IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received 18 December 2023, accepted 5 February 2024, date of publication 13 February 2024, date of current version 27 February 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3365828

SURVEY

Exploring the Landscape of Hybrid Recommendation Systems in E-Commerce: A Systematic Literature Review

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This work was supported in part by the Swedish Knowledge Foundation as part of the Industry Graduate School for Data Intensive Applications (DIA), Linnaeus University (https://lnu.se/dia). The work of Ilir Jusufi was supported in part by the Knowledge Foundation, Sweden, through the project ''Rekryteringar 21, Universitetslektor i spelteknik'' under Contract 20210077.

ABSTRACT This article presents a systematic literature review on hybrid recommendation systems (HRS) in the e-commerce sector, a field characterized by constant innovation and rapid growth. As the complexity and volume of digital data increases, recommendation systems have become essential in guiding customers to services or products that align with their interests. However, the effectiveness of single-architecture recommendation algorithms is often limited by issues such as data sparsity, challenges in understanding user needs, and the cold start problem. Hybridization, which combines multiple algorithms in different methods, has emerged as a dominant solution to these limitations. This approach is utilized in various domains, including e-commerce, where it significantly improves user experience and sales. To capture the recent trends and advancements in HRS within e-commerce over the past six years, we review the state-of-the-art overview of HRS within e-commerce. This review meticulously evaluates existing research, addressing primary inquiries and presenting findings that contribute to evidence-based decision-making, understanding research gaps, and maintaining transparency. The review begins by establishing fundamental concepts, followed by detailed methodologies, findings from addressing the research questions, and exploration of critical aspects of HRS. In summarizing and incorporating existing research, this paper offers valuable insights for researchers and outlines potential avenues for future research, ultimately providing a comprehensive overview of the current state and prospects of HRS in e-commerce.

INDEX TERMS E-commerce, hybrid recommendation systems, recommendation systems, systematic literature review.

I. INTRODUCTION

The ever-increasing complexity and volume of available digital data has resulted in the creation of numerous recommendation systems [1], [2]. Recommendation systems aid businesses by directing their customers to relevant products or services believed to match their interests [3]. Various types of recommendation systems, like collaborative filtering, content-based, and knowledge-based recommendation systems are used in producing tailored recommendations for customers [4].

However, not all algorithms are suitable for every situation and they can also be ineffective due to their inherent limitations that can restrict their performance in unique

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

contexts. These limitations, although varying across algorithms, commonly revolve around challenges related to sparse data, issues with cold start problems, and the difficulty in accurately capturing customer preferences.

To tackle these challenges, hybridization has emerged as a powerful technique that combines various algorithms using different weighting approaches to overcome the weaknesses of individual algorithms [5]. Hybridization refers to the practice of integrating multiple algorithms and employing diverse weighting methods to mitigate the limitations associated with individual algorithms [6], [7]. It is employed in many fields like e-commerce, online streaming services, music recommendations, social media and more, consistently delivering favorable outcomes for business owners [8].

Recommendation systems have been an integral part of e-commerce, enhancing sales and user experience [3]. Notably, for companies such as Alibaba, Ebay and Amazon, recommender systems based on hybridization serve as a core component of their business model, exemplifying the significant impact and effectiveness of this approach [9], [10], [11]. These advantages have led business owners to invest in recommendation systems, while also inspiring researchers to undertake extensive studies in this field, particularly within the realm of e-commerce [8]. There are several research studies that are solely focused on hybrid recommendation systems (HRS) developed for or applicable to e-commerce.

Despite the abundance of individual research efforts [12], no systematic literature review specifically focusing on HRS in the e-commerce context exists to date. The specific reason for choosing the e-commerce domain is twofold. Firstly, the field of recommendation is experiencing rapid growth, mirroring the growth in the e-commerce sector itself. The user base of e-commerce platforms is expanding daily, contributing to substantial sales figures. Consequently, efficient recommendation algorithms are in high demand. Secondly, the e-commerce sector offers extensive opportunities for development and innovation in this context.

Considering these factors, we have undertaken a systematic literature review on HRS in e-commerce over the past six years. This time frame allows us to capture the most recent advancements and trends in the rapidly evolving field of recommendation systems. Our research objective is to provide a state-of-the-art literature review that serves as a valuable tool for summarizing, evaluating, and synthesizing existing research in this field. Such a review aids researchers interested in this domain by promoting evidence-based decision-making, enhancing the understanding of research gaps, minimizing bias, improving time efficiency, and maintaining transparency.

The remainder of the article is organized as follows. Section II introduces fundamental concepts in the domain of recommendation systems. Section III outlines the research method we follow in this review study. We also discuss various validity threats in Section IV. Section V presents findings as answers to our research questions defined in Section III. Section VI explores critical aspects of HRS, while Section VII discusses relevant studies from the literature and shows why this review study is required. We conclude the article in Section VIII with a high-level overview of our findings.

Our ultimate aim is to furnish a comprehensive overview of the current state of the HRS in e-commerce, providing valuable insights for researchers and identifying future research avenues.

II. BACKGROUND

In this section, we delve into the foundations of recommendation systems and introduce some prominent recommendation algorithms that form the basis of our discussion.

A. RECOMMENDATION SYSTEMS

A recommendation system is a framework that recommends products or services to users based on their previous purchases, interests, and other relevant data [13]. It is used in a wide range of industries like e-commerce, social media, multimedia streaming platforms, etc. [8]. Its major goal is to improve the user experience by offering tailored recommendations [14]. Recommendation systems also assist e-commerce business owners in generating traffic to their websites or other platforms and converting shoppers to customers [15]. In the following, we present several widely used recommendation algorithms.

1) Collaborative filtering: This recommendation algorithm analyzes user preferences, calculates user similarity, and predicts item recommendations by comparing their ratings with other users for the same item [16]. This recommendation system is commonly seen on platforms like Netflix and Amazon [17].
2) Content-based Recommendation System: User preferences, created by users, and item descriptions are utilized in content-based recommendation systems to produce recommendations. These systems employ filtering techniques to match items with candidates based on the items previously rated by the user and provide recommendations accordingly [16]. An example of this is the music streaming service Spotify. When you listen to songs and playlists, Spotify looks at the characteristics of the music you enjoy, such as genre, tempo, and artist [18].
3) Knowledge-based Recommendation System: In this recommendation system, products are recommended based on user requirements and preferences, relying on domain knowledge to satisfy the user. These types of recommendation systems do not require specific user information, as the decisions are independent of the individual [16]. A perfect example of this type of recommendation system is an online learning platform like Coursera. They consider the user's educational background, courses they have taken, and career goals, among other factors, to recommend courses that align with their objectives [19].

4) Typicality-based Recommendation System: User neighbors are identified using the typicality degree of user groups. Items are grouped into clusters, and user groups are formed based on the typicality degree. A typicality matrix of users is then built to measure user similarity and select the neighbors. The system predicts the rating that the user would give for an item by considering the ratings of neighbors for that specific item [16]. LinkedIn uses a typicality-based recommendation system for job suggestions [20].

For enterprises looking to scale, the benefits of a robust recommendation system are manifold, including increased sales and enhanced user experience. These advantages justify making an investment in a robust architectural recommendation system. However, several fundamental issues confront recommendation systems, including data sparsity, cold start challenges, lower accuracy, precision issues, information overload, and more [21], [22]. Implementing a single conventional algorithm to recommend products while accommodating evolving user behavior in the face of these challenges is quite demanding. To address the limitations of conventional algorithms like collaborative filtering and content-based filtering within such a complex environment, hybrid recommendation systems (HRS) are developed.

B. HYBRID RECOMMENDATION SYSTEM

A hybrid recommendation system (HRS) combines two or more algorithms to create recommendations that are more accurate, tailored, and aware of changing customer behavior. By harmoniously weaving together two or more techniques, it forges recommendations that not only boast remarkable accuracy but also possess the finesse to adapt seamlessly to the evolving preferences of customers. This dynamic approach ensures that the recommendations provided are not simply personalized but also remarkably in tune with the ever-transferring panorama of user behavior. The advantages of a hybrid recommendation system over traditional recommendations are manifold, and although only a select few have been discussed, they hold significant importance. Below, we discuss the key advantages of using an HRS.

1) ADVANTAGES OF HRS OVER TRADITIONAL RECOMMENDATION SYSTEM

1) *Enhanced Accuracy and Personalization*: Surpassing the limitations of the single RS, the HRS is capable of producing more accurate and tailored recommendations depending on the user's interests and preferences by combining several recommendation algorithms [23].
2) *Scalable and Flexible*: HRS is more scalable than the single RS as it is capable of accommodating a larger number of users and is also competent when it comes to flexibility, as it can produce recommendations understanding the changes in user behavior and application [24], [25].
3) *Improved Robustness*: As discussed, data sparsity, inconsistencies, and biases are the main concerns of a single RS, where it is incapable of producing accurate recommendations. HRS, on the other hand, can function robustly in this context and can also better manage changes in user preferences, user behavior, item properties, and other aspects [26].
4) *Wider Coverage*: Single recommendation systems have a limited recommendation space and can only recommend certain products, but HRS can transcend these limits and provide recommendations that are more diversified and wide-ranging [27].

These advantages are just a few reasons why researchers and e-commerce businesses have invested considerable time, effort, and resources in researching HRS. Recent advancements in accuracy, algorithm combinations, and adaptability are notable developments. Given the vast array of innovations and progress in this field, it can be challenging to keep up with the state of the art in HRS for academic purposes.

2) EVOLVING TRENDS AND FUTURE IMPLICATIONS

There has been an observed increase in accuracy, adaptability, and the use of algorithm combinations in recent advancements in HRS. To address challenges like data sparsity and the cold start problem, the trend is moving towards integrating deep learning with traditional algorithms such as collaborative filtering and content-based filtering, showing promising results. This evolution suggests that future HRS will lean more towards incorporating advanced AI and machine learning techniques, offering even more dynamic and personalized user experiences. To remain competitive and cater to the changing and diverse needs of users, these systems will become increasingly crucial in the continuously evolving field of e-commerce.

In this article, we present a systematic literature review to identify the most promising research in this area, aiming to keep up with the state of the art in HRS for academic and practical purposes.

III. RESEARCH METHOD

The methodology of this literature review strongly adheres to the guidelines provided by Kitchenham et al. [28]. The methodology consists of four definite phases: *Framing Research Questions*, *Search Strategy*, *Study Selection*, and *Data Synthesis* as shown in the figure 1.

