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Recommendation Systems: A Systematic Review

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Abstract
This article presents a comprehensive and objective systematic review of existing research on recommendation systems with regards to core theory, latest studies, various applications, current attitudes, and potential future applications. The research is mainly based on exploring professional peer-reviewed studies and articles and using their abstracts to create a comprehensive and unbiased review of existing research. The following search terms were used to identify articles and studies for the research: recommendation systems; recommender systems; core theory of recommender systems; current attitudes towards recommendation systems; latest studies on recommendation systems; applications of recommendation systems; potential studies on recommendation systems; and future potential applications of recommendation systems. The research also used the advanced search filter to locate recent studies for comparison by limiting the search by year to find studies published from 2021 onwards. Most literature on this area highlights the importance of recommendation systems in almost all aspects of modern life. Specifically, recommendation systems have become critical components in business, health care, education, marketing, and social networking domains. Additionally, most studies identified reinforcement of learning and deep learning techniques as significant developments in the field. These techniques form the backbone of most modern recommendation systems. The primary concern that could hinder further evolution systems is their consequent filter bubble effects which many studies showed to be problematic. Healthcare is a central area that shows tremendous potential for these systems. Although recommender systems have been implemented in this domain, there remains a lot of untapped potential that, if unleashed, could revolutionize medicine and healthcare. But the problems facing these systems have to be tackled first to establish trust.
Keywords: Recommendation systems, Recommender systems, Deep learning, Reinforcement learning
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1. Introduction

Recommendation systems (also known as recommender systems) are a category of information systems built to predict the preference or rating a user is likely to give to an item. There are many areas where recommender systems are utilized, with commonly known examples as playlist curators for audio and video content platforms, e-commerce sites product recommenders, or social media platforms content recommenders and content recommendation systems for the open web. Recommender systems can function reliably using a single input, like videos or music, or a combination of multiple inputs such as items watched along with ratings and comments from friends. The classification of recommendation systems falls under two broad categories: collaborative filtering and individualized learning (Sundaresan, 2011). Collaborative filtering is a more traditional form of recommendation where the system utilizes feedback data from users to create personalized recommendations. On the other hand, individualized learning recommends items based on past user behavior rather than relying solely on feedback data.

One can trace the origins of the recommender system back to the early days of online commerce. eBay, for example, utilized a recommendation system to suggest items that buyers might be interested in purchasing (Sundaresan, 2011). More recently, recommendation systems have been used in various other areas, including social networking and media services, eCommerce stores, and open web content. One of the primary benefits of using a recommender system is that it can help users find items or information they might not have found or would not have considered purchasing. For example, if you are looking for a new movie to watch, a recommender system could suggest similar movies that have been rated highly by other users. One of the primary drawbacks of using recommender systems is that it can be difficult for the systems to recommend items or pieces of information that are not already popular. For example, when looking for an obscure horror movie, the recommender system might not be able to provide any recommendations.

This paper aims to produce a comprehensive and unbiased systematic review of existing research on recommendation systems regarding the core theory, latest studies, various applications, current attitudes, and potential applications in the future. The research uses Google Scholar to identify relevant articles on the topic. Google Scholar is a database of scholarly articles and books that can be useful for finding research on recommendation systems. The search criteria avoid too many constraints to reduce bias. However, articles on platforms whose domain names end with '.edu' are eliminated from the review as one cannot trust their quality given that they could be written by students and lack the element of peer review. Primarily the research focuses on exploring professional peer-reviewed studies and articles and using their abstracts to create a comprehensive and unbiased review of existing research. The following search terms are used to identify articles and studies for the research: recommendation systems; recommender systems; core theory of recommender systems; current attitudes towards recommendation systems; latest studies on recommendation systems; applications of recommendation systems; potential studies on recommendation systems; and future potential applications of recommendation systems. The research also used the advanced search filter to find recent studies for comparison by limiting the search by year to find studies published from 2021 onwards specifically.

2. Review

2.1 Review of Core Theory

Isinkaye et al.'s (2015) study on recommendation systems is one of the most cited works on Google Scholar. Researchers present recommendation systems as an important cog in the efficient running and use of the interweb. According to the study, recommender systems help prevent information overload in a world where users are constantly bombarded with massive data streams (Isinkaye et al., 2015). Recommender systems achieve this feat by filtering through dynamic data and customizing the information generated to a specific user. Isinkaye et al. (2015) highlighted that these systems are an important part of modern life, both for users and service providers. By providing personalized recommendations, providers can keep users engaged with their service and reduce the time they spend searching for information. This research has significantly impacted the development of recommender systems and is still in use today. It serves as an example of how academic work can have a real-world impact on the way we live our lives.

