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Review

AI-Driven Recommendations: A Systematic Review of the State of the Art in E-Commerce

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Abstract: Electronic commerce has a strong connection with recommendation processes. There are various forms of recommendations, ranging from virtual assistants to online suggestions made in real time. Different algorithms and technologies are utilized for each form, and the choice of technique is dependent on the task at hand. For instance, artificial intelligence may utilize deep learning or machine learning techniques. The type of data also plays a role in determining the techniques used. Predictive modeling is applied to textual data, while image data requires image processing followed by AI algorithms for prediction. This study aimed to investigate the extent to which artificial intelligence is utilized in recommender systems for electronic commerce, as well as the current and future trends in the field. This was achieved through a systematic literature review of scientific articles from the past decade, using WosViewer for data collection and the Bibliometrix R package for analysis. The findings demonstrate that artificial intelligence works in conjunction with other technologies, such as blockchain, virtual reality, and augmented reality, to enhance the consumer experience throughout the e-commerce process.

Keywords: e-commerce; WosViewer; Bibliometrix; recommender systems

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1. Introduction

E-commerce greatly benefits from the application of informatics, with recommender systems (RSs) playing a key role in providing personalized recommendations to customers. Recommender systems (RSs) are becoming increasingly important in e-commerce, as they help to personalize the shopping experience for customers. However, it should be noted that there is some ambiguity in the current literature regarding the taxonomy of RSs, with a mix of algorithms and approaches being used. This has led to confusion regarding the role of artificial intelligence (AI) in RSs and the potential benefits and drawbacks of using AI-based techniques in e-commerce. The traditional approach is typically content-based but it can also include clustering techniques, which are a part of machine learning (ML), a branch of AI. Some authors consider content-based RSs more effective than traditional systems [1], while others feel otherwise.

In this paper, we aimed to provide a comprehensive understanding of AI-based recommender systems for e-commerce. We conducted a systematic literature review of research on RSs with a focus on AI techniques, addressing the gaps in knowledge related to the most commonly used techniques, the effectiveness of AI-based RSs, their benefits and drawbacks, and how they compare to traditional RSs.

Recommender systems (RSs) employ statistical and artificial intelligence techniques to anticipate user preferences [2]. The design of RSs has a significant effect on the diversity of overall sales [3]. Evaluating RSs is challenging because user preferences and environmental limitations are constantly changing and evolving with advancements in technology.

RSs operate within a dynamic information space, where users may have diverse information requirements, and it is essential to evaluate any recommendation algorithm before incorporating it into a production environment [4]. However, this task is challenging, as user data and preferences continuously evolve and change [5]. Li [6] found that recommender systems may have a positive or negative effect on sellers, depending on the precision of the recommender system, and Li [7] found that recommender systems may have a positive or negative effect on sellers, depending on the targeting precision of the recommender system. However, some authors [8] found that recommender systems have a positive effect on sales, while others [9] found that recommender systems may have a positive or negative effect on manufacturers, depending on the precision of the recommender system. Thus, the impact of AI-based recommender systems on the competitive landscape of electronic commerce remains unclear. Further research is required to establish the influence of such systems on the competitiveness of the e-commerce sector.

Users are also evolving. They are becoming proactive and well-informed, and they prioritize privacy. As a result, it may require effort from sellers to establish trust with these users. Currently, blockchain technology is utilized to address trust and security issues [10], while deep learning is disrupting the recommendation process [11]. The focus of the research has shifted over time, having started with segmentation, clustering, and classification, then moving on to content-collaborative-filtering and user modeling. The focus is now on exploring neural graph-collaborative-filtering.

The aim of this systematic literature review was to examine the use of artificial intelligence (AI) techniques in the design and implementation of recommender systems (RSs) for e-commerce. This systematic literature review aimed to provide a comprehensive overview of the current state of AI-based recommender systems in e-commerce. The AI-driven techniques covered in our review refer to the use of artificial intelligence methods and algorithms such as data science; machine learning methods such as clustering, classification, and association rule mining; deep learning approaches, including deep neural networks, convolutional neural networks, and recurrent neural networks; and augmented reality and virtual assistant technologies, such as chatbots and virtual shopping assistants used to enhance the accuracy and personalization of recommendations in e-commerce platforms.

To the best of our knowledge, this type of research has not been conducted to date. One recent study that reviewed AI-based techniques for recommender systems mentioned that the use of advanced AI techniques, such as fuzzy techniques [12], transfer learning, and genetic algorithms, is expected to improve the accuracy of recommender systems [13]. Recently, authors [14] pointed out that AI in e-commerce mainly focuses on RSs, and that the main research themes are sentiment analysis, optimization, trust, and personalization. Although sentiment analysis is an AI technique, there is a lack of research on the AI techniques utilized for optimization, trust, and personalization in RSs. Our focus was on studying AI-based techniques for recommender systems in e-commerce. In particular, the present study aimed to not only analyze the AI techniques used in recommender systems, but also to evaluate their effectiveness. While many articles have been published on the topic, few have rigorously examined the performance of these techniques. Therefore, this study sought to fill this gap by conducting a comprehensive evaluation of various AI-based recommender-system approaches. We believe that such a study will provide valuable insights into current user needs and help to predict future trends in this field.

2. Theoretical Background

Recommender systems are a technology used not only in e-commerce but in other areas as well. The technology employed can vary, and ranges from decision rules to artificial intelligence virtual assistants and personalized recommender systems, notifications, emails, or applications. There are several approaches, including collaborative filtering, context-aware filtering, and hybrid approaches. Collaborative filtering leverages the historical behavioral data of a user community to identify patterns of preferences [15]. They can operate in memory or offline and utilize linear methods, such as matrix factorization (MF) and graph-based methods, as well as nonlinear methods, such as deep neural networks (DNN), among others. Context-aware recommender systems incorporate both contextual information about the user and historical data about the products.

In the field of recommender systems, there is a growing interest in understanding the interplay between various aspects, such as behavioral research, intelligent systems, decision support systems, e-commerce, augmented reality, deep learning, and virtual assistants. AI-driven techniques play a pivotal role in enhancing the capabilities of these aspects, leading to more effective recommender systems. For example, intelligent systems powered by AI can process large datasets to provide accurate and personalized recommendations based on user behavior, preferences, and decision-making processes.

Augmented reality has the potential to enhance the user experience by providing a more immersive and interactive recommendation process. Deep learning algorithms, particularly those based on neural networks, have proven to be effective in handling large and complex datasets, making them well-suited for recommender systems. Virtual assistants, such as Amazon's Alexa and Google Assistant, are becoming increasingly popular, and provide users with personalized recommendations and information at their fingertips.

Each of these aspects brings unique strengths and challenges to the field of recommender systems, and a comprehensive understanding of their interplay is crucial for the development of effective and innovative recommender systems. For example, while intelligent systems can provide highly accurate recommendations, they may not always align with the user's preferences and decision-making processes. On the other hand, behavioral research can provide valuable insights into user behavior and decision-making processes but may not always have the ability to handle large and complex datasets effectively.

The Scopus database offers valuable insights into the topic of e-commerce, with 41,000 articles on "e-commerce" and 68,000 articles (many duplicates) on "electronic commerce." This extensive collection of literature reveals that the widespread adoption of e-commerce can be attributed to advancements in the Internet, personal computers, big data, cloud computing, and AI, with AI playing an increasingly important role in driving innovation and growth in the e-commerce sector. Although the number of articles on the subject has fluctuated over time, with the largest surge between 2008–2011, the number of articles has increased again since 2019. Interestingly, the computer science field has nearly four times as many articles as the business field on this topic, reflecting the multidisciplinary nature of e-commerce research.