1) In the first phase, Research Questions are formulated based on the research objective.
2) The second phase involves identifying relevant studies through appropriate databases and formulating search queries related to the research questions.
3) The third phase includes a comprehensive evaluation and selection procedure of research studies throughout various stages, which will be further elucidated.
4) Finally, in the last phase, data is aggregated and summarized, patterns and trends are identified, and

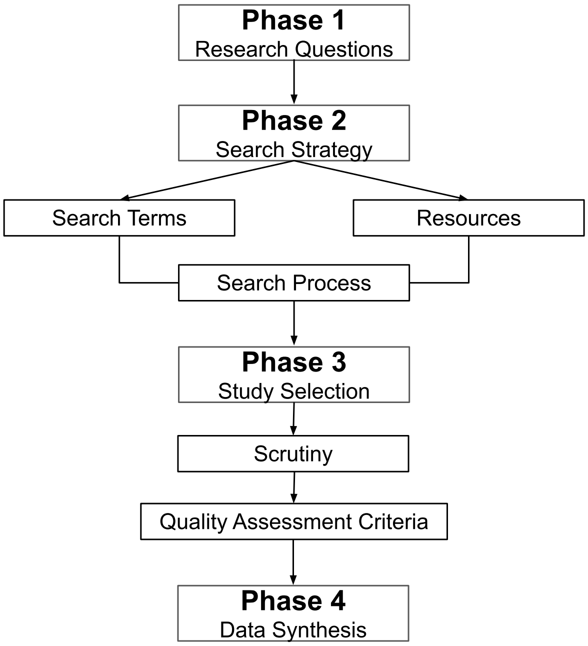

FIGURE 1. Our research method.

connections are made between the findings of individual studies.

A. RESEARCH QUESTIONS

As part of the literature review, a set of research questions has been formulated, which will be addressed and answered by the end of the paper. The research questions are as follows:

RQ1: How have approaches and models developed in the previous six years?

RQ2: What are the diverse algorithm combinations employed to construct hybrid recommendation systems?

RQ3: What challenges are authors striving to counter, and what is the suitable recommendation system combination to address those specific challenges?

B. SEARCH STRATEGY

In this systematic literature review, we followed a structured and systematic way to extract the relevant studies for inclusion in the review. The entire procedure is detailed as follows:

1) SEARCH TERMS

Search terms consist of keywords, phrases, and word combinations utilized in databases to locate relevant studies. Typically, these terms are formulated based on the research questions and may include abbreviations, synonyms, alternative spellings, and variations of keywords. To refine and broaden the search, these search terms are combined using Boolean operators like AND and OR. Therefore, we generated specific search terms by identifying the main terms from the research questions, finding their synonyms, and utilizing Boolean operators (AND, OR) to connect the main terms. The search query that we formulated to look for relevant articles is as follows:

(("hybrid recommendation system" OR "hybrid recommender system") AND ("e-commerce" OR "electronic commerce" OR "e-trade"))

2) RESOURCES

For this systematic literature review, we have comprehensively selected six electronic databases: Scopus, Springer, Science Direct, IEEE Explorer, Web of Science, and ACM Digital Library. We selected these databases due to their extensive coverage of academic journals, conference proceedings, and scholarly publications. We aim to gather a comprehensive and varied range of relevant literature for our review by effectively utilizing these databases.

3) SEARCH PROCESS

An extensive search on all six electronic databases is made using the search terms developed in the search process. A thorough exploration was done on the databases to find the relevant studies. The search results were then compiled and merged to create a comprehensive dataset for easy analysis. By doing this, we ensured that a wide range of studies from different sources are included in the review, enhancing the overall scope and reliability of the findings.

C. STUDY SELECTION

A thorough search using the queries was conducted, resulting in the extraction of 977 studies. The studies were sourced from a range of databases, where the majority comes from Springer (416) and Scopus (348). Web of Science contributed 80 studies, while Science Direct and IEEE Explorer accounted for 46 and 60 studies, respectively, and ACM comes with the lowest contribution of only 26 studies. Further, the studies are filtered based on the titles which also helped eliminate duplicates and resulted in 157 unique studies. Subsequently, we filtered the studies based on the abstract and the Inclusion and Exclusion criteria, resulting in a reduced count of 53 studies. Finally, a quality assessment was performed, leading to a final count of 48 studies meeting the inclusion criteria.

1) SCRUTINY

There are two phases of scrutinizing the studies; in the first phase, the duplicated studies are found and removed, and those that do not have suitable titles. After completing the first phase of scrutinizing, there are 157 studies left. The second phase of scrutinizing involves reading the abstract and removing the studies that do not fall under the inclusion criteria. After the second round of filtering, there are 53 studies that meet the inclusion criteria.

2) QUALITY ASSESSMENT

A set of quality assessment questions was developed, as shown in Table 2, to evaluate the credibility, completeness, and relevance of the selected studies extracted during the

TABLE 1. Inclusion and exclusion criteria.

Inclusion Criteria	Exclusion Criteria
1. Studies published in English	1. Studies not published in English.
2. Studies implementing Hybrid recommendation systems	2. Studies not implementing hybrid recommendation systems or implementing a single architecture algorithm.
3. The implementation must be in or suitable for e-commerce	3. Studies in fields other than or not suitable for e-commerce are excluded.
4. The paper must be published between 2018 and 2023	4. Studies published outside the years 2018-2023 are excluded.
5. Studies capable of addressing at least one research question	5. Studies with missing fields such as publication year, journal, etc., are excluded.

TABLE 2. Quality assessment questions.

	Questions
QA1	Is the research question clearly stated and aligned with the objective of the review?
QA2	Does the study provide a clear description of the research methodology employed?
QA3	Does the study provide a rigorous evaluation of the hybrid recommendation system, including the metrics used and the evaluation criteria?
QA4	Is the data collection process adequately described, including the data sources and data collection techniques used?
QA5	Does the study contribute novel insights or approaches to the field of hybrid recommendation systems in e-commerce?

second phase of scrutiny. Each question had three options: Yes, No, and Partly. These options were scored as follows: "Yes" = 1, "No" = 0, and "Partly" = 0.5. Each paper was assigned option values, and its quality score was calculated as the sum of these values. To ensure the reliability of the findings, only relevant studies with acceptable quality scores greater than 3.5 were considered as shown in Appendix B (Table 7). After conducting the quality assessment on the 53 studies obtained during the second phase of scrutiny, we identified 48 relevant studies, as detailed in Appendix A (Table 6). The quality assessment helped us ensure that the research questions were addressed with relevant studies.

D. DATA SYNTHESIS

The main objective of data synthesis is to summarize evidence from the 48 selected studies directly addressing our research questions. The idea is to synchronize the selected studies to improve clarity. Our data synthesis encompassed both qualitative and quantitative data. Quantitative data include counts of algorithms used, challenges, and the year of publication. On the other hand, qualitative data comprised insights into the types of algorithms, challenges, and metrics of various hybrid recommendation systems (HRS).

The process of synthesizing data was executed as follows, and we used Python visualization libraries such as Matplotlib[1] and Plotly[2] to plot the results:

- *RQ1: Evolution of Approaches and Models* – The data related to the evolution of hybrid recommendation system approaches are organized coherently. For this research question, I used a line graph to illustrate the distribution and popularity of different models and approaches over the past six years.
- *RQ2: Diversity of Employed Algorithms* – For this question, we delved into the combinations of algorithms used in HRS. To visualize the data of the combinations, we used Sankey diagrams,[3] showcasing the range of algorithms employed and their respective combinations.
- *RQ3: Addressing Challenges with Suitable Combinations* – Here, we delved into the challenges that authors were trying to solve using HRS. We used a heatmap to represent better the combination of algorithms and the count of challenges that they are trying to solve.

This data synthesis not only provided answers to our research questions but also portrayed a detailed picture of the current landscape of HRS in e-commerce. We were able to uncover trends, identify gaps, and suggest potential areas for future research and development.

IV. THREATS TO VALIDITY

In this section, we outline potential threats to the validity of our findings, adhering to the guidelines established in [28]. Five potential challenges could affect the validity of the study, and it is crucial to ensure the reliability and robustness of the research process.

A. INTERNAL VALIDITY

One possible threat to validity is the formulation of research questions. To mitigate this risk, we have formulated research questions that align with the research objectives. However, the specificity and directness of these questions are essential to ensure that the research maintains its focus.

B. EXTERNAL VALIDITY

We have followed a systematic and structured approach to gather relevant studies, which includes defining appropriate search terms and using Boolean operators to refine and broaden the search. While we have strived to keep this approach comprehensive, there is still a possibility of omitting compatible studies if our search terms are not sufficiently broad.

[1] https://matplotlib.org
[2] https://plotly.com
[3] https://developers.google.com/chart/interactive/docs/gallery/sankey

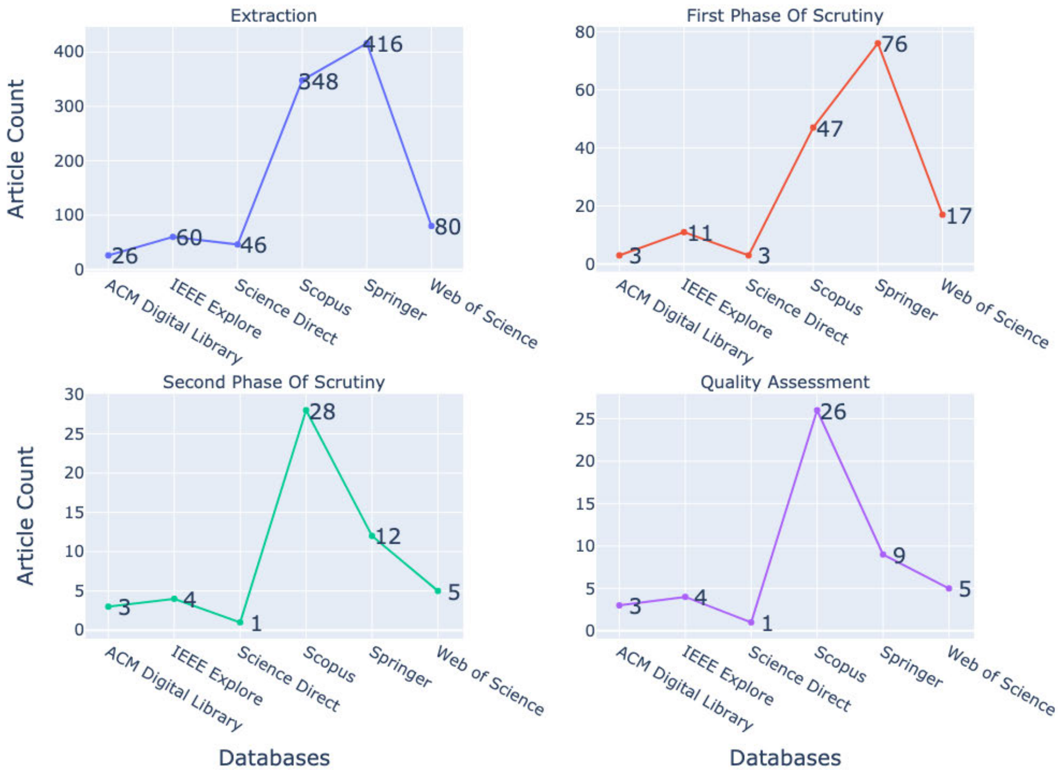

FIGURE 2. Phases of filtering along with the contributions of each electronic database.

