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Machine Learning For Recommendation Systems: A Comprehensive Bibliometric Review

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Abstract
In the face of growing digital information, recommendation systems play a pivotal role in enhancing user experience by delivering personalized suggestions across domains such as e-commerce, healthcare, education, and entertainment. This bibliometric review investigates the application of machine learning (ML) techniques in recommendation systems from 2015 to 2025, using the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework to ensure methodological transparency and rigor. A total of 337 peer-reviewed publications were initially retrieved from the Dimensions database. Through systematic filtering using Rayyan and full-text analysis via Zotero, 61 articles were selected for detailed review. The analysis reveals a shift from traditional methods—like k-Nearest Neighbors, Decision Trees, and Matrix Factorization—towards advanced deep learning techniques, including Neural Collaborative Filtering (NCF), Autoencoders, and Recurrent Neural Networks (RNNs). Hybrid models, particularly those combining NCF with GRU-based RNNs, show superior performance in modeling dynamic and sequential user behavior. Despite technological progress, key challenges persist, including scalability, interpretability, and ethical concerns. This study not only charts the evolution of ML-driven recommendation systems but also highlights emerging research directions, advocating for robust, transparent, and context-aware models capable of real-time adaptation.
Keywords— *Machine learning, Deep Learning, Recommendation Systems, Bibliometric, VOSviewer, PRISMA*

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I. Introduction

In today's digital era, users are exposed to a vast amount of information daily. Recommendation systems help by suggesting relevant items—like products, movies, or courses—based on user preferences. These systems play a key role in improving user experience in e-commerce, education, social media, entertainment, and more. Machine Learning (ML) has become the foundation of many modern recommendation systems. It enables systems to learn from user behavior and make intelligent suggestions. In recent years, Deep Learning (DL), a branch of ML, has gained popularity for its ability to handle large, complex data and improve recommendation accuracy[1], [2].

This study presents a bibliometric review of research from 2015 to 2025, focusing on how ML and DL techniques have been used in recommendation systems. By analyzing scientific publications from the Dimensions database [3] and using tools like VOSviewer [4] and Rayyan [5], the paper explores the basics of Recommendation Systems, Machine Learning, and popular techniques used in ML-Based Recommendation Systems. The goal is to provide an overview of the most commonly used ML and DL methods in recommendation systems and highlight gaps and future research opportunities.

II. Background

The fundamental principles of machine learning in recommendation systems are introduced in this section to facilitate a deeper understanding of subsequent discussions. A recommendation system is a data-driven model that can leverages machine learning algorithms to analyze user behavior, preferences, and interactions, generating personalized recommendations [2], [6], [7]. These systems rely on pattern recognition and predictive analytics to enhance user experience across various domains, including e-commerce, tourism, entertainment, and education etc. [8], [9]. Machine learning has transformed recommendation systems, addressing persistent challenges such as cold start problems, data sparsity, and dynamic preference adaptation. Traditional recommendation models, such as collaborative filtering and content-based filtering, have evolved with the introduction of deep learning, reinforcement learning, and hybrid approaches[10], [11]. One of the key advancements in machine learning-based recommendation models is their ability to automate feature extraction, learn complex user-item relationships, and adapt recommendations in real-time. Unlike earlier rule-based systems, modern machine learning algorithms enable context-aware, scalable, and highly accurate recommendation strategies. However, implementing machine learning in recommendation systems does not necessarily require deep neural networks; various traditional machine learning techniques, such as clustering, matrix factorization, and decision trees [12], [13], [14] remain widely used in specific applications

Categories of Machine Learning for Recommendation Systems

Machine learning techniques used in recommendation systems can be broadly classified into three main categories based on their learning paradigm. Figure 1 shows the categories.

