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A Comparative Study of Similarity Based and Artificial Intelligence Based Recommendation Systems

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ABSTRACT

With the rapid development of internet applications and the continuous growth of data, there is an increased need for recommendation systems that can filter, prioritize, and efficiently deliver relevant information. In order to mitigate the problem of information overload, these systems provides suggestions or recommendations for personalized information. Recommendation systems address the challenges by processing large volumes of data and delivering personalized contents and services. Recommendation systems can be classified into similarity-based and AI-based approaches, each having its own strengths, and limitations which make them suitable for different application scenarios. This paper presents a comprehensive study of similarity-based and AI-based recommendation systems, focusing on their methodologies, applications, usability and suggests suitable recommendations models for real-time applicability. Furthermore, this analysis highlights key strengths and limitations of each approaches such as performance, scalability, and system limitations, offering insights into their effectiveness and applicability to modern recommendation tasks.

Keywords: Similarity-based recommendation system, AI-based recommendation system, Hybrid recommendation system, comparative study.

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1. INTRODUCTION

The explosive growth of available digital information and the increasing number of internet users have created a significant challenge of information overload while searching for content on the web. Retrieving information in such environment can be compared to searching for a needle in the sea. Information retrieval systems, such as Google and other search engines, have partially solved the information overload problem, but they often lack prioritization and personalization of content. Due to these limitations, the retrieved information may appear too irrelevant and may not be helpful to users.

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This situation has created the need of such recommendation systems that can understand user interests and identify relevant information in a more personalized manner, similar to a friend.

Recommendation systems addresses the challenge through personalization of contents based on users' preferences, interests, and behaviors. These recommendation systems are intelligent software tools designed to help users for discovering items from a vast amount of internet data. Recommendation systems commonly work with content-based, collaborative and hybrid filtering approaches. Traditional similarity-based recommendation systems use memory-based techniques that computes similarity functions between users or items and generate recommendations based on the similar users or items. Another approach is AI-based recommendation systems, which uses machine learning, and deep learning techniques for identifying complex, and non-linear patterns. Both similarity-based and AI-based recommendation systems have their own advantages and disadvantages. Although several literature reviews and case studies of recommendation systems exist, there is still a need for studies that clearly analyze and compare the strengths and limitations of different recommendations approaches. The motivations for comparing similarity-based and AI-based recommendation systems arise from increasing diverse applications and growing demand for real-time and scalable recommendation solutions. While similarity-based recommendation systems are simple to implement, but their performance may degrade while dealing with large-scale, sparse, and dynamic datasets. On the other hand, AI-based recommendation systems have demonstrated improved accuracy and adaptability by learning complex patterns from data, but requires higher computational resources and large amount of data for training models. Due to this difference, it becomes important to understand the usability, effectiveness and the limitations of the approaches. However, existing studies often focus on individual methods rather than providing a clear and structured comparison between similarity and AI-based recommendation systems.

2. FUNDAMENTALS OF RECOMMENDATION SYSTEM

Recommendation Systems are intelligent software tools designed to help users for discovering items over the internet. These systems suggest items to users by analyzing their past behaviors, preferences, and data patterns. It collects data, preprocesses, and analyzes then predicts user's preferences and likeness for certain items or product. Recommendation systems can be categorized into several types, including content-based filtering, collaborative filtering, hybrid recommendation systems, and more recent approaches such as knowledge-based and context-aware recommendation systems. The different recommendation techniques have been shown in Figure 1 with the collaborative techniques and methods of recommendation systems. In traditional recommendation systems, the system works by filtering content through similarity approaches. In content-based recommendation systems, the model analyzes a user' historic interactions, such as browsed history and liked items, then identifies similar items to recommend accordingly. For example, if a user has purchased a particular shoe, the system may recommend later similar shoes, that user may like. This approach is effective when users have strong and consistent preferences for certain item. In collaborative filtering, the system identifies similar users based on behavior and historic patterns for generating recommendations. It actually finds similar users based on likeness and preferences and then would recommend one user's preferences to another. For example, the two users u and v have watched a movie, and user v later watches another movie, and then the system may recommend user u watch another movie, assuming their similar interests. Hybrid filtering system, "combines both content-based and collaborative filtering techniques" for extracting more advanced and hidden similarity patterns for improving recommendation performance. By using the strengths of both approaches, hybrid systems perform better for handling sparse data and accuracies in recommendations.

