IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 19 February 2024, accepted 6 March 2024, date of publication 18 March 2024, date of current version 25 March 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3377120

RESEARCH ARTICLE

OntoCommerce: Incorporating Ontology and Sequential Pattern Mining for Personalized E-Commerce Recommendations

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This work was supported by the University of the Punjab, Lahore, Pakistan.

ABSTRACT The abundance of information on online purchasing websites makes it challenging for customers to locate products that match their preferences. However, the cold-start problem arises when there isn't enough previous data, making it harder to make accurate recommendations for new customers or products. The enormous number of possible customers and products in a recommendation system leads to sparse data, which makes it harder to generate relevant recommendations and causes the sparsity problem. In addition, existing e-commerce recommender systems have difficulty making accurate product recommendations because they disregard individual consumer characteristics. In order to overcome these limitations, a hybrid recommender system combining ontology and sequential pattern mining (SPM) techniques is proposed. The strategy entails constructing an ontology that encompasses customer and product-related knowledge in the e-commerce domain. This ontology is then utilized to calculate customer preference similarities and generate predictions for the intended customer. The SPM algorithm is applied to the results of collaborative filtering to generate personalized recommendations for the customer. Experiments have demonstrated that the hybrid recommender system outperforms existing methods and resolves the cold-start problem and data sparsity in e-commerce recommender systems effectively. Even with limited initial data, the system generates accurate and individualized recommendations based on ontological domain knowledge and the customer's sequential purchase patterns. By integrating ontology and sequential pattern mining, this strategy enhances the precision and individualization of the e-commerce industry's recommendation process.

INDEX TERMS Collaborative filtering, e-commerce, hybrid recommender system, ontology, recommender systems, sequential pattern mining (SPM).

I. INTRODUCTION

E-commerce has rapidly expanded into a multibillion-dollar industry, with an increasing number of customers purchasing products and services online [1]. This surge in e-commerce offerings can be directly linked to the escalating demand from customers who prefer making their purchases online.

The associate editor coordinating the review of this manuscript and approving it for publication was Sangsoon Lim.

Customers frequently experience difficulty selecting products that precisely satisfy their requirements and align with their preferences, primarily as a result of the abundance of available information. In the realm of e-commerce, recommendation systems have become a viable option for addressing this issue.

To meet the needs and preferences of customers, e-commerce businesses rely on recommender systems to provide individualized product recommendations. These systems assist customers find relevant and interesting products, which can improve customer's satisfaction and buying habits. Recommender systems in e-commerce help overcome the problem of information saturation by automatically eliminating superfluous products and automatically recommending those that are essential based on each customer's individual preferences [2], [3], [4], [5]. Customer preferences refer to the specific products that align with their individual needs and interests. The primary goal of recommender systems is to enhance the process of discovering unique and engaging products for individuals; which they may not have encountered otherwise. This is accomplished through the utilization of various software tools and methodologies that seek to provide personalized product recommendations [6].

It is often said that due to advancement in the artificial intelligence the web is shifting from a search-focused era to one of discovery. But what exactly is the difference? Searching is what we do when we actively seek something specific information. Discovery, on the other hand, is when something amazing, previously unknown, or unexpectedly, beyond our capacity to request, finds us [7].

Recommender systems in e-commerce aim to predict and assess a customer's preference or rating for a particular product in order to provide personalised suggestions [4], [8]. Numerous areas have successfully incorporated conventional recommender systems, for example, collaborative filtering (CF) and content-based (CB) techniques. These systems are crucial for recommending books on Amazon and videos on Netflix [9], [10].

CF methods are used in e-commerce to propose products to target customers based on the preferences of similar customers [11], [12]. Through the examination of the past purchasing behaviours of two customers, it becomes possible to assess the degree of similarity in their personal tastes. The calculation of taste similarity between two customers involves the analysis of their historical purchasing patterns, taking into account their previous buying behaviors and preferences. In contrast, content-based recommender systems function by recommending products with similar content or characteristics to those items that the consumer has previously indicated a preference for [13] and [14].

However, previous research has shown that traditional recommender systems have problems in the e-commerce domain. These problems include the cold-start [15], [16] and rating sparsity [17], [18] problems, which make them less useful. The cold-start issue arises when a recommender system lacks sufficient ratings for either new things or new customers who haven't yet given any products a rating. According to [11], this makes it difficult to provide precise recommendation. On the other side, there is a sparsity issue when there are much less customers who have provided ratings than there are products [17], [18]. The recommender system has trouble making recommendations if the target customer's ratings don't match up with enough other users' ratings.

In addition, when it comes to e-commerce, traditional CB and CF recommenders face certain limitations. They do not adequately account for the diverse characteristics of online shoppers, such as their purchasing behavior, preferences, and historical sequential patterns. As a result, the recommendations generated by these methods may lack accuracy and relevance. Even while two customers may rate a product similarly, their unique traits and purchasing habits might be different, affecting their preferences for specific products.

The main aim of the recommender systems in the world of online shopping is to give accurate and relevant product recommendations. Achieving this goal involves going beyond just the customer ratings and including more customer data in the recommendation process. This challenge can be tackled by using techniques like ontologies [19] and the SPM algorithm [20], [21] to merge customer-specific information, create personalized shopper profiles, and enhance the recommendation process.

For example, in the realm of leisure products, there has been a proposal for a context-aware mobile recommender system that utilizes ontology for context modelling [19]. Similarly, another study employed the SPM algorithm to predict e-learning resources [21], [22]. However, when it comes to e-commerce recommendations, they stand apart from other fields because of the unique traits of the shoppers, including their browsing history, buying patterns, and personalized inclinations. Consequently, the recommendation process must include these new customer characteristics.

We propose OntoCommerce, a cutting-edge hybrid e-commerce recommender system that uses ontologies and the SPM algorithm to provide customers individualized product recommendations. The proposed method capitalizes on the benefits of each technique while compensating for their weaknesses. In our hybrid strategy, ontology is utilized to represent and organize consumer and product information. This allows for an exhaustive understanding of customer and product attributes. In addition, the SPM method is employed to identify and analyze sequential patterns in the historical perusing and purchasing behaviors of consumers, thereby facilitating the identification of significant associations and preferences. In summary, this study uses ontology subject knowledge, previous purchase habits, and ratings to personalise e-commerce recommendation systems. It solves cold-start and sparsity challenges for more accurate recommendations. For instance, when a new customer signs up on an e-commerce platform with no prior data, OntoCommerce utilizes ontology to infer potential preferences based on general product categories, attributes or customer preferences. Additionally, it employs SPM to analyse similar customers' purchase histories, identifying sequential patterns to generate tailored recommendations for the customer. This combination of ontology and SPM enables OntoCommerce to provide personalized recommendations to new customers, enhancing their shopping experience and fostering increased engagement on e-commerce platforms.