C. CONSTRUCT VALIDITY

During the study selection phase, a considerable number of studies (977) were identified from various databases. To filter such a large number of studies, we employed a series of filters based on different criteria, resulting in a final count of 48 studies. There is always a possibility that some compatible studies may have been inadvertently excluded during the filtering process. The choice of databases may also have influenced this, potentially posing a completeness threat to the review.

D. CONCLUSION VALIDITY

There is a concern about bias in the quality assessment phase. There may be unintentional favoritism or bias against some studies based on personal preferences. Our review focuses on the past six years, and this limitation may restrict the applicability of our findings to a broader historical context.

To address these potential threats to validity, it is essential to regularly review and audit our methodology throughout the review process. Despite the few mentioned threats in the literature review, we have diligently addressed them to maintain the validity of our research. Our aim has been to refine the methodology to achieve the most comprehensive and dependable results.

V. RESULTS

In order to address the research question and visualize the findings, a systematic tracking of each paper was conducted. The 48 studies that passed the final phase of filtering were organized into a track, facilitating the visualization and analysis of the research questions. Below, we address the three research questions through qualitative discussions and visualizations.

RQ1: APPROACHES AND MODELS DEVELOPED IN THE PREVIOUS SIX YEARS?

In Figure 3, one algorithm emerges from the graph displaying a distinct trend: deep learning. The trend for deep learning algorithms demonstrates a significant increase in their usage over time. In contrast, there is no discernible trend for machine learning algorithms. Collaborative filtering, on the other hand, does not exhibit any specific trend; nonetheless, the graphs indicate its continued widespread usage, as none of the years show a decrease below the mean value of 50 percent. A decreasing trend was observed in Content-based filtering from the years 2017 to 2023, and then a sudden spike was seen in 2023. Despite this, no clear trend can be concluded. While some research terms both collaborative filtering and content-based filtering as machine learning algorithms, there are reasons why we did not encompass them under the umbrella of machine learning. The first reason is that the primary purpose of these algorithms is to provide recommendations, whereas traditional machine learning algorithms typically have broader applications such as regression, classification, clustering, etc. Secondly, there is no training phase for traditional collaborative filtering and content-based filtering, which is usually present in machine learning algorithms. A third and significant reason is that including them in the machine learning category would introduce substantial bias in the plots, making it difficult to discern the accurate trend of traditional machine learning algorithms. Given these considerations, we opted to plot collaborative filtering and content-based filtering separately.

Regarding "other algorithms and techniques," which represent unconventional approaches beyond regular algorithms, there is no clear trend observed in the graph. The usage of these algorithms in HRS in the field of e-commerce appears to be minimal. However, despite the low usage, noteworthy algorithms have been developed or used, which are elaborated in the following.

- *Association Rule Mining*: A technique that identifies interesting associations or relationships between items and is often used to find patterns in user behavior and suggest items that are frequently purchased or viewed together [29].
- *Attention Mechanism*: A mechanism inspired by human attention processes that focuses on specific parts of input data to improve the quality of recommendations by emphasizing important features or items [30].
- *Custom Algorithms*: Algorithms specifically designed for a particular recommendation system. These algorithms can be tailored to the unique characteristics and requirements of the system, potentially leading to better performance.
- *Demography-based Algorithms*: Algorithms that take demographic information of users (e.g., age, gender, location) into account to provide personalized recommendations [31].
- *Firefly*: A nature-inspired optimization algorithm used in recommendation systems to improve the accuracy of recommendations by simulating the behavior of fireflies in finding optimal solutions [32].
- *Global Pooling*: A technique that aggregates information from all users or items in a recommendation system to make predictions [33].
- *Heterogeneous-based Ranking*: An approach that combines multiple types of data sources (such as textual content, user profiles, and social network interactions) to generate recommendations [34], [35].
- *Knowledge Graph*: A representation of information as interconnected nodes, where each node represents a concept or entity and edges represent relationships between them. In recommendation systems, knowledge graphs enhance recommendations by considering semantic relationships [36], [37], [38].
- *Lexicon-based Analysis*: A method that involves analyzing the sentiment, tone, or meaning of textual content to make recommendations.
- *Linear Discriminant Analysis*: A technique used in recommendation systems to reduce the dimensionality of data while preserving the differences between classes [39].
- *Location-based Ranking*: A recommendation approach that utilizes the geographical location of users to suggest relevant items or services [40], [41].
- *Logical Language-based Rule Generation*: Creating recommendation rules using logical expressions and linguistic constructs. This approach enables recommendations based on user-specified conditions and rules [42].
- *Ontological Similarity*: A measure of similarity between items based on their semantic relationships and attributes. Ontological similarity enhances recommendations by considering the semantic meaning of items [43], [44], [45].
- *Popularity-based Recommendation*: A straightforward approach based on the assumption that items that are frequently chosen by others are likely to be of interest [46], [47].
- *Principal Component Analysis*: A dimensionality reduction technique used in recommendation systems to reduce noise and redundancy in data [48], [49].
- *TF-IDF*: Term Frequency-Inverse Document Frequency is a numerical representation of the importance of words in a document relative to a corpus [50], [51], [52].
- *Time-aware Model*: A recommendation model that considers the temporal aspect of user behavior, such as the time of interaction with items [53], [54].
- *Web Mining*: The process of extracting useful information from web data [55], [56], [57].

Interpretation of Results for RQ1: There are two major findings from the results of research question 1. The first one is an increase in the trend in the usage of deep learning algorithms. This spike in the usage of deep learning algorithms, especially in the field of recommendation systems, may be attributed to their ability to handle complex relationships and patterns within extensive datasets [58]. They are capable of capturing user preferences and behavior, making them highly effective in generating personalized and accurate recommendations [59]. The increase in the availability of computational power further facilitated the implementation of deep learning models in recommendation systems [60]. This direction aligns with the expansive path of Artificial Intelligence applications, where deep learning has shown remarkable success in various domains.

The second finding is the continued usage of collaborative filtering, despite being an older model, due to its effectiveness and simplicity [61]. Its intuitive approach, which leverages item or user similarity, has proven straightforward and robust, making it a dependable choice in scenarios where complex algorithms are not necessary or the data is sparse [62]. The contextual factors influencing these trends may include evolving technological advancements, user behaviors, and the enduring chase for improved recommendation accuracy.

In summary, the spike in deep learning algorithm usage is driven by its capacity to handle intricate patterns, while collaborative filtering persists due to its simplicity and effectiveness in capturing user preferences. It is important

FIGURE 3. Algorithms and year ratio.

to note that all conclusions are based on the analysis of the 48 studies obtained in the final phase of filtering.

Summary of RQ1: Identified an increasing trend in deep learning algorithms, the sustained usage of collaborative filtering, and irregular trends in content-based filtering.

RQ2: DIVERSE ALGORITHM COMBINATIONS TO CONSTRUCT HYBRID RECOMMENDATION SYSTEMS

If we examine Figure 4, we can observe the distribution of algorithms used in the studies. The nodes on the left side of the plot represent individual algorithms, indicating their frequency of utilization throughout the studies, regardless of their combos. Among the algorithms, collaborative filtering emerges as the most commonly used, accompanied by content-based filtering, machine learning, deep learning, and other algorithms.

In line with the definition of hybrid recommendation systems (HRS), which combine multiple algorithms to overcome their limitations, we also investigated the combination of algorithms in our research. Figure 4 displays the right-side nodes, representing the combination of algorithms along with their respective counts. Each algorithm is separated by a "+". Notably, the majority of the studies reviewed in the literature contain collaborative filtering, content-based filtering, and machine learning in their HRS. An interesting observation is that many studies preserve the aggregate of collaborative filtering and content-based filtering as a foundational base, enhancing it further with an additional algorithm to improve overall performance.

Interpretation of Results for RQ2: The limitations of individual recommendation techniques are addressed by the combination of collaborative filtering and content-based filtering, which stands as a strong foundational base for many recommendation systems [63]. Collaborative filtering may encounter challenges in scenarios with the cold start problem or data sparsity [61], whereas content-based filtering can overcome these challenges by providing recommendations based on item characteristics, even for a less-rated or new item [59]. By combining these two approaches, recommendation systems can benefit from the strengths of both methods, resulting in more accurate recommendations [63]. This combination is enhanced by incorporating additional algorithms into the hybrid recommendation system, as seen in Figure 4. This hybridization is an effective approach to handling the complexities and challenges of providing personalized recommendations. The growing practice of integrating these principles into recommendation systems demonstrates a deliberate effort to improve the quality and effectiveness of recommendations.

Summary of RQ2: Many reviewed studies in the literature commonly employ collaborative filtering and content-based filtering as a foundational base, often enhancing it with additional algorithms to improve overall performance.

RQ3: CHALLENGES AUTHORS STRIVING TO COUNTER AND SUITABLE RECOMMENDATION SYSTEM COMBINATION TO ADDRESS THOSE

Authors working in the e-commerce field encounter several challenges in dealing with HRS. In Figure 5, when observing the heatmap graph, the x-axis represents the combination of algorithms. There is one or more algorithm used in every

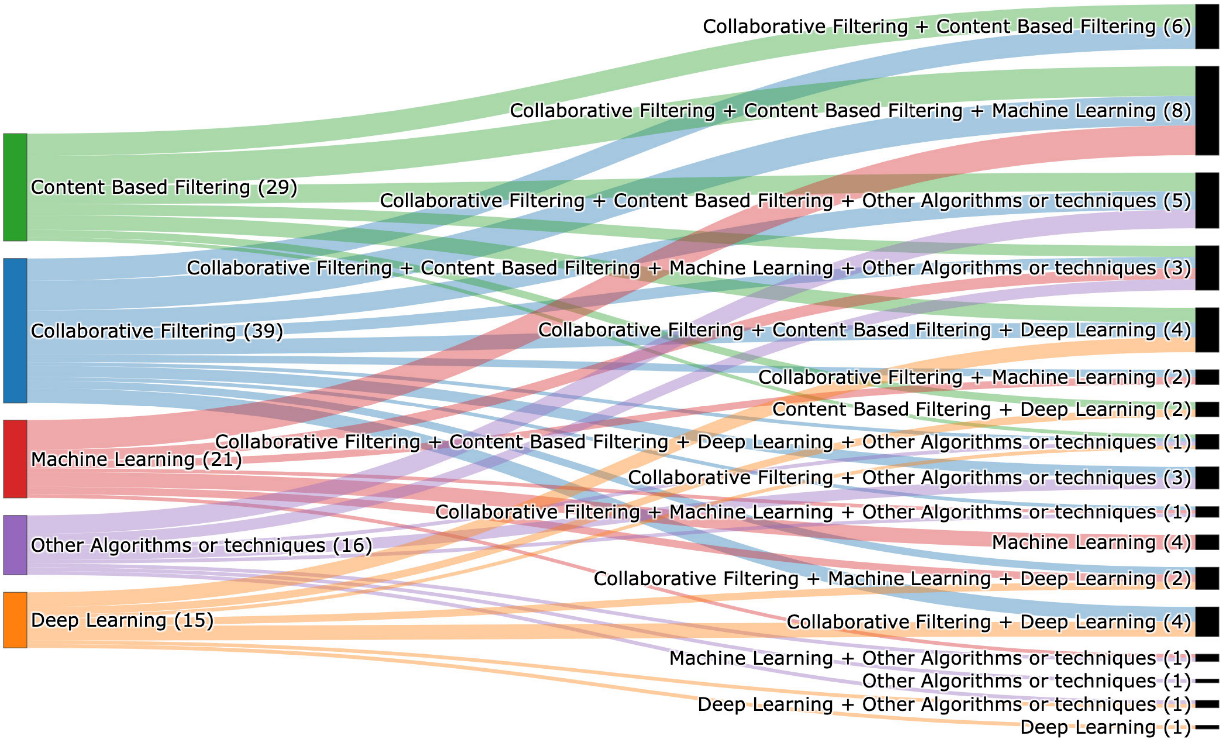

FIGURE 4. Algorithms and their combinations.

combination, and those algorithms are separated by the symbol "+". These combinations are employed to address the challenges, with the corresponding challenges depicted on the y-axis. In the heatmap, lower values are depicted with shades of deep blue, intermediate values with shades of green, and higher values with shades of yellow. It is obvious from the heatmap that the distinguished challenge authors are attempting to cope with is the "ineffectiveness of conventional algorithms." While addressing this particular undertaking, authors attempt to reevaluate current algorithms, identify their limitations, discuss why they are ineffective, and develop corresponding solutions.