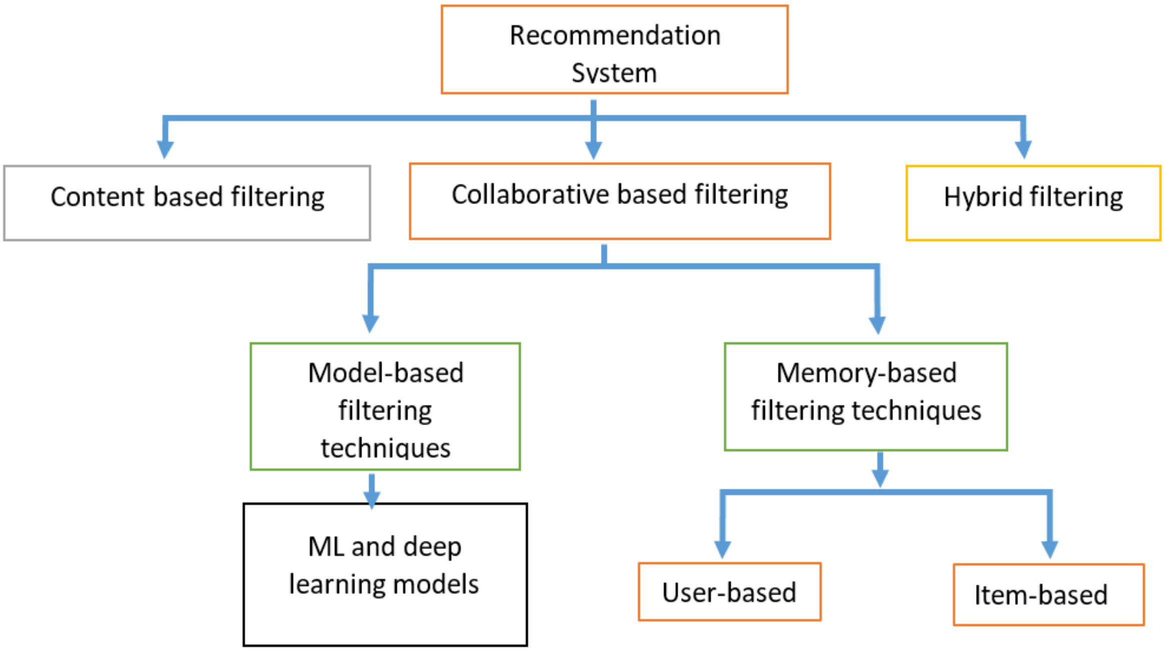

Figure 1: Recommendation System

AI based recommendation systems utilize machine learning and deep learning methods to learn complex, non-linear patterns from data. These models treat recommendations as a machine learning problem, often uses neural networks for capturing hidden relationships that traditional models fail to identify. Common AI-based techniques include neural collaborative filtering, autoencoders, recurrent neural networks (RNNs) for sequential modeling, and graph neural networks (GNNs) for social and knowledge-graphs based recommendations. Neural collaborative filtering replaces traditional dotproduct similarity measures, such as matrix factorizations with neural network. In this approach, users, and items are embedded as vectors, and their interactions are processed through multi-layer perception to predict preferences, enabling the capture of non-linear interactions. Autoencoders compresses user-item interaction matrix with low-dimensions "latent" representations, and reconstructs matrix, while allowing missing ratings to be predicted during reconstructions. These models are effective in denoising sparse data and learning robust features and are widely used in large-scale platforms such as Netflix, YouTube, particularly for implicit feedback scenarios. Hybrid AI-based models further combine collaborative, content-based filtering with deep learnings to provide more diverse and robust recommendations. Recommendation systems rely on different types of data including explicit and implicit feedbacks. In explicit feedback systems, users are directly prompted to provide ratings or reviews for items, which are then used to construct and improve the recommendation model (Isinkaye et al., 2015). The accuracy of recommendations in such systems largely depends on the quantity and quality of ratings provided by the users. Implicit feedbacks infers user preferences by monitoring users actions such as purchase history, navigations patterns, and time spent on web pages (Isinkaye et al., 2015). Hybrid feedbacks approaches combine both implicit and explicit in order to minimizing their limitations and improving overall system performance. The general recommendation workflow consists of multiple stages. In the first stage the system includes data collection and preprocessing, where user-item interaction data and profiles are collected and cleaned for further processing. In next step, feature engineering, it focus on extracting meaningful features from the data followed by candidate generations, where a large set of potentially relevant items are identified from vast collections. Another stage is scoring or ranking which further applies more complex algorithms, for ranking candidates based on predicted relevance for specific user. Finally, post-processing and filtering are applied to refine the ranked list, and the delivery and feedback loop present recommendations to users while continuously collecting new interaction data to improve the system.