Traditionally, recommender systems have used methods like content-based filtering and collaborative filtering to create product recommendations. However, the accuracy and scalability of these methods can be limited in large e-commerce environments with a large number of products and customers. Researchers have suggested employing ontologies and sequential pattern mining in e-commerce recommender systems to resolve these limitations. Ontologies offer a structured representation of domain knowledge, which includes the relationships between products, customers, and their characteristics. In contrast, collaborative filtering calculates rating similarities and predicts customer preferences. The primary benefit of hybridizing techniques is the capacity to capitalize on the strengths of each technique while overcoming their weaknesses [23], [24]. The customer behavior data can then be analyzed using sequential pattern mining to identify patterns of customer interactions and preferences. It can be applied to produce product recommendations that are more pertinent and accurate.

This research work contributes significantly to the field of e-commerce recommendation systems. Firstly, we introduce a novel hybrid knowledge-based approach for recommending products to online shoppers. This approach integrates ontology domain knowledge, encompassing information about both the shoppers and the available products. Additionally, by considering the shoppers' historical sequential purchasing patterns, we can generate more personalized recommendations tailored to each individual shopper. Secondly, we combine ontology subject knowledge with the ratings of shoppers to figure out how similar they are and make correct recommendations. This combination enhances the accuracy of predictions and ensures that the recommendations align closely with the shopper's preferences. Thirdly, the cold-start problem, which occurs when there is insufficient data or information available for new shoppers, is effectively tackled by the proposed hybrid knowledge-based approach. Through the utilization of ontology domain knowledge, acquired by integrating ontology into the recommendation process, we are capable of delivering relevant recommendations, even in situations where shoppers have limited data. Additionally, the approach mitigates the sparsity problem by leveraging the shopper's sequential access patterns to predict their preferred products when ratings are sparse.

For the rest of the paper, the parts are organized as follows: In the next section (Section II), we go into an examination of the relevant literature, covering topics such as recommendation methods, SPM, and e-commerce-specific recommender systems. In Section III, we describe the methodology and model behind our recommended recommendations, and in Section IV, we offer the results of our experimental examination and discussion. Finally, in Section V, we concluded our work and provide suggestions for further study.

II. RELATED WORK

This section covers the most significant ideas, theories, and methods in recommendation strategies, focusing on sequential pattern mining and ontology-based methods for e-commerce applications. By examining the most recent advancements in this field, we cast light on the significance and relevance of these techniques for enhancing the e-commerce user experience. After concise descriptions of collaborative filtering, ontology-based recommender systems, and sequential pattern mining, the pros and cons of these methods will be discussed. In addition, we will emphasize the research community's advancements and contributions, as well as the implications for future research and development. The primary goal of our study is to provide a thorough and in-depth understanding of the existing knowledge in the domains of sequential pattern mining and ontology-based recommender systems in the context of ecommerce. This will pave the way for further investigation and development in this field.

FIGURE 1. The process of generating recommendations in collaborative filtering.

Extensive research has been undertaken in the field of computer science pertaining to recommender systems, which have been successfully deployed across several areas such as e-commerce, music, and movies. In the early stages, recommender systems mostly used basic algorithms, for example collaborative filtering and content-based filtering, to generate recommendations by assessing the likeness of user preferences. These systems were constrained by a lack of data and the difficulty of capturing the underlying relationships between users and objects. However, as technology has advanced and more data has become available, more sophisticated recommender systems have been developed.

A. COLLABORATIVE FILTERING

It is a common method used in online shopping for generating personalized product recommendations for customers. This proposition is founded upon the assumption that people who have shown comparable preferences in the past would persist in displaying such preferences in the future. Utilized in online commerce, collaborative filtering examines user ratings to identify commonalities and trends. It involves locating users with similar inclinations and using their ratings to infer the intended user's own tastes. On the other hand, it may identify products that other users have expressed interest in and use their ratings to generate predictions. The K Nearest Neighbors (KNN) procedure is a widely used method in collaborative filtering. The K-nearest neighbors (KNN) procedure is a kind of collaborative filtering approach that operates by leveraging the notion of neighborhoods [24]. It takes into account users' and things' rating habits to determine how similar they are to one another and then finds their k closest neighbors. Predictions and suggestions are then generated based on the ratings provided by these neighbors as shown in figure 1.

B. CONTENT-BASED FILTERING

Content-based recommender systems (CBRS) leverage item contents and user preferences to recommend products [6]. CBRS analyses item descriptions, traits, and features to provide user-specific suggestions, unlike collaborative filtering systems that depend primarily on user-item interactions. The core of CBRS is content-based similarity calculation. CBRS may recommend comparable things based on a customer's past preferences. Items are represented by keywords, characteristics, or metadata in CBRS, while customer preferences are recorded via interaction history or explicit preferences. These characteristics are utilised to create customer and item profiles for recommendation creation. The recommendation algorithm matches item content to customer profile choices. Cosine similarity, which measures item and user preference similarity, is typically used for this matching [13].

CBRS can provide suggestions without past customer interaction data, which is a major benefit. CBRS avoids the collaborative filtering cold-start issue by concentrating on item properties and user preferences. CBRS also provide transparency in the recommendation process by using item properties and user preferences. CBRS employ content analysis and user profiling to provide personalised recommendations based on customer preferences [15].

C. HYBRID RECOMMENDER SYSTEMS

By merging numerous recommendations approaches, hybrid recommender systems are essential to improving the performance of recommendation systems [25], [26], [27]. Hybridization's primary objective is to overcome the shortcomings of each individual recommender system and enhance the system as a whole [28], [29], [30], [31]. The literature has a variety of hybridization techniques, including weighted, switching, mixed, feature combination, cascade, feature improvement, and meta-level approaches [32]. These strategies assist the system in harnessing the advantages of many recommendation systems, hence enhancing the correctness and diversity of the recommendations provided.

Traditional recommendation systems often face several challenges, such as the cold-start problem, the lack of data, and the tendency towards specialisation [33]. Hybridization serves to mitigate these constraints by merging several methodologies and capitalizing on their complementary capabilities. Hybrid systems has the capability to address situations in which a single recommendation strategy may encounter difficulties. This ability arises from their integration of multiple recommendation strategies, hence enabling the provision of suggestions that are both more precise and relevant to users. This methodology enables the development of a recommendation system that is more resilient and flexible, capable of delivering tailored recommendations even in intricate and ever-changing e-commerce settings.