Additionally, the study also categorized the recommendation process into three stages: information collection, learning, and prediction or recommendation phases (Isinkaye et al., 2015). The recommender system collects data from users and sources during the information collection phase. This data can come from a user's past interactions with the service or publicly available data. In the learning phase, the recommender system begins to understand how a user likes and uses information (Isinkaye et al., 2015). This understanding helps in predicting what content will be relevant to that particular user. Finally, in the prediction or recommendation phase, the recommender system recommends content to a user based on this understanding. The study also highlighted the importance of user feedback in developing recommender systems. Without feedback, the system will not be able to improve its predictions over time (Isinkaye et al., 2015). In addition, providing feedback can help users to influence the recommendations shown to them. The system can use that information to personalize future recommendations to a user.

Indeed, the phases highlighted by Isinkaye et al. (2015) appear to form the basis of the criteria followed by all platforms in implementing recommender systems. While evaluating different recommender systems, Shani and Gunawardana (2010) discovered that for a recommender (algorithm) to provide personalized predictions to a user or user group, it must first receive some data as input. This data aids the algorithm in learning a user's preferences or approximate preferences based on a closely related archetypal profile (Shani & Gunawardana, 2010). A person's activity data (for example, shared items) gets analyzed to understand the items within it and their relationships. This understanding forms the algorithm's personalized recommendations to a user.

There are two main categories of systems: collaborative (which relies on the past behavior of users and items to make recommendations) and content-based (which relies on item attributes to make recommendations). The core theory behind recommender systems is that people are more likely to be interested in items similar to other items they liked before. This similarity can be measured using various methods, such as cosine similarity or Euclidean distance (Yildirim et al., 2020). The algorithm then uses this measure of similarity to make recommendations. For example, if a user has liked several items similar to item A, the algorithm may recommend that the user also like item A.

However, this ability to recommend items based on items already selected or viewed was not always easy. Yildirim et al. (2020) highlighted the problem that most recommenders that rely significantly on user history to make predictions face: the first-time user. It is difficult for such recommenders to understand user preferences or link them to a preexisting archetypal profile. This phenomenon is referred to as the cold start problem. According to Yildirim et al. (2020), deep learning is instrumental in solving this problem by aiding architectures that do not rely on customer data in making recommendations.

There are various ways of measuring the similarity between vectors, which is essential for many tasks such as recommendation systems. Two popular measures are cosine similarity and Euclidean distance. Cosine similarity measures the angle between two vectors, while Euclidean distance helps to determine the straight-line distance from one vector to another. Engineers can apply these measures to deep learning algorithms to find similar items in a dataset. For example, in a recommendation system, cosine similarity can be used to find items similar to the item being viewed or selected. Recommender systems can use the Euclidean distance to find similar items in popularity, rating, or other metrics.

Both measures have their benefits and drawbacks. Cosine similarity is faster than Euclidean distance but can result in more noise in the data. Euclidean distance is more accurate but can be slower. Choosing a measure that best suits the task at hand is important. Overall, cosine similarity and Euclidean distance are useful measures for finding similar items in a dataset. They can be used to recommend items, determine their popularity, and more. Choosing a measure that best suits the task at hand is important. Overall, cosine similarity and Euclidean distance are useful measures for finding similar items in a dataset. They can be used to recommend items, determine their popularity, and more.

There is no one-size-fits-all answer to the question of what the new trends are in the field of recommendation systems. However, some of the newer approaches that have been gaining traction in recent years include using deep learning techniques, incorporating user feedback, and using reinforcement learning.

Deep learning is a machine learning subfield concerned with modeling complex patterns in data. Recommendation systems are often used to predict a user's preference for a particular product or service. However, deep learning is capable of doing much more than that. Deep learning can also be useful in modeling the interactions between different data pieces and learning how to predict future events. It is a type of machine learning used to identify patterns in data, often used for tasks such as recognizing objects in pictures or understanding natural language. One of the most notable applications of deep learning in the recommendation field is "contextual targeting." This technique uses deep learning to target ads based on the context in which they are displayed. For instance, if a user is viewing an ad for a car rental company, the contextual targeting algorithm would show the user some additional ads for rental cars.

In their study of personality-aware recommenders, Dhelim et al. (2021) discovered that deep learning is becoming more important in aiding traditional recommendation systems in making better user recommendations. Deep learning methods can enhance personality-aware recommendation systems, which can learn representations of users and items better aligned with the user's personality (Dhelim et al., 2021). Engineers can do this by using a deep learning model to learn representations of users and items from data that includes personality information. They can then use the learned representations in a traditional recommendation system to make better recommendations for the user. This approach can improve the accuracy of recommendations and better match the predictions to the personality of the user (Dhelim et al., 2021). Additionally, deep learning can improve the understanding of user preferences and identify new uses for previously not considered items.