3. RELATED WORKS

Recommendation systems provide efficient way for finding similar preferences, and contents for helping in personalized content delivery. The recommendation systems use filtering process in which it filters content-wise and similar to user's behavior in collaborative filtering. The process includes information collection phase from both explicit and implicit feedbacks. Learning phase and prediction phase (Isinkaye et al., 2015). Several studies have conducted the survey, designs, and comprehensive reviews in which shows significant approach. Wang et al. (2023), surveyed causal-inspired methods, and provided taxonomy and formal definitions of biases, which helps solve the problem of biases and confounding in traditional recommenders, leading to better decisions.

3.1 SIMILARITY-BASED RECOMMENDATION SYSTEMS

Similarity-based recommendation systems identifies similar users based on collaborative filtering and provides item-based and user-based recommendations. Abbasi-Moud et al. (2021), have created a recommender system that uses semantic clustering to group attraction features from user reviews and sentiment analysis by adjusting preferences degrees, then recommends places based on extracted preferences and user locations using data from Trip Advisors. Raghavendra and Srikantaiah (2021), compared various similarity metrics in a collaborative filtering model used MovieLense datasets for movie recommendation system. Ye et al. (2021), developed a unified framework by integrating knowledge graphs with recommendation systems techniques for predicting DTIs, this model performed better over existing methods in handling sparsity and cold-start problems. Zanon et al. (2022), conducted a study incorporating aspect-based sentiment analysis for refining similarity metrics in content-based recommendation systems, enhanced recommendation quality by better aligning suggestions with user sentiments on specific item aspects. Troussas et al. (2023), developed a knowledge graph enriched with contextual signals and cosine similarity for recommendations and improved personalization in e-learning content delivery. Al-Hassan et al. (2024), proposed an enhanced fusion-based semantic similarity metric to improve user/item matching in collaborative filtering. Chibb et al. (2024), implemented a content-based recommendation systems using TF-IDF weighted Word2Vec embedding and cosine similarity for movie feature comparison, which improved recommendation relevance and diversity for users based on movie content analysis. The similarity-based recommendation systems have strengths such as simplicity and interpretability, while cold-start, sparsity, and scalability were the challenges.

3.2 AI-BASED RECOMMENDATION SYSTEMS

AI-based recommendation systems uses historic ratings to learn and extract non-linear relationships in datasets and give better recommendations. Priyadharshini et al. (2021), developed a machine learning-based system using random forest algorithm for recommending suitable crops and fertilizers based on factors like soil type, water availability, climate conditions for assisting farmers in making informed decisions, potentially increasing crop yield and revenue by considering multiple environmental and economic factors. Alatrash et al. (2021), developed a recommendation model that uses sentiment analysis via convolution neural network and natural language processing to classify learner sentiment in reviews and recommend relevant learning resources based on multi-level sentiment semantics and ratings, which aims to suggest top-preferred resources by analyzing past learner reviews on e-platforms. Afoudi et al. (2021), proposed a hybrid recommender approach combining content-based filtering and collaborative-filtering, supervised by an artificial neural network, and tested it on the MovieLense dataset, achieved improved precision and recall compared to traditional methods, by demonstrating hybrid model's effectiveness in handling information overload. Anand et al. (2021), built a system using K-means clustering on audio signal features and deep learning models to classify user emotions, then recommends songs from clustered data based on predicted mood, thus provides tailored music recommendations by matching audio similarities and user emotions to improve personalization. Tavakoli et al. (2022), developed eDoer, an AI-driven open recommender system that analyzes job vacancies for deriving skills, decomposing topics, and recommending personalized open educational resources with quality checks, improved learning outcomes, with personalized pathways for bridging education and employment need. Murad et al. (2023), explored techniques for implementing personalized recommendation systems in online learning environments and highlighted potential enhanced accessibility and effectiveness through tailored content delivery. Huang et al. (2023), implemented an AI-based personalized video recommendation systems in a systems programming and evaluated its impact showed improved learning outcomes, with personalized pathways for bridging education and employment need. Habil et al. (2023), explored AI-based recommendation systems as solutions for enhanced prediction and targeting while demonstrated potential for reducing information overload, boosting sales, and product development behavior predictions. Sun et al. (2023), proposed federated deep reinforcement learning framework for edge caching recommendation system for minimizing system costs, and improved quality of experience through decentralized, privacy-preserving caching decisions. Liu et al. (2023), showed effective user behavior modeling as key for improving recommendation accuracy with complex patterns and covered sequential, multi-model, and side-information integrations. Patel and Patel (2023), proposed AgriRec, a machine learning model using soil, water, farm size, and market price data for seasonal crop predictions and achieved better performance than benchmarks in crop and fertilizer recommendations. Sellamuthu et al. (2023), proposed an AI model analyzing drug-gene interactions for safer, optimized recommendations and reported enhanced predictions of interactions for better decision-making and reduced risks. Tran and Huh (2023), developed a novel machine learning model incorporating time factors for capturing evolving user's interest for more accurate predictions. Zhou et al. (2024), proposed a federated deep reinforcement learning approach reported enhanced caching efficiency and user experience while maintain data privacy. Thus, these works have commonly reported better adaptability and accuracy as the strengths of the AI-based recommendation systems and Computation costs, data dependency as core limitations.