The heatmap also indicates that the challenges of cold start and data sparsity are also frequently addressed. Following these are challenges related to enhancing accuracy, tracking changes in user interests, dealing with information overload, and improving precision. It is important to note that, aside from the challenges mentioned, a total of 19 distinct challenges were identified among the 48 analyzed articles. While we elaborate on all these challenges, we have chosen to graph a subset of them that authors more commonly attempt to solve. It is worth mentioning that each paper may focus on one or more of these challenges. It is worth mentioning that every paper might also recognize one or more of these challenges. As observed in Figure 4, the combination of collaborative filtering and content-based filtering serves as a constant base, with extra algorithms incorporated in most of the combinations. This pattern is again evident in Figure 5 as the majority of combinations have the base combination of collaborative filtering and content-based filtering. Some of the key challenges addressed include:

- *Accuracy*: Need for improved accuracy in recommendation algorithms.
- *Ineffectiveness of traditional algorithms*: Limitations of existing recommendation algorithms.
- *Data sparsity*: Insufficient data for accurate recommendations.
- *Information overload*: Challenges in handling a large amount of information.
- *Complexity of tracking user interests*: Challenges in understanding and predicting user preferences.
- *Complexity of tracking similar users*: Difficulties in identifying similar user profiles.
- *Precision*: Need for precise and personalized recommendations.
- *Cold start*: Difficulty in providing recommendations for new users or items.
- *Shortcomings of cost and time prediction*: Limitations in predicting cost and time using recommendation algorithms.
- *Targeting goods*: Challenges in targeting specific products to users.
- *Gray sheep*: Difficulties in handling users with unique preferences.
- *Long-tail items*: Challenges in recommending less popular or niche items.

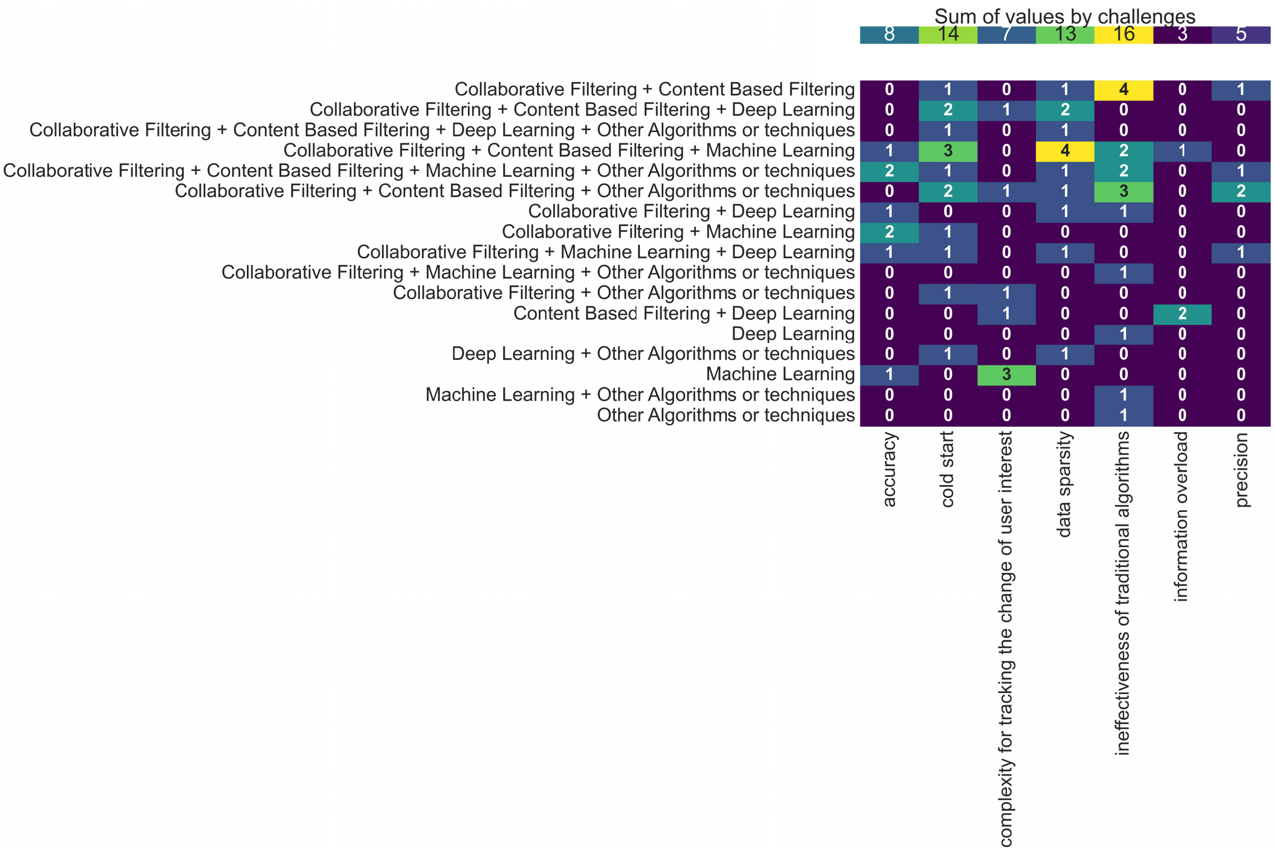

FIGURE 5. Challenges count.

- *Use of only direct user information*: Limitations of using only explicit user data for recommendations.
- *Limited algorithms*: Need for a wider range of recommendation algorithms.
- *Calculation of product ratings*: Challenges in determining product ratings using simple metrics.
- *Influence of social networks*: Incorporating social network influence in recommendations.
- *Ranking quality*: Need for improved quality in ranking recommendations.
- *Simplicity*: Challenges in providing simple yet effective recommendations.
- *Purchase conversion rates*: Difficulties in predicting purchase conversion rates.

However, to address all the major challenges, such as cold start, data sparsity, and ineffectiveness, the constant base of collaborative filtering and content-based filtering is augmented with additional algorithms. Figure 5 indicates that eighty percent of the combinations for overcoming these challenges rely on the constant base of collaborative filtering and content-based filtering.

Interpretation of Results for RQ3: The rationale behind the trend to address fundamental challenges can be attributed to the inherent strength of collaborative filtering and content-based filtering. These techniques provide robust functions efficiently handling challenges like cold start and data sparsity. Collaborative filtering excels in capturing user preferences through collaborative patterns, while content-based filtering addresses challenges associated with new or less-rated items. The synergy between these approaches creates a stable foundation, forming the cornerstone for subsequent enhancements [64]. The consistent reliance on collaborative filtering and content-based filtering reflects a strategic choice made by researchers to build upon a strong foundation while incorporating additional algorithms to fine-tune and optimize system performance [64], [65], [66], [67]. This strategic combination, as observed in the majority of instances, reflects an efficient approach to building recommendation systems that have successfully navigated a spectrum of challenges [66]. This trend not only mirrors the current state of recommendation system research but also suggests a standardized and effective methodology embraced by the academic community for overcoming key hurdles in the field.

Summary of RQ3: The research findings highlight a prevailing trend where eighty percent of recommendation system solutions for major challenges, including cold start and data sparsity, center around the consistent use of collaborative filtering and content-based filtering as a foundational base.

A. SUMMARY OF FINDINGS

In summary, our investigation reveals significant trends in the development of approaches and models for HRS in e-commerce over the past six years. The utilization of deep learning algorithms has displayed amazing growth. Despite this, collaborative filtering and content-based filtering algorithms stay extensively used. The maximum commonplace method for constructing hybrid recommendation structures includes combining collaborative filtering, content material-based filtering, and machine learning algorithms. This consistent base is augmented with additional algorithms to deal with essential challenges such as the cold start problem, obstacles of traditional algorithms, and data sparsity.

It is crucial to highlight that these conclusions are drawn from the evaluation of 48 studies acquired in the very last phase of filtering. The subsequent phase, "Analysis and Discussion," will delve into a comprehensive exploration of the findings, imparting deeper insights and implications.

VI. ANALYSIS AND DISCUSSION

In this section, we examine and discuss the results of the systematic literature review on hybrid recommendation systems (HRS) in e-commerce. We explore a number of factors of these systems, consisting of metrics, data sparsity, emerging algorithms and combinations, keywords, evaluation datasets and data types, and future directions. The following subsections offer targeted insights into these factors and highlight fascinating applications of these concepts.

A. TABLE OVERVIEW AND READER NAVIGATION GUIDE

Table 3 consolidates key findings and methodologies from various studies on hybrid recommendation systems. The table provides a comprehensive insights into the studies analyzed in this research. Additionally, it presents an overview of algorithm combinations, evaluation datasets, and challenges addressed making it easier for readers to navigate and delve deeper into papers based on the provided information.

B. METRICS

Developing a hybrid recommendation system is a complex task, and an important aspect of this is selecting suitable evaluation metrics for its performance. A wide range of metrics is used in various research works, including the commonly used ones like Root Mean Square Error, Mean Average Error, Precision, Recall, F1-score, Accuracy, and Hit Ratios are used. However, some newer evaluation metrics have been identified and deserve discussion and attention.

For illustration, Guia et al. [72] used different metrics to evaluate the quality of the recommended products for the users. For each product, an average over all score is created based on discrete factors that involve both users and products. The products that are with high overall scores are recommended to the users. For comparison purposes, they also developed a traditional collaborative filtering where the recommended products are generated from this algorithm. As all the products are given a score based on different factors now the score of recommended products by the hybrid recommendation system is compared with that of the recommended products by the collaborative filtering.