D. ONTOLOGY-BASED RECOMMENDER SYSTEMS

Ontology-based recommender systems have been proposed as a possible remedy to the aforementioned limitations of traditional recommender systems. The term "ontology" refers to a structured and systematic representation of knowledge or conceptual frameworks within a particular domain [34]. In the domain of electronic commerce, ontology is a valuable instrument for representing the fundamental concepts and interrelationships associated with products, product attributes, customers, and their respective preferences [35]. Consider, for instance, an online store that sells electronic goods such as smartphones, laptops, and cameras. We can develop an ontology that represents the relationships between these products, their characteristics, and consumers' preferences. Our ontology may include concepts such as "smartphone", "camera", and "laptop", as well as their corresponding characteristics, such as "screen size", "battery life", "camera resolution", "processor speed", and "operating system". We can also include concepts such as "customer", "purchase history", "preferences", and "reviews".

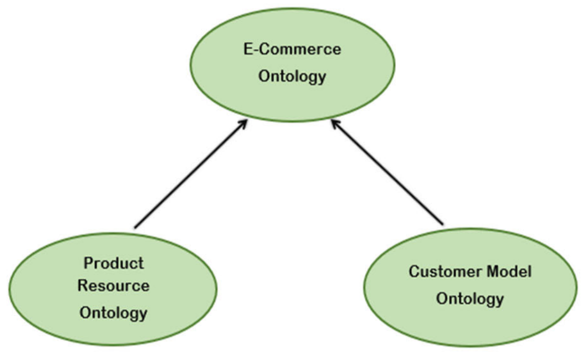

FIGURE 2. E-commerce top-level ontology structure.

This ontology can be used to create a system that provides clients with product recommendations, taking into account their interests and past purchasing behavior. By using the ontology, the system is capable of aligning the customer's preferences with the product's characteristics, hence facilitating the recommendation of the most appropriate items. In the realm of e-commerce, the use of ontology has the prospective to augment the accuracy of product recommendations, increase the overall customer experience, and ultimately bolster sales. Figure 2 shows the top-level ontology framework for e-commerce. It is made up of two classes: customer resource ontology and product resource ontology. The customer class includes information about the customer, such as personal information, topology, and how they use the internet. The product resource class holds information about the goods, like what kinds of electronics and clothes they are, and so on.

Numerous studies on ontology-based recommender systems have produced optimistic outcomes in terms of improved accuracy and personalized recommendations. For example, in [36] an ontology-based product recommendation system for B2B marketplaces is presented. The system uses an ontology, a structured representation of domain knowledge, in order to effectively recommend products to business customers. This ontology enables the system to comprehend the relationships between various products, user preferences, and business contexts. The strategy aims to improve the overall user experience in B2B marketplaces by increasing the accuracy and relevance of product recommendations.

E. SEQUENTIAL PATTERN MINING

Sequential pattern mining has also been used to identify user behavior patterns. A recommender system for e-commerce item recommendations was developed in [3] using sequential pattern mining. It captured the relationships between users and products through the use of sequential patterns and generated recommendations based on these patterns. The study's results reveal that the sequential pattern mining-based method improved the accuracy of the recommendations when compared to traditional collaborative filtering strategies. Sequential Pattern Discovery Using Equivalence Classes (SPADE), Generalized Sequential Pattern (GSP), PrefixSpan, FreeSpan, and MAPres are the most popular sequential pattern mining algorithms [37].

In this research work, we suggest an e-commerce recommender system that uses both ontology and sequence pattern mining. The system employs an ontology as a means of representing domain knowledge and to provide an organized demonstration of the associations between users and objects. Utilizing the sequential pattern mining technique, user behavior patterns are identified and recommendations are generated based on these patterns. We modified the GSP algorithm to improve e-commerce product recommendations by overcoming the sparsity and cold start problems. This algorithm is a sequence mining technique that can extract the customers' browsing history from e-commerce websites, allowing the system to predict and recommend products based on the customers' past purchasing patterns. The GSP algorithm is well-suited for this task as it not only captures customers' purchasing behaviour for a personalized browsing experience but also effectively addresses the sparsity issue.

The e-commerce recommender system can effectively match consumers with products that satisfy their requirements and preferences by analyzing their previous purchases, resulting in increased customer satisfaction and loyalty.

III. OUR RECOMMENDATION MODEL: ONTOCOMMERCE

This research introduces an innovative methodology for constructing a hybrid recommender system tailored to e-commerce products, incorporate ontology with the SPM technique. The recommendation model comprises several components, including the customer model ontology, product resource ontology, ontology-based recommendation engine, General Sequence Mining algorithm, and the final recommendations section, collectively encapsulating the recommendation methodology as shown in Figure 3.

To make recommendations, the methodology consists of three fundamental phases: First, an ontology will be developed to represent user and product domain-related knowledge. This ontology will function as a structure for organizing and classifying data. Second, the ontology domain expertise will calculate similarities and predict user ratings. By utilizing the data recorded in the ontology, it will be possible to determine how similar users are to one another and to foresee their preferences and ratings. Next, a collaborative filtering (CF) engine will generate a catalogue of the top N products. This engine will analyze user preferences and behavior to identify products that are likely to interest them. Lastly, apply the GSP algorithm to the top N products identified by CF recommendation engine. This algorithm will further refine the recommendations by taking into account additional criteria, such as user preferences, popularity, and other pertinent factors. The output of this procedure will be the customer's final recommendations.

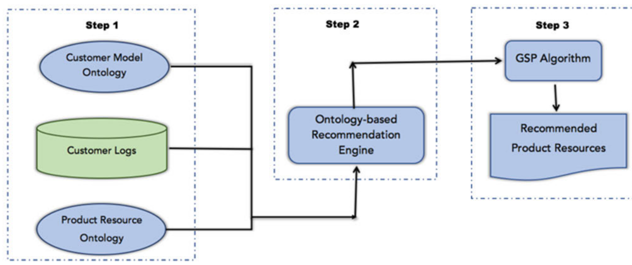

FIGURE 3. An e-commerce hybrid recommendation model employing ontology and SPM.

The objective is to improve the user's retail experience by recommending products pertinent to their interests and requirements, based on their perusing and purchase history.

The ontology-based approach enables a more precise and personalized recommendation, while SPM captures the user's sequential purchasing patterns and preferences.

A. DEVELOPMENT OF CUSTOMER AND PRODUCT RESOURCES ONTOLOGY

In the ontology-based approach, the Shopper ontology plays a crucial role in the collection of pertinent information about customers as shown in Figure 4. The ontology begins with the root node "Shopper" and divides into three principal offspring nodes: "Personal Data," "Topology," and "Internet Usage."