To gain a general understanding of the field, we conducted a search using the Scopus database to investigate the co-occurrence of keywords in e-commerce research. Figure 1 depicts the co-occurrence of various keywords, including "recommendation systems," "electronic commerce," "data mining," "deep learning," "machine learning," "behavioral research," and "collaborative filtering," among others. The list of articles considered for the analysis consisted of 2000 publications related to e-commerce published within the last five years. The list was obtained from the Scopus database solely for the purpose of providing an overview of research trends in this domain. The co-occurrence was established based on a minimum threshold of five occurrences for each keyword.

The primary question that remains is: What are the AI techniques utilized in building diverse recommendation systems for e-commerce? We chose to focus on AI-driven techniques because they have been shown to significantly improve the performance and effectiveness of recommender systems, which are crucial for enhancing user experience, personalization, and decision-making in e-commerce settings.

We were also interested in exploring evidence related to the effectiveness of AI-based techniques in recommender systems.

Given the vastness of the AI and recommender system fields, and their growing importance in e-commerce, our analysis first took a general look at the literature on these topics. Specifically, we sought to identify the different AI techniques used in recommender systems and their effectiveness in improving sales and user satisfaction. Gaining a comprehensive understanding of these systems and their AI-driven techniques is critical for informing future research and practical applications that aim to enhance the competitive landscape of electronic commerce.

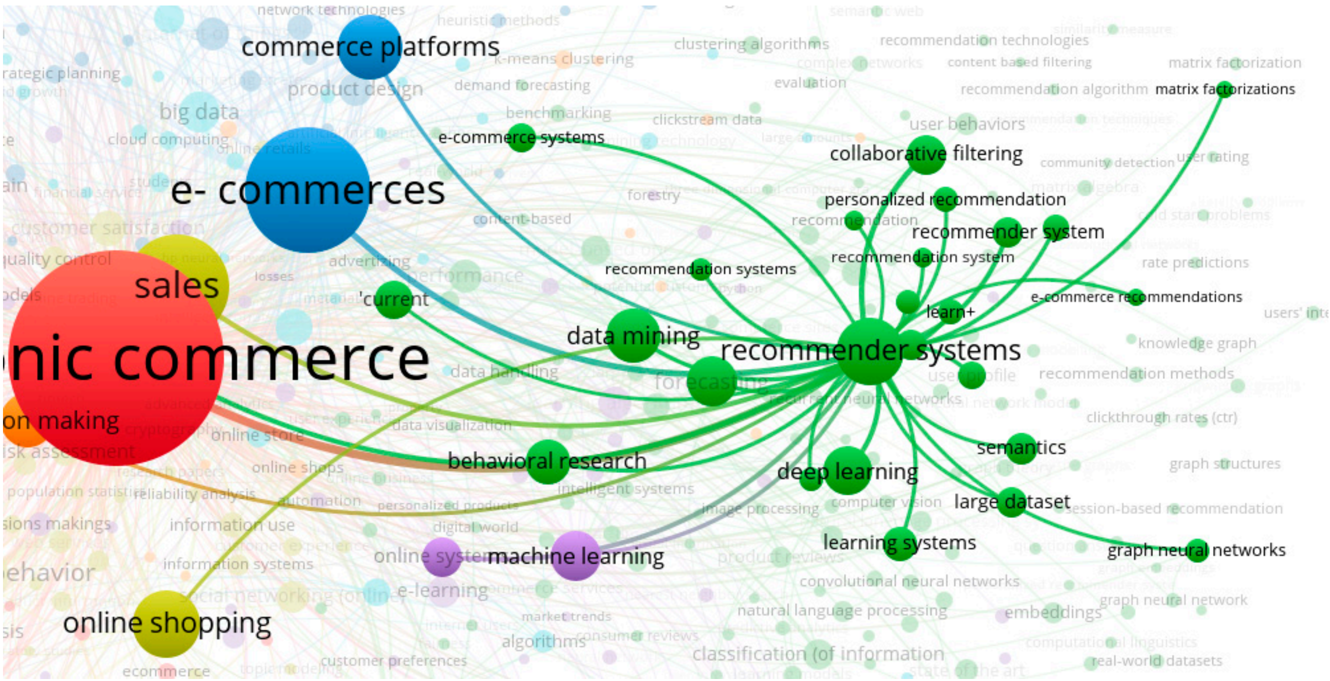

Figure 1. Co-occurrences of "recommender systems" in a list of 2000 articles written on the subject of e-commerce in the last 5 years (eWOS Viewer).

The materials and methods applied in this research will be fully explained in the subsequent section.

3. Materials and Methods

We conducted a systematic literature review, adopting a well-defined plan and criteria for search and exclusion.

Systematic literature reviews (SLRs) are a type of secondary empirical study that aims to offer a structured overview of a particular research field. The methodology followed in an SLR is well-defined, which helps to minimize the possibility of biased literature results, although it does not eliminate the likelihood of publication bias in the primary studies.

The current SLR adhered to the steps outlined in [16], which involved three primary phases: namely, planning the SLR, executing the SLR, and reporting the SLR. This section details the planning of the study, including the research questions, data sources, search strategy, and the classification and evaluation criteria.

The objective of this SLR iwa to investigate the present state of AI-based techniques in recommender systems for e-commerce and identify potential gaps and opportunities for future work through a review of existing research. The main research question that guided this study is:

What are the most commonly used AI-based techniques in recommender systems for e-commerce, and how effective are these systems in the context of e-commerce?

To gain specific insights into the relevant aspects of AI-based techniques in recommender systems for e-commerce and their effectiveness, this research posed a range of related questions. These included inquiries into the bibliometric key facts of the articles, the research type of each article, the specific characteristics of AI-based techniques, and their application scenarios. The study also examined the type of research carried out thus far (theoretical, proposal, empirical), along with the type of research forums where these works have been published and presented. The precise research questions addressed by this SLR are presented in Table 1.

Table 1. Research questions.

Research Question Number	Research Question
RQ1	What are the bibliometric key facts about AI-based techniques in recommender systems for e-commerce
RQ2	What are the most commonly used AI-based techniques in recommender systems for e-commerce
RQ3	How effective are AI-based recommender systems for e-commerce?
RQ4	What are the benefits and drawbacks of AI-based recommender systems for e-commerce?
RQ5	How do AI-based recommender systems for e-commerce compare to traditional recommender systems?
RQ6	What direction is the research on AI-based recommender systems for e-commerce headed?

To gather academic publications, we utilized several databases, including ACM Digital Library, IEEExplore, ISI Web of Science, ScienceDirect, and Springer. To expand our search to non-academic publications, we utilized Google Scholar, which allowed us to access a wide range of sources, including industry/professional conferences, workshops, online journals/magazines, and corporate blogs.

To ensure that our search was focused and efficient, we applied specific criteria to our data sources, which helped us to avoid assessing hundreds of thousands of articles.

The time frame selected was 2011–2021, including the entire year of 2021. In this section, we provide a detailed explanation of the keyword selection process used in our systematic literature review (SLR) to ensure a comprehensive and representative sample of the relevant literature. The keyword selection was based on a thorough examination of the literature and our research objectives, which focus on artificial intelligence (AI), recommender systems (RS), electronic commerce (e-commerce), and consumption behavior.

The selection of keywords was guided by the following principles:

1. Relevance to core concepts: We aimed to identify keywords that represent the central concepts of our research topic. For instance, we used "artificial intelligence" and "machine learning" as synonyms, as machine learning is a subset of AI and frequently employed in RS literature. Similarly, we included both "recommender systems" and "recommendation systems" since they are interchangeable terms used in the field. We also used "electronic commerce" to represent the broader domain of e-commerce.
2. Inclusivity: We sought to ensure that our search would include articles discussing the use and impact of AI and RS in e-commerce. By combining these terms with the other core concepts, we were able to capture a wide range of studies addressing the research question, including those that explored the effects on consumption behavior as a result of AI-driven recommendations in e-commerce settings.
3. Database search functionality: We recognized that different databases have unique search functionalities and may interpret Boolean operators differently. Therefore, we adapted our use of Boolean operators for each database to improve the precision and relevance of our search results.