Another trend that is gaining traction in the recommendation field is the incorporation of user feedback. This is particularly important when it comes to improving the accuracy of a recommendation system. For example, if a user has given a rating of 4 out of 5 stars to a product, they would likely be interested in purchasing it. Incorporating this type of feedback into a recommendation system can help ensure that relevant products get recommended to users. According to Shao et al. (2021), user feedback is critical for developing and improving recommendation systems. By incorporating user feedback, recommendation systems can become more personalized and accurate (Shao et al., 2021). Additionally, user feedback can help to identify new items or content that users may be interested in. There are a number of ways to incorporate user feedback, such as through ratings, reviews, and clicks. They can provide a quantitative measure of how users feel about an item and can help identify which items are most popular with users (Shao et al., 2021). By incorporating user feedback, recommendation systems can better meet users' needs. Additionally, user feedback can help improve the recommendations' overall quality. Consequently, it is important to consider user feedback when designing and improving recommendation systems.

In their survey of news recommenders, Iana et al. (2022) stated that a "…lack of explicit user feedback …pose additional challenges for the recommendation models (p.1). This statement is a powerful observation and explains the current trend in the area of recommender systems, whereby more and more systems are valuing the incorporation of user feedback. According to Shao et al. (2021), user feedback is critical to improving customer interest matching and building highly performant recommendation systems.

Another trend that is gaining traction in the recommendation field is reinforcement learning. This technique involves using a machine-learning algorithm to learn how to perform a task by trial and error. In recommending products, architects and engineers can use reinforcement learning to learn which products users are likely to purchase and recommend those products to them. In recent years, reinforcement learning has emerged as an essential technique for cracking complex optimization problems in various domains, including recommendation systems. According to Huang et al. (2021), reinforcement learning algorithms can be used to learn a user's preferences from interactions with a recommender system and then make recommendations that maximize the expected reward for the user. This approach has been shown to outperform traditional recommender systems with reference to accuracy and user engagement (Huang et al., 2021). In addition, reinforcement learning can be used to personalize recommendations in a way that traditional recommender systems cannot by learning the user's favorite items, interests, and preferences.

Many other studies found similar results. For instance, Munemasa et al. (2018) found that deep reinforcement learning algorithms could generalize better than traditional ones. Recommendation systems become better as they gather and learn from more data over time (Shin & Bulut, 2021; Sun & Zhang, 2018). Shi et al. (2019) found that it was not easy to differentiate reinforcement learning from recommendation systems as they shared overwhelmingly similar features and objectives. Specifically, all these studies shared the same theme - they found that recommendation systems were more likely to find new, better recommendations for the user in the future (Munemasa et al., 2018; Shin & Bulut, 2021; Sun & Zhang, 2018). Gupta and Katarya (2021) found that the best algorithms also showed a high degree of flexibility - they could learn how to recommend items even if they had not been recommended previously. These findings suggest that deep reinforcement learning is a powerful tool for making better recommender systems. They can help improve the accuracy of recommendations and increase user engagement and satisfaction with the system. They also highlight a trend toward using reinforcement learning in these systems. In other words, deep reinforcement learning is crucial for improving the overall quality of online experiences.

One of the key benefits of reinforcement learning for recommendation systems is its ability to learn from data never seen before. Traditional recommender systems rely on pre-determined recommendations based on historical data (Ke et al., 2021). While this approach has proved to be effective in some cases, it is often limited in its ability to personalize recommendations for individual users. On the other hand, reinforcement learning can help figure out how to recommend items based on user feedback even if the data used to train the algorithm has not been seen before. This ability to adapt and improve recommendations over time makes it a great tool for improving the overall experience of using recommenders.

One of the main challenges when using reinforcement learning for recommendation systems is how to effectively reward users for their feedback (Ke et al., 2021). In traditional recommender systems, rewards are typically provided as direct rewards (such as points or vouchers) given to the user after they have made a purchase. While this approach has proved effective in some cases, it can often be difficult for users to understand and appreciate the rewards offered. In contrast, reinforcement learning algorithms typically learn how to recommend items based on user feedback without receiving direct rewards (Huang et al., 2021). This means that users are not necessarily aware of the impact their feedback has had on the recommendations made by the system. As a result, it is often difficult for users to feel incentivized to provide feedback. To address this challenge, some researchers have developed methods for rewarding users more intuitively and meaningfully.