Under the "Personal Data" node are several attributes pertaining to the personal information of the customers. These characteristics include age, name, gender, education, income, and purchase volume. Each attribute offers valuable insight into the characteristics of customers. For example, the "gender" attribute branches into two nodes, "female" and "male," allowing the system to distinguish between male and female consumers. Similarly, the "education" attribute contains nodes representing various levels of education, including matriculation, bachelor's, and master's degrees.

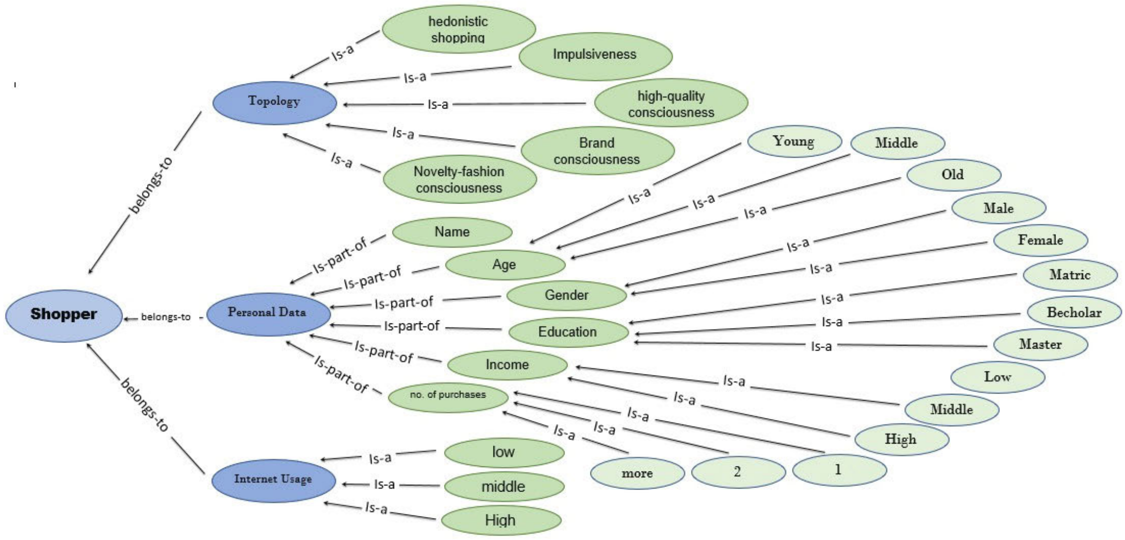

FIGURE 4. The general structure of the customer model ontology that is being proposed.

The "age" attribute is categorized into three nodes: youthful, middle-aged, and elderly, allowing the system to evaluate preferences based on age. The "income" attribute provides information regarding the income levels of consumers, differentiating between low, intermediate, and high income. The "number of purchases" attribute provides nodes representing various quantities of purchases, including 1, 2, 3, and more than 3 purchases.

Moving on to the "Topology" node, it consists of nodes that represent various aspects of shoppers' preferences and tendencies in shopping behavior. These nodes include "Perfectionism or High-Quality Consciousness," "Brand Consciousness," "Novelty-Fashion Consciousness," "Recreational, Hedonistic Shopping Consciousness," and "Price and Value for Money Shopping Consciousness". During the account registration procedure, an online questionnaire was administered to the consumer in order to ascertain their topology [38]. Each of these nodes captures specific characteristics that influence shoppers' decision-making processes. For example, the "Perfectionism or High-Quality Consciousness" node indicates the shoppers' inclination towards high-quality products, while the "Brand Consciousness" node reflects their awareness and preference for well-known brands. The other nodes provide insights into their preferences for novelty, fashion, recreational shopping experiences, and considerations of price and value for money. The "Internet Usage" node focuses on the shoppers' level of internet usage in their shopping activities. It includes three nodes: low, middle, and high. This attribute helps the system understand the extent to which shoppers rely on online platforms and digital resources for their shopping needs. Table 1 shows some definitions of classed used in ontology.

In addition to the E-shopper Ontology, the hybrid recommender system incorporates the Product Ontology. This ontology revolves around the characteristics of products. The root node is "Product Resources" and it branches out into two children nodes:

TABLE 1. Customer profile upper level ontology.

Class Name	Definition
Shopper	Represents individuals engaging in shopping activities on the e-commerce platform, serving as the root node of the ontology.
Personal Data	Encompasses attributes related to the personal information of shoppers, including age, name, gender, education, income, and purchase volume.
Topology	Consists of nodes representing various aspects of shoppers' preferences and tendencies in shopping behavior, such as perfectionism, brand consciousness, and fashion sense.
Internet Usage	Represents the level of internet usage in shoppers' shopping activities, categorized into low, middle, and high.
Product Resources	Represents the root node of the Product Ontology, focusing on the characteristics of products available on the e-commerce platform.

"Electronics" and "Apparel." The "Electronics" node represents products that primarily consumer electronics products e.g. smart phone, laptop, server, camera, etc., while the "Apparel" node represents products associated with consumer cloths and accessories. Similarly, there are many product categories and each category have different characteristics [39]. A glimpse of product resource ontology is displayed in Figure 5. By utilizing the rich domain knowledge encapsulated within these ontologies, the hybrid recommender system can enhance the accuracy and personalization of recommendations in the e-commerce setting. The proposed strategy integrates many recommendation strategies and utilizes ontological information to address the shortcomings often seen in conventional recommendation methods. These constraints include the cold-start problem, data scarcity, and overspecialization. The hybridization of recommendation techniques and the incorporation of ontology-based knowledge enable the system to provide customers with more effective and personalized recommendations, ultimately augmenting the purchasing experience.

In our research, we adopted a unified ontology approach to effectively manage and integrate diverse aspects of the system, including customer data, product resources, and e-commerce functionalities. Rather than treating these components as disparate entities, we recognized the value of consolidating them into a single ontology framework. This approach enables a comprehensive understanding of the system's intricacies and facilitates seamless communication and interaction between different elements. By establishing connections through common attributes, relationships, and dependencies, we ensured that the ontology serves as a robust foundation for organizing and analyzing data within the system. This integrated ontology framework not only enhances the efficiency of information retrieval and processing but also promotes a holistic view of the system, facilitating informed decision-making and effective implementation of e-commerce strategies.