While we acknowledge that no keyword selection process can guarantee the identification of every important study in the field, we believe that our chosen keywords, combined with the use of Boolean operators and appropriate database search functionality, provide a comprehensive and representative sample of the relevant literature.

Our search strategy was designed to be inclusive, covering a wide range of publications while still maintaining focus on our research objectives, which are centered on AI and RS in e-commerce. The keyword selection process, as described above, was instrumental in identifying pertinent publications for our SLR, enabling us to contribute valuable insights to the field of AI and RS in e-commerce and their impacts on various aspects, including consumption behavior.

Table 2 summarizes the results of the keyword search conducted on ACM Digital Library, IEEE Xplore, and ISI Web of Science to identify relevant studies on the use of artificial intelligence (AI) and recommender systems (RS) in electronic commerce (e-commerce) and their impact on consumption behavior. In the selected time frame of 2011–2021, we employed Boolean operators 'OR' and 'AND' based on each database's search functionality to improve the precision and relevance of our search results. It is important to note that the restrictiveness of 'AND' can vary across databases. In some cases, using 'AND' may not be as limiting as in others, which could affect the breadth of the search results. By understanding the nuances of each database's search functionality and adapting our use of Boolean operators accordingly, we were able to optimize our search strategy to find the most pertinent publications for our study. The table below lists the keywords used in the search, the databases searched, and the number of articles found for each keyword search.

Table 2. Keywords search over ACM Digital Library, IEEExplore, and ISI Web of Science (E-Publication Date: 1 January 2011 TO 31 December 2021).

Database	Keywords Used in Search	Number of Articles
ACM digital library	["electronic commerce"] AND ["recommender systems"] AND ["consumption behavior"]	20
IEEExplore	("All Metadata":"artificial intelligence") AND ("All Metadata":"electronic commerce") AND ("All Metadata":"consumption behavior")	4
	("All Metadata":"recommender systems") AND ("All Metadata": "electronic commerce") AND ("All Metadata":"artificial intelligence")	198
	("All Metadata":"recommendation systems") AND ("All Metadata": "electronic commerce") AND ("All Metadata":"artificial intelligence")	39
Clarivate	((ALL = ("electronic commerce")) AND (ALL = ("recommendation systems")))	54
	Within search results: "artificial intelligence"	2
	Within search results: "machine learning"	1
	((ALL = ("electronic commerce")) AND (ALL = ("recommender systems")))	176
	Within search results: "artificial intelligence"	6
	Within search results: "machine learning"	10
	((ALL = ("electronic commerce")) AND (ALL = ("artificial intelligence")))	115
	Within search results: "recommender systems"	9
	Within search results: "consumption behavior"	0
	((ALL = ("electronic commerce")) AND (ALL = ("machine learning")))	111
	Within search results: "recommender systems"	11
	Within search results: "consumption behavior"	1

Table 3 presents the results of the keyword search conducted on ScienceDirect, Springer and Scopus to identify relevant studies on the use of AI and RSs in e-commerce and their impact on consumption behavior. The table lists the keywords used in the search, the number of articles found for each keyword search, and the databases where the articles were found.

Table 3. Keywords search over ScienceDirect, Springer and Scopus. (E-Publication Date: 1 January 2011 TO 31 December 2021).

Keywords Used in Search (Title-Abstract-Keywords Search)	Science Direct	Springer	Scopus
"artificial intelligence" and "electronic commerce" and "consumption behavior"	13	2	9
"recommender systems" AND "electronic commerce" AND "artificial intelligence"	92	54	121
"recommendation systems" AND "electronic commerce" AND "artificial intelligence"	73	106	46
"recommendation systems" AND "electronic commerce" AND "machine learning"	113	50	64
"recommender systems" AND "electronic commerce" AND "machine learning"	120	59	137

Table 4 summarizes the final number of articles considered for the systematic literature review after screening for eligibility. The table lists the keywords used in the search, the number of articles found for each keyword search, and the number of duplicates and articles in languages other than English. The table provides a summary of the articles that will be included in the systematic literature review.

Table 4. The articles considered to include in SLR.

Keywords Used in Search	Number of Articles	Duplicates	Other Language than English
"artificial intelligence" and "electronic commerce" and "consumption behavior"	9	131	4
"recommender systems" AND "electronic commerce" AND "artificial intelligence"	120		
"recommendation systems" AND "electronic commerce" AND "artificial intelligence"	45		
"recommendation systems" AND "electronic commerce" AND "machine learning"	63		
"recommender systems" AND "electronic commerce" AND "machine learning"	138		

The exclusion criterion was to only include documents written in English. Four articles did not meet this criterion; hence they were excluded. After eliminating duplicates and non-English articles, the dataset was comprised of 240 articles. Among these 240 articles, one article was retracted and excluded from the dataset. The resulting dataset consisted of 37 journal articles, 1 book chapter, 200 conference papers, and 1 review. These remaining articles were assessed based on the availability of their full text and their relevance to the research subject. The articles in Table 4 provided the basis for our systematic literature review and ensured that our analysis is comprehensive and focused on relevant studies in the field of AI and RS in e-commerce and their impacts on consumption behavior.

The first step in our systematic literature review (SLR) involved analyzing the title and abstract of each study to determine if it was a good fit for our review. We strictly excluded personal websites or web pages from our analysis. Additionally, any papers where the emphasis was not on AI-based techniques for recommender systems in e-commerce were excluded. In the end, we analyzed a total of 165 articles. Table 5 provides the main information on the dataset analyzed, including the timespan, sources, authors, documents, growth rate, document age, average citations, references, and document types.

Table 5. Descriptive Statistics of the Analyzed Dataset on AI-based Techniques for Recommender Systems in E-commerce.

Description	Results	Description	Results
MAIN INFORMATION ABOUT DATA			
Timespan	2011:2021	AUTHORS	
Sources (Journals, Books, etc.)	102	Authors	480
Documents	165	Authors of single-authored docs	5
Annual Growth Rate%	4097	AUTHORS COLLABORATION	
Document Average Age	399	Single-authored docs	7
Average citations per doc	9297	Co-Authors per Doc	356
References	4434	International co-authorships%	1576
DOCUMENT CONTENTS		DOCUMENT TYPES	
Keywords Plus (ID)	1052	Article	34
Author's Keywords (DE)	451	conference paper	130
		Review	1

In the second round, we were left with a set of papers that had been deemed relevant in the first round. In this round, we considered the full text of each paper. If an article only had an abstract but no full text or represented a summary of a workshop, it was excluded. Non-academic or non-professional papers were also eliminated. We excluded papers that discussed AI-based techniques but only referred to e-commerce as an application domain without providing a concrete design and implementation of recommender systems (RSs) for e-commerce approach.

The publication sources and their impacts were analyzed based on their h-index quality measures. The most impactful publication sources related to research on the subject were explored. The articles were analyzed based on their total citations to determine the most widely cited documents within the dataset. The most salient topics, concepts, themes, and trends regarding AI techniques for recommender systems in e-commerce were identified.

In the initial stage of our analysis, we utilized WosViewer to gain an understanding of the subject. Subsequently, we conducted our own calculations using Python. The plots were generated using the Bibliometrix R package and Biblioshiny web application. We then proceeded to present and discuss the outcomes of our analysis. The figures included in this article are based on our own data processing. In Section 5, we present the results of the main clusters that we identified.