1. Supervised Learning
2. Unsupervised Learning
3. Reinforcement Learning

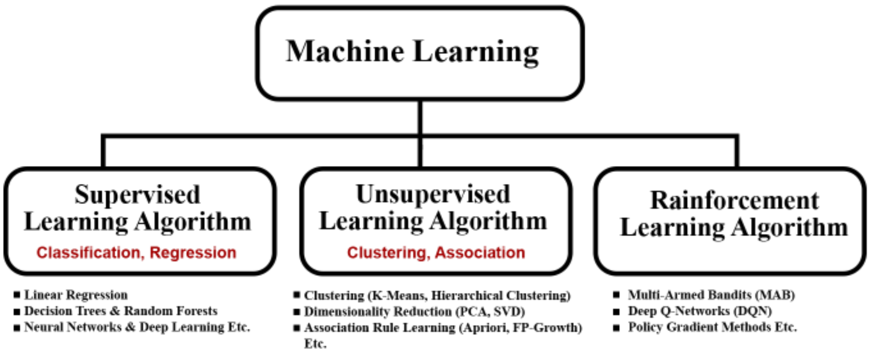

Figure 1: Categories of Machine Learning in Recommendation Systems

Supervised learning involves training models using labeled data, where the algorithm learns to map inputs to desired outputs [15], [16]. Supervised learning is commonly used in recommendation systems to predict user preferences, rate predictions, and make personalized recommendations. Popular supervised learning algorithms in recommendation systems include:

1. Linear Regression: Used to predict numerical ratings.
2. Decision Trees and Random Forests: Useful for classification-based recommendations.
3. Neural Networks and Deep Learning: Enhances recommendation accuracy by learning complex patterns from user data.

Supervised learning is widely used in personalized recommendation engines, such as Netflix and Spotify, where past user interactions help predict future preferences.

Unsupervised Learning

Unsupervised learning works with unlabeled data [17], discovering hidden patterns and relationships in user-item interactions. This approach is useful when labeled data is unavailable or costly to obtain. Key unsupervised learning techniques used in recommendation systems include:

1. Clustering (K-Means, Hierarchical Clustering): Groups users or items based on similarity.
2. Dimensionality Reduction (PCA, SVD): Reduces the complexity of large datasets while preserving key features.
3. Association Rule Learning (Apriori, FP-Growth): Identifies frequent item sets in transaction data, commonly used in market basket analysis.

Unsupervised learning is widely used in content-based filtering and customer segmentation, allowing businesses to offer recommendations without explicit labels.

Reinforcement Learning

Reinforcement learning (RL) optimizes recommendation systems by learning from user feedback and interactions [18], [19]. Unlike traditional methods, RL-based recommenders continuously adapt and improve recommendations over time based on exploration-exploitation trade-offs. Common reinforcement learning techniques in recommendation systems include:

1. Multi-Armed Bandits (MAB): Balances exploration (trying new recommendations) and exploitation (recommending known preferences).

2. Deep Q-Networks (DQN): Uses deep learning for dynamic recommendations based on real-time user behavior.
3. Policy Gradient Methods: Optimizes long-term engagement by modeling user decision-making processes.

Reinforcement learning is applied in real-time recommendation systems such as dynamic ad targeting, personalized news feeds, and interactive learning platform

Categories of Machine Learning-Based Recommendation Systems

The categorization of recommendation systems is based on the nature of the data being processed, accessibility, and the capabilities of the underlying machine learning models. Figure 2 shows the categories which include:

