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Unveiling the Latest Trends and Advancements in Machine Learning Algorithms for Recommender Systems: A Literature Review

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Abstract

This paper presents a comprehensive literature review of the research and application of machine learning (ML) algorithms in recommender systems (RS). The study aims to identify recent trends, explore real-life applications, and guide researchers in positioning their research activities in this domain published in 2023 (Jan-June). The findings are categorized into different domains including education, healthcare, ML algorithms (auto-encoders and reinforcement learning), e-commerce, and digital journalism. The review highlights the enhanced recommendation accuracy, increased scalability, personalization and context awareness, diverse ML techniques, and strategies for handling cold start and data sparsity, and the foundation for future advancements in ML algorithms for RSs considering the application in manufacturing enterprises.

Keywords: Machine learning; Recommender system (RS); Personalization; Review; Manufacturing; Scalability

1. Introduction

Recommender systems (RS) have widely adopted in various online applications, enabling users to suggest relevant products, services, and content [1]. RSs are designed to suggest items or content to users based on their preferences and interests. These systems can be found in various domains such as e-commerce, streaming platforms, social media, etc. Today, RSs are used in many information-based large companies such as Google, Twitter, LinkedIn, and Netflix [2]. There are a few studies investigating the application of RSs in manufacturing. For example, Yao et al. [3] proposed hybrid machine learning method to provide feasible conceptual design solutions for inexperienced designers by recommending appropriate additive manufacturing design features through a case study. Previous studies in recommendation algorithms commonly employ two types of features: collective local features and graph-related features. Collective local features capture the aggregated characteristics of individual user and item information [4]. These features encompass various aspects, including a user's demographic attributes, interests, item specifications, transaction contexts, and temporal usage patterns that reflect user behavior and preferences [5]. As the field of RSs evolved, researchers began exploring the use of machine learning (ML) algorithms to enhance recommendation accuracy and address the limitations of traditional approaches [6]. ML, a subfield of artificial intelligence (AI), focuses on developing algorithms that can automatically learn and improve from data [7]. Here are some key points highlighting the integration of ML algorithms in RSs:

A) Enhanced Recommendation Accuracy: ML algorithms bring the potential to capture complex patterns and relationships in user-item interactions, leading to more accurate recommendations [8]. ML algorithms can learn from historical data, user feedback, and contextual information to make personalized recommendations.

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B) Increased Scalability and Flexibility: ML algorithms can efficiently handle large-scale datasets, making them suitable for RS with millions of users and items [9]. They offer flexibility in modeling various aspects of user preferences, item characteristics, and contextual factors.

C) Personalization and Context Awareness: ML algorithms enable personalized recommendations by learning user preferences and tailoring suggestions to individual users [10]. Context-aware RSs consider situational factors such as time, location, and device to provide more relevant and timely recommendations [11].

D) Diverse ML Techniques: ML algorithms play a key role in enhancing RSs with different applications. Decision trees, random forests, and gradient-boosting methods are used for content-based filtering, while neural networks and CNNs capture complex item features and user representations. Reinforcement learning algorithms further contribute to optimal recommendation strategies. Integration of these diverse ML techniques improves RSs by enhancing recommendation accuracy and personalization [2].

E) Handling Cold Start and Data Sparsity: ML algorithms offer strategies to mitigate the cold-start problem, where limited data is available for new users or items. Techniques like matrix completion, transfer learning, and feature engineering can be employed to handle data sparsity and make recommendations in such scenarios [2,12].

F) Revolutionize Manufacturing Enterprises: ML algorithms can optimize production processes, supply chain management, maintenance planning, and product quality control [3].

The objective of this paper is to provide researchers and practitioners with valuable insights into the RS field and the utilization of ML techniques. The study focuses on three main goals: (i) identifying recent trends in the use and research of ML algorithms in RSs, (ii) exploring real-life applications of RSs employing ML algorithms, and (iii) guiding new researchers positioning their research activities in this domain.

2. Background and methods

RSs can be categorized into four main approaches (see Fig. 1): collaborative filtering, content-based filtering, hybrid filtering, and other personalized services. Collaborative filtering: These systems analyze user data to identify similarities among users and recommend items based on the preferences of similar users [13]. For example, in an online music store, the system suggests songs purchased by users with similar music tastes. Content-based filtering: RSs using this approach focus on item data and recommend items with similar attributes to the ones the user is interested in [11]. For instance, when a user searches for a computer online, the system suggests computers with similar specifications and features. Hybrid filtering: These systems combine both collaborative and content-based filtering techniques [14]. They consider both user and item data to generate recommendations. For example, on a social network, the system may recommend profiles similar to the user's interests (collaborative filtering) and then use the recommended profiles to find new similar profiles (content-based filtering). Knowledge-based RSs, also known as configuration systems [15], rely on various techniques, such as rule-based reasoning, ontologies, knowledge graphs, semantic analysis, and natural language processing, to extract and represent knowledge about users and items [16]. Demography-based RSs are a specialized class of recommendation systems that leverage demographic information to generate personalized user recommendations [17,18]. A community-based RS is a type of RSs that utilizes the collective wisdom and opinions of a community of users to generate personalized recommendations [19,20]. ML algorithms can be classified into four main categories: supervised, unsupervised, semi-supervised, and reinforcement learning [2].