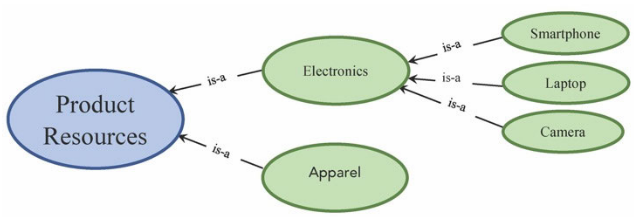

FIGURE 5. The structure of the product resource ontology being proposed.

B. IDENTIFYING SIMILARITIES AND MAKING PREDICTIONS

The recommendation engine in e-commerce analyses preprocessed ontology domain information about the products and customer evaluations on products to discover similarities and predictions for the target consumer. Adjusted Cosine Similarity is used to compute ontological similarities between products. Ontological similarity $\mathrm{Sim}(p_i, p_j)$ amid two products i and j is calculated using the formula given by Eq. (1) in the research paper, where r is the rating matrix and r_c is the rating vector for the target customer c.

$$Sim(p_i,p_j) = \frac{\sum \left(r_{c,i} - \bar{r}_c\right) * \left(r_{c,j} - \bar{r}_c\right)}{\sqrt{\left(\sum \left(r_{c,i} - \bar{r}_c\right)^\wedge 2\right)} * \sqrt{\left(\sum \left(r_{c,j} - \bar{r}_c\right)^\wedge 2\right)}} \tag{1}$$

where p_i and p_j are the two products being compared, the target customer's rating for product 'i' is represented by $r_{c,i}$, $\bar{r}_c$ represents the ontological average rating given by the target customer for all products. In contrast to pure CF, our technique computes the mean rating $\bar{r}_u$ using ontological information.

By employing the evaluations of the k most comparable products ascertained in the previous stage, the predicted ratings for the intended customer are then calculated. The objective is to estimate the rating specified to a product by the target customer by analyzing the ratings given to analogous products by customers who are most similar to the target customer (nearest neighbors). The predicted rating can be computed using collaborative filtering algorithms, for example, user-based or item-based approaches. Using a formula similar to Eq. (2) from the e-commerce context, the predicted rating for product i by customer c can be computed as follows:

$$P_{c,i} = \frac{\sum_{t \in N} \left(Sim\,(i,j) \times r_{c,t}\right)}{\sum_{t \in N} \left(|sim\,(i,j)\,|\right)} \tag{2}$$

The set of products that are similar to i based on their attributes and the user's preferences is denoted by N. $r_{c,t}$ represents the rating assigned to product t by customer c. Sim(i, j) indicates the similarity between two products based on their characteristics and the user's preferences. This approach basically calculates an average weighted by the similarity between items and the user's preferences of the ratings they provided for similar products. The anticipated rating generated as a result may be used to generate customized product recommendations for the customer.

C. CREATING A LIST OF TOP N RECOMMENDED PRODUCTS

The collaborative filtering (CF) recommendation engine uses anticipated customer ratings and ontology domain knowledge to compile the N most highly recommended products. The hardest thing for recommender systems is figuring out how customers will rate goods that they haven't even seen or thought about yet.

Our hybrid recommendation algorithm that we proposed relies on the calculation of prediction, similarity, and recommendations by 1) The product ratings given by the target customer. 2) Product ratings provided by customers other than the target customer c_t. 3) The knowledge related to the domain of the customer and products represented in the ontology.

The problem of recommendation can be reformed and presented as follows: Let C denote the set of all Customers $C = \{c_1, c_2, c_3 \ldots c_n\}$, let P be the set of all possible products $P = \{p_1, p_2, p_3 \ldots p_n\}$ that are eligible for recommendation *and* assuming O represents the entire collection of ontological domain knowledge, denoted by $O = \{o_1, o_2, o_3 \ldots o_n\}$ pertaining to the user and products. The rating "r" indicates a customer's preference for a product. Assuming C, P and O as the sets of customers, products, and ontology domain knowledge, respectively, the function f

Algorithm 1 Generate Ontology and GSP based Recommendation List

Input:
Set of products
$P = \{p_1, p_2, p_3, \ldots\ldots\ldots\ldots p_m\}$
Ontology Domain Knowledge
O = {Customer, Products}
Rating value of Customers "r"
r ε {1,2,3,4,5}
Output:
Ontology and GSP based Product Recommendation List
Procedure
1: **foreach** i ε p, j ε p, o ε O, **do**
2: Compute ontological similarity Sim(p_i, p_j) using eq(1)
3: **End foreach**
4: Compute predicted ratings $p_{c,i}$ using eq(2)
5: Generate GSP based Final Product Recommendation List

is responsible for generating recommendations. The collection of products this function recommends is represented by the top N list. The recommendation function may be defined mathematically as follows:

$$F : C \times P \times O \rightarrow \ top\, N.$$

The generated list of recommended products is arranged in order of similarity in product ratings by both the target user and other users (as expressed in Eq. (1)). Algorithm 1 outlines the process for generating ontology and GSP based recommendation list.

D. CREATING CONCLUSIVE RECOMMENDATIONS USING THE GSP ALGORITHM

The last phase of the recommendation process is using the GSP algorithm to enhance the top N recommendations, taking into account the user's historical browsing or purchase patterns. The GSP algorithm, a sequence mining method, may be summarized as a three-step procedure.

During the first step, the determination of support for each item takes place, namely the calculation of the number of transactions or browsing sessions that include each item. This process helps identify the things that occur often. The next crucial step in the GSP algorithm is the generation of possible frequent item-sets, sometimes referred to as candidate item-sets, followed by the determination of which of these candidates are really frequent. The pruning phase is a last crucial step in the process. Candidate item sets that have support counts below the minimal support criterion are deleted via a process called pruning. The last user recommendations would come from the remaining frequent item-sets.

The GSP algorithm was employed to generate a recommendation list of the top N items, following the methods described in the aforementioned study [23]. The recommended approach employs a weighted strategy that integrates collaborative filtering (CF) with ontology and the Generalised Sequential Pattern (GSP) algorithm. This facilitates the recognition of consecutive purchasing patterns that are encompassed inside the sets of items. In the domain of recommender systems, certain sequences within a particular sequential pattern exhibit a higher level of relevance compared to others. This is because certain sequences are more likely to be seen by customers. Moreover, when the minimum support is reduced, there is a substantial rise in the quantity of frequent sequential patterns, and conversely, there is a decrease in the quantity of patterns observed when the minimal support threshold is increased. Identifying the most significant sequences within a sequential pattern is a notable problem. In order to address this issue, a weighted Sequential Pattern Mining (SPM) approach is employed, drawing upon the methods outlined in prior research endeavours [38], [40]. The proposed methodology involves the assignment of weights to items in order to accurately reflect their relative significance within the sequence. Specifically, each product i is given a non-negative real value w, which serves as a quantitative representation of its relevance. Meaningful sequential patterns may be generated by allocating greater weights to items inside significant sequences. Moreover, the use of weights facilitates the process of modifying the quantity of sequential patterns. Table 2 presents the outcomes of the recommendation outcomes prior to and subsequent to the implementation of the SPM algorithm on the top N recommendation list.