3.3 HYBRID RECOMMENDATION SYSTEMS

The hybrid recommendations combines both similarity-based and AI-based recommendation systems for overcoming the limitations of similarity-based and AI-based recommendations alone. Feng et al. (2021), introduced RBPR, a hybrid collaborative filtering model combining Probabilistic Matrix Factorization and Bayesian Personalized Rankings, and incorporated explicit ratings for predicting user's interest outperformed state-of-the-art methods on MovieLens and Netflix datasets in new user scenarios, providing better personalized recommendations. Al Fararni et al. (2021), reviewed existing tourism recommendation techniques and proposed a conceptual framework for hybrid systems leveraging big data and AI to promote tourism in different regions, and reported more relevant and context-aware recommendations. Khanduri and Prabakeran (2022), proposed a hybrid model which combine graph-based analysis with collaborative filtering for generating personalized recommendation lists by using both node relationships and similar user preferences. Zamanzadeh Darban and Valipour (2022), proposed GHRS, used autoencoders for feature extraction from combined attributes, graph-based features for user similarity, and clustering for hybrid recommendations on MovieLense dataset outperformed accuracy and cold-start problems. Sharma et al. (2022), proposed a hybrid filtering algorithm by combining collaborative and content-based approaches for automating product recommendations and achieved better accuracy and reduced limitations compared to individual methods. Walek and Fajmon (2023), developed a hybrid systems combining collaborative/content-based filtering with a fuzzy expert system enhanced recommendation accuracy for online store products. The common architectures were collaborative filtering models with content-based and AI-based models such as fuzzy expert systems for better and scalable recommendations accuracies. These hybrid models have achieved better accuracy for recommending and reduced limitations to individual filtering methods. While small datasets, real-time data availability remains key challenges.

3.4 APPLICATION OF RECOMMENDATION SYSTEMS

Recommendation systems have several domain-specific applications, such as in E-commerce, streaming platforms, education systems, and healthcare. The recommendation systems are being used in E-commerce for recommending items by analyzing the user's interests. Similarly, recommendation systems also provide users with personalized content on streaming platforms and in educational systems. Huang et al. (2023), implemented AI-enabled personalized video recommendation systems in flipped classrooms and evaluated its impact which significantly improved engagements and outcomes, especially for moderately motivating students. Sun et al. (2023), proposed a federated deep learning model for reducing high-costs for hindering effective edge caching in mobile networks for heterogeneous user networks. Walek and Fajmon (2023) developed a hybrid system for handling uncertainty for e-commerce product suggestions due to a lack of precision. Ali et al. (2023), surveyed deep learning-based medication recommendation systems for solving the challenges such as data sparsity and need for precise predictions. Patel and Patel (2023), proposed AgriRec, a machine learning model for multi-factor guidance for crop selection and fertilizer predictions for maximizing yield/profits. V. M. R. M. et al. (2023), developed a case-based reasoning recommender by integrating e-learning with IOT for tracking individuals' motives for tracking and resource suggestions. Yoon and Choi (2023), proposed a real-time context-aware recommender system by utilizing sensor data and mobile technologies for delivering dynamic tourism recommendations improves user satisfactions and experience. Chibb et al. (2024), implemented a content-based systems using TF-IDF weighted Word2Vec embedding for capturing semantic similarities from textual metadata like plots. Kethineni et al. (2024), developed a web-based deep learning system for recommending optimal crops, fertilizers, and pesticides to boost yield and sustainability. Wu and Chi (2024) designed a three-tiered recommendation system for e-commerce platforms to address new visitors, returning customers, and new businesses at different user stages, thereby maximizing engagement and retention. Papastratis et al. (2024) combined a deep generative model for meal planning with ChatGPT to provide interactive, explanatory recommendations and personalized nutritional guidance, addressing the lack of creativity and adherence to static, non-interactive systems. The challenges were the real-time behavioral data, and interactions of users to real-world cases, and future scope is in integration with advanced IoT sensors, machine learning for predictive context, and broader testing in diverse tourist locations.