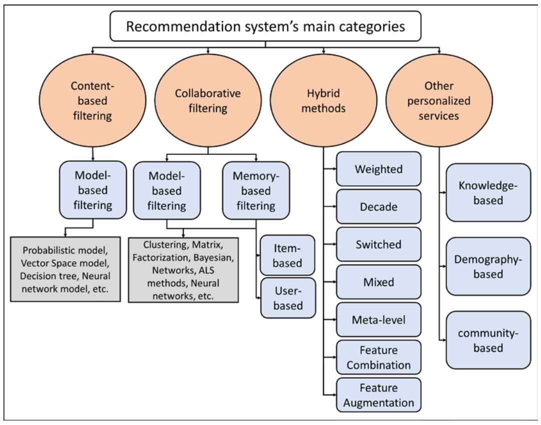

Fig. 1. The main categories of recommendation systems

Table 1. Literature review papers distribution in machine learning algorithms for recommender systems (2023)

Main topics	Available literature papers	Publication channel
Educational RS (4)	[21–24]	Applied Artificial Intelligence; IEEE Access; International Journal of Engineering Trends and Technology; Education and Information Technologies
Health RS (3)	[25–27]	Journal of Medical Internet Research; International Journal of Environmental Research and Public Health; Expert Systems with Applications
ML algorithms in RS (2)	[28,29]	Mathematics; Energies
E-Commerce RS (1)	[30]	Applied Sciences (Switzerland)
Digital Journalism RS (1)	[31]	Expert Systems with Applications

Given the abundance of studies and considerable research interest in the field of ML application in RSs and considering the limitations in the scope and space of this paper, our focus will be solely on the latest journal review papers published in 2023 (Jan-June). This review research has been conducted in May 2023. To ensure a systematic approach, this paper adopts a three-step protocol consisting of data search, data analysis, and report generation, forming the basis of our comprehensive literature review [32]. To guide the examination, the review addresses the following three research questions (RQs): (1) What are the current trends in the use and research of RS when implementing ML algorithms? (2) What are the emerging trends in the use and research of ML algorithms when developing RS?

By addressing these research questions, the review aims to provide insights into the trends, developments, and sources of research related to the utilization of ML algorithms in RS. The data search encompassed through the search string TITLE-ABS-KEY (("recommendation system" OR "recommender system") AND "machine learning") was applied to search for journal literature review articles in English on the Elsevier Scopus database. Due to a significant number of literature, we limited the search only to 2023 which resulted in 189 journal papers. Next, the abstracts of the identified publications were scanned to determine the initial sample of the relevant literature. Based on the selection criteria, which explicitly addressed the ML application for RS as the main topic of study and contributions that explicitly addressed the scope of the research (e.g., reviews, definitions, frameworks), a subset of 11 articles was selected for full-text reading.

3. Literature review results

3.1. Research perspectives and opportunities in Educational Recommender Systems

The amount of data generated by educational institutions is used to make recommendations for a wide range of areas [21]. Maphosa and Maphosa [21] reviewed 272 articles published between 2007 and 2021. Research indicates that many college students enter their studies without a clear career path and often change their majors' multiple times. RSs have assisted students in selecting their majors using techniques like the nearest neighbor algorithm. Educational RS utilizes collaborative filtering and nearest-neighbor algorithms to rank and recommend items based on user ratings and preferences. Content-based recommendations and data mining techniques are also used to generate personalized learner recommendations. RS in education uses collaborative filtering and content-based techniques to recommend learning materials and courses to students. RS also assists in selecting suitable majors and provides teaching patterns for educators. Future research can explore integrating bibliometric analysis and the PRISMA methodology to provide a comprehensive overview of RSs research in higher education. This approach can provide valuable insights into the current status and future trends of RS in this domain, benefiting researchers, policy-makers, and practitioners. Furthermore, there is a need for more research on RS in higher education from developing countries, as AI applications such as RS can significantly impact student learning outcomes.