In another study outlined by Zaval et al. [107], two distinct metrics were employed: Hit Ratio and Normalized Discounted Cumulative Gain (NDCG). The Hit Ratio measures the percentage of recommendations that align with the user's actual preferences or actions, such as clicks, purchases, or interactions with the recommended items. NDCG, on the other hand, assesses the ranking quality by considering the relevance of recommended items and their position in the list. Interestingly, the authors of this study adapted these commonly used metrics in a unique way, with the Hit Ratio determining whether the item appears in the top-N recommendation list, and NDCG assigning higher scores to hits at the top. These metrics not only aid in evaluation but also play a role in ranking recommendations presented to the user.

Shanthi et al. [68] used various evaluation metrics, including Root Mean Square Error, Precision, and Recall. However, the authors introduced two distinctive metrics: Simplicity Score and Time (ms). The Simplicity Score evaluates the ease of understanding and implementing the recommendation system, while Time measures the system's efficiency in generating recommendations for users.

Shah et al. [106] employed several evaluation metrics, but two notable ones are Diversity and Personalization. Diversity assesses the dissimilarity among recommended products, with higher diversity generally resulting in greater user satisfaction. Personalization, on the other hand, measures the dissimilarity between the recommended products generated for different users, aiming to provide a tailored and aligned experience. A higher personalization score indicates a stronger alignment between the recommended product list and the specific tastes and preferences of individual users.

These evaluation metrics provide researchers and developers with valuable insights into the effectiveness, ranking, simplicity, time efficiency, user satisfaction, and personalized experience of HRS.

C. DATA SPARSITY

Data sparsity is one of the major challenges faced by recommendation systems, as illustrated in Figure 5. The sparsity within the data significantly contributes to decreased accuracy. The rationale for discussing the Data Sparsity challenge, despite other challenges like the cold start and ineffectiveness of traditional algorithms, lies in the deployment of specific algorithms by various researchers to tackle this challenge. While numerous studies propose that algorithm combinations can mitigate data sparsity, some researchers opt for dedicated algorithms to address this issue. Among them, we will delve deeper into three data sparsity handling techniques that stand out from the rest.

In the study by Bai et al. [71], data sparsity is a major challenge the authors aim to address. According to them, the

TABLE 3. Hybrid recommendation systems: approaches, datasets, and challenges.

Refs	Combination of Algorithms	Datasets Used for Evaluation	Types of Data Used	Challenges Addressed
[68]	Logical Language-Based Rule Generation (LLRG), Location-Based, and Heterogeneous-Based Approaches.	Multiple UCI Datasets	User ratings, user reviews, user demographics, product content, and purchase history.	Ineffectiveness of traditional algorithms.
[69]	Content-based recommendation algorithm, item-based collaborative filtering recommendation algorithm, and demography-based recommendation algorithm.	Offline experimental data, and Dangdang.	Purchase history, product content, and user demographics.	Ineffectiveness of traditional algorithms, precision.
[70]	Gaussian Mixture Models, Collaborative Filtering, and Content-Based Filtering.	Epinions, and Tencent.	User ratings and product content.	Data sparsity, information overload.
[71]	Collaborative filtering and clustering techniques.	Not specified.	User ratings, review tags, product content, and purchase history.	Data sparsity.
[72]	KNN for finding nearest neighbors and KNN to find nearest products.	Amazon Product Reviews and artificial data.	User ratings, user reviews, product content, and purchase history.	Accuracy.
[73]	Community detection algorithm, Word2Vec, and linear regression.	Yelp dataset.	User ratings, user reviews and purchase history.	Accuracy, influence of social networks.
[74]	User-based Collaborative Filtering, item-based Collaborative Filtering, and K-Means.	MovieLens.	User ratings, user reviews, product content, user demographics, and purchase history.	Ineffectiveness of traditional algorithms.
[75]	Time-aware preference model, Collaborative Filtering, and Content-Based Filtering.	Open University Learning Analytics, MovieLens, and Book Crossing.	User ratings, user reviews, product content, and feedback.	Cold start, ineffectiveness of traditional algorithms.
[76]	Preference Weight Calculation, Item Rating Prediction, and Common Weight.	MyOpinions.	User ratings, and product content.	Ineffectiveness of traditional algorithms, precision.
[77]	Genetic-based fuzzy F-means clustering, kernel fuzzy C-means algorithm, Genetic kernel fuzzy C-means algorithm, and probabilistic neural network.	Not specified.	User ratings, user reviews, and weblogs.	Complexity for tracking the change of user interest.
[78]	User-item rating matrix and demographic similarities.	MovieLens.	User ratings, and user demographics.	Cold start.
[79]	Combines features of content-based filtering and the robustness of matrix factorization using an incremental algorithm.	MovieLens.	User ratings and product content.	Cold start, data sparsity.
[80]	Collaborative Filtering with Time Variance algorithm and Content-based filtering with winnow algorithm.	Million Song and MovieLens.	User ratings, and product content.	Accuracy.
[81]	Collaborative Filtering, XGBoost Classification Method, Convolution Neural Network improved network with Attention Mechanism.	Amazon product dataset.	User ratings, user reviews, and product content.	Cold start, data sparsity, long-tail items.
[82]	Neural networks and collaborative filtering	Amazon product data	User rating, user review, and product content	Ineffectiveness of traditional algorithms
[83]	Setup 1: Utilizes fuzzy ART to cluster users based on ratings and product content. Setup 2: Tailored for new users, integrates their information with ratings.	MovieLens	User rating, product content, user demographics, and purchase history	Information overload
[66]	Collaborative filtering and FireFly with Weighted CrowSearch Algorithm (FF-WCSA)	Amazon reviews	User rating, user review, product content, user demographics, and purchase history	Data sparsity, complexity for tracking the change of user interest
[84]	Gated graph neural network, attention mechanisms, collaborative filtering, session memory, attention-weighted information fusion	Yoochoose and Diginetica	Click events	Purchase conversion rates
[85]	Content-based filtering, collaborative filtering, and linear discriminate analysis, principal component analysis, and adaptive network-based fuzzy inference system	Last.FM, and Book-Crossing	User rating, and user demographics	Cold start, data sparsity, ineffectiveness of traditional algorithms, accuracy, precision, ranking quality
[86]	Content-based filtering, collaborative filtering, K-nearest neighbors, gray distance-based partitional clustering, and hierarchical clustering	The Movies and Netflix	User rating, product content, and purchase history	Accuracy and ineffectiveness of traditional algorithms
[87]	Content-based filtering, collaborative filtering, and bidirectional encoder representations from transformers	Amazon fine foods ratings and Amazon movie ratings	User rating, user review, and product content	Cold start and data sparsity
[88]	Density-based spatial clustering of applications with noise and collaborative filtering	MovieLens	User rating, and product content	Ineffectiveness of traditional algorithms
[89]	Content-based filtering and collaborative filtering	UCSD's Julian McAuley	User rating and product content	Cold start, ineffectiveness of traditional algorithms

TABLE 3. ***(Continued.)*** **Hybrid recommendation systems: approaches, datasets, and challenges.**

Refs	Combination of Algorithms	Datasets Used for Evaluation	Types of Data Used	Challenges Addressed
[90]	Collaborative filtering based on K nearest neighbors and association rule based	MSWeb, and CourseRegistration	User rating	Ineffectiveness of traditional algorithms
[91]	Content-based filtering and collaborative filtering	Artificial data	Product content	Ineffectiveness of traditional algorithms
[92]	Content-based filtering, collaborative filtering, and association rule mining	MovieLens	User rating, product and content	Gray sheep
[93]	Collaborative filtering, conditional variational autoencoder, and recurrent neural network	Movielens , and Amazon women's clothing dataset	User rating, product content, and product images	Accuracy
[94]	Content-based filtering and collaborative filtering	MovieLens	User rating, and product content	Cold start
[7]	A number of self-generated formulae for determining "influence features" that are further used to produce recommendations	Not mentioned	Purchase history	Complexity for tracking the change of user interest
[95]	Content-based filtering and collaborative filtering	Movielens	User rating, product content, user demographics and purchase history	Targeted promotion of goods
[96]	K-means and Funk-Singular Value Decomposition	Ali Cloud Tianchi	User rating	Cold start, accuracy
[97]	Matrix factorization, generalized matrix factorization, multi-layer perceptron, and deep neural recommender networks	MovieLens and OPUS	User rating, product content, user demographics, and purchase history	Data sparsity, complexity for tracking the change of user interest, cold start
[98]	Content-based filtering and collaborative filtering	MovieLens	User rating, product content, surveys, and purchase history	Cold start and precision
[99]	Content-based filtering and collaborative filtering	Last.fm	User rating, user demographics, and product content	Ineffectiveness of traditional algorithms
[100]	Developed a completely new set of algorithms based on machine learning techniques and combined for producing recommendations	Artificial Data	User rating, user review, product content, purchase history	Complexity for tracking the change of user interest
[101]	Content-based filtering, collaborative filtering, and AlexNet	Amazon review dataset	User rating, user review, product content, and images rated by users	Data sparsity
[59]	Content-based filtering and multilayer perceptron	MovieLens	Product content and user demographics	Complexity for tracking the change of user interest, information overload
[102]	Autoencoder recommendation constructor and common dimension projector	Million Song	Product content and song heard history	Cold start
[103]	Preference propagation, recommendation module, cross and compress unit, and knowledge graph embedding module	MovieLens, Book Crossing, and Last.FM	Product content, user demographics, and purchase history	Cold start, data sparsity
[104]	Random forest, neural networks, support vector machines, k-nearest neighbors, and naive Bayes	MovieLens	User rating, user review, product content, user demographics, and watch history	Complexity for tracking the change of user interest
[105]	Content-based filtering, collaborative filtering, and several distance measures and deep learning algorithms used in four different setups	Amazon product data	User rating, product content, user demographics, purchase history, and surveys	Use of only direct user information, limited algorithms, calculation of product rates by the simplest metrics
[106]	Content-based filtering (cascade approach), singular vector decomposition, and collaborative filtering	The Movies	User rating and product content	Data sparsity
[107]	Collaborative filtering item-based algorithm, collaborative filtering user-based algorithm, log-likelihood similarity, and neural collaborative filtering	Not mentioned	Feedback, user rating, and product content	Data sparsity, complexity for tracking similar users
[108]	Collaborative filtering and content filtering are integrated with weighing fusion technique and web mining techniques to track user behaviour	MovieLens	User rating, product content, and user demographics	Ineffectiveness of traditional algorithms
[109]	Collaborative filtering and graph-based algorithms	The Movies	User rating, product content, and user demographics	Simplicity
[110]	K-nearest neighbors and singular vector decomposition	Not mentioned	User rating	Ineffectiveness of traditional algorithms
[111]	Collaborative filtering, semantic similarity, neural networks, and parallel mini-batch gradient descent	Book Crossing Dataset and Amazon's movie dataset	User rating	Accuracy and precision
[112]	Multilayer perceptron, autoencoders, and word2vec	Goodreads	User rating and user reviews	Ineffectiveness of traditional algorithms

primary cause of data sparsity arises from users providing reviews only when they are genuinely interested in a product. To tackle this issue, the authors utilize user information and item metadata. This information contributes to a feature matrix, which, in turn, reduces data sparsity. In their approach, items are initially grouped into clusters based on their attributes. For items with limited rating data, feature supplementation methods predict ratings using neighboring items within the same clusters. The authors introduce a technique named "Integrating Similarity," which considers both item clustering and user behavior. This involves a user-item category tendency matrix based on user preferences for item categories. This matrix calculates the integrating similarity between users, enabling recommendations within the same cluster and helping overcome data sparsity. Additionally, the authors construct a user-item category tendency matrix that captures user interactions with various item categories. Integrating this matrix into the recommendation process further aids in handling data sparsity. To summarize, the authors employ a combination of techniques, including item clustering, feature supplementation, integrating similarity calculation, and user clustering.