3.5 COMPARATIVE STUDIES ON RECOMMENDATION SYSTEMS

There have been several comparative studies analyzing recommendation systems for different application areas. De Croon et al. (2021) conducted a systematic review including 73 studies that implemented and evaluated HRSs targeted at laypersons; analyzed recommended items, techniques, and user interfaces; and derived five reporting guidelines for future HRS research. Urdaneta-Ponte et al., (2021), conducted a systematic review of 98 articles from 2015-2020 across databases like IEEE, ACM, Scopus, and WoS, analyzing recommendation systems in education, including types of education, developmental approaches, and elements recommended. Javed et al. (2021), conducted a comprehensive review comparing content-based recommendation systems with context-based systems by incorporating situational factors like time, location, and user state. Seth and Sharaff (2022), provided a comparative review of hybrids in recommender systems, along with combinations of collaborative and content-based in real-world deployment environments. Roy and Dutta (2022), conducted a systematic review of recent advancements across applications, analyzed techniques and evaluation methods, provided a state-of-the-art, highlighted gaps in handling modern issues. Lacroux and Martin-Lacroux (2022), conducted an experimental study comparing recruiters' trust and behavior toward algorithmic recommendations versus human expert recommendations, including consistent/inconsistent scenarios and individual factors like personality traits. Marcuzzo et al. (2022), provided a comprehensive survey of recent developments in recommendation systems, focusing on deep learning hybrids inspired by NLP and computer vision, highlighted solid improvements over traditional methods and identified ongoing challenges accuracy, scalability, and personalization. Ko et al. (2022), reviewed over 135 articles from 2010-2021, systematizing models with content-based, collaborative, hybrids techniques, and application fields, further analyzed trends by year and service domains, provided a reliable overview of practitioners. Hasan et al. (2023), reviewed communication technologies, standards, protocols, and cyber-security principles in smart grids, and provided correlations between elements and recommendations for enhanced protection. Zhang et al. (2023), surveyed methodologies across various scholarly recommendation types, analyzing, and techniques like content-based and collaborative filtering. Da Silva et al. (2023), conducted systematic review of recent ERS studies for supporting teaching and learning, used hybrid techniques most common; need for multidimensional evaluations and addressing limitations. Lahoud et al. (2023), compared five recommender approaches, including a hybrid knowledge-based with ontology and case based reasoning, achieved high personalization and accuracy for guidance. Ali et al. (2023), conducted systematic survey of deep learning based medication recommendation models, and classified models, compared performance, datasets and metrics; and also highlighted the issues. Necula and Păvăloaia (2023), conducted a systematic review of AI techniques in e-commerce recommenders over the past decade, identified trends in machine learning/data science applications and future directions. Nyamathulla and Dhanamjayulu (2024), conducted a comprehensive review of BESS technologies, and highlighted the key applications, challenges, and recommendations, with degradation and thermal management as the key issues of such systems. Masciari et al. (2024), performed a systematic literature review analyzing AI-based recommenders, identified prevalent ethical challenges and gaps in current research practices. Chang and Park (2024), conducted a comparative experiment examined ChatGPTs' recommendations versus standard AI systems affect consideration set formation in retailing, revealed differences in consumer responses, with implications for personalization and trust. Chaudhari et al. (2024), conducted a review of hybrid recommendation systems, analyzed combinations and advancements, provided insights into benefits, challenge, a state-of-the-art hybrid models. Wu et al. (2024), surveyed applications of LLMs in recommendation tasks, including prompting, fine-tuning, and alignments, with classified approaches and highlighted performance gain in personalization and reasoning. Traditional recommendation system often overlook contextual information and rely heavily on content similarities (Urdaneta-Ponte et al. 2021), leads less accurate personalization in dynamic environments like e-learning and other limitations were the information overload in online education leads to challenges in finding relevant educational resources (Seth and Sharaff, 2022; Roy and Dutta, 2022), single technique recommender systems face limitations like cold-start or sparsity, reducing overall effectiveness, smart grids face vulnerabilities in cyber-physical systems, lacking comprehensive security standards and protocols (Hasan et al. 2023). With these limitations there is need of a comparative study of similarity-based and AI-based recommendation systems which clearly highlights the strengths and limitations, suggests sustainable solutions for using recommendation systems to education and healthcare sectors effectively.

4. COMPARATIVE ANALYSIS AND RECOMMENDATIONS OF SIMILARITY-BASED AND AI-BASED RECOMMENDATION SYSTEMS

The comparative study of the recommendation systems includes different methodologies, performance, scalability, computational complexity, interpretation, and real time usability have been taken as the key points of this comparative study of AI-based and similarity based recommendation system.

