RESEARCH ARTICLE

Dynamic Hybrid Recommendation Approach for Improving Accuracy in E-Commerce with Limited User Data

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Abstract

The 'Cold Start' problem, characterized by insufficient transaction history leading to inefficient personalization, represents one of the frequent challenges encountered in e-commerce systems. This issue, along with data sparsity resulting from limited product interactions, further complicates the reliability of conventional recommendation engines. The objective of this research is to design a novel hybridized recommendation system that enhances both security and suggestion accuracy by dynamically adapting to user interactions in digital environments. By leveraging contextual information and sequential user behavior patterns, the proposed method addresses gaps left by traditional recommender systems. A research methodology is employed that integrates context awareness and sequential pattern mining, combining conventional and advanced recommendation techniques within a unified framework. This hybrid strategy tackles challenges posed by Cold Start scenarios while optimizing the use of scarce user interaction data. Preliminary findings indicate that the hybrid approach significantly improves recommendation performance, particularly in settings with limited historical data. By utilizing contextual and sequential information, the proposed system outperforms existing methods in terms of accuracy and personalization. In conclusion, the study demonstrates the effectiveness of hybrid recommendation systems in addressing fundamental e-commerce challenges such as data sparsity and the Cold Start problem. The adaptability of the approach enables accurate predictions without requiring extensive user history. Future research will focus on the scalability of this strategy across diverse e-commerce platforms to deliver more individualized user experiences.

Keywords: e-commerce, hybrid, recommendation system (RS), security.

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1 Introduction

In the digital age, social media platforms have evolved beyond simple communication tools into complex ecosystems that facilitate a myriad of interactions across vast online communities. These platforms serve as dynamic environments where users exchange a diverse array of content, from text and images to videos and detailed personal data [1]. This exchange is powered by sophisticated algorithms that enable rapid, scalable, and continuous dissemination of information across various devices including smartphones, tablets, and desktop computers [2].

Initially conceptualized to foster personal connections, social media's utility has been extensively harnessed by businesses to transform consumer engagement strategies. The integration of social media into e-commerce has revolutionized the industry, enabling businesses to leverage these platforms for marketing, customer engagement, and direct sales [3, 4]. This symbiotic relationship between social media and e-commerce has not only enhanced the functionality of these platforms but has also redefined user interaction paradigms within digital spaces [5].

The proliferation of social media has coincided with significant advancements in the technologies that support these platforms. E-commerce entities are increasingly adopting sophisticated recommender systems that utilize deep learning techniques to enhance the relevance and personalization of content and product recommendations [6–8]. These systems are crucial in managing the vast amounts of data generated by users, enabling businesses to extract valuable insights that drive decision-making processes [9, 10].

The effectiveness of recommender systems is rooted in their ability to synthesize and analyze large datasets to deliver tailored experiences to users based on their preferences, behaviors, and interactions. These systems employ various methodologies including collaborative filtering, content-based filtering, and hybrid approaches that combine multiple techniques [11, 12]. The precision of these recommendations significantly depends on the underlying security measures that protect the integrity and confidentiality of user data [13–15]. In light of recent advancements and the critical role of data security in enhancing user trust and system reliability, our study proposes the development of a hybridized recommender system specifically designed for e-commerce applications. This system integrates robust security measures within its architecture to safeguard user data while improving the accuracy and efficiency of its recommendations [16]. The proposed model leverages advanced algorithms for web log mining and pattern recognition, enabling it to identify and predict user preferences with heightened accuracy. It also incorporates machine learning techniques to optimize collaborative filtering processes and integrate contextual data for new users, enhancing the system's adaptability and responsiveness to dynamic user interactions [17, 18]. This inclusive framework has been rigorously tested in various e-learning environments, demonstrating its ability to manage large datasets and provide reliable, secure, and personalized content recommendations. The system's architecture allows for continuous learning and adaptation, ensuring that it remains effective in the face of evolving user behaviors and preferences [19, 20].

The results of this study highlight the potential of our hybrid recommendation model to significantly enhance online shopping experiences in e-commerce systems. By integrating robust security protocols and advanced data analysis techniques, the model not only addresses the challenges of data sparsity and information overload but also fosters a safer, more engaging, and personalized user experience. This system represents a pivotal step forward in the design of next-generation recommender systems that prioritize both performance and security [21, 22]. In conclusion, the development of secure, efficient, and user-centric recommender systems is essential for the sustained growth and viability of e-commerce platforms. Our study contributes to this field by proposing a novel approach that integrates advanced security measures into the recommender system framework, thereby enhancing the overall security and functionality of e-commerce platforms [23, 24]. The insights garnered from this research could serve as a foundational blueprint for future innovations in the realm of digital commerce technology. The potential research questions to address the objectives of your study are given below:

RQ1: What are the specific vulnerabilities in current e-commerce recommender systems that can be mitigated by integrating advanced security protocols?

Objective: To identify and analyze the key security weaknesses in existing e-commerce recommender systems and determine how the implementation of advanced security protocols can address these vulnerabilities to enhance system integrity and data protection.

RQ2: How does embedding robust security measures within recommender systems affect their ability to deliver personalized and accurate product suggestions?

Objective: To evaluate the impact of incorporating security measures into the architecture of recommender systems on their core functionality, specifically focusing on the precision and personalization of product recommendations to ensure that security enhancements do not compromise system performance.

RQ3: In what ways does the proposed hybrid model improve user trust and data privacy compared to traditional recommender systems?

Objective: To compare the effectiveness of the proposed hybrid recommender system with traditional models in enhancing user trust and safeguarding data privacy, thereby assessing the potential benefits and improvements in user experience facilitated by the hybrid model.

2 Literature Study

Li et al. [24] proposed using an efficient recommender method to facilitate online business transactions and create a successful E-Commerce scheme. This study presented a social recommendation system (RS) that could produce personalized product recommendations based on social relationships, recommendation trust, and preference similarity. It could be thought of as a thorough evaluation of recommendation sources in contrast to conventional collaborative filtering techniques. The fundamental tenet of this programmed was "similarity breeds connection," which describes how users share numerous characteristics with those who are closer to them. In this model, the accuracy of product recommendations was found after deriving the social relation between the customer "c" and product "j". The mathematical representation could be stated as follows.

$$SR(c,j) = \frac{\overline{R_c} + \sum_{p \in SN} Relation(c,p)(R_{p,j}) - \overline{R_p}}{\sum_{p \in SN} |Relation(c,p)|} \tag{1}$$

It also suggested that if someone possessed the information of connections in a network, anyone could infer some of those attributes. But the reality was that, people were being affected by the suggestions and opinions of people with similar interests, shopping interests as well as close friends [24].

Shinde et al. [25] reported the personalized recommendation technique for reducing the overload of information issue on World Wide Web. They described a novel algorithm such as center-bunching based clustering (CBBC), used to implement the center-bunching based clustering hybrid personalized recommender system (CBBCHPRS). The mechanism of this system followed the following two phases.