Yang and Fan [69] aimed to address data sparsity through two distinct phases of implementing the hybrid recommendation system. This study integrates three diverse recommendation approaches: content-based recommendation, item-based collaborative filtering recommendation, and demography-based recommendation. In the first phase of dealing with data sparsity, specifically in item-based collaborative filtering, the authors recognized the impact of hyperactive users on recommendations. To mitigate their potential distortion, they introduced an innovative approach to similarity calculation. By incorporating a logarithmic transformation, they reduced the undue influence of these users on similarity metrics, thus enhancing the accuracy of the algorithm. In the second phase, within the context of demographic-based recommendations, the challenge of data sparsity was addressed by introducing a parameter alpha. This parameter helped alleviate potential issues stemming from items purchased by a limited number of users. As a result, this approach led to more balanced and accurate recommendations. Although these adjustments may seem minor within the existing algorithms for handling data sparsity, they prove to be both simple and effective in practical implementation.

Manohar et al. [77], to form a hybrid recommendation system, the authors tried to combine the clustering algorithm called Genetic Algorithm-Based Fuzzy C-Means (GAFCM) with Probabilistic Neural Network (PNN) and Kernel Fuzzy C-Means (KFCM), along with feature extraction techniques. They aimed to solve data sparsity by incorporating GAFCM to form user clusters based on access behavior. GAFCM can adapt to changes in user behavior and engagement, helping to create more accurate user clusters even when there is data sparsity. This enhances the quality of user profiling and subsequent product recommendations.

We also tried to provide a list of the algorithms used to handle data sparsity.

- *Gaussian mixture model*: A probabilistic model that represents a mixture of multiple Gaussian distributions to describe complex data patterns [113], [114].
- *Matrix factorization*: A technique used in recommendation systems to decompose a user-item interaction matrix into matrices that capture latent factors for users and items [49], [115].
- *Novel algorithm*: A newly developed algorithm or method that introduces innovative approaches to solve a specific problem.
- *ALS Algorithm*: Alternating Least Squares Algorithm, a matrix factorization method commonly used in collaborative filtering for recommendation systems [116].
- *Group Mutual Recommendation*: Group Mutual Recommendation, a method that provides recommendations based on the preferences of groups of users [117].
- *Group User Clustering*: Group User Clustering, a technique that groups users with similar preferences to improve recommendation accuracy [118].
- *Association rules mining-based algorithm*: A recommendation method that discovers associations or patterns in user behavior data to make recommendations [119], [120], [121], [122].
- *Bayesian network model*: A probabilistic graphical model that represents the probabilistic relationships among a set of variables [123], [124].
- *Genetic-based fuzzy clustering algorithm*: A clustering algorithm that combines genetic algorithms and fuzzy clustering to group data points with uncertain memberships [125].
- *Singular Value Decomposition*: A matrix factorization technique used to reduce the dimensionality of a matrix and capture latent features [126], [127].
- *Fusion layer*: A component in recommendation systems that combines information from multiple sources to make accurate recommendations [128].
- *Sparsity Minimizing Collaborative Filtering*: A collaborative filtering approach to reduce data sparsity issues in recommendation systems [129].
- *Sparsity Diminishing Collaborative Filtering*: A collaborative filtering technique that addresses data sparsity by taking into account the density of user-item interactions [130].

Addressing data sparsity in recommendation systems is crucial for accuracy. Researchers employ diverse strategies, such as user-item matrices, innovative algorithms, and demographic-based adjustments. These approaches effectively mitigate data sparsity and enhance recommendation quality.

D. EMERGING ALGORITHMS AND COMBINATIONS

The literature review reveals the emergence of new algorithms and combinations for HRS in e-commerce. For instance, the study by Shanthi et al. [68] combines location-based and heterogeneous domain-based methods to provide better-tailored product recommendations. The incorporation of location-based recommendations guarantees that users receive recommendations aligned with their regional preferences, encompassing localized trends and preferences. Conversely, the heterogeneous domain-based recommendations factor in the complexities of diverse product categories and domains, acknowledging that user preferences can change across different domains. Furthermore, an intriguing aspect of this hybrid model is its superior processing time, accuracy, and ease of assessment compared to traditional algorithms. This model can be aptly labeled as a straightforward, time-efficient, and effective approach for implementing hybrid recommendations.

Ming et al. [81] attempt to build a hybrid recommendation system by combining collaborative filtering, XGBoost classification, IA-CN model, and the FireFly with Weighted CrowSearch Algorithm. The algorithm that requires attention in this study is the FireFly with Weighted CrowSearch Algorithm. It is a fusion of the Firefly algorithm and the weighted CrowSearch algorithm, harnessing the extensive search space of Fireflies and the collaborative nature of CrowSearch to enhance accuracy and efficiency in generating recommendations.

Patro et al. [85] employ collaborative filtering, content-based filtering, and the Adaptive Neuro-Fuzzy Inference System to create a hybrid recommendation system. The Adaptive Neuro-Fuzzy Inference System warrants discussion as it effectively handles complex data patterns by combining neural networks and fuzzy logic. This improves the effectiveness and accuracy of the hybrid recommendation system. The algorithm creates a predictive mechanism considering user preferences for personalized recommendations, addressing the limitations of traditional approaches.

The usage of the Bidirectional Encoder Representations from Transformers-Multi Content-Adaptive Recurrent Unit-Global Pooling-SoftMax Activation Function (BERT-MCARU-GP-SoftMax) model in Karn et al. [87] also demands attention. Collaborative filtering and content-based filtering are combined, integrating the BERT-MCARU-GP-SoftMax model with an attention mechanism to determine user review sentiment polarity. A sentiment-enhanced user matrix is integrated into the hybrid recommendation model, enhancing personalization and accuracy.

Li et al. [84] combine several algorithms, including collaborative filtering, dwell-time-based attention, attention mechanisms, and Gated Graph Neural Networks (GGNN), in a hybrid recommendation framework. Two algorithms requiring attention are Dwell-Time Information Utilization and GGNN. Dwell time refers to the time spent by a user within a session, which the study utilizes to enhance recommendations. GGNNs capture complex dependencies between items in sequential data, particularly modeling transition relationships between items within a session.

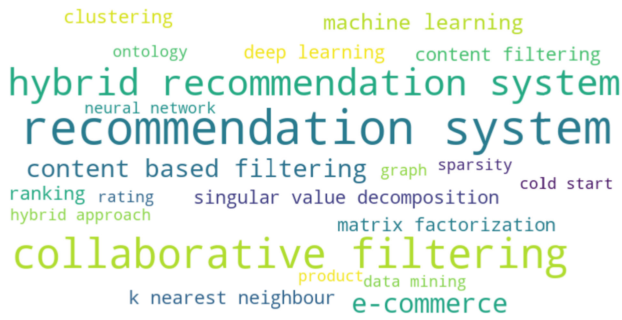

FIGURE 6. **Keywords from reviewed studies.**

The reviewed literature showcases emerging algorithms and combinations for e-commerce hybrid recommendations. These innovations enhance personalization and accuracy, whether through sentiment analysis like BERT-MCARU-GP-SoftMax, complex data handling using an Adaptive Neuro-Fuzzy Inference System, or dynamic session modeling with GGNNs. These advancements mark a significant step forward in effective HRS.

E. UNVEILING KEYWORDS FROM REVIEWED STUDIES

Keywords play a crucial role in any academic study as they act as the backbone that connects researchers' content to the potential audience. These carefully selected terms serve as guideposts, directing researchers and curious readers closer to the heart of the study. In this section, we delve into the importance of keywords that have emerged from the collective body of research. By identifying the prominence and frequency of these keywords across different studies, we gain acumen into the common trends, techniques, and areas of priority within the domain. We followed a meticulous process for collecting and preprocessing the keywords, involving identification, extraction, and curation. All these curated keywords are transformed into a broad word cloud, a visual representation that encapsulates the broader themes underlying the diverse research efforts. While there are a total of 131 keywords after curation, where we are not going to discuss all the keywords here, we attempted to visually represent the keywords commonly used in the studies. We plotted only the keywords whose count is more than 2. This plot provides an opportunity for a quick yet insightful overview of the most resonant concepts, showcasing the interplay between factors. Our analysis of recurring keywords, depicted visually, unveils predominant concepts. The term "recommendation system" stands out, followed by "collaborative filtering" and "hybrid recommendation system."

Here is the corrected text with some grammatical improvements:

F. EVALUATION DATASETS AND DATA TYPES

To evaluate the performance of HRS, researchers utilized various datasets in their experiments. Some commonly

TABLE 4. Frequently used datasets for evaluation.

Dataset	Number of Usages
MovieLens	16
Amazon	8
Book Crossing	4
Artificial Data	3
The Movies	3
Million Song	2
Last.fm	3

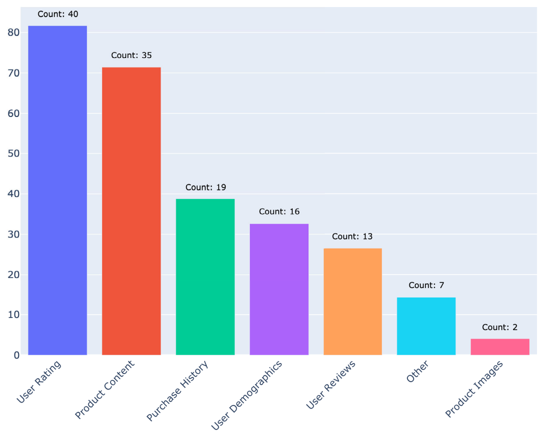

FIGURE 7. Data usage.

employed datasets include MovieLens, Amazon, Book Crossing, and The Movies. In total, there are 23 different datasets that researchers collectively used. Some researchers employed one or more datasets to evaluate their hybrid recommendation system. Table 4 displays the most frequently used datasets along with their counts. These datasets provide diverse user-item interaction data, item attributes, and contextual information, enabling researchers to assess the effectiveness and generalizability of their proposed algorithms and approaches.

Additionally, to showcase the various types of data used to construct recommendation systems, a visual presentation is depicted in Figure 7. The x-axis represents the data type, while the y-axis represents the percentage of studies utilizing a particular data type. Above each bar, the count of studies using that specific type is indicated. "User Rating" and "Product Content" are the most commonly used types, with percentages of 81 and 71, respectively.