Thongchotchat et al. [22] analyzed 40 papers on RSs utilizing learning styles. The systematic literature studies revealed advancements, prospects, and obstacles in educational RS, particularly in utilizing learning styles for recommendations. Most systems focused on attribute-related recommendations, while research in educational recommendations and learning style theories requires further investigation and growth. The analysis also highlighted the need for assessing and comparing RSs based on different learning theories to enhance learning outcomes. Combining theories of learning styles can enhance flexibility and recommendation capacity. Questionnaires were the most popular method for identifying learning styles, but there is a need for further research on the power and performance of different online attributes. Different recommendation algorithms, including rule-based and collaborative filtering, were commonly used, but there is potential for exploring hybrid and ensemble algorithms for greater accuracy. These findings contribute to the enhancement of e-learning systems and classification models such as decision trees, logistic regression, or support vector machines, are often employed to classify learner attributes, preferences, or learning styles, enabling personalized and tailored recommendations.

Pal et al. [23] screened 40 papers to identify RSs that specifically support the teaching/learning environment. The analysis focused on different techniques and approaches used for implementation, as well as evaluation measures employed to assess the quality and accuracy of the recommendation framework. The following techniques are discussed: (1) Deep Neural Networks: Using deep neural networks to recommend resources based on learners' interests; (2) User Feedback: Incorporating user feedback; (3) Content-Based and Collaborative Filtering: Combining content-based and collaborative filtering in the LeCoRe approach; (4) Web-Based Personalized Recommendations: Leveraging past ratings and attention-based CNN techniques for personalized recommendations on MOOCs platforms; (5) Multi-Personalized RS for E-Learning: Considering learners' preferences, interests, and history through content-based and collaborative filtering; (6) Learners' Annotation Activities: Utilizing learners' activity annotations for personalized recommendations; (7) Hybrid Filtering: Integrating content-based, collaborative filtering, and hybrid filtering approaches; (8) LSTM and RNN: Utilizing LSTM and RNN deep learning techniques for sequence-based course recommendations. Future research in this field can focus on refining recommendation algorithms, developing standardized evaluation measures, utilizing diverse educational datasets, integrating intelligent tutoring systems and adaptive learning technologies, and enhancing the accuracy and personalization of RSs in the context. These advancements will contribute to more effective and engaging educational experiences for learners.

da Silva et al. [24] studies 15 literature review studies in the field of evaluating educational RS (ERS). Evaluation methodologies for ERSs include offline experiments, user studies, and online experiments. User studies and offline experiments are commonly used, while real-life tests are less frequent due to cost and complexity. User satisfaction assessment is common in user studies, often combined with other experiments. Accuracy investigation (to measure the effectiveness and alignment between the recommendation and the customer's desired option) is the most prevalent research goal. There is a need for more real-life tests to understand recommender impact. Offline experiments use larger datasets, while user studies involve smaller samples. Future research should focus on real-life tests, evaluating pedagogical effectiveness, and exploring diverse evaluation approaches. Research opportunities in the field of ERSs have been identified based on the gaps observed in the analyzed papers. Three main strands of research opportunities were identified: (1) Study of overlooked user attributes: existing ERS models often neglect important user attributes such as emotional state and cultural context; (2) Increase studies on ERS application in informal learning situations: ERS research predominantly focuses on formal learning contexts, while the design and evaluation of recommenders for informal learning settings are overlooked; (3) Studies on the development of multidimensional evaluation frameworks: existing evaluation of ERS primarily emphasizes accuracy and user satisfaction, overlooking other critical factors such as student performance, learning gains, and technological quality. The advancements in Educational RS have significant implications for the manufacturing industry, particularly in the domain of on-site training and learning factories.

3.2. Research perspectives and opportunities in Health Recommender Systems

According to Sun et al. [25], health RSs (HRS) are specialized information retrieval systems that provide users with relevant health-related items based on their specific needs. These systems aim to assist and motivate users in making informed decisions about their health and encourage behavior change. A total of 51 studies of HRSs were included in the systematic review and the health domains included general health promotion, lifestyle, generic health service, and some other domains. Sun et al. [25] found that hybrid recommender systems, collaborative filtering, and knowledge-based systems are commonly used in building HRS. Collaborative filtering showed limited usage in health, with only a few studies demonstrating its relevance. Some studies compared different recommender techniques to identify optimal algorithms. For future research, Sun et al. [25] highlighted that it is important to report and disclose detailed information. Further studies are needed to evaluate multiple domains, including clinical effectiveness, patient perspectives, economic considerations, organizational aspects, sociocultural factors, and ethical and legal considerations. It is also noted that there is a need for more papers that combine clinical trials and simulations in the experimentation process, despite the potential benefits of such an approach.