- Firstly, the user's opinions were gathered in the user-item rating matrix form. Then they were clustered offline with CBBC and were stored in the database.
- In the second part, these clusters were chosen by the active users with good rating quality. In this case the recommendations were generated online.

This process helped in getting good quality and more effectiveness of the recommender mechanism for active users alleviating the issues like sparsity, cold-start and first-rater [25].

They also reported the quality of the product by the equation as follows.

$$Rating = \frac{\sum_{i=1}^{n}(Q_i \times avg\_rating)}{\sum_{i=1}^{n} Q_i} \tag{2}$$

where n = number of selected clusters, Qi = Quality of product, avg_rating = average rating of product.

Aher et al. [26] studied the association and clustering algorithm like data mining methods to overcome the problems in course recommendation system. The course recommendation system comments about choices of various students for a specific collection of courses. This method followed the rule of association algorithm with a combination of simple K-means-clustering technique. This technique showed brilliant application in Massively Open Online Courses (MOOC). This could also help in building intelligence RS [26]. Carmona et al. [10] examined the process of extracting valuable data from user-spared history databases linked to e-commerce systems. The data used for this data extraction or data mining study came from Google Analytics and included information from server logs and particular tools. Additionally, they discussed the series of steps including data collection, processing, extraction, and knowledge analysis. The use of ontology in the integration of semantics into data mining techniques was demonstrated by Dou et al. [27]. The incorporation of the knowledge domain into a process was the semantics of data mining. In order to address the problem of visiting a location without any activity history, Yin et al. [17] investigated the recommender mechanism. When someone toured an unfamiliar city without being familiar with its intricate geography, it seemed to be quite difficult. Therefore, they put out the idea of a location-based content-aware recommendation engine. This system discussed both local preferences and personal interests to provide a specific collection of activities (like concerts and exhibitions) or venues (like restaurants) [38–43]. Yang et al. [28] suggested a novel algorithm on recommender mechanism which had an increasingly significant role in one's day to day life. This study demonstrated the exploitation of recommendation accuracy from the information of social networks. A social recommendation mechanism based on collaborative filtering had been proposed in this survey. They proposed a mathematical equation for the rating prediction which was calculated using Equation 3.

$$\widehat{R_{u,i}} = \frac{\sum_{v \in T} S_{u,v} \cdot R_{v,i}}{\sum_{v \in T} S_{u,v}} \quad (3)$$

where T is the set of rates within maximum limit.

Choi et al. [29] investigated CF methods-based recommendation services for people who have trouble navigating online malls. This proposal provided a temporal purchasing pattern that was the outcome of the recommendation technique's sequential pattern analysis (SPA). Users who were unhappy with the skewed and erroneous results obtained when individual preferences were ignored found this to be beneficial. There were two key goals for this survey. To increase the quality of recommendations, implicit CF grading was done first, and then CF and SPA were integrated. This study demonstrated that the hybridization of CF and SPA shown remarkable efficiency over the separate ones, and that the implicit rating in CF was a better option than the explicit one.

They also reported the CF based recommendation being predicted by the equation mentioned in Equation 4.

$$CFPP(a,i) = \overline{R_a} + \frac{\sum_{b-1}^{k} \cdot sim(a,b) \cdot R_{b,j}}{\sum_{b-1}^{k} |sim(a,d)|} - \overline{R_b} \quad (4)$$

where k = number of users, a's neighbor, $sim(a,b)$ = similarity between a and b.

Tarus et al. [30] stated the made a new revolution by suggesting the hybrid recommendation technique for the web of online learning resources. According to their theory, the problem of information overload could be solved by the implementation of hybridization technique and combining the traditional form of CF and CB method. In this approach, the context awareness incorporated the contextual information and targeted the learner to learn the contextualized data and the pattern of user's sequential access more accurately. To achieve exceptional accuracy, Nilashi et al. [31] created a unique hybrid mechanism for recommending items based on collaborative filtering (CF). With greater efficiency, this theory and technique was able to resolve the sparsity and scalability issues. Technology for dimensionality reduction and ontology have firmly established this method. The two real-world datasets approach was assessed in this study to increase the efficacy for CF's scalability and sparsity problems.

They predicted the resource "b" for target learner "l" as stated in following Equation 5.

$$P_{l,b} = \frac{\sum_{u=1}^{n} (R_{u,b} - \overline{R_u}) \times \text{sim}(c_l, c_u)}{\sum_{u=1}^{n} \text{sim}(c_l, c_u)} \quad (5)$$

where Ru, b = rating given by learner u. $Sim(cl, cb)$ = contextual similarity between l and u.

Lv et al. [32] proposed a recommender mechanism for the areas of e-commerce along with social networking sites, video websites etc. for customer's convenience. This technique represented the feature of learning model for sharing knowledge amongst various modalities. Furthermore, this real-world dataset experiment inferred that people might pay attention on selecting items by dealing with multi-modal data. This multimodal data (IRIS) promisingly showed brilliant accuracy as well as interpretability towards top-N recommendation task. Ji et al. [2] studied the diversion of personalized information to increase the recommendation accuracy. They proposed a hybridized recommender mechanism which was dealing with the customer's reviews, ratings and social data. The model went through three group experiments along with six steps such as review transformation, feature generation, community detection, model training, feature blending, and prediction and evaluation. This study was well-explained with brilliant accuracy results obtained from the experimental data on social communities and review texts.

Yang et al. [33] studied the e-commerce application from the user's ratings and reviews on goods and services available in various e-com websites such as Trip Advisor, Amazon etc. Generally, the rating systems face some problems such as profile injection attacks due to the introduction of collaborative recommender mechanisms. For the reduction of these tasks numerous detection methods were proposed. In this study, they analyzed a step wise method to detect anomalous attacks or ratings to overcome the hard issues in feature extraction and similarity calculation.

2.0.1 Overview of Deep Learning Architecture

The term "Deep learning" has been derived from artificial neural network study due to which it is otherwise known as "new-generation neural network". The deep learning can be explained as the class of machine learning process used to represent the learning exploitation by various films of information-processing which form the layers in the stages of hierarchical architectures [34]. This technique of deep neural network emerges with an incredible noteworthy achievement in several fields such as NLP, RSs, computer visions and image processing. Researchers are investigating tirelessly in a pursuit for the exploitation of a wide sort application of deep neural network. Depending on the architecture, deep learning architecture technique could be classified broadly into three major categories such as generative, discriminative and hybrid deep architectures. But, the batch size in case of learning method must be chosen carefully for optimum results. A comprehensive comparison of the major deep learning architectures commonly used in modern recommender systems is presented in Table A1 (Appendix C).