The category "Other" encompasses data types beyond the regular ones. The other data types are provided in Table 5. Among all the types of data, web-logs data requires discussion. Manohar et al. [77], constructed a web log file using user sessions. They involved 1,000 users participating on 20 online purchasing websites across 25 domains, categorized by product categories. This data was then employed for evaluating their model.

The utilization of these diverse datasets empowers researchers to meticulously assess the effectiveness of their HRS. The richness and distinctiveness of the datasets contribute to the comprehensive improvement of HRS, facilitating the advancement of more robust and versatile algorithms. Researchers can also continue to refine their approaches, ultimately advancing the field of HRS in the ever-changing landscape of e-commerce.

G. FUTURE DIRECTIONS

In light of the systematic review performed in this study, the contemporary landscape of HRS within the realm of e-commerce has been comprehensively explored, revealing several promising avenues for future research and innovation. As generation advances, opportunities stand up to refine recommendation systems' overall performance, accuracy, and user revel. Future research could explore novel hybrid approaches integrating reinforcement learning, graph-based models, and adversarial networks to capture complicated users' behaviors and preferences. Additionally, the opacity of certain recommendation algorithms increases issues about explainability and transparency. Crafting hybrid models that provide accurate predictions regarding comprehensible factors fosters users' faith. Integrating multimodal data fusion strategies into hybrid structures should yield a more holistic know-how of user preferences and object attributes within the context of present-day e-commerce platforms. Further, as users interact throughout numerous devices, locations, and contexts, hybrid models that adapt dynamically to transferring contexts and offer tailor-made recommendations based on precise circumstances could be evolved.

Addressing biases and promoting fairness is an ongoing venture; future studies ought to contain hybrid models that uphold ethical standards and mitigate biases in recommendations. Integrating user feedback and interactions directly into the recommendation method complements system performance; hybrid models involving customers in refining recommendations through interactive interfaces could be explored. The establishment of standardized evaluation metrics and benchmarks for HRS holds large importance. Looking ahead, future research could embody complete assessment frameworks that keep in mind factors like diversity, novelty, and user engagement. In precis, even as this systematic review imparts a radical expertise in the contemporary panorama, the area of HRS within the e-commerce realm is properly organized for innovation and development, contributing to the improvement of stronger, tailored, and user-focused recommendation systems that increase the e-commerce journey for all stakeholders.

In conclusion, the analysis and discussion of metrics, data sparsity, emerging algorithms and combinations, keywords, evaluation datasets and data types, and future directions provide valuable insights into HRS's current state and potential advancements in e-commerce. These findings contribute to understanding effective recommendation techniques, address challenges in data sparsity, highlight emerging algorithms, and guide future research in this dynamic field.

VII. RELATED WORK

There have been several systematic literature reviews conducted in the domain of recommendation systems [12],

TABLE 5. Types of data and explanations.

Data Type	Explanation
Feedback	Data collected from users providing opinions, ratings, or reviews about products, services, or experiences.
Interactions with Products	Records of how users engage with products, such as clicks, views, purchases, and adding items to carts.
Weblogs	Data from server logs capturing user activities on websites, including page visits, clicks, navigation paths, and timestamps.
Survey	Data collected through structured questionnaires or interviews, often designed to gather specific information from participants.

[131], [132], [133]. These systematic literature reviews play a critical role in the know-how of the sector, offering precious insights and context for the prevailing studies. Although there are a few literature reviews on hybrid recommendation systems (HRS), there are very few or none that have performed a systematic literature review on HRS in the specific domain of e-commerce. We tried to find relevant works similar to ours and provided a summary of the relevant works below.

Ccano et al. [12] provide a state-of-the-art review of HRS, covering a decade-long period up to 2016. This literature review claims to be the first quantitative work solely dedicated to HRS. It aims to address relevant challenges while offering insight into recommendation algorithms and associated data mining techniques used to tackle these challenges. HRS are generally categorized into several types, and the authors of this review attempted to classify them based on these categories. They observed that collaborative filtering served as the foundation, often combined with various techniques in a weighted manner. The primary challenges identified in the review are cold start and data sparsity. However, the authors also recognized emerging challenges such as adapting to changing user contexts, evolving user preferences, and providing cross-domain recommendations. The widely used datasets for testing are often related to movies. Accuracy metrics dominate the evaluation process, but the authors suggest a need for the development of new evaluation metrics to enhance testing procedures.

Zhang et al. [131] state that the use of deep learning has significantly increased, offering the potential to address various challenges in web applications, including recommendation systems. Therefore, the research aims to provide a comprehensive overview of recent efforts in deep learning-based recommendation systems. This includes summarizing existing research, highlighting challenges, and suggesting future directions. Since few literature reviews focused on deep learning in recommendation systems, the authors conducted a systematic literature review to fill this gap. The review encompassed 100 relevant studies. In conclusion, this survey contributes to organizing and categorizing existing work in this field. It offers an overview of the state of the art, identifies emerging trends, and highlights challenges and open issues in deep learning-based recommendation systems.

There have been several literature reviews conducted in the field of recommendation systems, but Alamdari et al. [132] holds a special place in the related work. It sticks out as it undertook an extensive systematic literature review focused particularly on Recommendation Systems inside the e-commerce domain. This review affords a comprehensive overview of recommendation systems in e-commerce, encompassing numerous algorithms, strategies, and implementations. The authors also delve into the prominent algorithms, making it easier for readers to navigate the literature review. The survey is designed to achieve three objectives: investigate the strengths and weaknesses of conventional techniques used in the selected studies, identify the challenges and propose answers, and suggest avenues for improving the accuracy and capability of recommendation systems in e-commerce.

The systems termed Value-Aware Recommendation Systems (VARS) are gaining increasing attention due to their capability to optimize economic value for organizations in the commercial sector. De et al. [133] note that this rise in attention has piqued the authors' interest, leading to the performance of a systematic literature review on Value-Aware Recommendation Systems. This systematic literature review aims to explore the realm of VARS, including key algorithms, optimized cost categories, an examination of their applications, and commonly used datasets. The review follows the PRISM guidelines, shedding light on the limitations of VARS approaches and charting the course for future research. It strives to address notable existing gaps in VARS and proudly claims to be the first literature review exclusively focused on Value-Aware Recommendation Systems. This uniqueness enhances the review's significance in understanding the potential of this emerging field.

These reviews help researchers offer valuable insights as they are essential resources in the realm of recommendation systems. While no literature review focused on HRS in the e-commerce domain, which could provide more insights to researchers in the e-commerce domain, our goal is to bridge this gap of not having a literature-relevant review specific to HRS in e-commerce.

VIII. CONCLUSION

This review study offers a comprehensive overview of research on hybrid recommendation systems (HRS) within

TABLE 6. Publication details of reviewed studies.

Publication Type	Year	Publication Name	Refs
Article	2018	A Personalized Hybrid Recommendation Procedure for Internet Shopping Support	[68]
Article	2018	A hybrid recommendation algorithm–based intelligent business recommendation system	[69]
Article	2018	A hybrid recommender system for Gaussian mixture model and enhanced social matrix factorization technology based on multiple interests	[70]
Article	2019	A Hybrid Two-Phase Recommendation for Group-Buying E-commerce Applications	[71]
Article	2019	A hybrid ontology-based recommendation system in e-commerce	[72]
Article	2019	Recommendation Based on Review Texts and Social Communities: A Hybrid Model	[73]
Article	2020	A hybrid recommendation system with many-objective evolutionary algorithm	[74]
Article	2020	A novel time-aware hybrid recommendation scheme combining user feedback and collaborative filtering	[75]
Article	2020	Generating items recommendations by fusing content and user-item based collaborative filtering	[76]
Article	2020	Online products recommendation system using genetic kernel fuzzy C-means and probabilistic neural network	[77]
Article	2021	A hybrid recommendation system based on profile expansion technique to alleviate cold start problem	[78]
Article	2021	Featured hybrid recommendation system using stochastic gradient descent	[79]
Article	2021	Hybrid Recommendation Using Temporal Data for Accuracy Improvement in Item Recommendation	[80]
Article	2021	Hybrid recommendation scheme based on deep learning	[81]
Article	2021	Unifying paragraph embeddings and neural collaborative filtering for hybrid recommendation	[82]
Article	2022	Design and application of handicraft recommendation system based on improved hybrid algorithm	[83]
Article	2022	Hybrid Recommendation System Based on Collaborative and Content-Based Filtering	[66]
Article	2022	Session-based Recommendation via Memory Network and Dwell-time Attention	[84]
Article	2023	A Conscious Cross-breed Recommendation Approach Confining Cold-start in Electronic Commerce Systems	[85]
Article	2023	A hybrid semantic recommender system enriched with an imputation method	[86]
Article	2023	Customer centric hybrid recommendation system for E-Commerce applications by integrating hybrid sentiment analysis	[87]
Conference	2018	A hybrid recommendation system based on density-based clustering	[88]
Conference	2018	Hybrid Weight Factorization Recommendation System	[89]
Conference	2018	Hybrid recommendation based on implicative rating measures	[90]
Conference	2019	Efficient Hybrid Recommendation Model Based on Content and Collaborative Filtering Approach	[91]
Conference	2019	Hybrid approach for recommendation system	[92]
Conference	2019	Time-varying Item Feature Conditional Variational Autoencoder for Collaborative Filtering	[93]
Conference	2019	User and item preference learning for hybrid recommendation systems	[94]
Conference	2020	A Meta-Level Hybrid Recommendation Method Based on User Novelty	[7]
Conference	2020	Bio-inspired collaborative and content filtering method for online recommendation assistant systems	[95]
Conference	2020	Hybrid Recommendation Algorithm based on User Behavior	[96]
Conference	2020	Neural hybrid recommender: recommendation needs collaboration	[97]
Conference	2020	Towards Personalized Hybrid Recommender System using Average Visit Intervals	[98]
Conference	2020	User-item-based hybrid recommendation system by employing mahout framework	[99]
Conference	2021	A Hybrid Recommender System: Uniqueness of Choices by Using Machine Learning Technique	[100]
Conference	2021	A multi source graph-based hybrid recommendation algorithm	[101]
Conference	2021	Deep learning for recommendation systems	[59]
Conference	2021	EASE Em: Hybrid Recommendation System for Item Cold Start Problem	[102]
Conference	2021	HRS: Hybrid Recommendation System based on Attention Mechanism and Knowledge Graph Embedding	[103]
Conference	2021	Multi-agent recommender system	[104]
Conference	2021	Product Valuation Modeling in Hybrid Recommendation Systems	[105]
Conference	2021	Weighted Hybrid Recommendation System Using Singular Value Decomposition and Cosine Similarity	[106]
Conference	2022	A Novel Approach to Recommendation System Business Workflows: A Case Study for Book E-Commerce Websites	[107]
Conference	2022	AERS: Adaptive and Efficient Hybrid Recommendation System based on Web usage Mining	[108]
Conference	2022	Hybrid Recommendation System with Graph based and Collaborative Filtering Recommendation Systems	[109]
Conference	2022	User Product Recommendation System Using KNN-Means and Singular Value Decomposition	[110]
Conference	2022	User preference Based Personalized Collaborative Filtering for Large Scale Recommender Systems	[111]
Conference	2023	Recommender System for E-Commerce Application based on Deep Collaborative Conjunctive Model	[112]

the e-commerce domain over the past six years. The motivation for this review stems from the increasing significance of recommendation systems in the rapid growth of e-commerce. The primary aim of this literature review is to provide researchers with a profound understanding of the evolving trends, challenges, and solutions specific to HRS in e-commerce. We initiated the review by introducing the concepts of recommendation systems and HRS in the background section, emphasizing their pivotal roles in enhancing user experiences and contributing to business success.