4. Results

4.1. Scientific Sources

Of the 34 journal articles analyzed, 10 were published by Elsevier, nine by Springer, three by the IEEE Computer Society, one by ACM, and four by MDPI. The Institute of Electrical and Electronics Engineers Inc. had the largest number of conference articles published, with a total of 42 out of 130. Springer published 48 conference papers and the Association for Computing Machinery published 28. The annual scientific production is shown in Figure 2 and exhibits an annual growth rate of 14.82%.

The most influential sources were CEUR Workshop Proceedings and ACM International Conference Proceeding Series, which have the highest h-index and g-index scores, as well as a significant number of citations and published articles. The sources with the lowest impact, on the other hand, were those with lower scores in all metrics, such as the Proceedings of the 5th International Conference on Communication and Electronics

Systems, ICCES 2020, and the Proceedings of the Annual Hawaii International Conference on System Sciences.

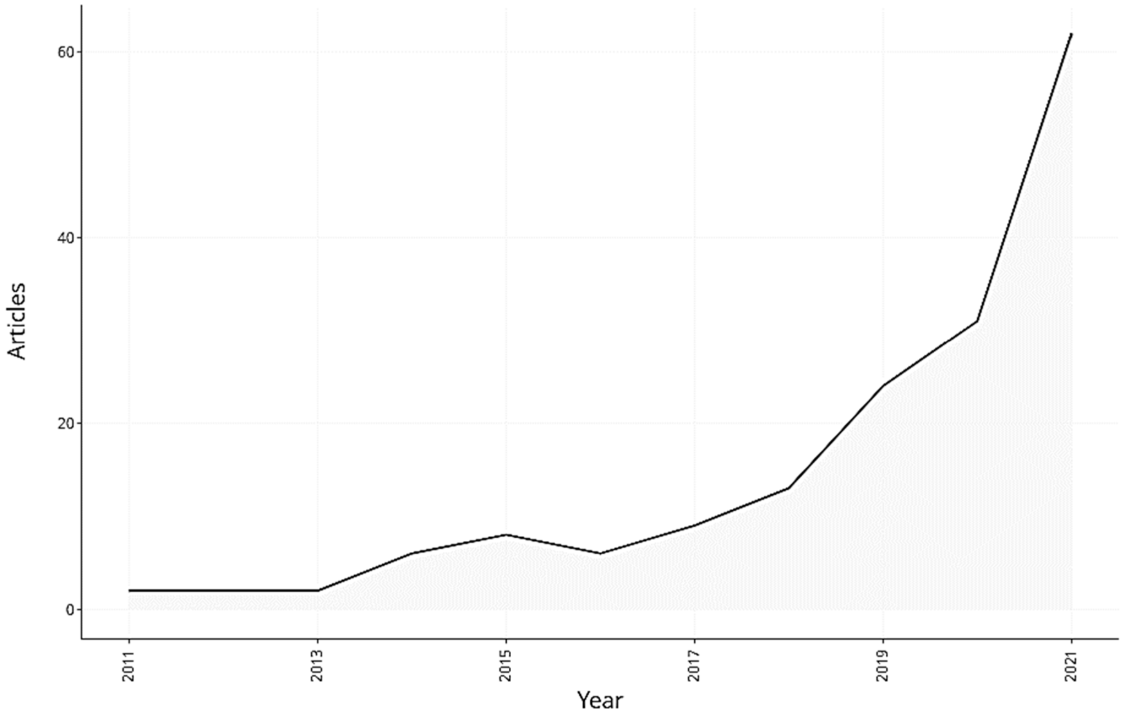

Figure 2. Annual growth rate of scientific articles published on the subject (last decade).

4.2. The Bibliometric Key Facts about AI-Based Techniques in Recommender Systems for e-commerce

This section analyzes the most common words and the primary themes and trends. The top ten most frequent words are shown in Figure 3.

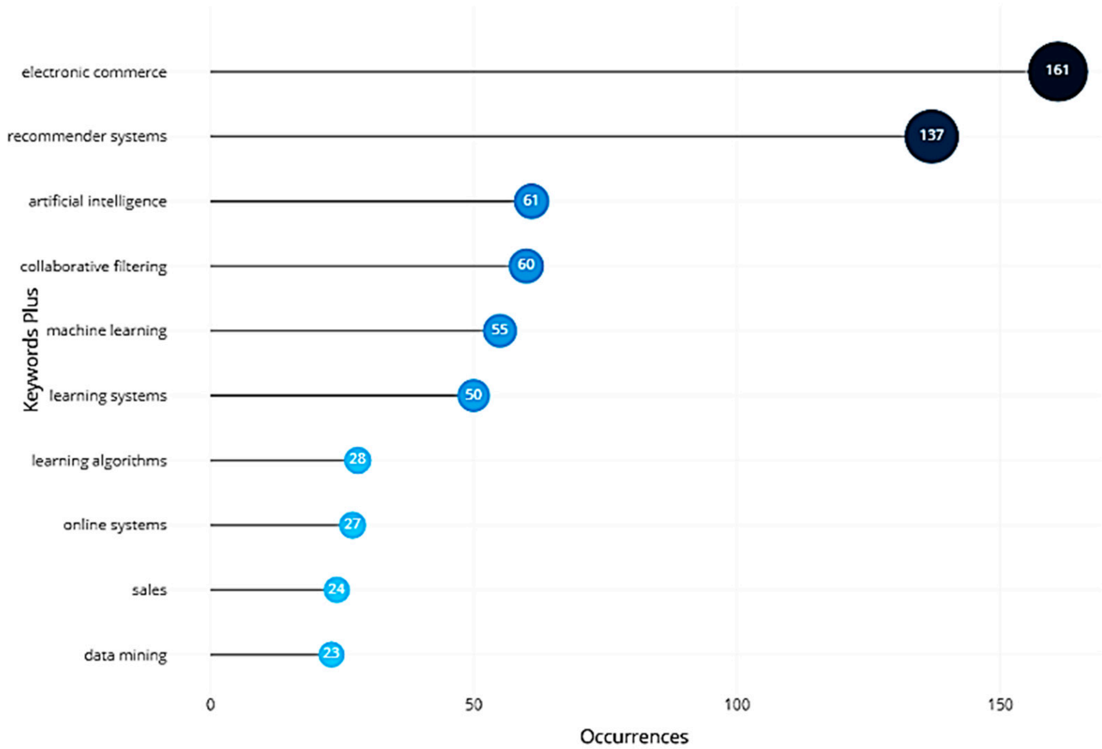

Figure 3. Most frequent words (last decade).

In addition to counting the frequency of terms, we also analyzed the dynamics of the words. Figure 4 displays the term trends.