1. Content-Based Filtering
2. Collaborative Filtering
3. Hybrid Recommendation Systems

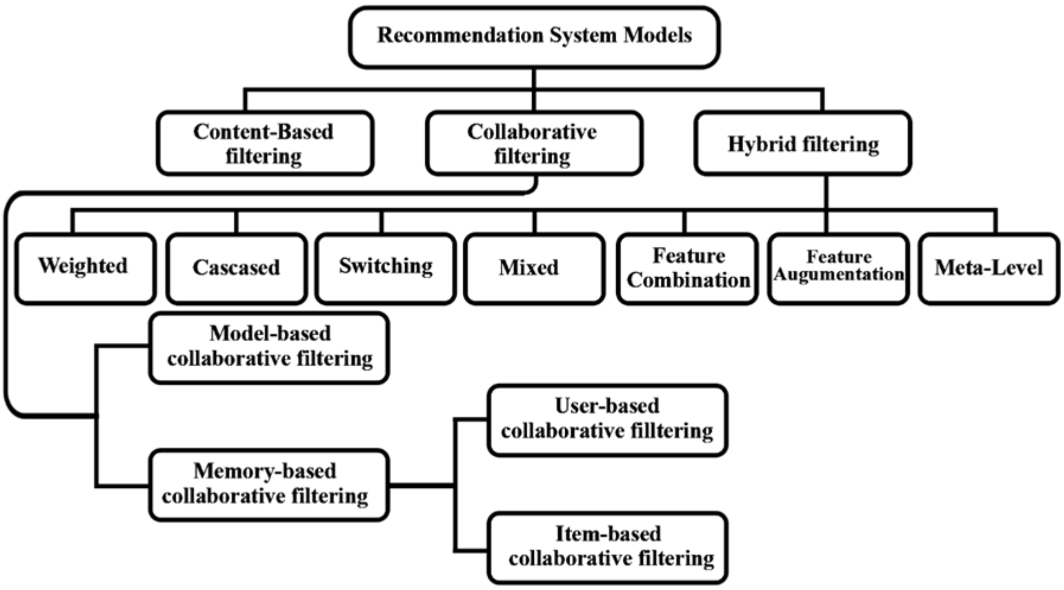

Figure 2: Categories of Machine learning-Based Recommendation Systems

Content-Based Filtering

Content-based recommendation systems generate suggestions by analyzing the attributes of items and matching them to a user's previous interactions. [20], [21] These systems rely on feature extraction techniques and machine learning algorithms such as decision trees, Naïve Bayes, and k-nearest neighbors (KNN) to recommend items that are similar to those a user has engaged with in the past. However, content-based filtering has limitations, such as the cold-start problem, which occurs when new users have no prior interactions.

Collaborative Filtering

Collaborative filtering models predict user preferences by analyzing the behavior and interactions of similar users [22], [23], [24]. These models are categorized into two main types:

1. User-Based Collaborative Filtering: Identifies users with similar preferences and recommends items based on their interactions.
2. Item-Based Collaborative Filtering: Identifies relationships between items based on user preferences and suggests items with similar patterns of interaction.

Collaborative filtering relies on techniques such as matrix factorization, Singular Value Decomposition (SVD), and deep learning-based embedding to improve recommendation accuracy. However, it faces challenges such as sparsity issues when insufficient user-item interaction data is available.

Hybrid recommendation systems

Hybrid recommendation systems combine multiple approaches to enhance accuracy and mitigate the limitations of individual techniques. These models integrate content-based filtering and collaborative filtering or leverage advanced deep-learning architectures to improve recommendations [21], [23], [25]. Hybrid systems are commonly used in industries such as e-commerce, entertainment, and online learning platforms. Popular hybrid models include:

1. Weighted Hybridization: Assigns different weights to multiple recommendation models based on their predictive performance.
2. Switching Hybridization: Dynamically switches between recommendation models depending on context.
3. Cascade Hybridization: Uses one model to generate an initial recommendation list and another to refine it further.

Deep learning techniques such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and attention-based transformer models are increasingly integrated into hybrid recommendation systems to enhance performance. These models improve personalization, scalability, and real-time recommendation accuracy

III. Methodology

This bibliometric review followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines [26] to ensure methodological transparency, rigor, and reproducibility throughout the study selection and analysis process. The aim of the review was to map and analyze research trends in the integration of machine learning within recommendation systems. A structured and comprehensive search was conducted using the Dimensions database [18], focusing on peer-reviewed journal articles published between 2015 and 2025. The Boolean search combined the terms "Recommendation System" and "Machine Learning" with related keywords such as "Collaborative Filtering," "Deep Learning," "Content-based," "Hybrid," "Personalization," and "Pattern Based." Filters were applied to limit the results to articles within the relevant Fields of Research (FoR 4611 – Machine Learning and 4602 – Artificial Intelligence), and the search was restricted to the title and abstract. This search strategy is illustrated in Figure 3.

