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The Increase In The Use Of Recommender Systems: A Survey

Morad Ali Hassan
[1]*Department of Computer Science, University of Bani Waleed, Libya*

Abstract: *Recommender systems have become increasingly popular in recent years, with many applications in various domains. In this survey paper, we aim to provide an overview of the current state-of-the-art in the field of recommender systems and highlight the latest trends in their development. We review the different techniques and developments of recommender systems that have been used widely. Also, analyzing the growth of recommender systems over time and discuss the reasons behind their increasing popularity. Furthermore, examining how the Covid-19 pandemic has affected the use of recommender systems and discuss the potential long-term impact on their development. We also analyze how the Covid-19 pandemic has affected decision-making processes and discuss how recommender systems can help mitigate some of these effects. In addition, explore how recommender systems affect decision-making processes and discuss their potential benefits and drawbacks.*

Keywords: *Recommender Systems, Decision-Making, Personalized Experience, Covid-19.*

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I. INTRODUCTION

In today's digital age, personalized experiences have become the driving force behind customer satisfaction and engagement. Companies like Netflix and Amazon have transformed the way we consume entertainment and shop online by leveraging advanced recommender systems. These intelligent algorithms analyze vast amounts of customer data to predict and suggest content or products that are tailor-made for individual preferences.

When you log into Netflix, the platform uses your viewing history, ratings, and similar user data to recommend shows or movies that align with your interests. Similarly, Amazon offers personalized product recommendations based on your browsing history and purchase behavior. This level of personalization not only enhances the user experience but also enables companies to drive higher conversions and sales.

As these recommender systems continue to evolve and improve, they are becoming increasingly sophisticated in understanding individual preferences and delivering more accurate suggestions. This revolution in personalized experiences has empowered consumers to discover new content and products that they might not have otherwise explored, creating a win-win situation for both consumers and businesses.

In this paper, we will explore how the use of recommender systems has increased and the impact they have on transforming personalized experiences across various industries and the impact of a new pandemic like Covid-19 on these systems.

II. MOST USED RECOMMENDER SYSTEMS TECHNIQUES

Recommender systems are essential tools for assisting users in finding relevant information in large information spaces (Adomavicius & Tuzhilin, 2005). There are several techniques commonly used in recommender systems, including collaborative filtering, content-based filtering, and hybrid approaches (Bobadilla et al., 2015).

Collaborative filtering is one of the most widely used techniques in recommender systems. It relies on the idea that users with similar preferences in the past will have similar preferences in the future. This technique identifies neighbors with common interests and generates recommendations based on the favorite items of those neighbors (Su & Khoshgoftaar, 2009). However, collaborative filtering has limitations, such as the cold start problem, where it struggles to make recommendations for new users or items that have limited data (Burke, 2002).

Content-based filtering is another popular technique in recommender systems. It focuses on the characteristics of the items themselves and recommends items that are similar to those that a user has liked in the past. This technique does not rely on user preferences or feedback from other users. However, content-based filtering may suffer from the overspecialization problem, where recommendations are too similar and do not introduce users to new items (Bobadilla et al., 2015).

Hybrid approaches combine multiple techniques to overcome the limitations of individual methods. By leveraging both collaborative filtering and content-based filtering, hybrid recommender systems can provide more accurate and diverse recommendations (Bobadilla et al., 2015). These systems can take advantage of the strengths of each technique and mitigate their weaknesses.

In recent years, deep learning has gained significant interest in recommender systems. Deep learning-based recommender systems can learn feature representations from scratch and have shown impressive performance in various research fields. By utilizing neural networks, these systems can capture complex patterns and relationships in user-item interactions, leading to more accurate recommendations (Zhang, Yao, & Xu, 2018).

Session-based recommender systems (SBRSs) have also emerged as a new paradigm in recommender systems. Unlike traditional recommender systems that model long-term user preferences, SBRSs aim to capture short-term and dynamic user preferences based on session contexts. These systems provide more timely and accurate recommendations that are sensitive to the evolving needs of users (Hidasi et al., 2015).

Incorporating contextual information is another approach to enhance recommender systems. Multidimensional recommender systems can provide recommendations based on additional contextual information beyond user and item information. This approach supports multiple dimensions, extensive profiling, and hierarchical aggregation of recommendations (Adomavicius, Sankaranarayanan, Sen, & Tuzhilin, 2005).