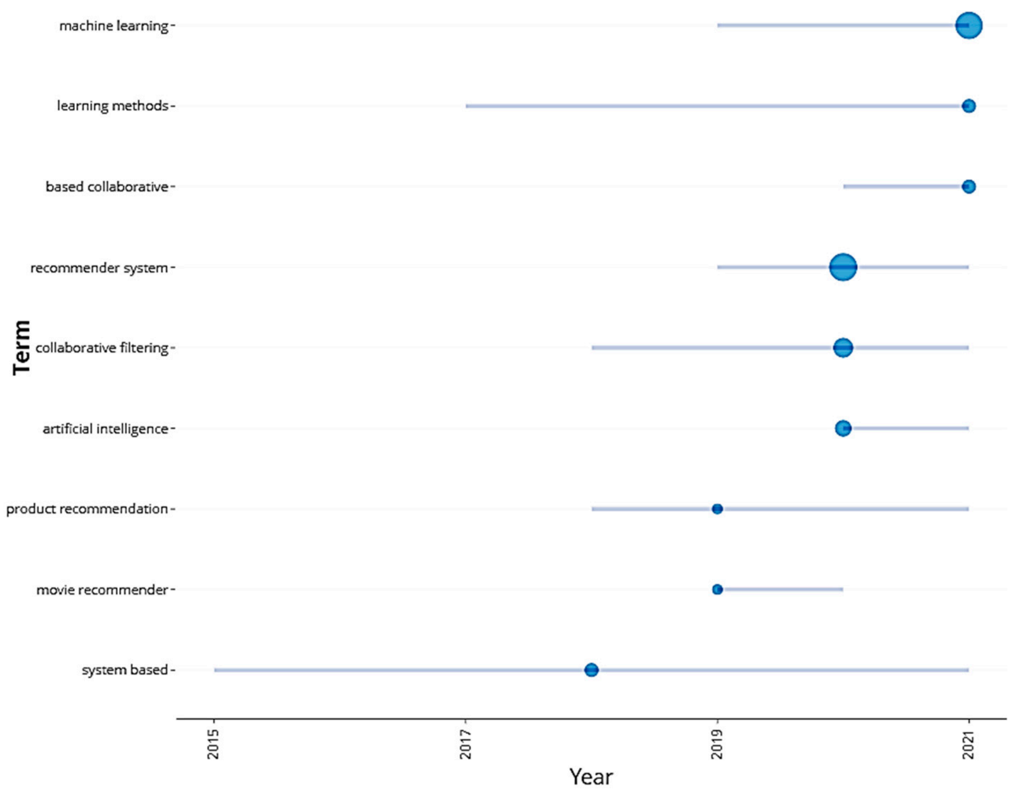

Figure 4. Trending terms (titles) (last decade).

We observed a steady pattern in the occurrence of the term "AI" that was comparable to "collaborative filtering" and "machine learning." Nonetheless, "machine learning" seems to be more prevalent in current academic discussions. The trends were generated based on the keywords assigned by the authors and publishers for each document. We also used the title as a source for the plotting of term trends (Figure 4). To count the occurrences of bigrams (such as "artificial intelligence", "machine learning", "recommender systems"), we applied stemming to the words. Bigram analysis and stemming are common techniques in natural language processing for processing parts of phrases, in this case, the titles.

Overall, there was a clear upward trend in the frequency of these keywords over the years, with the largest increase occurring between 2017 and 2019. The most common keywords were electronic commerce, recommender systems, and data mining. These results suggest that the use of machine learning techniques in electronic commerce has been steadily increasing in recent years, and this trend is likely to continue in the future. In order to identify clusters of documents or groups that encompass a wider subject matter, we clustered the keywords and plotted the themes of motor, niche, basic, and decline. Figure 5 depicts the thematic evolution of the entire subject.

As the thematic evolution shows, deep learning and machine learning are the driving themes in the field. It appears that k-NearestNeighbour and k-Means clustering are utilized for clustering and, along with text processing, represent a specialized theme. It is noteworthy that subjects such as technology adoption are in decline, although there are currently studies demonstrating that consumers are more receptive to interactive recommendations [17]. Some of the strongest relationships included consumption behavior and decision trees, e-commerce systems and big data, electronic commerce and data mining, and websites and consumer behavior. The topics with the highest number of occurrences included electronic commerce, data mining, and learning systems. To gain further insights into AI and to observe the recent trends, we plotted the thematic evolution for the period of 2020–2021. The predominant theme in recent years has been deep learning, in addition to machine learning and data mining, as indicated in Figure 6.

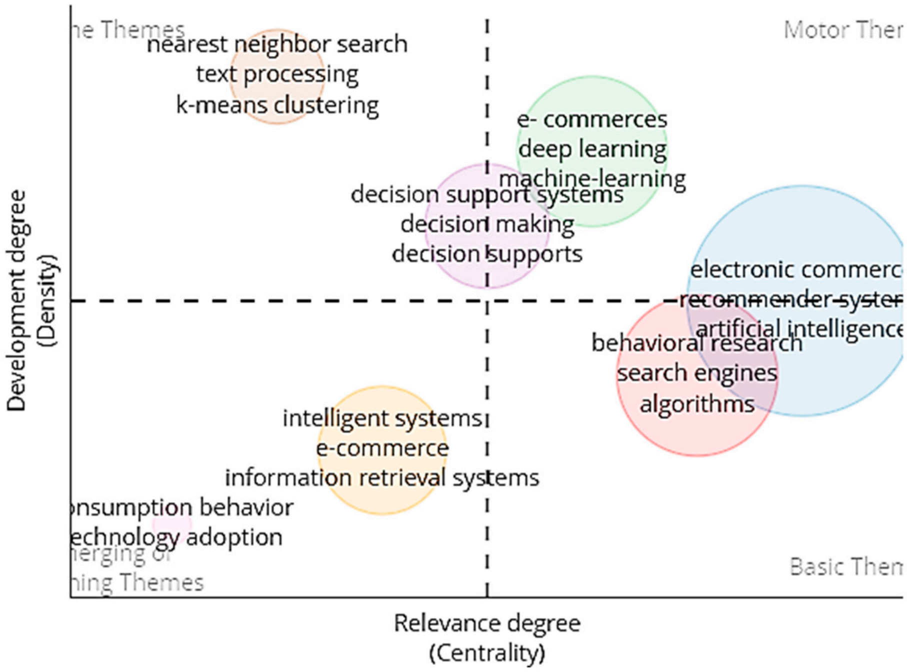

Figure 5. Thematic evolution (keywords plus) (last decade).

