calculated the similarity by the user's purchase behavior and the user's comparison behavior and item-sequences. And a recommender system based on dynamic analysis of customers, UIBB, a system proposed by Farah Tawfiq Abdul Hussien et al. that used a statistical method with customers' behavior –without using similarity-. Both systems depend on customer behavior, and both made the same experiment with the same number of recommenders. To evaluate the performance of the system, they usually use the experimental results to calculate the precision, recall, and F-function:

Table 3: Performance measures.

$\text{precision} = \dfrac{\text{correctly recommended items}}{\text{total recommended items}}$
$\text{Recall} = \dfrac{\text{correctly recommended items}}{\text{total useful recommendations}}$
$\text{F} = \dfrac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$

5. DISCUSSION AND RESULTS

Because the datasets used in the two studies are different, we computed the increased percentage in precision between the traditional collaborative filtering based on users (BUCF and CFUB) – they experimented in the same dataset- and each recommender system they proposed:

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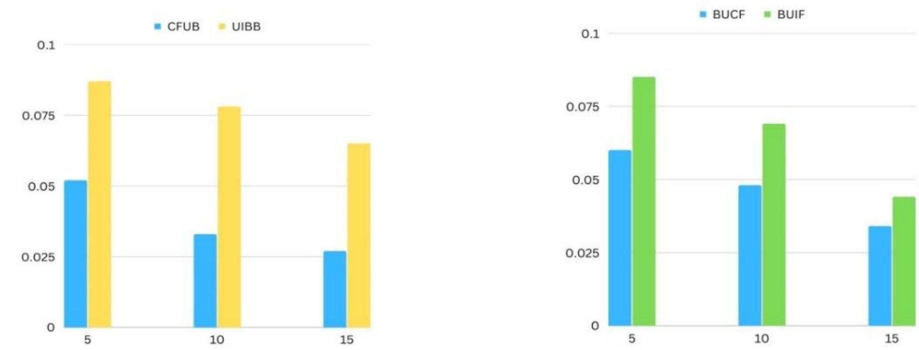

Figure 3: Comparison of precision

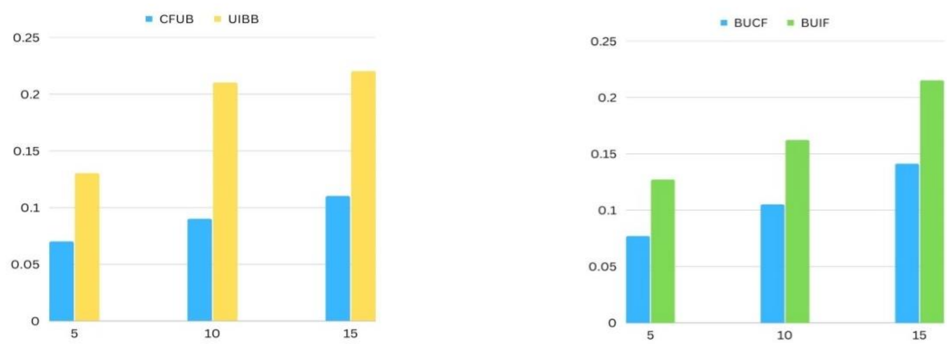

Figure 4: Comparison of recall

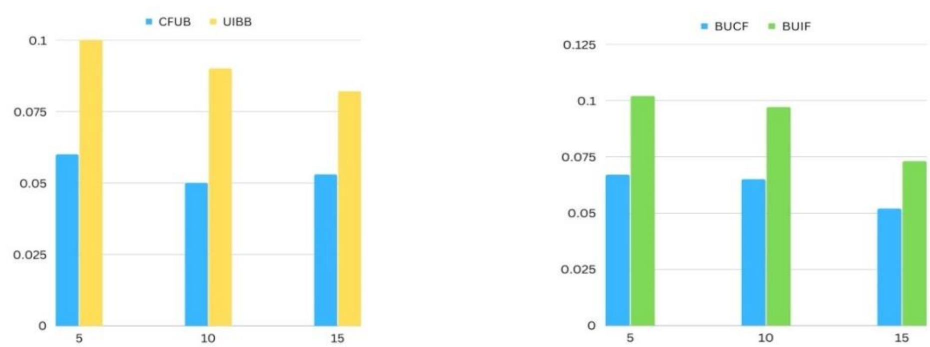

Figure 5: comparison of F1-function

Table 4: A comparison between the increased precision in BUIF and UIBB.

R no.	BUIF	BUCF	increased	UIBB	CFUB	increased
5	0.085	0.06	29.411%	0.087	0.052	40.229%
10	0.069	0.048	30.434%	0.078	0.033	57.692%
15	0.044	0.034	22.727%	0.065	0.027	58.461%

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Table 5: A comparison between the increased recall in BUIF and UIBB.

R no.	BUIF	BUCF	increased	UIBB	CFUB	increased
5	0.127	0.077	39.370%	0.13	0.07	46.153%
10	0.162	0.105	35.185%	0.21	0.09	57.142%
15	0.215	0.141	34.418%	0.22	0.11	50%

Table 6: A comparison between the increased f-function in BUIF and UIBB.

R no.	BUIF	BUCF	increased	UIBB	CFUB	increased
5	0.102	0.067	34.313%	0.1	0.06	40%
10	0.097	0.065	32.989%	0.09	0.05	44.444%
15	0.073	0.052	28.767%	0.082	0.053	35.365%

As shown in the tables above, the experimental results showed a better performance of UIBB than BUIF. Also in UIBB, the cold-start problem has been solved by providing a recommendation depending on the preferences matrix of the products for customers with no accounts. According to Farah Tawfiq Abdul Hussien et al., the continuous updating of the preferences matrix of the products and the customers helps to reduce sparsity, diversity, and scalability problems. But the dataset used by them is specialized in computers and their peripheral instruments, so the diversity and scalability haven't been examined in the experiment. Additional parameters are required for solving them in larger e-commerce sites with different things and stuff. Also, they did not take into account the difference in users' preferences.

6. CONCLUSION

No matter which type of business you have, traditional or electrical, to succeed in the business and compete with others you should know your customers so you can offer them the products and services they need. With the development of technologies (for example, big data and data mining) recommendation systems facilitate this operation besides making it more efficient, less costly, and less time consumption. Consumer behavior is the key to better orienting customer service. By using artificial intelligence, we can acquire and retain customers through recommender systems. In a competition to generate the best recommender system and to overcome their weaknesses, many algorithms have been proposed.

Real-time data is the primary motivator for CRM systems since 2017. This may require real-time communication with the backend. A recommendation system implemented in the backend can enrich the customer's experience by proposing a collection of related products. Algorithms running in the back also use data to detect serious customers according to their behavior through making synchronization with their accounts; this is an important step to follow up with selected customers using trained machines. These advanced technologies are enabled by (Web Socket API) to link a user's browser and a server to start a full-duplex interactive communication session. With the help of the API,

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the IT manager may communicate with a server and receive event-driven responses without having to ask the server repeatedly and manually for a response.

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