2.0.2 Generative Deep Architecture

The exploitation of recommender mechanism can be restricted by introducing the Generative adversarial neural network with generative deep architectures. This generative deep architecture represents various vertices diagnosed in heterogeneous network present in a continuous vector space. These varieties of architecture models try to characterize the visible data having correlation properties of higher order [2, 35–38]. Generally, these architectures are applied to unsubstantiated learning techniques. The main purpose of this theory is to obtain specific supervisory information like target class labels. Most common examples of this system are AEs, RBMs, DBNs, DBMs and the newly introduced GAN [33].

2.0.3 Discriminative Architecture

The exploitation of recommender mechanism can be restricted by introducing the Generative adversarial neural network with generative deep architectures. This generative deep architecture represents various vertices diagnosed in heterogeneous network present in a continuous vector space. This information overload motivates the development of a recommender system (RS) that is designed to recommend a review subset with a high content score and other unique product attributes together with related sentiments. They also utilize personal, local, and implicit data from IoTs. RS together with a unique methodology that modifies modern methods a little, such collaborative filtering. It also explains how they have developed and yielded outcomes, and it lists some subjects for further application that have been chosen for their historical, current, and potential significance. This work proposes a hybridised forecast for RS for security of the system application for e-commerce, taking into account the benefits and drawbacks of collaborative filtering (CF) and content-based filtering (CB) approaches [38].

Such kind of deep architectural models generally are used for providing a discriminative function in pattern classification. They usually encounter the characterization of posterior distributions of visible data acclimatized classes. Specifically, these Discriminative deep architectures are used to control deep learning. Standard examples of such architectures are MLP, RNN, and CNN. To generate recommendations, collaborative filtering depends on interactions between users and items. Collaborative filtering may not function properly if a new user joins the platform or if a new item is added to the inventory. Contrarily, content-based screening necessitates precise and sometimes unavailable extensive item descriptions or metadata. By integrating the best features of both strategies, hybrid systems might lessen these problems [39–41]. There is a "rich get richer" effect when popular things are recommended by collaborative filtering. Contrarily, content-based filtering may present recommendations that are identical to what the user has previously viewed, resulting in a lack of variety. These inclinations can be countered by hybrid systems, which combine content-based and collaborative signals. The phenomenon known as "filter bubbles," in which users are only shown recommendations for content that they have already seen or found appealing, can result from pure collaborative filtering. Furthermore, customers may only receive recommendations for products that are like what they have already engaged with, which might diminish serendipity [41]. Combining various recommendation algorithms allows hybrid systems to introduce serendipity. With an increasing number of users and objects, collaborative filtering may become computationally costly [44]. Requiring comprehensive item descriptions or metadata can make content-based screening resource-intensive as well. Combining several recommendation algorithms and making the most use of their computational resources can make hybrid systems more scalable. By merging content-based and collaborative signals, hybrid systems can offer recommendations that are more tailored to each user [44]. In a hybrid approach, content-based filtering would be used to suggest items that align with the user's interests, while collaborative filtering would be used to suggest items that are popular among people with similar tastes. Systems that are hybrid may be more resilient to shifts in user behavior or item availability. For instance, a hybrid system can adapt by changing the weights of various recommendation algorithms in response to changes in a user's preferences over time.

2.0.4 Gaps & Motivation

The need to recommend a review subset with a high content score and other distinctive product qualities together with associated sentiments was spurred by this deluge of information. A recommender system (RS) was created in response to this need. They also use implicit, local, and personal data from IoTs. RS combined with a special approach that slightly alters contemporary techniques, such collaborative filtering. It covers several topics for future application that have been selected for their historical, contemporary, and potential significance. It also describes how they have evolved and produced results.

This paper considers the advantages and disadvantages of content-based filtering (CB) and collaborative filtering (CF) techniques to provide a hybridized forecast for RS for security of the system application for e-commerce.

- Establishing trust is important for e-commerce. By ensuring that users are confident that their data is handled securely, recommender systems' security features help to build user confidence.
- By addressing algorithmic biases and guaranteeing that recommendations are unaffected by malicious activity or manipulations, security-based recommender systems promote fairness.
- It should be up to users to decide how recommender systems use their data. The main goal of security-based research is to create frameworks for managing user permission and transparent data ownership.

3 Methodology

The main objective of this article is the recommendation of a tiny set of high contexts scored reviews along with a suitable and illustrative coverage of issues, sentiments and the product aspects [43–45]. Here, in this article, a number of greedy iterative algorithms have been selected for study. A selective subset of reviews has been arranged to have the equal statistic distribution of aspect as compared to the entire set prepared for product. There has been proposed an algorithm which greedily selects only one review in one chance [47]. That review is again selected next to make its inclusion be better recommended for the entire subset of review. Let us take one example. If "X0" be the review of entire subset for a typical product. Let Rk be the review subset which is formed already by k iterations of algorithms. The algorithm picks up a review $rk + 1$ in the $(k + 1)$-th iteration such that $Rk \cup rk + 1$has proportion of aspects and opinions closest to that of X0. The dataset has been collected from the internet source which has been mentioned in the data source section. The collected data has been processed and analysed using following equations.

So far as product purchasing in e-commerce is concerned, people demand suggestions, advice or recommendations from someone with professional expertise or someone with close contact (friends) upon which they can have a trust. However, it is well-known that the close friends might not have interest or expertise in the assured products and also it is obvious that someone cannot make a trust on the experts who give suggestions about the product features because people do not have any acquaintance with those experts. The product type also diverges when the consulting sources vary. Another important thing is that, in the current situation people always need security when they use to custom these technical devices. Therefore, a proper and effective recommender mechanism for product review record must be implemented to overcome such situations. In this context, we have proposed a social recommendation technique which expansively employs trust analysis, preference similarity analysis, as well as social relation analysis along with implementing a security feature. Fig.1 shows the architecture of the proposed recommender mechanism. Various modules have been described to analyses the constructed network format and objectives of the mechanism have been discussed as follows.

There are three modules which have been introduced for the analysis of information from the constructed network format. These three modules centralize themselves meeting at one point which can be ascribed as the fourth module. The main objectives of these four modules can be labelled as follows.

- Module-1 represents the prediction of trust value of the recommendation which corresponds to the quality of reputation or the rate of success according to the rating records of the customer or the product recommendation by the users.
- Module-2 describes the analysis of preference similarity between two users/customers based on each customer's rating record for a specific product.
- Module- 3 analyses the degree of close relationship between the customers according to the records of their explicit closeness or implicit interactions through the social media network.
- Module-4 is the module of personalized recommendation of product which is a center point of the three modules. This module analyses the individual factor of product evaluation along with the rating of individual factors with admiration of categories of products.

Each and every customer visiting or using the E-commerce website, is always provided a list of products recommended. This recommendation is provided by the E-commerce system itself, which is determined individually based on their rating report of preference similarity, trust analysis, and social relationship.

The security option is used before entering into the modules. As the users enters the e-commerce app, it moves forward through the security step which resists the data and information overload in RS. The overall process has been described in the subsections is shown in Figure 1.