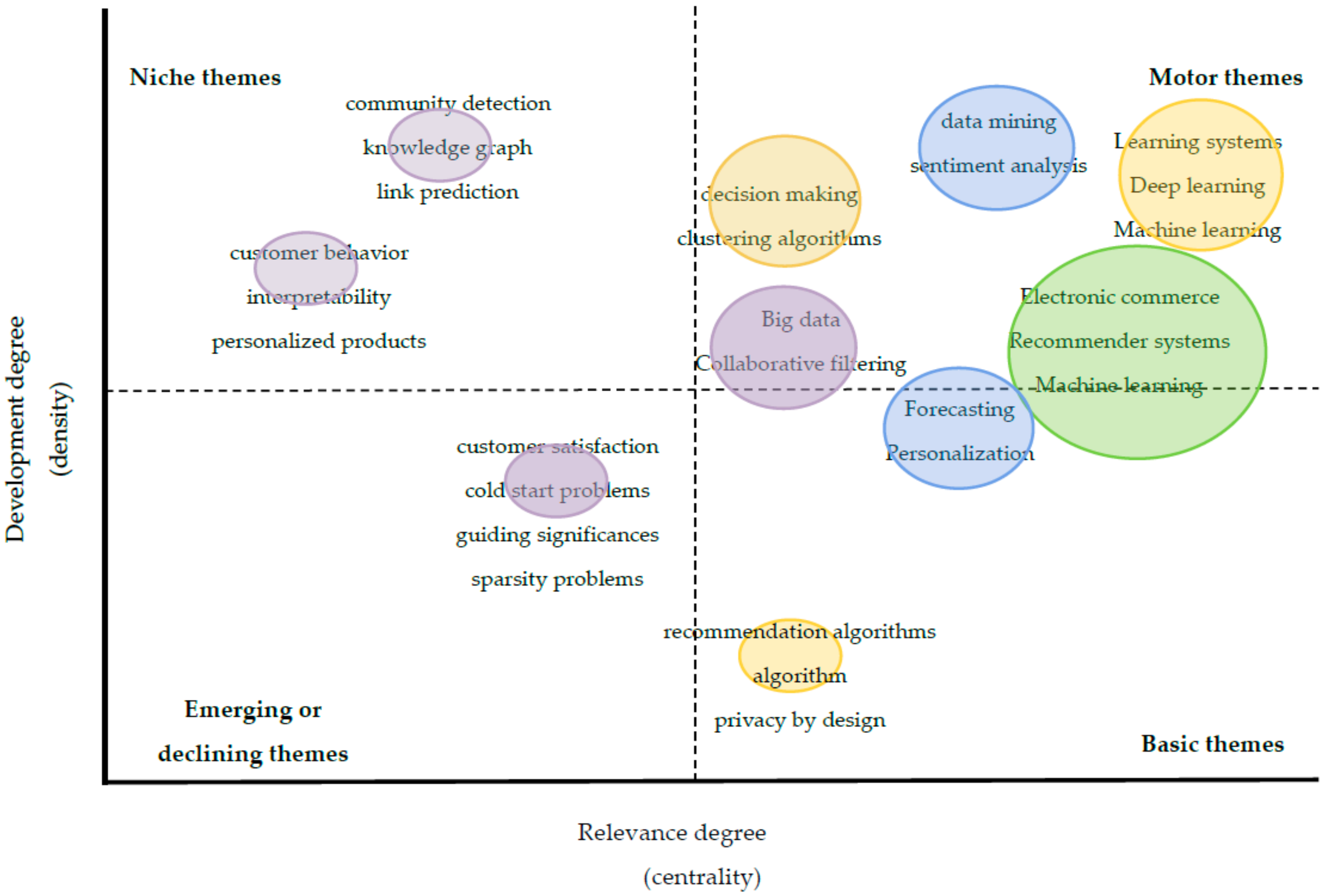

Figure 6. Thematic evolution in 2020–2021 (keywords plus).

Thematic analysis is a qualitative research method used to analyze and identify patterns or themes within a dataset. In the context of scientific networks, measures such as Callon's centrality and density, as well as rank centrality and density, can be used to assess the importance and connectivity of nodes. We used Biblioshiny, which employs these measures to analyze bibliographic data and visualize scientific networks based on keywords plus metrics.

Rank centrality and rank density are measures used to quantify the importance or centrality of nodes in a network. Rank centrality measures the importance of a node based on the number of incoming links it has from other nodes, while rank density measures the importance of a node based on the number of links it has to other nodes. Callon's centrality and density are similar measures to rank centrality and rank density, but they are specifically used in the analysis of scientific networks. Callon's centrality measures the importance of a node based on the number of other nodes it is connected to, while Callon's density measures the intensity of connections between nodes. These measures are useful for understanding how scientific ideas and concepts are connected and how they develop over time. Biblioshiny calculates these measures to identify the most central and connected clusters in a scientific network, as well as the nodes that frequently cite, or are cited by, other nodes.

Table 6 presents the results of a cluster analysis for different thematic clusters, including data mining, electronic commerce, decision trees, collaborative-filtering algorithms, forecasting, feature extraction, information-filtering system, classification (of information), sentiment analysis, embeddings, big data, e-commerce recommendations, e-commerce recommender system, and information-retrieval research. The table displays measures of network connectivity, such as Callon's centrality and density, as well as rank centrality and density, which reflect the relative importance of the nodes within each cluster. The analysis provides insights into the connectivity and relative importance of nodes within each cluster, which can be useful for understanding the structure of these thematic areas.

Table 6. Cluster Analysis of Selected Themes: Callon's Centrality, Callon's Density, Rank Centrality, and Rank Density.

Cluster	Callon's Centrality	Callon's Density	Rank Centrality	Rank Density
data mining	5.23	41,16	15	1
electronic commerce	40.35	92,47	17	6
decision trees	3.30	204,68	14	9
collaborative filtering algorithms	6.94	285,81	16	15
forecasting	3.18	240,44	13	12
feature extraction	0.22	308,33	6	16
information filtering system	0.17	242,22	4,5	13
classification (of information)	1.39	44,44	9	2
sentiment analysis	2.40	196,67	11	8
embeddings	0.44	333,33	8	17
big data	2.74	172,84	12	7
learning systems	1.86	281,25	10	14
e-commerce recommendations	0.17	233,33	4,5	11
e-commerce recommender system	0.25	50,00	7	4
information retrieval research	0.00	225,00	2	10

Electronic commerce has the highest Callon's centrality and Callon's density scores, indicating that it is the most central and connected cluster in the network. This is not surprising, given that electronic commerce is a broad and diverse field that touches on many other areas, such as data mining, machine learning, and e-commerce recommendations.

The decision trees and collaborative-filtering algorithm clusters have high rank centrality scores, indicating that they are frequently cited by other clusters in the network. This suggests that decision trees and collaborative-filtering algorithms are important methods in the field of data mining and electronic commerce, respectively.

The feature extraction and embeddings clusters have high rank density scores, indicating that they cite other clusters frequently. This suggests that these clusters are important for understanding the techniques and methods used in data mining and machine learning.

The information-retrieval research cluster has a high rank density score but a relatively low rank centrality score, suggesting that it is an important cluster for understanding the field of information retrieval, but it may not be as central or frequently cited as some other clusters.

While the thematic analysis did not explicitly group papers by the specific AI techniques used in their development, it provided a general understanding of the structure of the field and the importance of different thematic clusters.

5. Discussion

Section 5 focuses on the remaining research questions, which were not fully addressed in Section 4. We will start with the second research question, which aims to identify the most used AI-based techniques in recommender systems for e-commerce. We will then move on to the third research question, which explores the effectiveness of AI-based recommender systems in e-commerce. Subsequently, we will examine the benefits and drawbacks of using AI-based recommender systems in e-commerce, as well as how they compare to traditional recommender systems. Finally, we will address the direction of research on AI-based recommender systems for e-commerce, as outlined in the sixth research question. By answering these research questions, we hope to provide a comprehensive understanding of the current state and future potential of AI-based recommender systems for e-commerce.

5.1. AI-Based Techniques in Recommender Systems for e-commerce

The objective of our research was to carry out a systematic literature review on the topic of recommender systems for e-commerce, with a focus on AI techniques. As previously mentioned in the Introduction, recommender systems are evolving alongside technological advancements. Conventional recommender system approaches typically employ content-based scoring [18], collaborative filtering, or more frequently, a hybrid approach [19]. As the trend analysis has indicated, collaborative filtering has been improved by AI techniques, with one trend leaning towards semantic web and taxonomies/ontologies, and another towards AI.

Data science and machine learning techniques, such as decision trees and feature extraction, are commonly used in recommender systems for e-commerce. This is consistent with the clusters identified in the analysis, where decision trees and collaborative-filtering algorithm clusters have high rank centrality scores, indicating that they are frequently cited by other clusters in the network, and the feature-extraction cluster has a high rank density score, indicating that it cites other clusters frequently.

Augmented reality, deep learning, and virtual assistants are emerging AI-based techniques that can enhance the performance of recommender systems for e-commerce. These techniques can be related to the clusters identified in the analysis, such as the electronic commerce cluster, which has the highest Callon's centrality and Callon's density scores, indicating that it is the most central and connected cluster in the network. This is not surprising, given that electronic commerce is a broad and diverse field that touches on many other areas, such as data mining, machine learning, and e-commerce recommendations.

5.1.1. Data Science and Machine Learning Techniques Used in Developing RSs for E-Commerce

The articles grouped in this section of our analysis pertains to studies that focus on research that employs taxonomies, ontologies, and machine learning to generate recommendations. For instance [2] employed a probabilistic topic modeling approach to uncover hidden topics, which served as the foundation for calculating item and term similarity for generating recommendations. Some other authors used unstructured reviews to construct a structured semantic representation of database items, enabling the application of semantic queries and additional machine learning analytics [20–22].