According to Table 2, the recommendation system creates a list of the top N products for the customer before using the SPM approach. Upon implementing the SPM method, the ultimate recommendation outcomes are arranged in accordance with the sequential purchasing behavior of the customer, which has been extracted from transactional data. This phenomenon demonstrates the inclination of customers towards certain products, hence enhancing the efficacy of the recommendations provided and elevating the overall quality of the suggestions. The Sequential Pattern Mining (SPM) method employs a weighting mechanism to give significance to individual products within a sequence. This weighting process ensures that only the most crucial sequences are considered when generating the ultimate recommendations. This methodology is especially advantageous for e-commerce platforms that own a substantial inventory, since it enables the customization of recommendations to align with the unique requirements and inclinations of individual customers.

TABLE 2. Illustrative use case of the SPM algorithm.

Customer	Before applying GSP	OntoCommerce
c_1	(i_{11}, i_{22}, i_{33}, i_{43})	(i_{22}, i_{33}, i_{43}, i_{11})
c_2	(i_{22}, i_{35}, i_{43}, i_{56})	(i_{43}, i_{56}, i_{35}, i_{22})
c_3	(i_{33}, i_{42}, i_{51}, i_{55})	(i_{51}, i_{42}, i_{55}, i_{33})

IV. EXPERIMENTAL EVALUATION

Evaluating recommendation algorithms' performance is crucial for enhancing recommendation accuracy and precision and therefore, customer happiness. Experiments were run on an actual dataset to assess the performance of the suggested hybrid recommendation strategy that combines CF, ontology, and SPM. Comparisons to various recommendation algorithms, such as CF and Ontology with CF (Onto+CF), were used to assess the method's precision and efficiency. The purpose of these experiments was to examine whether or whether the proposed hybrid recommender system, known as OntoCommerce, could improve prediction quality and precision by integrating traditional CF algorithm, ontology domain knowledge, and SPM. E-commerce companies used customers' levels of satisfaction with recommendations as a key indicator of the effectiveness of their recommendation systems.

A. THE METHODOLOGY USED IN THE EXPERIMENT

The studies were conducted with a sample size of 500 e-commerce platform customers. During the 6-month trial period, the system made recommendations to clients based on their individual preferences. On a scale from 1 (“Not relevant”) to 5 (“Very relevant”), customers were asked to rate the usefulness of the products they purchased. In order to better their shopper profiles and ontology, customers were also asked to review a few products and input some basic information as part of the registration procedure. Customers' preferences and ontology domain knowledge were used to predict product ratings, and the recommender system generated customized recommendations. Over the course of 6 months, we collected customer order evaluations and used Python and the Protégé ontology editor to construct our algorithms and ontology. Customers' purchase habits were analyzed using the GSP algorithm, which allowed us to identify recurring trends.

B. THE DATASET

The hybrid recommendation system OntoCommerce's effectiveness was evaluated using a real-world dataset comprised of customer evaluations obtained from an online purchasing platform. For comparison, two additional algorithms, CF and CF+Onto, were also studied. The dataset included 300 products, and 4000 product ratings were gathered during a 6-month period. The dataset was then divided into a training set that included 70% of the data and a test set that included 30% of the data to compare the results of the algorithms. The products that are sold on the website are summarized in Table 3.

C. RESULTS OF EXPERIMENTS

In this section, the hybrid recommendation algorithm that is used by the OntoCommerce recommender system is examined in comparison to both the conventional CF system and the technique that combines CF with Onto. E-commerce product ratings are used as the basis for the evaluation, which is carried out with the use of a real-world dataset. The performance and accuracy of the proposed technique are compared to those of the other two algorithms using the metrics of Mean Absolute Error (MAE), Precision, and Recall. Using these measures, we compare our technique to making recommendations to the standard CF and the CF+Onto method. To ensure reliability of the results, the experiment is repeated three times using fresh random data for both the training and testing sets each time. Each statistic is given an average value after being analyzed. In addition to this, the recommender algorithm takes into account the amount of acceptance that a user has given for a suggestion.

In spite of the limited number of datasets that are openly accessible for use in e-commerce recommender systems, it has been shown that the hybrid algorithm is capable of producing accurate results in experimental situations. As a direct consequence of this, the product recommendations made by customers have significantly improved.

TABLE 3. Products information.

Category	Number of Products
Electronics	64
Gifting Items	25
Home Decor	25
Kitchen Items	23
Salt Lamp	32
Stationery	14
Toys	36
Home Accessories	22
Fashion	39
Customized	20
Total	300

1) ANALYSING THE ACCURACY AND SENSITIVITY TO NEIGHBOURHOOD SIZE

The reliability of forecasts and recommendation is influenced by the size of the neighborhood [41]. To determine how neighborhood size affects the precision of forecasts, the “mean absolute error” metric is computed for each algorithm across different neighborhood sizes. This enables us to understand the algorithms' responsiveness to variations in the size of the neighborhood and assess the precision of their forecasts [42], [43], [44]. The mean absolute error (MAE) is a way to measure how much the predicted and actual scores differ on average. A lower mean absolute error (MAE) means that the prediction is more accurate. E-commerce prediction accuracy may be assessed using widely known assessment methods, such as "mean absolute error" [45] as a reference. The equation (3) used for the computation of mean absolute error (MAE) is written:

$$\mathrm{MAE} = \frac{1}{n}\sum\nolimits_{i=0}^{n} |p_i - r_i| \tag{3}$$

based on the actual rating provided to the product by the consumer, indicated as p_i, this equation calculates the anticipated rating, denoted as r_i, for a certain product i. Different neighborhood sizes were tested in order to determine which of the three algorithms under consideration (CF, CF+Onto, and OntoCommerce) provided the most accurate predictions. Figure 6 shows the outcomes and the correlation between the size of the neighborhood and the success of the forecast. the experiment's sample size is indicated by the number n.

One can conclude from figure 6 that the most accurate predictions are obtained when the size of the neighborhood is 20. For all three algorithms, the quality of predictions decreases when the number of neighbors exceeds 20, as observed in figure 6. As a result, the optimal neighborhood size of 20 was chosen and will be utilized in the remaining experiments.