3.1 Module-1

The first module shows the analysis of trust value of recommendation on the products. When the issues of information complexity are faced with a very large amount, then the consumers seek recommendation and suggestions from experts/friends. It can also be stated that the predication accuracy of recommendation is associated with a positive attitude to the trust of recommendation of recommenders such as expertise reputation.

The trust value of suggestion or recommendation can be analyzed by the person's success rate of recommending a product which is made by the customer c1 to all other users through a social networking format (see Equation 6).

$$RecSet(q) = \{c_{1,i} : c_1 \neq q \in S, X \in X_0, R_{a,x} \neq R_{c1,x} \neq \emptyset\} \tag{6}$$

where X denotes the set of all the products shown by e-retailers. q is a customer, c_1 and x are two different customers whereas S shows the set of all customers while R is the evaluation of rating for various customers.

The study of the trust value of product recommendations is displayed in the primary module. When a consumer encounters a significant quantity of information complexity, they turn to friends or specialists for advice. Additionally, it may be said that factors like expertise reputation and a positive attitude towards the recommenders' recommendations and their trustworthiness are related to how accurate recommendations are predicted.

The degree to which an individual is successful in promoting a product that was created by a consumer (c_1) to every other user via a social networking format can be used to assess the trust value of a suggestion or recommendation.

A successful recommendation of products can be done if and only if the rating value of the recommendation becomes very close to the target customer's rating. The successful recommendation set can be calculated by the user q as Equation 7.

$$CorrectSet(q) = \{c_1, i \in RecSet(q) \mid Y(c_1, x) - R_{c_1,x} \mid < \varepsilon\} \tag{7}$$

where Y is the set of rating values of c1and x while ε is the threshold rating value represented by a vary tiny real number. The value of the recommendation trust of c_1 towards a specific product d can be formulated as Equation 8:

$$Trust(q, d) = \frac{|\{(c_1, x) \in CorrectSet(q), x = d\}|}{|\{(c_1, x) \in RecSet(q), x = d\}|} \tag{8}$$

After knowing the trust value of recommendation (TR) in the social networking format, the rating made by the customer qfor the product d can be predicted using Equation 9.

$$\mathrm{TR}(c_1, d) = \overline{R}_{c_1} + \frac{\sum_{q \in S} Trust(q, d)(R_{q,d} - \overline{R}_q)}{\sum_{q \in S} |Trust(q, d)|} \tag{9}$$

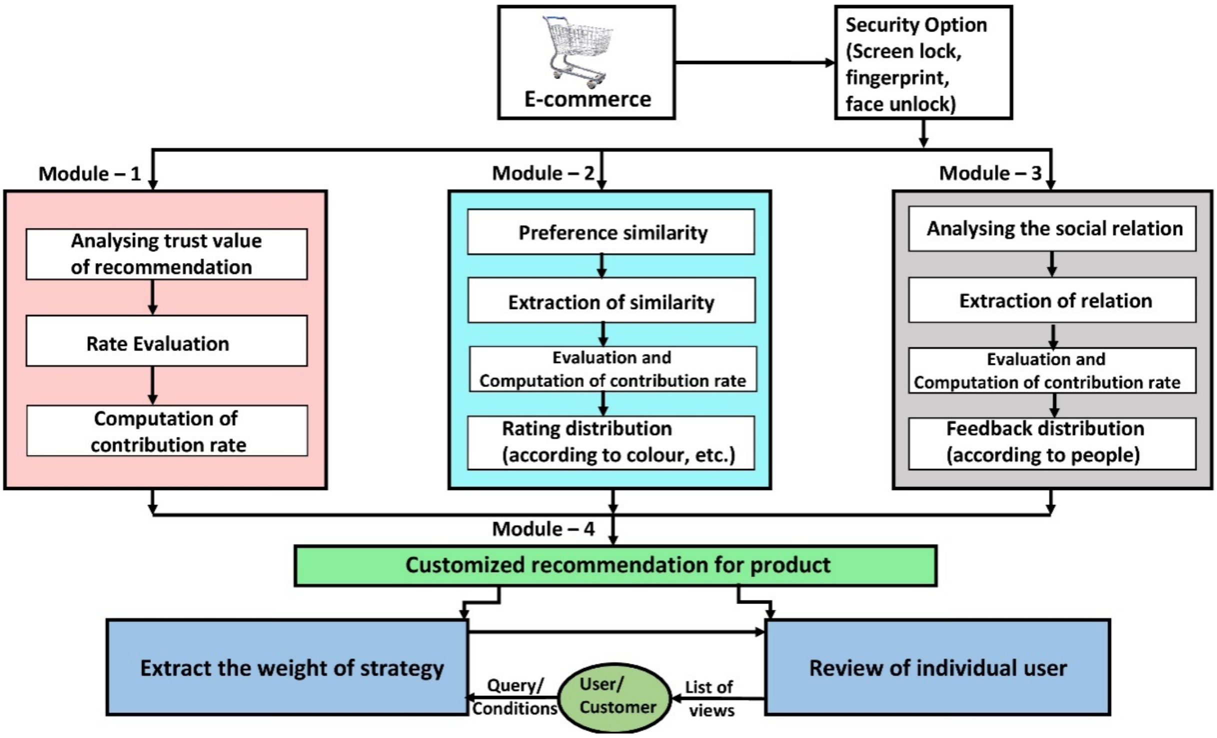

Figure 1. Architecture of the proposed hybrid recommendation model.

where $\overline{R_{c1}}$ is the view of customer c_1, dis the object and q is the user who needs recommendation for the specific product d, the recommendation rating can be calculated using the above formula.

3.2 Module-2

In general, the individuals with comparable inclinations on product purchasing from online market, will be keen on similar items, despite the fact that they may not have the foggiest idea about one another. In view of the movements of customers in a predetermined social setting, a gathering of customers with a similar resemblance level can be recognized. The inclination of a designated customer towards a particular item can be anticipated by a gathering of different users with a similar inclination comparability. The inclination comparability level of two customers can be assessed by their item purchase or rating records.

If we consider the customer q for a product d, then we can predict the average rating of the product by q as,

$$R_q = \frac{1}{x_0} \sum_{d \in X_0} R_{q,d}, \quad \forall q \in S \tag{10}$$

If we consider the preference similarity of two customers such as q and c_1, then it can be analysed by Pearson correlation rule such as,

$$Similarity(c_u, c_q) = \frac{\sum_{d \in I_q \cap I_{c_1}} (R_{c_1,d} - \overline{R_{c_1}})(R_{q,d} - \overline{R_q})}{\sqrt{\sum_{d \in I_q \cap I_{c_1}} (R_{c_1,d} - \overline{R_{c_1}})^2} \sqrt{\sum_{d \in I_q \cap I_{c_1}} (R_{q,d} - \overline{R_q})^2}} \tag{11}$$

The higher value indicates the higher preference similarity of the two customers and it should be noted that, there is an appearance of negative value showing the degree of dissimilarity. Using this formula (Eqn.12), we can analyze the rating of customer c_1 on product d as,

$$P(c_1, q) = \overline{R_{c_1}} + \frac{\sum_{q \in S} (Similarity(c_1, q))(R_{q,d} - \overline{R_q})}{\sum_{q \in S} |Similarity(c_1, q)|} \tag{12}$$

The above equation (Eqn.12) predicts the relative level of interest of customer c_1 on product d.