Additionally, various studies have focused on incorporating machine learning (ML) to classify and group user preferences, beyond the use of taxonomies or semantic webs. This application of ML has demonstrated the wide range of ML techniques and related technologies.

Several studies utilized a range of ML techniques and related technologies to classify and cluster user preferences. The AdaBoost machine learning algorithm was used by [23]. Additionally, clustering, decision trees, and association rule mining were used by [24]. The difference factor' K-NN collaborative filtering method, known as DF-KNN, was used by [25]. Agglomerative clustering algorithms was used by [26]. Support vector machines (SVM), decision trees, and inductive logic programming were applied by [27,28]. Non-linear kernel techniques were employed to assess individual behaviors [29]. A Gibbs sampling-based latent Dirichlet allocation classifier framework was used to classify product reviews into positive, negative, and neutral [30]. Finally, advanced distributed machine learning algorithms, such as variants of distributed Kalman filters, distributed alternating least square recommenders, and distributed mini-batch stochastic gradient descent (SGD)-based classifiers, and highly scalable distributed computation and machine learning platforms, including Apache Spark, Spark MLlib, Spark Streaming, Python/PySpark, R/SparkR, and Apache Kafka, were utilized in a high-performance, distributed, and fault-tolerant architecture by [31]. Table 7 summarizes the various machine learning techniques and related technologies used to classify and cluster user preferences in the context of recommender systems for e-commerce. These methods go beyond the use of taxonomies or semantic webs and allow for the handling of uncertainty, providing a multigranular context, and accurate classification and clustering of user preferences. The table below provides an overview of the specific algorithms used by different studies. This information can be useful for researchers and practitioners looking to incorporate machine learning into their recommender systems to improve recommendation relevance and accuracy.

Table 7. Studies Employing ML Techniques for Improving Recommender Systems in E-commerce.

Study	Techniques/Technologies Used
[8]	Probabilistic topic modeling, item and term similarity calculation
[20–22]	Unstructured reviews, structured semantic representation, semantic queries, additional ML analytics
[28]	AdaBoost algorithm
[29]	Clustering, decision trees, association rule mining
[30]	Difference Factor K-NN collaborative filtering (DF-KNN)
[31]	Agglomerative clustering algorithms
[32]	Support Vector Machines (SVM), decision trees, inductive logic programming
[33]	SVM, decision trees, inductive logic programming
[34]	Non-linear kernel techniques
[35]	Gibbs sampling based latent Dirichlet allocation classifier framework

The use of these algorithms allowed for the assessment of individual behaviors and classification of product reviews. The benefits of these techniques include the ability to handle uncertainty, provide a multigranular context, and classify and cluster user preferences. The limits of these techniques include the need for advanced distributed machine learning algorithms and high-performance, distributed, fault-tolerant architectures.

Recently, conversational agents have gained attention among scholars and practitioners due to their increased capabilities for providing both informative and entertaining interactions [32]. This is consistent with previous studies that found both hedonic and utilitarian motivations for engaging with digital avatars [33].

The authors of these studies focus on improving the relevance of recommendations in e-commerce by considering user profiles, context data, and collaborative filtering with the aid of AI techniques. They employ methods such as taxonomies, ontologies, machine learning, probabilistic topic modeling, and gradient-based learning algorithms to make accurate recommendations. The recent trend in the studies has shifted towards AI, specifically LSTM neural networks [34] and knowledge-based trees [35], to overcome the problem of context space. Additionally, conversational agents [36] have gained interest as they can offer both informative and entertaining interactions.

5.1.2. Augmented Reality, Deep Learning, Virtual Assistants

Studies conducted in the field of augmented reality or virtual assistants are closely linked to the concept of intelligent agents. In the past decade, researchers have focused on developing personalized interaction techniques. Researchers [37] developed a deep neural network ranking model that utilizes user-specific features and their interactions, and dynamically re-ranks recommendations based on real-time user feedback. Other studies [38,39] used a deep learning neural network to recommend movies. Other authors [40–42] combined neural networks with other AI techniques, using a sentiment score computation based on the combination of a support vector machine and artificial neural network, along with frequency computation on specific nutrition features, to recommend products. Some of the latest developments in the field of deep neural networks include deep reinforcement learning (DRL), automated machine learning (AutoML), and graph neural networks (GNNs) [11]. Studies involving image processing have also been conducted, with researchers exploring ways to recommend relevant images based on clothing and footwear dataset quality queries [43]. Additionally, researchers have investigated the potential for extracting meaningful information from images and applying it to online recommendation systems to enhance the online shopping experience [44,45]. Eye-tracking experiments at supermarket shelves [46] were used to study virtual reality, while [47] explores deep learning, causality, and active exploration with bandits, and highlights business considerations and implementation challenges. Furthermore, recent discussions on graph embedding techniques for extracting the semantics of explicable recommendations can be found in [48].

To provide a more organized and structured overview of the various studies in the field of augmented reality, deep learning, and virtual assistants, we present Table 8 below. The table includes information on the techniques and approaches employed in these studies, as well as the main outcomes and contributions of each research work. This table serves as a useful reference for readers who are interested in gaining an overview of the different methods used in this field and their potential benefits for improving the accuracy and personalization of online recommendations.

The studies from this field aim to recommend relevant images to customers based on their queries, in order to improve the customer's shopping experience. The studies also explore the use of deep learning, eye-tracking experiments, graph-embedding techniques, and other methods to extract meaningful information from images. These studies demonstrate the potential benefits of using these techniques to improve the accuracy and personalization of online recommendations; however, the authors also mention the challenges that come with their implementation in a business context.

Table 8. Studies on Augmented Reality, Deep Learning, and Virtual Assistants in Recommender Systems.

Study	Methodology/Techniques Used	Applications/Findings
[37]	Deep neural network ranking model	Utilized user-specific features and their interactions to dynamically re-rank recommendations based on real-time user feedback.
[38,39]	Deep learning neural network	Used to recommend movies.
[40–42]	Artificial neural networks, SVM	Computed sentiment scores and frequency on specific features, to recommend products.
[43]	Image processing	Recommended relevant images based on clothing and footwear dataset quality queries.
[44,45]	Deep learning	Explored ways to extract meaningful information from images and applying it to online recommendation systems to enhance the online shopping experience.
[46]	Eye-tracking experiments	Used to study virtual reality.
[47]	Deep learning, causality, and active exploration	Explored the use of bandits to recommend products, and highlighted business considerations and implementation challenges.
[48]	Graph embedding techniques	Discussed graph embedding techniques for extracting the semantics of explicable recommendations.

The practical implications of our research can be significant in various fields, including decision-making, policymaking, and product development. Our findings can provide valuable insights and support evidence-based decision making by offering a clearer understanding of the subject under study.

5.2. AI-Based Recommender Systems for E-commerce Effectiveness

The studies that we included in this SLR do not explicitly address the question "How effective are AI-based recommender systems for e-commerce?". However, authors [49] found that the social recommender system they proposed outperforms other benchmark methodologies in terms of recommendation accuracy. This suggests that the social recommender system is effective.

In terms of consumer behavior, research suggests that AI-based recommender systems may manipulate consumer preferences. Some authors [50] found that the ratings presented by a recommender system serve as an anchor for the consumer's constructed preference, and that viewers' preference ratings are malleable and can be significantly influenced by the recommendations received. Knowledge-based recommender agents improve the consumer decision-making process by reducing the shopping duration and effort spent in searching for suitable products [51,52]. Chinchanachokchai [17] found that expert consumers prefer user-based collaborative-filtering systems, whereas there is no difference between the two systems among novice consumers. These findings suggest that AI-based recommender systems may improve consumer decision-making for experts but may not have the same effect for novice consumers.