Yera [26] reviewed 967 papers focused on food recommendations for diabetic patients using the PRISMA 2020 framework. Various research approaches were identified, including ontologies, optimization methods, rule-based systems, and user interaction. Challenges were found in generalizing and incorporating diabetes-related knowledge, as well as reproducing and generalizing results. Different approaches such as optimization methods, data mining techniques, and interactive systems were identified, but limitations exist in terms of specific datasets, evaluation protocols, and generalization. The lack of a common framework and integration with AI-based methods pose challenges for future progress. To advance nutritional RSs for diabetic patients, the following research directions have been identified: (1) Establish a consolidated framework for further research; (2) Better formalize the research problem and unify the definition and output of recommendations; (3) Utilize domain knowledge from the medical and nutritional fields; (4) Incorporate user preferences more effectively for personalized recommendations; (5) Explore the use of fuzzy tools for handling uncertainties; and (6) Develop explainable recommendation approaches to align with ethical guidelines.

Etemadi et al. [27] identified, taxonomically classified, and compared current HRS research systematically. Five sub-classes of applied approaches are identified, with collaborative-based approaches being the most common. The evaluation factors in HRS primarily focus on accuracy, precision, recall, and time, but scalability, security, and reliability should be addressed. Most articles use a real test-bed environment for assessment, with Python being the most widely used assessment tool at 15%. The reviewed papers ethical challenges related to privacy and data sharing, the proliferation of healthcare standards and the need for interoperability, the cold-start problem in making recommendations for new items and users, scalability challenges in handling a large amount of data, the importance of reliability in HRSs, the need for accuracy in healthcare system results, patients and their relatives disagreement over treatment recommendations, authorization and access to electronic medical records, convincing people to trust and use healthcare systems, and legal aspects concerning the use of artificial intelligence in medicine. These challenges and research directions are crucial for advancing HRSs and require further exploration and consideration. Worker well-being is of paramount importance in the manufacturing industry, especially in the context of Industry 5.0. Health RSs offer valuable insights and recommendations for maintaining worker health, which is crucial for ensuring a safe and productive manufacturing environment.

3.3. Research perspectives and opportunities in Auto-Encoders and Reinforcement Learning

Chen et al. [28] provided an overview of auto-encoder concepts, variants, applications, and their relationships with shallow and deep learning models. It explores the use of auto-encoders in different fields with available toolkits. Auto-encoders gained popularity in unsupervised learning for their ability to process large amounts of unlabeled data. The survey offers the examination of auto-encoder, covering theory, features, perspectives, relationships with other models, toolkits, applications, and future trends. It explores potential areas such as constructing hybrid models, incorporating attention mechanisms, integrating supervised learning, drawing inspiration from neuroscience and cognitive science, and optimizing parameter adjustment with improved algorithms (such as gradient descent or ADAM). Future studies in auto-encoders are suggested as (1) Hybrid Models: combining auto-encoders with other models for improved performance; (2) Attention Mechanism: integrating visual attention mechanisms to enhance feature learning; (3) Supervised Learning Integration: using supervised learning to boost auto-encoder performance. (4) Neuroscientific and Cognitive Science Approaches: aligning auto-encoder structures with biology and cognition; (5) Optimization Algorithms: developing advanced algorithms to automatically adjust model parameters.

Sivamayil et al. [29] analyzed 127 publications focusing on the applications of Reinforcement Learning (RL) in marketing, robotics, gaming, automated cars, natural language processing (NLP), internet of things (IOT) security, RSs, finance, and energy management. RL is suitable for dynamic contexts due to its ability to learn independently through trial and error interactions. RL has the potential to revolutionize energy management by optimizing energy usage in real-time and improving the functioning of renewable sources. While most energy management system applications are tested in simulations, there is a need to implement them in real-world settings. RL-based RSs show high prediction accuracy, and RL is expanding its presence in gaming applications. In the financial sector, RL is predominantly used in trading applications, but there is room for exploration in credit risk analysis. RL holds promise for enhancing the energy efficiency of HVAC systems, although further research is needed to handle real-world complexity. Future studies in RL can explore algorithmic improvements, real-world implementations, transfer learning, robustness and safety, explainability, ethical implications, multi-agent RL, and cross-disciplinary applications. These areas of research aim to enhance RL algorithms, apply them in practical settings, address challenges, ensure safety and interpretability, consider ethical implications, study multi-agent interactions, and explore diverse application domains. Within the manufacturing industry, the application of auto-encoders and reinforcement learning holds promise for optimizing production line configurations, improving equipment setup based on historical data and real-time performance metrics, and addressing the complexity of manufacturing processes.