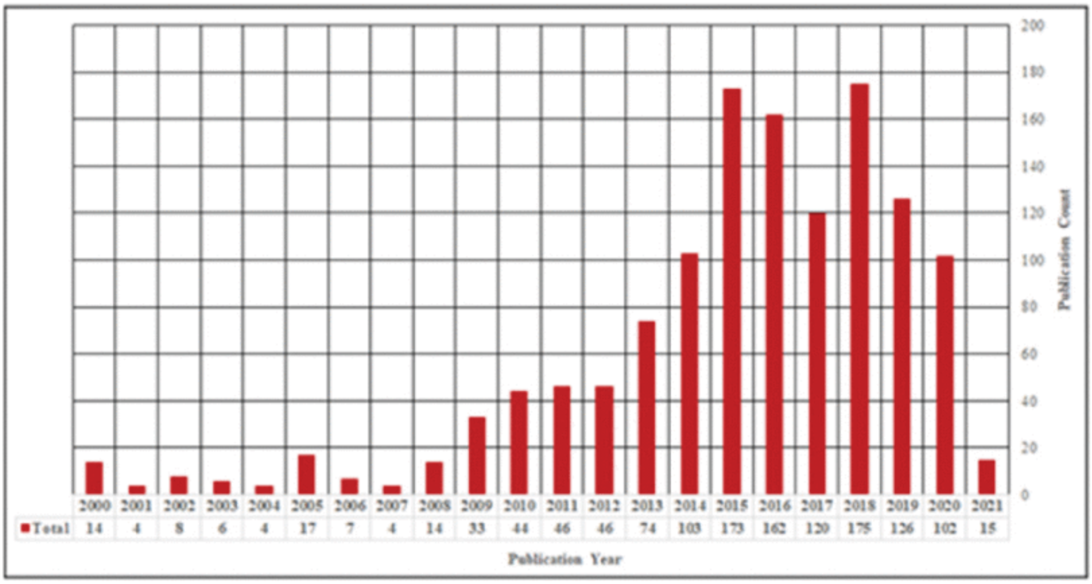
In conclusion, the most commonly used techniques in recommender systems include collaborative filtering, content-based filtering, hybrid approaches, deep learning-based methods, session-based recommender systems, and multidimensional recommender systems. Each technique has its strengths and limitations, and the choice of technique depends on the specific requirements and characteristics of the recommendation task.

III. THE INCREASE IN THE USE OF RECOMMENDER SYSTEMS

The increase in the use of recommender systems has revolutionized decision making in various domains such as business, government, and education. Recommender systems have become an integral part of modern online platforms, providing personalized recommendations to users based on their preferences and behavior (Thongasri et al., 2022). These systems have greatly improved the user experience, helping individuals navigate through the vast amount of available information and choose products or services that best suit their needs.

In recent publication by (Anandhan et al., 2022), that presents analysis of the research on social media recommender systems (SMRS) published between 2000 and 2021. The authors analyze the most productive authors, institutions, and countries, as well as the number of publications per year. The authors found that the number of publications on SMRS has increased steadily over time, with a significant increase in recent years. The figure below shows the number of publications per year.

Figure 1. Number of publications per year (Anandhan et al., 2022).



IV. THE INCREAS IN THE USE OF RECOMMENDER SYSTEMS AFTER COVID-19

In recent years, there has been a significant increase in the use of recommender systems across various industries (Stell et al., 2022). This surge in adoption can be attributed to the need for businesses to adapt and provide personalized recommendations to their customers, especially in the era of COVID19, where online interactions and transactions have become more prevalent. With the pandemic causing disruptions in traditional brick-and-mortar businesses, companies have turned to recommender systems as a way to replicate the personalized experience that customers would typically receive in physical stores. Recommender systems have proven to be invaluable tools for online industries during the COVID-19 pandemic, allowing businesses to not only stay afloat but also flourish by enhancing customer satisfaction and loyalty (Jha et al., 2012).

By utilizing recommender systems, these online industries have been able to claim a significant share of the market and effectively manage their customer relationships (Fazziki et al., 2022). Recommender systems have become a crucial tool for online industries in the last decades, particularly during the COVID-19 pandemic. The wide adoption of recommender systems in online industries over the last decades, especially during the COVID-19 pandemic, has been instrumental in enhancing customer satisfaction and driving business growth (Nurcarya et al., 2022). The use of recommender systems has offered online industries a competitive advantage, enabling them to provide personalized recommendations and improve customer relationship management.

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V. THE IMPACT OF RECOMMENDER SYSTEMS ON DECISION MAKING

Recommender systems have a significant impact on decision-making processes. Studies have shown that effective tradeoff support provided by recommender systems can have positive effects on various factors, including system acceptance, users' perceived decision quality, willingness to buy, and willingness to reuse the recommender system in the future. The design of the recommender system interface also plays a role in facilitating users' decision processes and enhancing their perceived domain knowledge and trust (Chen et al., 2013). Both online consumer reviews and recommendations from recommender systems influence consumers' decision-making, although there are differences in their effects. Recommendations from recommender systems are more influential, while recommendations from previous customers are more trustworthy. Understanding the interplay between these two types of recommendations can deepen our understanding of the influence of online recommendations on decision-making (Baum & Spann, 2014).

Recommender systems are not limited to simple low-risk decision-making processes. They can also be used to support more complex high-risk decisions, such as making decisions to be healthy, save money, and optimize time (Cena et al., 2020).