Generally, those who have similar preferences when it comes to buying products online will be interested in comparable products even though they may not know anything about each other. Customers with comparable levels of similarity can be identified in a group based on their motions inside a predefined social situation. A group of users who share a comparable propensity can predict a specified customer's preference for a specifically designated item. Two consumers' item purchase or rating histories can be used to determine how comparable their inclinations are.

3.3 Module-3

Usually, individuals gather item records by counseling their companions and accordingly their buying choices can be altogether affected by the recommendation of companions. Consequently, suggestions and recommendation list report given by the prediction of close social relationship between the users or customer. Companions' ought to be more precise as a result of the impact of social relationship. The closeness worth of a connection way between two clients is estimated by the most vulnerable tie strength (closeness) at the edge of the way. When there are various connection ways between two customers, the way with the most grounded closeness esteem is utilized to address the social connection strength between the two users.

Let us consider $\Gamma_{c_1,q}$ is the set of all the accessible pathways of relationship from customer c_1 to the adviser q and $\chi(l)$ is the bonding strength between the two. Let us consider l as the arbitrary function of the asymmetric relation pathway W. So, the pathway of social relationship and the bonding strength and closeness between two users can be evaluated using Equation 13.

$$Relation(c_1, q) = \max_{W \in \Gamma_{c_1,q}} \left\{ \{ \min_{l \in W} \{\chi(l)\} \right\} \tag{13}$$

In Equation (13), it is observed that the bonding strength $\chi(l)$ can be formulated by interactional as well as structural relationship and closeness among the users.

After getting the value of social relationship and closeness among the customers, the rating of user c_1 on product d can be predicted using Equation (14).

$$S_{Rel}(c_1, d) = \overline{R_{c_1}} + \frac{\sum_{q \in S} Relation(c_1, q)(R_{q,d} - \overline{R_q})}{\sum_{q \in S} |Relation(c_1, q)|} \tag{14}$$

The Equation 14 shows that how much the customer c_1 likes the product d.

3.4 Module-4

Though facing a similar category/product, still the customers will have the purchase criteria/conditions of their own. These conditions are expressively influenced by factors like personality traits (age, gender etc.) as well as economic status. The experimental analysis has been depicted in the result analysis part (Section.6).

To calculate the criterion of personalized recommendation, a large number of customers have been invited to participate in the experimental analysis. Let O_{pref} is the weight matrix of preference similarity for customer c_1 and oyz denotes the relative preference of both criteria such as y and z respectively. The matrix can be written as shown in Equation 15.

$$O_{\text{pref}} = \begin{bmatrix} 1 & o_{yz} & o_{yz} \\ 1/o_{yz} & 1 & o_{yz} \\ 1/o_{yz} & 1/o_{yz} & 1 \end{bmatrix} \tag{15}$$

Then the decision weight of user c_1 can be calculated on the factors such as trust value (O_T), preference similarity (O_S) and social relationship (O_R) such as,

$$\text{OTSR} = [O_T(c_1), O_S(c_1), O_R(c_1)] \tag{16}$$

Finally, the score of personalized recommendation for the product d according to user c_1 can be calculated by the following equation (Eqn.17).

$$\begin{aligned} R_{\text{personal}}(c_1, d) =& O_T(c_1) \cdot T_R(c_1, d) + O_S(c_1) \cdot P(c_1, q) \\ &+ O_R(c_1) \cdot S_{\text{Rel}}(c_1, d) \end{aligned} \tag{17}$$

Typically, people obtain item records by consulting with their friends, and as a result, friends' recommendations can have a major influence on what they choose to buy. In light of the likelihood of a close social relationship developing between users or customers, recommendations and suggestions are provided in the report. Because social relationships have an impact, companions should be more precise. As the most vulnerable tie strength (closeness) at the edge of the route, the closeness worth of a connection path between two clients is calculated. If two customers have different ways to connect, the method with the highest grounded closeness esteem is used to determine how strong their social connection is.

3.5 Implementation of Security in the Recommendation System

The curricle of current generation makes a move towards the claim for the consistent implementation and application of cloud computing in the daily routine. Although this application reveals several advantages in the field of household to technology, business to hospitality, selling and purchasing to economic development, still it reflects some refractive challenges such as security of data storage, integrity along with confidentiality. The major risk in this type of technology is to make trust in the owner of the cloud. However, the encrypted data cannot be used even in any kind of computation process and as a result of which one cannot store the encoded data. But it is obvious that the role of this cloud computing is very crucial in the case of recommendation systems.

The recommendation system has been widely implemented in the e-commerce network as well as in the processing fields of information. But in this widespread network, there exists the barrier and scar of security because it is believed that "The God himself is not secure having given man dominion over his work". So, security is badly needed to protect and protest the critical technique of hacking and stealing dataset. The recommendation mechanisms are very much reactive and susceptible to the attack such as profile injections by which some mischievous customers add some supplementary biased ratings in the report database with the intension of changing the result of a particular item. To overcome that vulnerability, we have implemented security in the proposed model such as fingerprint, face detection or screen lock password system.

3.6 Algorithm of the Proposed Model

Step 1: Opt for screen lock or fingerprint or face unlock.

Step 2: Analyse the trust value of recommendation. The value of the recommendation trust of c_1 towards a specific product d can be formulated as shown in Equation (a).

$$Trust(q,d) = \frac{|\{(c_1,x) \in CorrectSet(q), x = d\}|}{|\{(c_1,x) \in RecSet(q), x = d\}|} \quad \text{(a)}$$

Step 3: Analyse the preference similarity. If we consider the preference similarity of two customers such as q and c_1, then it can be analysed by Pearson correlation rule such as (see Equation (b)).

$$Similarity(c_1,q) = \frac{\sum_{d\in I_q \cap I_{c_1}} (R_{c_1,d} - \overline{R_{c_1}})(R_{q,d} - \overline{R_q})}{\sqrt{\sum_{d\in I_q \cap I_{c_1}} (R_{c_1,d} - \overline{R_{c_1}})^2}\sqrt{\sum_{d\in I_q \cap I_{c_1}} (R_{q,d} - \overline{R_q})^2} } \quad \text{(b)}$$

Step 4: Analyse the social relation. The pathway of social relationship and the bonding strength and closeness between two users can be evaluated as (see Equation (c)).

$$Relation(c_1,q) = \max_{W\in \Gamma_{c_1,q}} \left\{ \min_{l\in W}\{\chi(l)\} \right\} \quad \text{(c)}$$

Step 5: Sum up all the analysed value and customize the values. Finally, the score of personalized recommendation for the product d according to user c_1 can be calculated by the following (see Equation (d)).

$$R_{Personal}(c_1,d) = O_T(c_1)\cdot T_R(c_1,d) + O_S(c_1)\cdot P(c_1,q) + O_R(c_1)\cdot S_{Rel}(c_1,d) \quad \text{(d)}$$

Step 6: Review of individual. Finally, the score of personalized recommendation for the product d according to user c_1 can be calculated by the following Equation (e).

$$R_{Personal}(c_1,d) = O_T(c_1)\cdot T_R(c_1,d) + O_S(c_1)\cdot P(c_1,q) + O_R(c_1)\cdot S_{Rel}(c_1,d) \quad \text{(e)}$$

Step 7: Recommend to the new user.