The initial search yielded 337 records, which we exported in both .csv and .bib formats. The .bib file was uploaded to Rayyan [5], a web-based tool designed to streamline the screening process for systematic reviews. Rayyan's automated exclusion features removed 214 records: 206 that did not discuss key recommendation techniques and eight non-English articles. This left 123 records for manual screening based on titles and abstracts. Two independent reviewers conducted a blind review in Rayyan, categorizing each article as Include, Maybe, or Exclude. Any disagreements were resolved through discussion, resulting in the exclusion of 26 articles that were not relevant to machine learning-based recommendation systems.

We imported the remaining 97 articles into Zotero [27] for full-text screening. During this phase, we excluded 36 articles due to lack of full-text access. As a result, 61 articles met all inclusion criteria and we retained them for detailed bibliometric analysis. We carried out data extraction using Microsoft Excel by two reviewers working collaboratively. Our reviewer focused on extracting information related to the machine learning techniques applied in recommendation systems, this structured, and two-person review approach ensured accuracy, consistency, and depth in the analysis. The overall article selection process illustrated in Figure 4 (PRISMA flow diagram). For the bibliometric mapping and visualization of key patterns, co-authorship networks, and keyword co-occurrences, we used VOSviewer [4], a software tool specifically designed for constructing and visualizing bibliometric networks.

Data Sources and Search Strategy

The search strategy for this review consisted of two main components. The first component (C1) involved the keywords "Recommendation System" and "Machine Learning" to ensure a focus on intelligent recommendation technologies. The second component (C2) comprised associated terms such as "Collaborative Filtering," "Deep Learning," "Content-based," "Hybrid," "Personalization," and "Pattern Based" to enhance the specificity of the search. A Boolean logic expression of "C1 AND C2" was employed, resulting in queries like: "Recommendation System" AND "Machine Learning" AND ("Collaborative Filtering" OR "Deep Learning" OR "Content-based" OR "Hybrid" OR "Personalization" OR "Pattern Based") The literature was sourced from the Dimensions database [3], which offers extensive coverage of academic publications. The search was restricted to articles published between 2015 and 2024**,** and filtered by the Fields of Research (FoR) codes 4611 (Machine Learning) and 4602 (Artificial Intelligence)**,** ensuring relevance to current and impactful research as shown in Figure 3. The search was further limited to titles and abstracts to maintain precision in results.

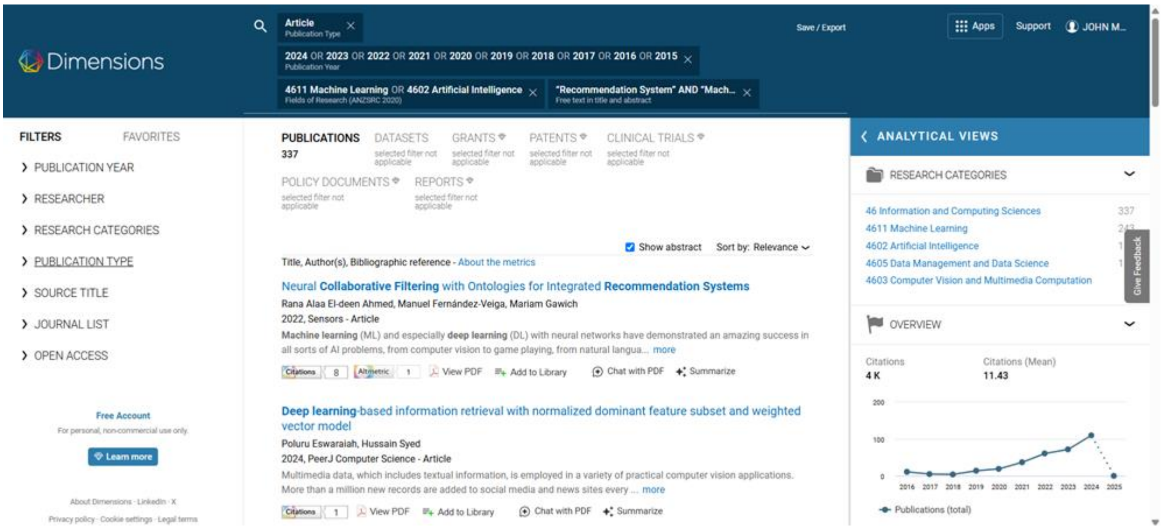

Figure 3: Screenshot of the Dimensions database search results showing filtered peer-reviewed articles related to recommendation systems in education, retrieved on April 10, 2025