The impact of recommender systems on decision-making is particularly relevant in the context of online stores, where effective product recommender tools are recognized as effective means to sell more products (Castagnos et al., 2009). User satisfaction with recommender systems is not only related to the accuracy of recommendations but also to how much they support the user's decision-making. Novelty is an important metric of customer satisfaction in recommender systems (Zhang, 2013). Integrating factors such as group composition and social connections among group members can also affect the outcome of group decision-making in recommender systems (Tran et al., 2021).

Context-aware recommender systems take into account influential and contextual variables to provide effective recommendations. These systems apply a trade-off in context to achieve the proper accuracy and coverage required for collaborative recommendations (Sujatha & Abirami, 2023). Algorithms, including recommender systems, play an important role in everyday decision-making processes (Martens et al., 2019). The main function of a recommender system is to facilitate users' decision-making, and the effectiveness, trust, and satisfaction perceived by users are important characteristics to study in the evaluation of these systems (Arana-Llanes et al., 2014).

Overall, recommender systems have a significant impact on decision-making processes, influencing factors such as system acceptance, perceived decision quality, willingness to buy, and willingness to reuse the system. The interplay between online consumer reviews and recommendations from recommender systems is also important to understand. The impact of recommender systems on decision-making extends to various domains, including communication aid recommendations and online stores. Factors such as novelty, group composition, and social connections can further influence decision-making in recommender systems. Context-aware recommender systems consider influential and contextual variables, and user experience is crucial in the design and evaluation of recommender systems for mobile devices.

VI. THE IMPACT OF COVID-19 ON DESCISION-MAKING AND RECOMMENDER SYSTEMS

Decision-making and recommender systems are two important areas of research that have been significantly impacted by the COVID-19 pandemic.

Decision-making is the process of selecting a course of action from a set of alternatives. It is a complex process that involves a variety of factors, including cognitive biases, emotions, and personal preferences. While recommender systems are software tools that help users discover new items that they are likely to be interested in. They are used in a wide range of applications, including e-commerce, music streaming, and social media.

The COVID-19 pandemic has disrupted human behavior and preferences in a number of ways. For example, people have become more risk-averse and have changed their spending habits. Additionally, people have been more likely to consume content that is related to the pandemic, such as news articles and health information. These changes in human behavior and preferences have made it more challenging for people to make decisions and for recommender systems to provide accurate and relevant recommendations.

A number of researchers have investigated the impact of COVID-19 on decision-making and recommender systems. For example, a study by (Bostan & Erev, 2020) found that people were more likely to make risk-averse decisions during the early stages of the pandemic. Another study by (Koren, 2021) found that recommender systems were less effective at predicting user preferences during the pandemic. Researchers have also proposed a number of ways to mitigate the negative impact of COVID-19 on decision-making and recommender systems. For example, (Argaman, 2020) argues that recommender systems should focus on recommending items that are relevant to users' current interests and needs. (O'Connor, 2020) presents a case study of how Netflix adapted its recommender system to the COVID-19 pandemic by focusing on recommending content that is relevant to users' current interests and needs.

VII. CONCLUSION

Recommender systems are becoming increasingly popular as the amount of information and content available to us continues to grow. They help us to discover new items that we are likely to be interested in, based on our past behavior and preferences.

The increase in the use of recommender systems is being driven by a number of factors, including:

- The growth of online commerce and entertainment: Recommender systems are widely used in e-commerce and entertainment platforms, such as Amazon, Netflix, and Spotify, to help users find the products and content that they are most likely to enjoy.
- The rise of artificial intelligence (AI): AI is enabling recommender systems to become more personalized and accurate. AI algorithms can be used to analyze large amounts of data about user behavior and preferences in order to make better recommendations.
- The increasing use of mobile devices: Mobile devices provide a convenient way for people to access recommender systems on the go. This has made recommender systems more accessible and useful to people in their everyday lives.

The increase in the use of recommender systems has a number of benefits. For example, recommender systems can:

- Help users to discover new items that they may not have found on their own.
- Save users time and effort by filtering out irrelevant items.
- Improve the user experience by making it easier for users to find the items that they are most likely to be interested in.

However, there are also some potential risks associated with the use of recommender systems. For example, recommender systems can:

- Lead to filter bubbles, where users are only exposed to content that reinforces their existing beliefs and biases.
- Reduce user autonomy and control over their own choices.
- Be used to exploit users' vulnerabilities and manipulate their behavior.

It is important to be aware of the potential risks associated with recommender systems and to use them responsibly. For example, users should be critical of the recommendations that they receive and should be aware of the possibility that they are being manipulated.

Overall, the increase in the use of recommender systems is a positive development. Recommender systems can help us to discover new items that we are likely to be interested in and improve our overall user experience. However, it is important to be aware of the potential risks associated with recommender systems and to use them responsibly.

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