3.7 Data Source

In our experimental analysis, we have conducted the investigation by inviting the customers of UK retailer Walmart, one of the popular online shopping sites [1]. We have conducted the experimental analysis by collecting the data from various users and the data source includes the preference similarity [43–47], trust value analysis [48] as well as social relationship [49] (bonding strength with friends and relatives) etc. We have used the category of product which is available in the e-website and the various preference similarity of those products with respect to the friends and experts. We have categorized the product and chosen only four different categories such as Health & Beauty, Entertainment & Living, Electronic Equipment and Jewellery. In total, 20 products have been selected for deciding the product recommendation and weight of similarity preference rating records from the participating users. First, we have invited a few users who frequently use this online shopping as the initial stage and then circulated the chain by

[1] https://www.kaggle.com/datasets/yasserh/walmart-dataset

inviting more new users through these initially invited customers. In this process, we have extended this social networking analysis specifically by circulating online inquiry/feedback form or questionnaires. These survey forms (see Figure A1 for product information and Figure A2 for social relationship information in Appendix) are distributed to know the purchasing experiences of customers on Walmart. And again, these have been further disseminated by these users to their friends and relatives who have had similar experiences. The process is continued till the satisfactory experience of shopping has been acquired. Finally, a branched social network have been assembled by all those invited customers who have agreed to take part in the experimental analysis.

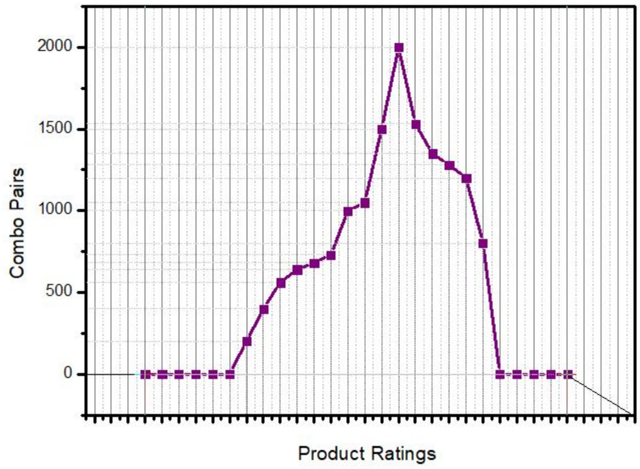

Figure 2. Trust value analysis.

4 Results & Discussion

The pre-existing techniques and their comparative analysis has been done by the authors in the previous study [35]. The various recommendation lists of the collected dataset has been experimented and investigated according to the user's interest. The result of the investigated dataset has been inferred as follows:

4.1 Trust Value Analysis

The predication of recommendation trust value on the products has been predicted using the dataset source. It is also believed that the analysis of review/recommendation accuracy is always associated with a positive attitude towards the trust of recommendation of recommenders such as expertise reputation or the relatives or friends. Figure 2 shows a bell-shaped distribution for the trust value analysis of customers. The curve has been plotted by taking the priority index values and the partial information of each and every individual.

4.2 Preference Similarity

When the users face problems with the preference analysis value that has high information complexity, then the customers want to go with seeking the help of relatives, friends or experts. It is obvious that the recommenders or the advisors with high expertise can make more believable and good product recommendations. Furthermore, the predication accuracy of recommendation is completely related with the trust (expertise reputation) on recommenders. According to our dataset, the recommendation trust of a recommender (whether it may be a expert or relative or a friend) is evaluated by his/her success rate of product recommendations and it has been plotted (see Figure 3). The shape has been observed to be normal bell-shaped.

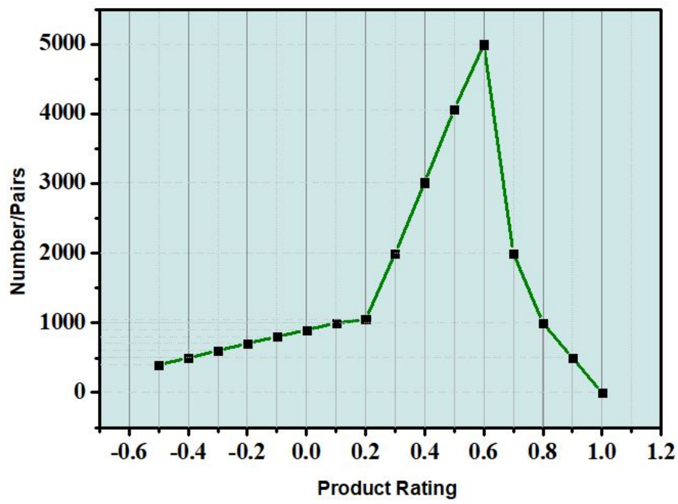

Figure 3. Preference similarity.

4.3 Social Relationship

When people go for online product purchasing, they need the recommendations of relatives and friends which have been seen to be considerably influenced by close relatives. Hence the suggestions by the close friends must be taken as more accurate due to the social relationship effect. The value of closeness of relationship and the weak bonding has been depicted in the Figure 4 which shows that the multiple bonds and relation paths created between two customers has higher preference as compared to others. It also shows the bell-shaped property.

Table 1. Overall Statistical Dataset of the Performed Experiment.

Description	Value
Total number of customers participated	2856
Total number of frequent users of e-commerce	1823
Average co-relation degree of a customer	3.256
Total number of recommendation rating records collected	10,892
Average recommendation trust value	0.311
Average preference similarity	0.428
Average strength of social relationship of users	6.241

Table 2. Impact of Age Factor on Purchase Conditions.