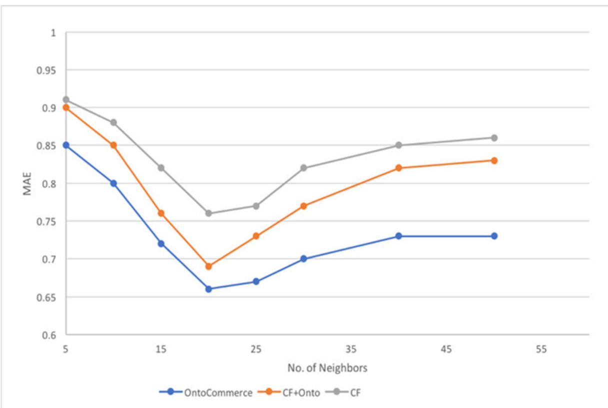

FIGURE 6. Neighborhood size sensitivity and prediction precision.

Figure 6 illustrates the variation in mean absolute error (MAE) for the OntoCommerce hybrid algorithm, CF, and CF+Onto as the neighbourhood size grows. For all three techniques, MAE drops as neighborhood size grows up to 20, but then rises beyond that. At the optimal neighborhood size of 20, Figure 6 demonstrates that the suggested hybrid approach has a mean absolute error (MAE) of 0.66. The CF+Onto method yields a Mean Absolute Error (MAE) of 0.69, whereas the CF algorithm produces an MAE of 0.76. The MAE values for OntoCommerce, CF+Onto, and CF are 0.73, 0.82, and 0.85 when the neighborhood size exceeds 40. These results indicate that the hybrid strategy significantly enhances MAE in comparison to CF alone, with improvements of 0.12 and 0.10 at neighborhood sizes of 40 and 20, respectively. This improvement shows how ontology and SPM methods work together to improve prediction accuracy. The results also show that the effectiveness of all three algorithms is significantly influenced by the size of the neighborhood. The hybrid strategy that has been developed exhibits a consistent level of superiority in terms of prediction accuracy when compared to the other methods, regardless of the size of the neighborhood. This results in more effective customer recommendations. At the ideal neighbourhood size of 20, the suggested hybrid method has a mean absolute error (MAE) difference of 0.03 compared to CF+Onto, but it is more accurate overall.

2) ASSESSING THE HYBRID METHOD AT DIFFERENT SPARSITIES

To determine how sparsity influences the precision with which predictions and recommendations can be made, a controlled experiment was conducted in which the dataset's sparsity was systematically altered. We sparsed the dataset by arbitrarily removing certain training set items while leaving the test set alone. Multiple runs of the experiment were conducted at varying degrees of sparsity. The degree of sparsity was determined using Equation (4) [26].

$$\text{Sparsity} = 1 - \frac{|\text{ratings}|}{|\text{products}| \cdot |\text{customers}|} \tag{4}$$

Figure 7 shows how the proposed hybrid strategy OntoCommerce compares to the others regarding prediction accuracy at different sparsity levels. At the outset, the rating matrix was found to be 66.7% sparse. All three algorithms showed a decline in prediction quality with increasing sparsity, as expected. In terms of sparsity, it is important to note that OntoCommerce does better than all the other methods.

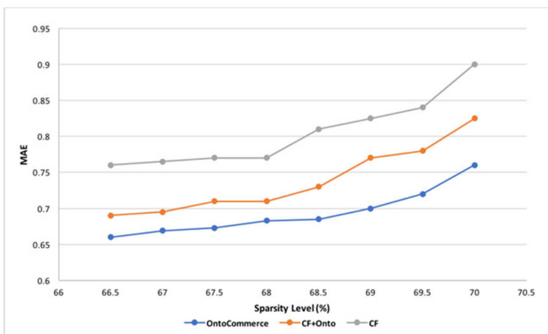

FIGURE 7. Assessment of prediction accuracy across various sparsity levels.

TABLE 4. A contingency table.

	Recommended	Not Recommended
Relevant	True Positive (tp)	False Negative(fn)
Irrelevant	False Positive(fp)	True Negative(tn)

3) QUANTIFYING PERFORMANCE

A large number of studies were done to test how well our proposed hybrid method, which uses collaborative filtering

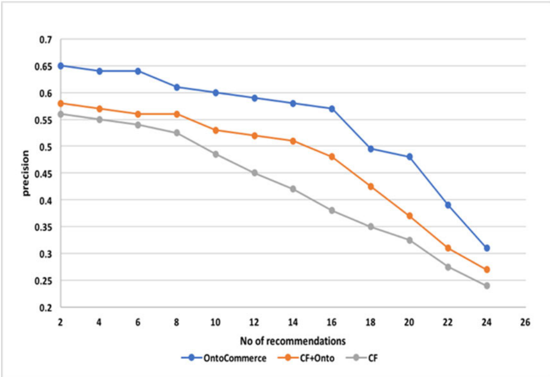

FIGURE 8. Precision evaluation of the algorithms' performance.

(CF), ontology (Onto), and sequential pattern mining (SPM), works. In this investigation, a comparison of the outcomes of CF+Onto, CF, and the proposed OntoCommerce was the primary objective. This review was done using normal measures, like accuracy, recall, and F-measure, which are usually employed in these kinds of studies. These measures have a big effect on the field of information search and are often used to judge how well recommender systems work. These review methods are often used by researchers in the field of recommender systems [8]. Accuracy and recall are measured by dividing ratings into two categories, "relevant" and "not relevant," using a binary scale. In our study, we rated products on a scale of 1-5, where ratings from 1 to 3 were categorized as "not relevant" or "not recommended", and ratings of 4-5 were considered "relevant" or "recommended".

This transformation allowed us to assess the precision and recall metrics using a contingency table, as depicted in Table 4 [6], [46]. Precision is a commonly used evaluation metric that quantifies the ratio of recommended products that align with the user's genuine interests. The calculation involves the division of the count of relevant products recommended by the system by the overall count of recommended products.

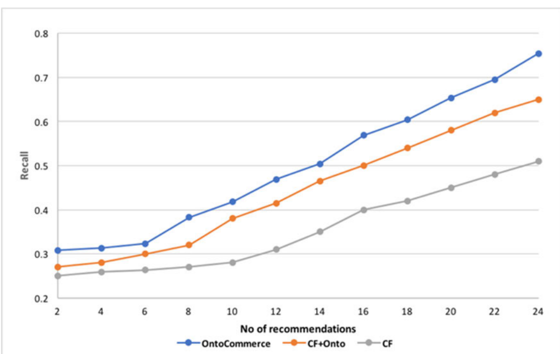

FIGURE 9. Recall evaluation of the algorithms' performance.