In terms of e-commerce businesses, research suggests that recommender systems have a positive effect on sales. Knowledge-based recommender agents reduce the shopping duration and effort spent in searching for suitable products, and increase the decision quality and the number of consumers who purchase the desired item [51]. The strength of recommendations has a positive effect on sales, and recommender systems help to reinforce the long-tail phenomenon of electronic commerce [8,53].

5.3. Benefits and Drawbacks of AI-Based Recommender Systems for E-commerce

The research suggests that AI-based recommender systems have several benefits for e-commerce. In addition to the benefits mentioned by [51], other authors [54] found that prepurchase ratings are complementary to post-purchase ratings and help in alleviating two severe issues that traditional recommender systems suffer from: data sparsity and cold start. However, none of these studies address the drawbacks of AI-based recommender systems for e-commerce. Therefore, we cannot say anything about the drawbacks of AI-based recommender systems for e-commerce based on these papers.

5.4. AI-Based Recommender Systems for E-commerce Comparison to Traditional Recommender Systems

The role of AI-driven techniques in recommender systems for e-commerce is to provide more accurate and personalized recommendations to customers and improve the efficiency of the recommendation process. The use of AI-driven techniques can also address the limitations of traditional recommender systems and provide new insights into user preferences and behavior.

There are authors who state that traditional recommender systems are commonly used in deployed recommender engines, and that simple personalized recommenders may achieve higher rankings than more advanced techniques. Researchers [1] found that utility-based recommender systems may or may not outperform traditional content-based recommender systems, depending on the recommendation context. Other authors, [55] found that best-seller lists are commonly used in deployed recommender engines. Therefore, it seems that traditional recommender systems are still commonly used, despite advances in AI-based recommender systems.

The role of AI-driven techniques is to analyze vast amounts of data, such as user preferences, purchase history, and behavior, to make more accurate and personalized recommendations to customers. They can also be used to incorporate contextual information such as time of day, location, and weather to provide more relevant suggestions. AI-driven techniques can also be used to improve the efficiency of the recommendation process and enhance the customer experience by reducing the search time for suitable products and increasing the decision quality.

In addition, AI-driven techniques can be used to address the limitations of traditional recommender systems, such as the cold-start problem and the inability to recommend products outside a user's historical preferences. AI-driven techniques can also be used to analyze unstructured data, such as user reviews and feedback, to gain insights into their preferences and interests.

Through our analysis, we have identified the benefits of AI-driven techniques, such as improved accuracy and personalization of recommendations, incorporation of contextual information, and the ability to analyze unstructured data. We have also shown that while traditional recommender systems are still commonly used, the use of AI-driven techniques can provide new insights into user preferences and behavior, and can address the limitations of traditional recommender systems. Our findings can inform decision-making and product development in the field of e-commerce and provide valuable insights for researchers and practitioners looking to implement or improve recommender systems.

5.5. AI-Based Recommender Systems for E-commerce Research Directions Heading

The research direction of AI-based RSs is moving towards exploring how to improve the efficiency of AI-based recommender systems. Furthermore, the literature suggests that the focus of research is also on the usage of content-based filtering and collaborative-filtering recommendations, along with the implementation of learning systems, machine learning models, and deep neural networks. Other emerging research areas include sentiment analysis and embeddings, which offer new possibilities to improve recommendation systems. Overall, it appears that the research direction is headed towards the development of more sophisticated and accurate AI-based recommender systems that can adapt to the changing needs and preferences of e-commerce customers.

Bawack [14] found that research on AI in e-commerce focuses primarily on recommender systems, and [56] found that the UbiCARS model-driven framework can be used to reduce complexity, abstract the technical details and expedite the development and application of state-of-the-art recommender systems in ubiquitous environments. However, Chinchanachokchai [17] found that expert consumers prefer user-based collaborative-filtering systems, whereas there is no difference between the two systems among novice consumers. Cha [57] found that AI recommendation systems have different effects on manufactured products and contents. These studies suggest that research for AI-based recommender systems is focused on recommender systems and ways to reduce complexity and abstract the technical details. Additionally, user-based collaborative-filtering systems are preferred for expert consumers, but there is no difference for novice consumers.

6. Conclusions

This systematic literature review aimed to provide a comprehensive understanding of the current state and future potential of AI-based recommender systems for e-commerce. We addressed various research questions, including the most-used AI-based techniques in recommender systems for e-commerce, their effectiveness, benefits and drawbacks, a comparison with traditional recommender systems, and the direction of research in this field.

Our analysis revealed that the most common AI-based techniques employed in recommender systems include machine learning, deep learning, augmented reality, and virtual assistants. These techniques enable the improved relevance, personalization, and accuracy of recommendations. However, the effectiveness of AI-based recommender systems may vary depending on the specific application, user profiles, and recommendation contexts.

The benefits of AI-based recommender systems for e-commerce include improved decision-making, reduced shopping duration and effort, increased sales, and the ability to overcome data sparsity and cold-start issues. However, our study did not provide enough evidence to determine the drawbacks of AI-based recommender systems, highlighting the need for further research in this area.

While traditional recommender systems are still commonly used, advancements in AI-based recommender systems show promising results. Future research should focus on understanding the contexts in which AI-based recommender systems outperform traditional systems.

The research direction in the field of AI-based recommender systems for e-commerce is moving towards more efficient, sophisticated, and accurate systems that can adapt to the changing needs and preferences of customers. Emerging research areas include sentiment analysis, embeddings, and the development of frameworks to reduce complexity and expedite the development of state-of-the-art recommender systems.

AI-based recommender systems have the potential to significantly improve the e-commerce landscape. However, more research is needed to better understand their effectiveness, drawbacks, and optimal applications. By continuing to explore this rapidly evolving field, we can harness the full potential of AI-based recommender systems to enhance e-commerce experiences for both consumers and businesses.

The use of AI and machine learning (ML) is often perceived as a "black box" approach; however, when combined with data science, predictive modeling, graph databases, semantic web, and natural language processing (NLP), these techniques have the potential to provide more transparency and explanatory power to the end-user.

Contributions:

1. We conducted a systematic literature review, providing a comprehensive understanding of the current state of AI-based recommender systems in e-commerce;
2. We analyzed the most commonly used AI-based techniques, their effectiveness, benefits, and drawbacks, offering insights into the practical implications of these systems;
3. We compared AI-based recommender systems to traditional systems, highlighting the need for further research to determine their optimal applications.

Future Directions:

1. Drawbacks of AI-based recommender systems: While our study identified various benefits of AI-based recommender systems, we found limited evidence regarding

their drawbacks. Future research should explore potential challenges, limitations, and negative consequences associated with the adoption of AI-based recommender systems in e-commerce;

2. Integration with other technologies: AI-based recommender systems can be combined with other emerging technologies, such as blockchain, Internet of Things (IoT), and 5G networks, to create innovative solutions for e-commerce. Future research should explore these synergies and their potential impact on the e-commerce landscape.

From the reviewed studies, it is evident that while RSs have evolved from collaborative filtering to AI, the core objective remains unchanged: to provide personalized recommendations and support to users. The increasing demand for customization and adaptiveness in RSs is a trend that can be observed in e-commerce.

Moreover, there is a growing expectation for increased interaction in RSs. As interaction increases, other techniques, such as virtual and augmented reality, could be employed to enhance the online-shopping experience. The growing popularity of personal online-shopping recommender systems suggests that users are becoming more receptive to this technology.

In conclusion, the interplay between behavioral research, intelligent systems, decision-support systems, e-commerce, augmented reality, deep learning, and virtual assistants is essential for the development of effective and innovative recommender systems. Further research is needed to understand the strengths and limitations of each aspect and to determine how they can be integrated in a cohesive manner to provide the best possible recommendation experience for users.

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