Age Group	Preference on Product purchase	Friends / Relatives	Experts
≤ 20	0.598	0.223	0.407
20-25	0.424	0.322	0.398
26-35	0.367	0.380	0.291
36-45	0.382	0.317	0.320
> 45	0.461	0.243	0.311

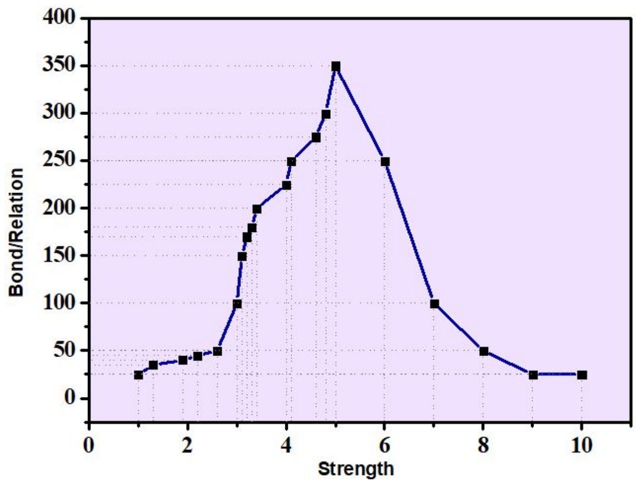

Figure 4. Social relationship.

4.4 Factors affecting the Purchase Conditions

From the data source (Table 1), a sum total of 2856 customers of e-commerce and social network have been collected to perform an experimental analysis. In the analysis, the different age groups along with their preferences and their comparison towards the experts and friends have been predicted. The explanation and description on various parametric factors have been described below.

4.5 Age

Table 2 shows the common decision factor after getting the ranking and rating records from the relative friends and experts with respect to various age groups and their significant divergence.

Table 2 shows the rating factor in case of young users (aged ≤ 20) are nearly equal to the rankings in case of old customers (aged > 45). It has been observed that the contemplated review of each and every individual preference shows the highest significance. When we consider the purchase preference in between the age group 26-45, it is observed that the level of comparative significance is nearly equal in case of friends and relatives but it is being weighted in a lesser amount in case of opinions of the experts.

4.6 Gender

Table 3 shows the common decision factor after getting the ranking and rating records from the relative friends and experts on the basis of gender.

Table 3 indicates the general ranking and impact of decision factor and its divergence with respect to the basis of gender. From the table it is predicted that the recommendation of experts is taken as highly significant in case of male users. Furthermore, it is also seen that, in case of female users, the preference similarity is highly preferred which are taken from the friends and relatives as compared to that of the opinion of the experts.

4.7 Product Category

Table 4 shows the factor depending on the type and category of various products.

Table 4 analyses the most significant ratings of the decision and priority index in case of the category of products. From the table it has been observed that

Table 3. Impact of Gender on Purchase Conditions.

Gender	Preference on Product purchase	Friends / Relatives	Experts
Female	0.491	0.486	0.398
Male	0.423	0.391	0.402

Table 4. Impact of product category on purchase conditions.

Type /Category of Product	Preference on Product purchase	Friends / Relatives	Experts
Health & Beauty	0.302	0.333	0.336
Entertainment & Living	0.401	0.491	0.202
Electronic Equipment	0.316	0.296	0.365
Jewellery	0.397	0.357	0.301

the preference for product buying is highest in case of “Entertainment & Living” categories which is best suited towards the opinion of friends and relatives but it is followed by least taken according to the opinion of the experts. The rest of the three categories such as “Health & Beauty”, “Electronic Equipment” and “Jewellery” show nearly equal preference values. It is also observed that the recommendation of experts is given prior in case of “Consumer Electronics” but it is reversed in the rest two. Similar study has been discussed by other researchers in various analysis [24].

5 Novelty of The Study

Customisation and suggestion dependability are severely hampered by the ’Cold Start’ issue and data sparsity, two enduring issues with traditional recommendation engines in e-commerce. Existing methods, in spite of improvements, have trouble incorporating dynamic security procedures and efficiently using contextual and sequential data to get around these problems. This work presents a unique hybrid recommendation architecture that tackles the limitations of sparse data situations and security issues. The proposed method combines sequential pattern mining and context-aware user modelling in a novel way, unlike traditional systems. It also incorporates dynamic security layers to safeguard user data without sacrificing suggestion accuracy. A novel fusion of conventional recommendation techniques and sophisticated algorithms is proposed to enhance recommendation performance in Cold Start circumstances, utilizing sequential access patterns and context perception models. The system’s security feature maximizes the utilisation of accessible data while guaranteeing that private user interactions are concealed. According to preliminary findings, the hybrid system significantly improves suggestion quality, especially in data-sparse contexts, while also outperforming current approaches in accuracy. By utilising contextual and sequential data in innovative ways, the model also successfully tackles the Cold Start issue and demonstrates the capability to generate accurate predictions with little user history. This research introduces a new method for hybrid recommendation systems by combining security, contextual awareness, and sequential pattern mining in e-commerce platforms. The model’s unique contribution over current methods is highlighted by its versatility and enhanced performance in sparse data settings. Future research will concentrate on expanding this innovative approach for larger e-commerce applications to ensure improved user experience and data protection.

Novel Integration: Although the methodologies are well recognised, our contribution is the special integration and use of various techniques in a single framework. In particular, unlike other approaches in the literature, ours combines contextual data, sequential user behaviours, and a dynamic security mechanism into a single system. This offers improved suggestion accuracy as well as strong user data protection in e-commerce systems, which hasn’t been fully explored in earlier studies.

Security-Enhanced Recommendation: A key innovative feature of the proposed system lies in the incorporation of real-time security measures into the suggestion process. Unlike current systems that typically prioritize efficiency and accuracy over security, this approach maintains recommendation quality while protecting user data, significantly enhancing practical utility in real-world e-commerce applications.

Performance in Sparse Data Conditions: The presented methodology specifically addresses data sparsity and the Cold Start problem through novel dynamic approaches. While pattern mining and context-awareness have been independently applied in existing works, this research introduces a synergistic strategy that enables both methods to function effectively with minimal user interaction data, thereby enhancing performance in scenarios where conventional systems typically falter.

Empirical Results: Initial findings demonstrate quantifiable improvement over existing techniques. Specifically, notable enhancements are observed over baseline models in both recommendation accuracy and security performance. This practical improvement validates the effectiveness and innovation of the integrated approach.

In conclusion, while building upon established techniques, this work presents a novel synthesis of existing approaches with particular emphasis on security and adaptability in sparse data environments. This comprehensive strategy addresses identified gaps in current literature and represents meaningful progress in the field of e-commerce recommendation systems.

6 Limitations of The Study

Privacy Issues: Users may be reluctant to divulge personal information while collecting and using user data for recommendations due to privacy concerns. Example: People who are worried about their data privacy are not interacting with others on the site. Algorithmic Prejudice: It is possible for the recommendation system to unintentionally reinforce preexisting biases, resulting in recommendations that are biased or unfair. Example: Recommendations that conform to preconceptions are often given to specific groups of people. Changeable Preferences Recommendation systems might not be able to promptly adjust to changes in user preferences as these preferences vary over time. An illustration would be a user's growing interest in a certain product area while the recommendations are not keeping up.