Criteria for Inclusion and Exclusion

To ensure the selection of high-quality and relevant research, the study followed a structured inclusion and exclusion process as follows;

Inclusion Criteria (I)

(I1) The study must have undergone peer review to ensure credibility.
(I2) The paper must be written in English for accessibility and standardization.
(I3) The research must be directly related to the predefined search terms and focus on recommendation systems.
(I4) The paper must fall under one of the following categories: research paper, experimental study, or review paper discussing recommendation systems and machine learning

Exclusion Criteria (E)

(E1) Studies that did not focus on recommendation systems or machine learning techniques were excluded.
(E2) Papers that did not discuss key recommendation techniques such as collaborative filtering, content-based filtering, or hybrid models were omitted.
(E3) Articles that failed to meet all inclusion criteria were not considered.
(E4) Documents such as editorial comments, tutorials, keynotes, anecdotal reports, and presentation slides that lacked rigorous scientific analysis were excluded.

This methodology ensured a comprehensive yet focused review of recent advancements and challenges in recommendation systems and machine learning.

Toolkit for research

Knowledge mapping is vital for identifying trends, tracking algorithmic progress, and visualizing research connections in recommendation systems. This study employed multiple tools for a thorough bibliometric analysis of machine learning applications. We utilized Rayyan [5] for screening and organizing articles, while Zotero [27] assisted in reference management and full-text verification. VOSviewer [4] generated visual maps such as co-citation and bibliographic coupling networks to highlight key research themes and influential contributors. We sourced data from the Dimensions database [3]. Microsoft Excel supported data cleaning, trend analysis, and determining which Algorithms used in each article. Together, these tools enabled a comprehensive assessment of the growth, impact, and future directions of machine learning techniques in recommendation systems.

IV. Literature Review

Recent studies on recommendation systems highlight the evolution and application of various models across domains such as e-commerce, healthcare, tourism, and e-learning etc [20], [28], [29]. A comprehensive review by [30] analyzed trends in recommendation models, identifying hybrid approaches as effective solutions to common challenges like data sparsity, cold start, and scalability. Researchers such as [31] and [32] have explored methods to enhance recommendation accuracy, leveraging deep learning, time series forecasting, and advanced machine learning algorithms. The integration of AI techniques, including neural networks and transfer learning, has significantly improved the predictive capabilities of modern recommendation systems, as demonstrated by [33] and [34].

Studies in specific applications, such as healthcare and tourism, emphasize the role of recommender systems in enhancing decision-making, improving personalization, and addressing data deficiencies in emerging markets. Out of chosen articles, Hybrid models emerged as the dominant technique, appearing in studies, followed by collaborative filtering, and content-based filtering. Studies like those by [35] and [36] highlight the impact of deep neural networks in improving personalized recommendations, while [37] discuss reinforcement learning and matrix factorization approaches. The effectiveness of machine learning in refining recommendations is evident in applications like STEM course selection [38], [39] and movie recommendations. Challenges such as privacy concerns, transparency, and dataset diversity persist [28], [40], driving ongoing research toward optimizing recommender systems for real-time applications.

V. Descriptive Findings

Study Selection Process

A total of 337 records were initially identified through database searches. Prior to the screening phase, Rayyan's inbuilt filtering tools automatically excluded 241 records for not meeting inclusion criteria, and eight non-English records were removed. This resulted in 123 records that proceeded to the title and abstract screening stage. Following manual assessment, we excluded 26 articles due to lack of relevance. We imported the remaining 97 articles into Zotero for full-text evaluation. During this stage, we excluded 36 articles due to unavailability of full-text access. Consequently, we retained 61 articles that met all inclusion criteria and for bibliometric analysis. The full selection process is illustrated in Figure 4, in line with the PRISMA framework [26]