Overall, reinforcement learning is a powerful tool that can improve recommendation systems' accuracy and user engagement. While some challenges still need to be addressed before reinforcement learning can be used in mainstream recommender systems, its promise is clear. As the field continues to develop, reinforcement learning will likely contribute an essential role in shaping the future of recommendation systems.

There are many new developments in the field of recommender systems. However, it is important not to get too bogged down in specific details. Instead, it is important to focus on a recommendation system's overall goal- to provide users with relevant and helpful recommendations. If used correctly, these new approaches can help to improve the accuracy of a system and make it more user-friendly.

2.2 Review of the Applications

A study found that the application areas of recommendation systems have been growing rapidly in the past few years (Konstan & Riedl, 2012). The study, conducted by researchers at the University of Minnesota, analyzed the growth of recommendation system applications in six different areas: e-commerce, information retrieval, social networking, content management, web search, and health care (Konstan & Riedl, 2012). The researchers found that the number of recommendation system applications in each area has grown significantly.

This review also identified other application areas where recommendation systems are being used such as in business process improvement (BPI) (Deng et al., 2017; Koschmider et al., 2011), customer relationship management (CRM) (Wang et al., 2009), employee productivity (Srivastava et al., 2018), medical decision support (MDS) (Herrmanny & Torkamaan, 2021; Schäfer et al., 2017), supply chain management (SCM) (Dadouchi & Agard, 2020), knowledge discovery in data streams (KDD) (Sultana et al., 2019), collaborative filtering (CF), and social recommendation (Chen et al., 2018; Yang et al., 2014). BPI uses recommendation systems to improve customer engagement, product development and delivery, and process improvement. Recommendation systems have been used in various applications in CRM systems, such as market segmentation, routing, customer lifetime value (LTV), and churn management. Employee productivity is enhanced through recommendation systems in areas such as task allocation, knowledge sharing, and team collaboration. Some

MDS systems now use recommender systems to provide personalized health care, support disease prevention, and optimize patient care. SCM recommender systems help optimize the flow of goods and resources in a supply chain, while KDD recommenders help identify knowledge gaps and recommend solutions. CF is being used for social media recommendation, content personalization, and spam detection. Finally, the social recommendation is used to recommend friends, products, and information to users. Although this review only identifies the use of recommendation systems in business, health care, education, marketing, and social networking domains, it is worth noting that the applicability of these systems is not limited to these specific domains.

A more recent study found that the growth of recommendation system applications has been spurred by the increasing use of online services (Ricci et al., 2021). E-commerce companies often rely on recommendation systems to help shoppers find the best products for their needs. Information retrieval systems recommend documents and articles to users based on their search queries. Social networking sites like Facebook use recommendation systems to show friends content they may be interested in (Chen et al., 2018; Ricci et al., 2021; Yang et al., 2014). Content management systems recommend articles, videos, and other information resources to users based on their interests. Web search engines like Google also use recommendation systems to suggest related web pages for users searching for specific terms (Ricci et al., 2021). Recommendation systems have become a fundamental aspect of daily life.

The study also found that the application areas of recommendation systems are not limited to just online services. Health care providers use recommendation systems to help patients find information about medical procedures and treatments (Herrmanny & Torkamaan, 2021; Ricci et al., 2021; Schäfer et al., 2017). Web-based health checkups allow users to receive health advice from a variety of professionals, including doctors, nurses, and nutritionists. According to Ricci et al. (2021), the growth of recommendation system applications is likely to continue because these systems have a wide range of potential applications. They can improve user experiences on websites and applications, help users find the information they need, and recommend content to people based on their interests. The study identified recommendation system applications in various areas across multiple industries.

Another study found potential applications of recommendation systems to gaming to provide personalized gaming experiences (Tondello et al., 2017). Another found applications of hybrid recommendation algorithms in travel websites and applications to provide personalized experiences (Logesh & Subramaniyaswamy, 2018). This demonstrates the versatility of these systems and their potential to improve the user experience on a wide range of websites and applications. The study also shows that recommendation system developers are developing new applications rapidly to meet users' needs. This underscores the importance of recommendation systems in online services and shows they have a long future ahead of them.

Overall, there seems to be a common thread between studies on the applications of recommendation systems. These systems are being used to improve the user experience on a diverse range of websites and other software platforms. They are also being used to recommend content to people based on their interests. This demonstrates the versatility of these systems and their potential to provide an improved online experience for users. The rapid development of new application areas is a testament to this fact. The growth of recommendation system applications is likely to continue because these systems have a wide range of potential applications.