4.1 EVALUATION CRITERIA AND COMPARATIVE PARAMETERS

For the comparison, we have considered criteria such as methodologies used in similarity-based and AI-based recommendation systems, and the performance of these systems when deployed in real environment. Another scalability criterion shows whether the models can be applied to larger environment, whether able to perform efficiently, or whether they involve computational complexity. Thus, it becomes important to identify the best approach for different application areas so that the selection of modalities is efficient for real-time usability. These criteria are important for real-world systems because they can clearly predict whether such modal would work in real time or not, and what would be the strengths of such modalities would be. Another reason, while integrating recommendation systems in real-world scenarios, several issues often arise, such as cold-start problems, data sparsity, and limitations in capturing non-linear relationships. Studying these aspects is important before developing such systems.

4.2 COMPARATIVE ANALYSIS OF SIMILARITY-BASED, AI-BASED, AND HYBRID RECOMMENDATION APPROACHES

The similarity-based, AI-based and hybrid recommendation systems are quite efficient in their respective fields; however, it is important to analyze their working methodologies, performance, scalability, computational complexities, interpretability, and real-time usability. The analysis further extends to the study of the strengths, limitations, and practical applicability of each approach while implementing real-world recommendation systems.

4.2.1 ANALYSIS OF SIMILARITY-BASED RECOMMENDATION SYSTEMS

Similarity-based recommendation systems work with memory-based filtering algorithms that finds similar tastes and recommends accordingly. These systems analyzes past viewed or liked items and identifies similar users or items for future recommendations. The main methodologies includes Pearson correlations, cosine similarities, and Jaccard indexes. These approaches are simpler to implement and often perform moderately while requiring less computational complexity. Due to their transparent working mechanism, they are easy to analyze, interpret and maintain. Similarity-based recommendation systems works well with small to medium-scale datasets, but they often fail to handle real-time cases effectively. These methods often suffer from data sparsity, cold-start problems, and have limitations in real-time adaptation, and capturing contextual factors. In large-scale deployments, they provide less accurate outputs and have limited capability in handling non-linear user preferences. The scalability is constrained for the number of users and items, which leads to lower performance while increasing numbers.

4.2.2 ANALYSIS OF AI-BASED RECOMMENDATION SYSTEMS

AI-based recommendation systems uses machine learning and deep learning techniques for representation learning. These model based filtering approaches are capable of capturing complex and non-linear relationships. They perform well on large and dynamic datasets and have reported improved accuracy compared to traditional methods. These model-based recommendation systems are scalable and achieve high accuracy, but they also involve higher computational complexity and training costs. Real-time usability and inference latency also remain key challenges for such systems.

4.2.3 ANALYSIS OF HYBRID RECOMMENDATION SYSTEMS

Hybrid recommendation systems combines both similarity-based and AI-based recommendation and often provide more reliable recommendations. They integrate explicit and implicit similarity measures with content-based and collaborative filtering techniques, performing better than single-modality systems. These method effectively addresses issues such as cold-start and data sparsity. These systems offer balanced performance while improving scalability to larger and diverse environments, and provides robust decisions. However, they often involve higher computational complexity, and requires careful model design and parameter tunings. Although hybrid systems reduce cold-start, and data sparsity issues, while combining similarity-based and AI-based methods increases system complexity and limits interpretability.

4.3 PERFORMANCE-BASED COMPARISON OF RECOMMENDATION SYSTEM

The comparative analysis of similarity-based and AI-based recommendation approaches is presented in Table 1. Similarity-based recommendation systems extract features from past user histories, identify similar user tastes, and generate recommendations accordingly. Some methods handle bias and different rating styles using Pearson correlation coefficients and cosine similarity measures. These systems perform well at small- to medium-scale business levels. Due to lower computational requirements for similarity calculations, their computational complexity is generally lower than that of other approaches.

4.3.1 PERFORMANCE AND CHARACTERISTICS OF SIMILARITY-BASED SYSTEMS

Similarity-based systems can easily explain why particular recommendations are generated leading to informed decision-making. The interpretability of such systems is high when they clearly indicate whether recommendations are produced using user–user or item–item collaborative filtering. In contrast, interpretability is low for deep learning systems that do not provide clear explanations for recommendations. Another important criterion is real-time usability, which determines whether the system can be applied to real-time datasets and provide sufficiently fast responses to live users. Recommendation systems exhibit high real-time usability if they can generate recommendations during browsing, whereas usability is considered low if significant computation time is required before generating recommendations.

4.3.2 PERFORMANCE AND CHARACTERISTICS OF AI-BASED RECOMMENDATION SYSTEMS

AI-based recommendation systems uses machine learning, and deep learning techniques for extracting complex and non-linear relationships from data. These model-based recommendation systems perform better on large-scale and diverse datasets, making it scalable for medium to large-level applications. Thus, they involves higher computational complexity during recommendation generation and often requires complexity during recommendation generation and often require complex computations in real-time scenarios, resulting in moderate real-time responsiveness. These systems, generally lack interpretability, as they are clearly unable to explain why specific recommendations are generated.