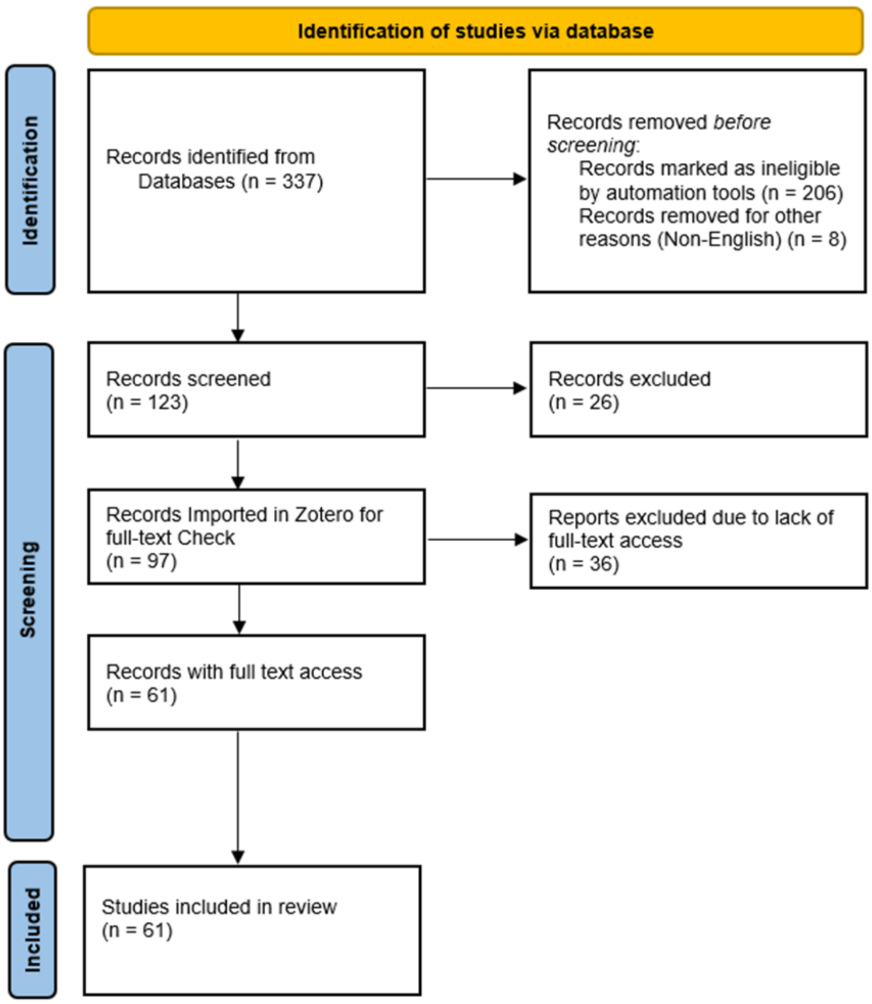

Figure 4: PRISMA Flow Diagram for Study Selection Process

Evolution of Machine Learning for Recommendation Systems (2015–2024)

The research landscape on recommendation systems (RS) and machine learning (ML) has experienced significant growth from 2015 to 2024, as illustrated in Figure 5 extracted from dimensions database. In 2015, studies in this domain were relatively limited, primarily centered on traditional collaborative filtering and content-based approaches. However, with advancements in deep learning, neural networks, and big data analytics, research on ML-driven recommendation systems expanded rapidly. By 2018, there was a notable increase in publications, with growing interest in hybrid recommendation models, deep learning-based methods, and reinforcement learning. From 2020 onward, the focus shifted toward fairness-aware machine learning, and real-time adaptive recommendation models, emphasizing transparency, ethics, and scalability [28], [41]. As of 2024, research on ML-powered recommendation systems continues to grow, underscoring its pivotal role in personalized content delivery across multiple domains.