2.3 Review of Current Attitudes on Recommendation Systems

There has been a recent shift in attitudes towards recommender systems. Previously, these systems were seen as a valuable tool to help users find new content. However, there has been a growing concern that recommender systems may have a negative impact on users. One study found that recommendation systems can potentially be used to manipulate people and influence their opinions. According to Helberger et al. (2016), recommender systems have inherent consequences. They lead to loss of diversity and dilution or manipulation of public discourse. Thus, people are beginning to see recommendation systems as harmful to social progress. According to Helberger et al. (2016), engineers will have to build diversity into the architecture of future recommendation systems to prevent harm to society.

Some of the main concerns around recommender systems are that they can create filter bubbles, where users only see content similar to what they have already viewed (Jiang et al., 2019). As if in agreement with Helberger et al. (2016), Jiang et al. (2019) found that recommender systems have the potential to influence preferences and beliefs, sometimes locking users in feedback loops that continue to feed and warp their learning system. This can limit users' exposure to new ideas and information. The filter bubble problem is a result of the way recommender systems operate. These systems take a user's past behaviors to predict what the user might want in the future. This can lead to a "filter bubble", where the user only sees information that is in line with their past behaviors and doesn't see anything that might be outside of their usual interests. This can lead to echo chambers where users only see information that reinforces their existing beliefs and never encounter new ideas. This can negatively impact users' understanding of the world and their ability to make informed decisions. Additionally, users may be more likely to rely on recommender systems instead of engaging with other sources of information.

This can lead to skewed knowledge and understanding and can ultimately harm users' education and career prospects.

There is some evidence that these concerns are valid. One recent study found that users who used a recommender system were more likely to agree with pre-selected political opinions than those who did not use a recommender system (Oh & Park, 2022). Additionally, a study found that users who relied on a recommender system were less likely to explore new content. However, there is also evidence that Recommender Systems can be beneficial. A study published recently found that users who used a recommender system were more likely to learn new information than those who did not use a recommender system since recommenders made quality recommendations for their use (Tarus et al., 2017a).

It is clear that there are both pros and cons to using recommender systems. It is also clear that experts are yet to arrive at a clear consensus on the negative impacts of recommender systems. It will likely be important for future research to explore these issues in greater detail so that people can better understand the implications of recommendation systems on users' lives. Until then, it is important to be aware of these systems' potential risks and use them responsibly.

2.4 Review of Potential Future Applications

Online recommendation systems have become increasingly popular, as they can give personalized predictions to users on the basis of past behavior. There are many potential future applications for recommendation systems, which could have a significant impact on a variety of different industries.

One potential application for recommendation systems is in the healthcare industry. Recommendation systems could be used to provide patients personalized recommendations for treatments or medication based on their personal health history. This could potentially help to improve health outcomes by ensuring that patients receive the most effective care possible. One study found that patient's medical history was a valuable resource that can be harnessed to deliver precise diagnoses in the future (Chen et al., 2018). However, the industry will have to resolve the issues of data security and privacy before people can fully trust recommendation systems in healthcare. Secure storage of medical data has been a concern for a long time. But blockchain technology and its high levels of security could finally solve this problem. Thus, healthcare is likely to be the next big frontier for recommendation systems in the future.

Another potential application for recommendation systems is in the education sector. Recommendation systems could be used to provide students with personalized recommendations for courses or programs based on their individual academic history. This could potentially help to improve educational outcomes by ensuring that students are taking courses that are best suited to their needs. Indeed, many studies already show the potential of recommenders in academia using data gathered from online learning platforms (Bodily & Verbert, 2017; Tarus et al., 2017a; Tarus et al., 2017b). Recommendation systems play a critical role in guiding students on virtual learning platforms, but there's a research gap on their wider application to all academia.

Finally, recommendation systems could also be used in the business world. Recommendation systems could be used to provide employees with personalized recommendations for products or services based on their individual work history. This could potentially help businesses to improve their productivity by ensuring that employees are using the most effective tools and services possible. Recommendation systems have the potential to impact a wide variety of different industries in a positive way. As such, it is important to continue researching and developing this technology to be used to its full potential.

3. Conclusion

In conclusion, recommendation systems have the potential to have a significant impact on a variety of different industries in the future. They continue to proliferate in many industry sectors, such as online commerce, social media, virtual learning platforms, streaming platforms, search engines, and many other areas. They help narrow down information based on different parameters to prevent information overload. However, some issues still need to be resolved before users can fully trust this technology. Secure storage of data and privacy concerns are two of these issues. Once engineers and architects address these concerns, recommendation systems could revolutionize many different sectors of society.

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