According to [6], we determined that a product was relevant if customer found it to be valuable. This exhaustive evaluation allowed us to gain a deeper comprehension of the usefulness of the hybrid algorithm and its capacity to accurately recommend suitable products to customers.

$$\text{Precision} = \frac{\text{correctly recommended products}}{\text{Total product recommendations}} = \frac{\text{tp}}{\text{tp} + \text{fp}} \tag{5}$$

The term "correctly recommended products" refers to the quantity of goods or services suggested by the system that are deemed valuable or relevant by the client. The phrase "Total recommended" states to the combined number of products that the system recommends to the customer. The evaluation of the effectiveness of the hybrid algorithm OntoCommerce implementation may be determined by analyzing the outcomes achieved, as shown in Figure 8. The comparison encompasses the two alternative methods, while the experiment is carried out using different quantities of recommended products.

The hybrid recommendation algorithm, which combines collaborative filtering (CF), ontology-based recommendation (Onto), and sequential pattern mining (SPM), exhibits superior accuracy performance when compared to other methods in comparison. This observation is supported by the findings presented in Figure 8, irrespective of the number of recommendations being considered. The hybrid recommendation algorithm, which combines collaborative filtering (CF), ontology-based recommendation (Onto), and sequential pattern mining (SPM), exhibits superior accuracy performance when compared to the other methods in comparison. This observation is supported by the findings presented in Figure 8, irrespective of the number of recommendations being considered. The metric evaluates the system's capacity to provide recommendations for all relevant things to the user while minimizing the omission of significant items. An item is deemed suggested when it aligns with the user's interests and preferences, as inferred from their previous interactions with the system.

$$\text{Recall} = \frac{\text{Correctly suggested items}}{\text{Items relevant to the user}} = \frac{\text{tp}}{\text{tp} + \text{fn}} \tag{6}$$

Figure 9 shows how well the suggested hybrid recommendation method (CF+Onto+SPM) does at recall compared to other methods in comparison. The experiment consisted of multiple iterations involving varying quantities of recommendations. Figure 9 shows that the method mentioned in this study does better than the other methods in comparison in terms of recall across different numbers of recommendation.

4) CUSTOMER SATISFACTION MEASURE

A survey of 100 consumers who made purchases on the e-commerce platform was conducted to gauge customer satisfaction with the provided recommendations. In prior research on recommender systems in e-commerce, "customer satisfaction" was identified as a crucial evaluation metric [2], [3]. The customers were surveyed about their level of satisfaction with the product recommendations generated by the system, with response options including "satisfied" and "not satisfied."

The percentage of consumers who were satisfied with each of the three evaluated recommendation systems is depicted in Figure 10. It is evident from the data presented that a substantial number of customers were satisfied. In the context of e-commerce, approximately 95% of participants were satisfied with the hybrid recommendation algorithm OntoCommerce recommendations. On the other hand, only 6% of those who participated thought the hybrid approach wasn't good enough. 78% of people were happy with the CF-Onto method and 60% were happy with the CF recommendation method.

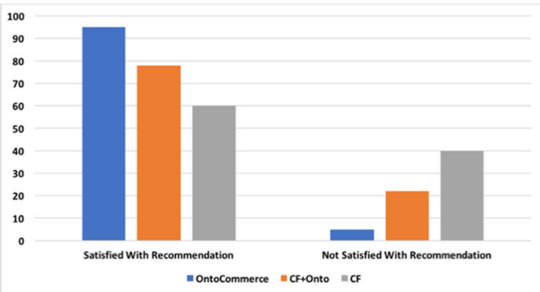

FIGURE 10. **Customer satisfaction with recommendations.**

D. DISCUSSION

The empirical results derived from experiments conducted in the domain of e-commerce offer compelling evidence supporting the superior performance of the hybrid algorithm OntoCommerce when compared to conventional recommendation algorithms, specifically collaborative filtering (CF) and collaborative filtering with ontology (CF+Onto). A significant advantage of the hybrid strategy lies in its strategic utilisation of ontology-based domain information to initialise client profiles prior to generating recommendations. This technique successfully deals the cold-start problem sometimes faced by traditional approaches like collaborative filtering (CF). By incorporating ontological domain knowledge into similarity computation and preference prediction, the hybrid approach effectively addresses the challenges of recommender systems lacking initial data.

Furthermore, the proposed methodology adeptly tackles the challenge of data sparsity through the utilisation of Sequential Pattern Mining (SPM). Utilizing customers' historical sequential access patterns extracted from weblogs provides insight into their resource preferences and enables accurate predictions of future resource selections, even in the absence of ratings. This dual mechanism not only improves the precision of recommendations, but also combats the sparsity issue and ensures robust performance.

Our unique methodology showcases the substantial contributions of both ontology and statistical parametric mapping (SPM) towards enhancing performance. This hybridization strategy leverages ontology to integrate nuanced customer characteristics such as topology and personal data, resulting in personalized recommendations tailored precisely to the preferences of each individual. The efficacy of the proposed method is rigorously assessed in our approach through the utilisation of mandated e-commerce assessment measures, including mean absolute error, precision, recall, and customer satisfaction.

Without a doubt, the results show that the hybrid algorithm is better in terms of accuracy, precision, and recall. Also, the overwhelming majority of consumers (95%) were pleased with the hybrid algorithm's recommendations (as depicted in Figure 10). Positive customer feedback confirms the hybrid method's efficacy and applicability in generating high-quality recommendations for products.

V. CONCLUSION

In this study, we introduce a novel hybrid recommendation system that combines the use of ontology with sequential pattern mining (SPM) techniques. The purpose of this system is to provide personalized product recommendations to clients within e-commerce applications. Our method utilizes ontology domain knowledge to capture information about customers and products, whereas SPM extracts historical sequential access patterns. The results obtained from the experiments demonstrate that our hybrid algorithm surpasses other comparable algorithms with regards to precision and performance. Furthermore, our method addresses the cold-start and data sparsity issues commonly encountered by traditional recommendation methods by utilizing ontology domain knowledge and SPM to make recommendations prior to the system gathering sufficient ratings. Our future endeavors will focus on refining our recommendation procedure through the incorporation of cutting-edge intelligent technologies from the field of deep learning. In general, our methodology presents a potentially viable resolution for enhancing the precision and efficacy of product recommendations within e-commerce settings.

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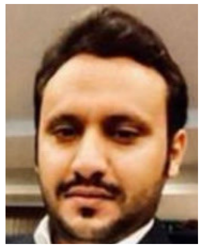

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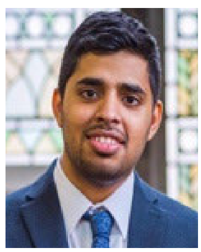

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