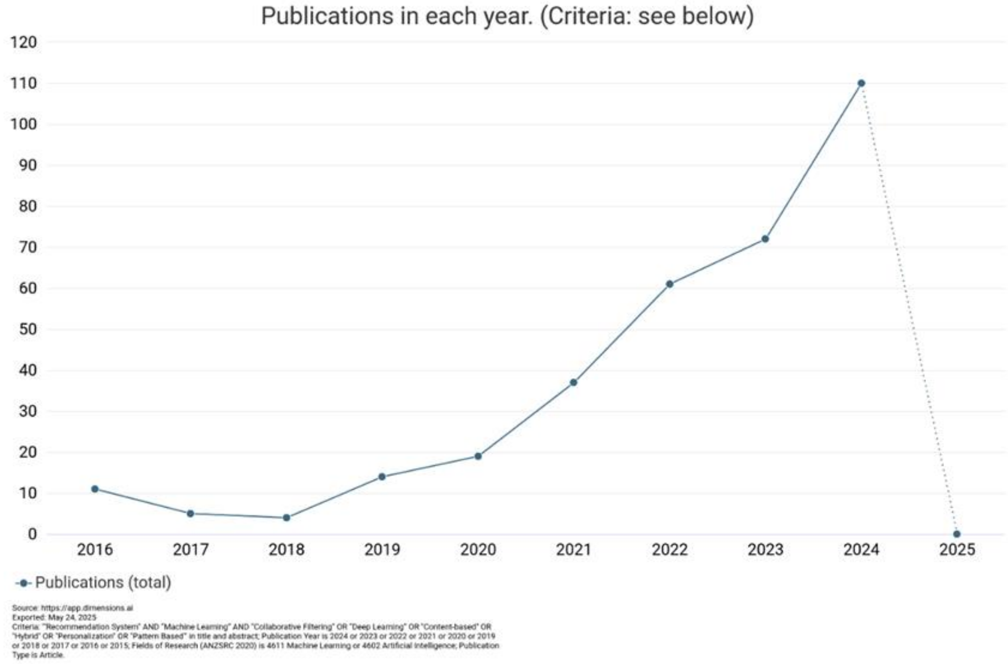

Figure 5: Annual publication growth trends in machine learning-based recommendation systems [3]

Machine Learning-Based Approaches

The integration of traditional machine learning techniques into recommender systems has introduced new capabilities such as classification, regression, and clustering to improve recommendation quality. Algorithms like k-Nearest Neighbors (k-NN), Support Vector Machines (SVM), Decision Trees, and Matrix Factorization have been widely adopted. ML-based recommenders can identify hidden user preferences, uncover patterns from historical interactions, and scale to large datasets. However, these models often depend on high-quality, engineered features and may not generalize well to evolving user behaviors unless continuously updated

K-Nearest Neighbors (KNN)

This Algorithm leverages similarity metrics to recommend items based on user or item proximity. KNN is praised for its simplicity and interpretability, making it suitable for small or moderately-sized datasets [42]. However, its performance degrades on large-scale datasets due to high computational complexity and sensitivity to sparsity. These papers [10], [43], [44], [45], [46] demonstrate the versatility and continued relevance of KNN in developing effective recommender systems across various domains.

Decision Trees and Random Forests

Decision Trees and Random Forests offer another avenue, especially for classification and regression-based recommendation tasks. These models are robust to noise, handle non-linear relationships well, and can work with both numerical and categorical data. Nevertheless, they can suffer from overfitting in sparse or dynamic user-item matrices and may not generalize well without frequent retraining. These studies [8], [47], [48], [49], [50] demonstrate the versatility of Decision Trees and Random Forests in various recommendation scenarios, from tourism and entertainment to agriculture and healthcare.

Support Vector Machine (SVM)

Support Vector Machines (SVM) applied in recommender systems, particularly for ranking and classification tasks. SVM can handle high-dimensional spaces and perform well with small, clean datasets. Their main drawback lies in scalability—SVMs are computationally expensive and less efficient in real-time or large-scale environments [51], [52]. Some of the studies used SVM for recommendation systems include [53], [54], [55], [56].

Matrix Factorization (MF)

Perhaps the most foundational ML approach in CF-based recommendation is Matrix Factorization (MF) [57], including algorithms like Singular Value Decomposition (SVD) [22], [58] and Alternating Least Squares (ALS) [59]. These methods reduce dimensionality by learning latent factors from the user-item matrix, enabling efficient prediction of unknown preferences. MF is known for its scalability and has been used in production-scale systems like Netflix However, it assumes linearity in interactions and lacks the flexibility to model complex, nonlinear behavior.