3.4. Research perspectives and opportunities in electronic-commerce recommender systems

Necula and Păvăloaia [30] investigated how AI is utilized in RSs for electronic commerce. The review identified various AI-based approaches such as content-based scoring, collaborative filtering, deep learning, and virtual assistants. These techniques aim to enhance recommendation relevance and accuracy, improve the customer shopping experience, and increase sales. The research direction in this field is moving towards developing more sophisticated and adaptable AI-based RSs. The most common AI techniques used include ML, deep learning, and other relevant algorithms, which, when combined with technologies like augmented reality, contribute to improved relevance and personalization. Benefits include improved decision-making, reduced shopping effort, increased sales, and overcoming data issues. Further research is needed to focus on contexts where AI systems outperform traditional ones. Research areas include sentiment analysis, embeddings, and framework development. AI-based RSs can enhance e-commerce in further research. Integrating with other technologies like blockchain, IoT, and 5G networks should be explored. Customization and interaction in RSs, interplay between various aspects like behavioral research are growing trends. The integration of e-commerce RSs with other technologies like blockchain, IoT, and 5G networks opens up new avenues for enhancing manufacturing processes.

3.5. Research Perspectives and Opportunities in Digital Journalism recommender systems

Fernandes et al. [31] The study analyzed the role of Data Science (DS) in Digital Journalism (DJ) and categorized the findings into different clusters. Cluster 1 focused on exploratory studies and ML approaches, exploring personalization, engagement metrics, and ML algorithms for news popularity prediction. Cluster 2 focused on text mining and sentiment analysis, investigating fake news detection and building reader confidence. Clusters 3 and 6 examined news recommendation and automated journalism, addressing ethical issues and user perception. Clusters 4 and 5 focused on event extraction and opinion mining, analyzing event dynamics and reader comments. Future research can focus on personalization, content automation, fact-checking, engagement metrics, and paywall mechanisms to enhance user experience, content optimization, information credibility, and business models in digital journalism. Applying digital journalism RSs in the manufacturing domain can facilitate effective communication within the organization, enabling timely dissemination of critical information, updates on production processes, and insights for decision-making at various levels of the manufacturing enterprise.

4. Concluding remarks

In this study, we aimed to address two main research questions (RQs) to gain insights into the use and research of ML in RSs. The findings of this study indicate that the integration of ML algorithms in various domains has shown promising results in improving efficiency, accuracy, and decision-making processes. The study's objective was to identify recent trends, explore real-life applications, and guide researchers in this domain. The findings from this paper demonstrate that most review papers in this field (RQ1), in 2023, are focused on the sectors of education [21–24] and then healthcare [25–27]. We found two papers reviewing ML algorithms including Auto-Encoders and Reinforcement Learning [28,29]. We also found papers considering RS applications in e-commerce [30] and journalism [31]. Turning to our RQ2 regarding the emerging trends in the use and research of ML algorithms in RSs, our review shed light on novel applications and advancements such as increasing interest in the integration of reinforcement learning algorithms for optimal recommendation. The review has shed light on several aspects:

1. Evolution of RSs: Over the years, RSs have evolved from simple popularity-based approaches to more sophisticated systems driven by ML algorithms. This evolution has been fueled by advancements in data collection, processing power, and algorithmic techniques, enabling RSs to provide personalized and context-aware recommendations.
2. ML Algorithms' Contribution: ML algorithms have significantly contributed to the success of modern RSs by enabling the analysis of vast amounts of user and item data.
3. Challenges and Opportunities: Although ML algorithms demonstrate significant potential, there are persistent challenges that need to be addressed, including data sparsity, cold-start problems, and algorithmic bias. These challenges present opportunities for further research and innovation in the field of RSs, aiming to develop effective solutions.
4. Real-World Applications in Manufacturing Enterprises: The literature review has highlighted various real-world

applications where ML-based RSs have been successfully employed. By leveraging ML algorithms, RS can provide personalized recommendations for optimizing production processes, supply chain management, maintenance planning, and product quality control.

In manufacturing, RSs will optimize the production line by recommending the most suitable equipment setup based on historical data, real-time performance metrics, and contextual information. There is a need for studies to focus on the application of RSs to analyze production data and predict the optimal configuration for achieving high productivity and minimizing downtime [33]. It is important to note that implementing ML-based RS in manufacturing enterprises requires careful consideration of data security, privacy, and transparency. Additionally, developing frameworks and guidelines for using ML-based RS in manufacturing enterprises will ensure these systems' long-term sustainability.

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