7 Conclusion and Future Scope

This comprehensive study reviews multiple recommender mechanism approaches based on various types of context awareness and sequential patterns for e-learners in e-learning environments. The integration of these recommendation mechanisms forms a hybrid recommendation approach, which is personalized according to the learner's context and sequential access patterns. A new model is proposed that demonstrates improved effectiveness and efficiency for this technique. Results indicate that the hybridized recommendation mechanism delivers superior recommendation quality along with enhanced performance in e-commerce technology applications.

Data Availability Statement

Data will be made available on request.

Funding

This work was supported without any funding.

Conflicts of Interest

The author declares no conflicts of interest.

Ethical Approval and Consent to Participate

This study involves an anonymous voluntary survey on shopping preferences with no collection of sensitive or identifiable personal data. It was conducted in accordance with the Declaration of Helsinki and qualifies for exemption from formal ethics committee review.

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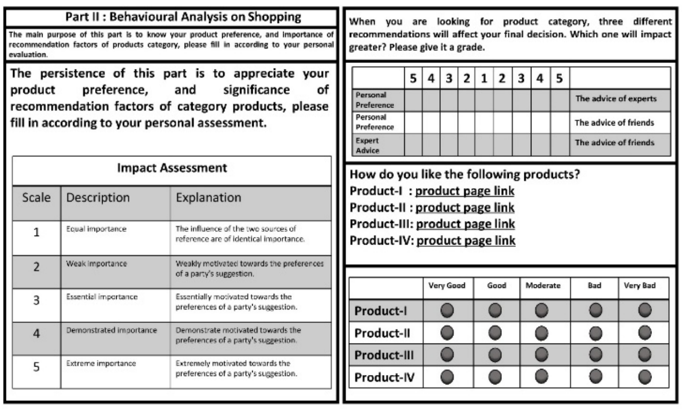
Appendix

List of Abbreviations

Abbreviation	Description
AE	Auto-Encoder
RBM	Restricted Boltzmann Machine
DBN	Deep Belief Network
DBM	Deep Boltzmann Machine
GAN	Generative Adversarial Network
IoT	Internet of Things
RS	Recommendation System
HR	Hybrid Recommender
CB	Content-Based Filtering
CF	Collaborative Filtering


Part II : Behavioural Analysis on Shopping

The main purpose of this part is to know your product preference, and importance of recommendation factors of products category, please fill in according to your personal evaluation.

The persistence of this part is to appreciate your product preference, and significance of recommendation factors of category products, please fill in according to your personal assessment.

Impact Assessment		
Scale	Description	Explanation
1	Equal importance	The influence of the two sources of reference are of identical importance.
2	Weak importance	Weakly motivated towards the preferences of a party's suggestion.
3	Essential importance	Essentially motivated towards the preferences of a party's suggestion.
4	Demonstrated importance	Demonstrate motivated towards the preferences of a party's suggestion.
5	Extreme importance	Extremely motivated towards the preferences of a party's suggestion.

When you are looking for product category, three different recommendations will affect your final decision. Which one will impact greater? Please give it a grade.

	5	4	3	2	1	2	3	4	5	
Personal Preference										The advice of experts
Personal Preference										The advice of friends
Expert Advice										The advice of friends

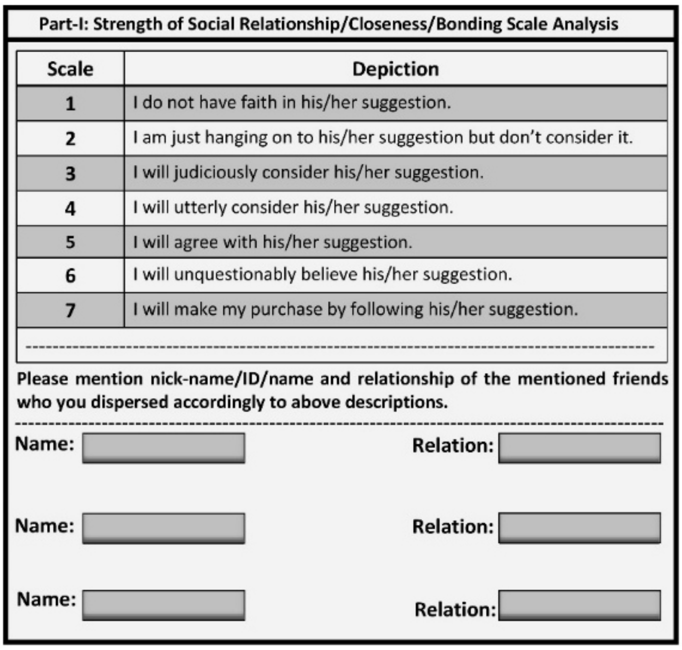
How do you like the following products?
Product-I : product page link
Product-II : product page link
Product-III: product page link
Product-IV: product page link

	Very Good	Good	Moderate	Bad	Very Bad
Product-I					
Product-II					
Product-III					
Product-IV					

Figure A1. Inquiry form for product information

Table A1. Comparisons between various deep learning techniques.

Acronym	Description	Main Application in RS	Learning Scenario	Strength	Limitations
Deep AE	The neural network which is trained for the reconstruction of their inputs under some restrictions	To learn the features of representations with lower dimensions gained from text reviewing	Unsupervised	Able to learn features represented with more complexities through an unsupervised scheme of learning	Less efficient to scalability in data with high dimensions depending on numerical optimization
DBM	Undirected deep neural network connection at each layer	Ensemble models	Unsupervised	Provides stronger feature abstraction through unsupervised training	High computational time due to the large parameter tuning
DBN	Consists of directly connected lower layer and indirectly connected two layers	Audio and video-based recommendation	Unsupervised	Powerful towards taking out useful and hidden topographies from audio data	Difficult to sequence due to the broad constraint initialization procedure
RBM	Bipartite, undirected graph including of the hidden and visible layer	Group-based recommendation	Unsupervised	Useful for learning low-rank illustrations	Not controllable as such the contrastive divergence can be used in learning the parameter
GAN	Deep neural network with generator and discriminator	Discriminative and generative information retrieve	Unsupervised/ Supervised	Appropriate for combined unsupervised and supervised learning	High parameter tuning requirements
CNN	Convolutional Neural Network	Image and sequence-based recommendation	Supervised	Effective for spatial and temporal pattern recognition	Requires large amounts of labeled training data



Part-I: Strength of Social Relationship/Closeness/Bonding Scale Analysis

Scale	Depiction
1	I do not have faith in his/her suggestion.
2	I am just hanging on to his/her suggestion but don't consider it.
3	I will judiciously consider his/her suggestion.
4	I will utterly consider his/her suggestion.
5	I will agree with his/her suggestion.
6	I will unquestionably believe his/her suggestion.
7	I will make my purchase by following his/her suggestion.

Please mention nick-name/ID/name and relationship of the mentioned friends who you dispersed accordingly to above descriptions.

Name: Relation:

Name: Relation:

Name: Relation:

Figure A2. Inquiry form for social relationship information

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