4.3.3 PERFORMANCE AND CHARACTERISTICS OF HYBRID RECOMMENDATION SYSTEMS

Hybrid recommendation systems combines similarity and AI-based recommendation approaches. These models consider both explicit and implicit features, enabling improved recommendation performance. Due to higher computational complexity, their performance varies on the model design, although they are scalable for medium-to higher-scale applications. Despite improved performance, hybrid systems are often less interpretable because the combination of similarity-based and AI-based methods makes it difficult to provide clear explanations for recommendations.

Table 1: Comparative Study of Similarity-Based, AI-Based, and Hybrid Recommendation Systems

Criteria	Similarity-Based	AI-Based	Hybrid
Methodology	Explicit similarity measures with memory based methods such as Pearson and cosine coefficients.	Machine learning and deep learning models, for non-linear feature extraction	Combination of both Similarity and AI-based recommendation systems
Performance	Moderate	High	High
Scalability	Limited	High	Moderate to High

Computational Complexity	Low	High	Moderate
Interpretability	High	Low	Medium
Real-time Usability	High	Moderate	High

4.4 COMPARATIVE STRENGTHS AND LIMITATIONS OF RECOMMENDATION SYSTEMS

Recommendation systems have significantly improved with recent advancements in feature selection and AI integration. For selecting an appropriate model, it is necessary to study their strengths and limitations so that the system can be integrate the systems.

4.4.1 STRENGTHS OF SIMILARITY-BASED, AI-BASED, AND RECOMMENDATION SYSTEMS

Similarity-based recommendation systems provide lower computational overhead, high interpretability, and efficient real-time usability due to fast similarity computation. Thus, they are applicable to small- to medium-scale businesses. AI-based recommendation systems provide higher accuracy due to deep learning techniques and the ability to capture non-linear relationships. These systems are less interpretable due to unclear reasoning behind recommendations and often involve higher computational costs, but they provide reliable decisions and can scale to high-end business applications and recommendations. Hybrid-based recommendation systems combines the advantages of both methods and deliver improved performance even in cold-start and sparse datasets. They provide more robust and flexible decision-making while remaining moderately complex computationally. These systems offer moderate interpretability and high real-time usability. Table 2 shows the comparative study of the strengths and limitations of recommendation systems.

4.4.2 LIMITATIONS OF SIMILARITY-BASED, AI-BASED, AND RECOMMENDATION SYSTEMS

Although recommendation systems have several advantages, each modalities has limitations. Similarity-based recommendation systems often suffers from cold-start problems, such as when a new user registers then no prior data is available to generate recommendations. Their performance degrades with diverse datasets, and they are limited in handling complex or non-linear relationships. Scalability also remains a challenge for such systems. AI-based recommendation systems are less efficient due to higher training costs and low interpretability, which can reduce the reliability of recommendation decisions. These models require large datasets for training, and real-time usability can be affected due to computational and interpretability constraints. Hybrid recommendation systems are affected by increased computational and model complexity. Their interpretability is also reduced due to the combination of both approaches, and these models require careful tuning and integration of multiple components.

Table 2: Comparative Study of Strengths and Limitations of Recommendation Systems

S.no.	Strengths/Limitations	Similarity-based	AI-based	Hybrid
1	Ease of implementation	High	Low	Moderate
2	Accuracy	Low	High	High
3	Scalability	Low	High	Moderate-high
4	Real-time usability	High	Moderate	High
5	Cold start Problem	High	Moderate	Low
6	Data sparsity	High	Moderate	Low
7	Training data	Low	High	High
8	Capturing non-linear relationships	Low	High	High
9	Computational complexity	Low	High	High
10	Interpretability	High	Low	Moderate

5. RESULTS

Recommendation systems are essential for recommending contents in current situation due to information overload problems. With recommendation systems users can find required content more effectively, than searching across large volumes of data. Instead of searching for a needle in the ocean, recommendation systems narrow the search to a manageable subset. When integrated with real-time applications, recommendation systems provide more informed results compared to traditional search mechanisms. AI-based recommendation systems perform better than other approaches due to the ability to capturing non-linear relationships during data extraction. They effectively addresses cold-start and data sparsity problems and provide real-time usability while being capable of integration into large-scale environments. However, they still face challenges related to implementation complexity and interpretability. Similarity-based recommendation systems are easier to implement, highly interpretable, and require lower computational resources, but they suffers from data sparsity and cold-start problems despite high real-time usability. These methods are suitable for low-complexity implementations.