Our research methodology, consisting of formulating research questions, developing a structured search strategy, applying rigorous study selection criteria, and conducting meticulous data synthesis, was designed with precision to ensure clarity and reproducibility. Our research questions were thoughtfully framed to address critical aspects of HRS, including the evolution of approaches, the diversity

TABLE 7. Results of quality scores for selected studies.

Title	QA1	QA2	QA3	QA4	QA5	Score	Ref.
A Multi Source Graph-Based Hybrid Recommendation Algorithm	1	1	1	1	1	5	[101]
A Meta-Level Hybrid Recommendation Method Based on User Novelty	1	1	1	1	1	5	[7]
Hybrid Recommendation Algorithm based on User Behavior	1	1	1	1	1	5	[96]
Hybrid Recommendation Scheme Based on Deep Learning	1	1	1	1	1	5	[81]
Hybrid Recommendation System Based on Collaborative and Content-Based Filtering	1	1	1	1	1	5	[66]
Hybrid Weight Factorization Recommendation System	1	1	1	1	1	5	[89]
Product valuation modeling in hybrid recommendation systems	1	1	1	1	1	5	[105]
Recommendation Based on Review Texts and Social Communities: A Hybrid Model	1	1	1	1	1	5	[73]
Unifying paragraph embeddings and neural collaborative filtering for hybrid recommendation	1	1	1	1	1	5	[82]
A hybrid semantic recommender system enriched with an imputation method	1	1	1	1	1	5	[86]
Customer centric hybrid recommendation system for E-Commerce applications by integrating hybrid sentiment analysis	0.5	1	1	1	1	4.5	[87]
User preference Based Personalized Collaborative Filtering for Large Scale Recommender Systems	1	1	1	1	0.5	4.5	[111]
A Hybrid Ontology-Based Recommendation System in e-Commerce	1	1	0.5	1	1	4.5	[72]
A Hybrid Recommender System for Gaussian Mixture Model and Enhanced Social Matrix Factorization Technology Based on Multiple Interests	1	1	1	1	0.5	4.5	[70]
A Hybrid Two-Phase Recommendation for Group-Buying E-commerce Applications	1	1	1	0.5	1	4.5	[71]
A Novel Approach to Recommendation System Business Workflows: A Case Study for Book E-Commerce Websites	1	1	0.5	1	1	4.5	[107]
A hybrid recommendation system based on profile expansion technique to alleviate cold start problem	1	1	1	1	0.5	4.5	[78]
A hybrid recommendation system with many-objective evolutionary algorithm	1	1	1	1	0.5	4.5	[74]
Hybrid Approach for Recommendation System	1	1	1	1	0.5	4.5	[92]
A Novel Time-Aware Hybrid Recommendation Scheme Combining User Feedback and Collaborative Filtering	1	1	1	1	0.5	4.5	[75]
A Personalized Hybrid Recommendation Procedure for Internet Shopping Support	1	1	1	0.5	1	4.5	[68]
AERS: Adaptive and Efficient Hybrid Recommendation System based on Web usage Mining	1	1	1	1	0.5	4.5	[108]
Bio-inspired Collaborative and Content Filtering Method for Online Recommendation Assistant Systems	1	1	1	1	0.5	4.5	[95]
Deep learning for recommendation systems	1	1	1	1	0.5	4.5	[59]
Design and Application of Handicraft Recommendation System Based on Improved Hybrid Algorithm	1	1	1	1	0.5	4.5	[83]
Featured Hybrid Recommendation System Using Stochastic Gradient Descent	1	1	1	1	0.5	4.5	[79]
Generating Quality Items Recommendation by Fusing Content based and Collaborative filtering	1	1	1	1	0.5	4.5	[76]
HRS: Hybrid Recommendation System based on Attention Mechanism and Knowledge Graph Embedding	1	1	1	1	0.5	4.5	[103]
Multi-Agent Recommender System	1	1	1	1	0.5	4.5	[104]
Neural Hybrid Recommender: Recommendation Needs Collaboration	1	1	1	1	0.5	4.5	[97]
Time-varying Item Feature Conditional Variational Autoencoder for Collaborative Filtering.pdf	1	1	1	1	0.5	4.5	[93]
Towards Personalized Hybrid Recommender System using Average Visit Intervals	1	1	1	1	0.5	4.5	[98]
User and Item Preference Learning for Hybrid Recommendation Systems	1	1	1	1	0.5	4.5	[94]
Weighted Hybrid Recommendation System Using Singular Value Decomposition and Cosine Similarity	1	1	1	1	0.5	4.5	[106]
Session-based Recommendation via Memory Network and Dwell-time Attention	1	1	1	0.5	1	4.5	[84]
Hybrid Recommendation System with Graph based and Collaborative Filtering Recommendation Systems	1	1	1	0.5	1	4.5	[109]
Recommender System for E-Commerce Application based on Deep Collaborative Conjunctive Model	1	1	1	0.5	1	4.5	[112]
Hybrid Recommendation Using Temporal Data for Accuracy Improvement in Item Recommendation	1	1	1	1	0.5	4.5	[80]
Hybrid recommendation based on implicative rating measures	1	1	1	1	0	4	[90]
A Hybrid Recommender System: Uniqueness of Choices by Using Machine Learning Technique	1	1	0.5	0.5	1	4	[100]
A hybrid recommendation algorithm–based intelligent business recommendation system	1	1	1	0	1	4	[69]
EASE Em: Hybrid Recommendation System for Item Cold Start Problem	1	1	1	1	0	4	[102]
Online products recommendation system using genetic kernel fuzzy C-means and probabilistic neural network	1	1	1	0	1	4	[77]
User-Item-Based Hybrid Recommendation System by Employing Mahout Framework	1	1	1	1	0	4	[99]
A Conscious Cross-breed Recommendation Approach Confining Cold-start in Electronic Commerce Systems	1	1	1	0	1	4	[85]
A Hybrid Recommendation System Based on Density-Based Clustering	1	1	0.5	0.5	0.5	3.5	[88]
Efficient Hybrid Recommendation Model Based on Content and Collaborative Filtering Approach	1	1	0.5	0	1	3.5	[91]
User Product Recommendation System Using KNN-Means and Singular Value Decomposition	1	1	0.5	0	1	3.5	[110]
Hybrid Framework Model for Group Recommendation	0	1	1	1	0	3	[134]
A Deep Hybrid Model for Recommendation Systems	0	0.5	1	1	0.5	3	[135]
An Enhanced Neural Graph based Collaborative Filtering with Item Knowledge Graph	0	1	1	1	0	3	[136]
A Novel Approach for Product Prediction Using Artificial Neural Networks	0.5	1	0.5	0.5	0	2.5	[137]
E-commerce Recommendation System Using Improved Probabilistic Model	0.5	0.5	0	0.5	0.5	2	[138]

of employed algorithms, and the challenges authors aim to address, along with identifying the most suitable recommendation system combinations for specific challenges. In crafting our search strategy, we carefully selected search terms, keywords, and word combinations relevant to our research questions. Our structured search covered six different databases: Scopus, Springer, Science Direct, IEEE Explorer, Web of Science, and ACM Digital Library, chosen for their extensive coverage of conference proceedings and academic journals. During the study selection phase, we initially identified 977 studies from all the databases. After applying various filtering techniques and conducting quality assessments, we narrowed our selection down to 48 studies.

Several noteworthy findings emerged while addressing our research questions.

- *RQ1: Evolution of Approaches and Models* – We examined how models and approaches have evolved in the last six years, observing a significant increase in the usage of deep learning algorithms, while collaborative filtering remained consistently popular.
- *RQ2: Diversity of Employed Algorithms* – The diverse combinations of algorithms employed in constructing hybrid recommendation systems demonstrated that collaborative filtering and content-based filtering algorithms served as solid foundations for most systems.
- *RQ3: Addressing Challenges with Suitable Combinations* – We delved into the challenges authors strive to overcome and the effective combinations of recommendation systems employed to tackle these specific challenges. The predominant focus was on addressing issues like data sparsity and the cold start problem, with collaborative filtering and content-based methods forming a solid base. Additionally, there is a growing need for more transparent recommendation algorithms, as this transparency can foster user trust and acceptance.

In analyzing the keywords, we presented a word cloud visualizing the most commonly used keywords, with "recommendation system," "collaborative filtering," and "hybrid recommendation system" as important concepts in the field.

Additionally, we explored the different datasets used, with the MovieLens dataset being the most frequently utilized in 16 out of 48 research studies. We also identified various types of data used, with user ratings featuring in nearly 40 studies. Furthermore, we outlined future directions, which include integrating emerging technologies, emphasizing transparency, exploring multimodal data fusion, developing dynamic recommendation systems, and standardizing evaluation metrics. The standardization of evaluation metrics is an area mature for analysis, promoting more comparable and consistent research outcomes. Moreover, investigating the privacy and ethical implications of recommendation systems in e-commerce is rapidly becoming important in an era where data privacy concerns are predominant.

Strengths of the Study: This review emphasizes the disciplinary nature and dynamic development of HRS in e-commerce. In addition, this study showcases how advanced technology and innovative algorithmic strategies are applied in this field in a comprehensive, systematic, and aggregated way. The systematic nature of this research demonstrates its reliability and deep insights into the matter of hybrid recommended systems applicable to the e-commerce field. It serves as a testament to how HRS has the potential to transform e-commerce by addressing challenges and utilizing data-driven insights.

Conclusive Insights: Besides explaining the state of HRS in e-commerce, our study also highlights the need for continuous innovation and exploration in this area. This review guides research directions by identifying emerging trends, challenges, and opportunities. It calls for developing sophisticated, transparent, and user-focused recommendation systems that can adapt to the ever-changing e-commerce landscape. This will ultimately enhance user experience, thus contributing to business growth in the digital era.

In conclusion, our study not only provides a detailed understanding of the current landscape of HRS in e-commerce but also highlights the need for continued innovation and research. These future directions will not only address the existing challenges but also unlock new possibilities, driving the next wave of advancements in e-commerce recommendation systems.

APPENDIX A PUBLICATION DETAILS OF REVIEWED STUDIES

See Table 6.

APPENDIX B RESULTS OF QUALITY SCORES FOR SELECTED STUDIES

See Table 7.

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