Hybrid methods perform better than similarity-based recommendation systems but often involve higher computational costs and may be slower in delivering real-time decisions. Overall, AI-based recommendation systems provide better performance compared to other modalities, as clearly shown in Table 2. AI-based recommendation systems commonly use algorithms such as random forests, artificial neural networks (ANNs), convolutional neural networks (CNNs), clustering, association rules, decision trees, regression, Bayesian classifiers, and other deep learning methods. This study provides clear guidelines for developers in selecting suitable modalities for their applications.

Similarity-based recommendation systems perform better for small-to medium-scale business due to its simplicity in implementation, and lower computational costs, gives informed decisions. AI-based recommendation systems are suitable for large-scale businesses, providing higher accuracy and effectively addresses cold-start and diverse dataset' challenges. Hybrid recommendation systems perform comparatively lower than AI-based systems due to higher computational costs, limits their real-time decision-making capabilities. Developers should use AI-based methods such as CNNs and reinforcement learning models for achieving better accuracy in medium-to large-scale business applications. Table 3 presents the recommended models based on different criteria.

Table 3: Recommended Recommendation methods based on Criterion

S.no.	**Criterion**	**Best Model**
1	Ease of implementation	Similarity
2	Accuracy	AI-based/Hybrid
3	Scalability	AI-based/Hybrid
4	Real-time usability	Similarity/ AI-based
5	Cold start handling	Hybrid
6	Non-linear modeling	AI-based/Hybrid
7	Interpretability	Similarity-based

Overall, Hybrid recommendation systems can be considered effectively due to higher accuracy, better handling of cold-start and sparse datasets, and ability to capture non-linear relationships. They can be implemented for real-time usability if computational complexity is efficiently managed. AI-based recommendation systems uses machine learning and deep learning techniques such as ANNs, DNNs, CNNs, RNNs, transformer and graph neural network models. Model selection can be guided by application requirements: ANNs for basic tasks, DNNs, for large-scale personalization, transformer-based models for large-scale parallel processing, and graph neural networks. Table 4 presents different AI-based Models and their applications.

Table 4: Selection of AI-Based Models and Their Applications

S.no.	**AI-based Model**	**When to choose**
1	Artificial Neural Networks (ANNs)	Basic AI-based recommender
2	Deep Neural Networks (DNNs)	Large-scale personalized recommenders
3	Convolutional Neural Networks (CNNs)	Image based or multimedia recommenders
4	Recurrent Neural Networks (RNNs)	Sequential or time-aware recommenders
5	Transformer-Based Models	For large-scale and excellent performance and parallel processing
6	Graph Neural Networks (GNN)	At user-item integration level and models natural relationships and for excellent performance

Transformer-based models and GNNs provide high accuracy but involve higher computational costs and resource requirements. For balanced trade-offs between accuracy and cost, neural collaborative filtering methods such as RNNs or LSTMs can be considered. CNNs are effective for multimedia-based recommendations.

6. DISCUSSION

Recommendation systems help in providing personalized information across internet-based applications. Several recommendation approaches exist, and the choice of modality depends on user needs and application requirements. Each recommendation method has their own strengths and limitations, which are clearly presented in this study. The analysis further guides the selection of appropriate models. Currently, AI-based recommendation systems perform better across most aspects, as shown in Table 2. Modern applications frequently use AI-based and hybrid systems to capture complex and non-linear user preferences. There is a need of lightweight and efficient recommendation systems that could provide informed decisions and is easier to implement. Several studies highlight the need of diverse datasets, and advanced classification methods for achieving accurate recommendations. Developers can select models based on requirements, such as similarity-based methods, for ease of implementations, AI-based and hybrid models for accuracy, and AI-based methods for scalability.

7. FUTURE RESEARCH DIRECTIONS

Future research directions focused on hybrid intelligent models, explainable AI, privacy-aware systems and resource-efficient recommendation frameworks. Recommendation systems needs more diverse datasets, and efficient algorithms for improving recommendation's accuracy in several domains such as education, healthcare and business. Explainable AI is essential for building transparent systems that clarify why certain items have been recommended. This explainability is evident in platforms such as Netflix, which provide reasons for recommendations based on viewing history. Similar approaches can be extended to healthcare and pharmaceutical industries. Ethical and privacy-aware recommendation systems are essential for future intelligent applications.

8. CONCLUSION

Recommendation systems are very important for today's intelligent systems are widely used in different application areas such as healthcare, agriculture, education, businesses and other decision-support systems. The comparative study highlights strengths and limitations of similarity-based, AI-based, and hybrid recommendation approaches based on real-time usability, ease of implementation, and accuracy parameters. The analysis recommends researchers and developers considering suitable recommendation systems to their work. However, ethical and privacy issues should be considered carefully while integrating recommendation systems in real-time and context-aware environments for ensuring responsible and reliable recommendations.

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