Table 1: Overview of Machine Learning Algorithms Used in Recommender Systems with Their Strengths and Weaknesses

Algorithm	Description	Strengths	Weaknesses
K-Nearest Neighbors (KNN)	A non-parametric algorithm that uses proximity (similarity metrics) between users/items to recommend.	Simple and interpretable, effective on small or moderate-sized datasets, and works well with similarity-based data.	Computationally expensive for large datasets, suffers from sparsity and high dimensionality.
Decision Trees	A classification model that splits data into subsets based on feature values, leading to predictions.	Handles non-linear relationships, is interpretable, and works with both numerical and categorical data.	Prone to overfitting, struggles with sparse data, and requires frequent retraining to maintain relevance.
Random Forests	An ensemble of decision trees that aggregates predictions from multiple trees to improve accuracy.	Robust to noise, handles non-linear relationships, and performs well with both numerical and categorical data.	Computationally intensive, overfitting in sparse or highly dynamic datasets, slower than single decision trees.
Support Vector Machines (SVM)	A classification and regression technique that finds a hyperplane to separate data points in high-dimensional space.	Works well with small, clean datasets, can handle high-dimensional data, effective for classification and ranking.	Computationally expensive, less efficient with large datasets, not suitable for real-time recommendations.
Matrix Factorization (MF) (e.g., SVD, ALS)	A dimensionality reduction technique used in collaborative filtering to learn latent factors from user-item matrices.	Scalable, efficient for large datasets, can handle sparse matrices, widely used in production systems like Netflix.	Assumes linearity in user-item interactions, limited flexibility to model complex, non-linear patterns.

Deep Learning Approaches

Deep Learning (DL) techniques represent a significant advancement in the field of recommender systems. DL models, such as Neural Collaborative Filtering (NCF), Autoencoders, Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Graph Neural Networks (GNNs), can automatically learn hierarchical features and model complex, nonlinear relationships in user-item interactions [1], [60]. These models are particularly effective in scenarios involving unstructured data, sequential behaviors, and multimodal content. Despite their power, DL approaches require large datasets, substantial computational resources, and often suffer from reduced interpretability and model explainability.

Neural Collaborative Filtering (NCF)

Neural Collaborative Filtering (NCF**)** combines the strengths of matrix factorization with multi-layer perceptrons to learn complex user-item interactions. It outperforms traditional CF in many contexts due to its capacity to model non-linearities [61]. Still, NCF models are data-hungry and computationally intensive, limiting their application in resource-constrained environments [2].

Autoencoders

Autoencoders, particularly Denoising Autoencoders (DAE) [62], have been effective in collaborative filtering tasks [63]. They learn latent representations by reconstructing the input matrix, often improving performance in sparse and noisy data scenarios. Their strength lies in dimensionality reduction and capturing complex correlations. However, Autoencoders often require careful regularization and tuning to prevent overfitting.[64]

Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are widely used in content-aware recommender systems, especially where visual or textual features play a role [65], such as recommending fashion items, artworks, or movies. CNNs are excellent at extracting spatial features but may not effectively model user interaction histories or temporal dynamics[66]. Moreover, training CNNs requires large labeled datasets and high computational resources.[67]

Recurrent Neural Networks (RNNs)

Recurrent Neural Networks (RNNs), including variants like Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) [68], are designed to handle sequential data and user behavior over time [69]. These models are suitable for session-based and dynamic recommender systems. Nonetheless, RNNs can suffer from vanishing gradient problems, and their sequential nature slows training and inference times, making them less ideal for real-time recommendations.

Table 2: Overview of Deep Learning Algorithms Used in Recommender Systems with Their Strengths and Weaknesses

Algorithm	Description	Strengths	Weaknesses
Neural Collaborative Filtering (NCF)	Combines matrix factorization and MLP to model non-linear user-item interactions.	Models complex, non-linear relationships and High predictive accuracy in large datasets	Data-hungry and Computationally intensive
Autoencoders (DAE)	Learns latent representations by reconstructing input matrix, effective in sparse data	Handles data sparsity and noise well and Effective dimensionality reduction	Susceptible to overfitting and Requires careful regularization and tuning
Convolutional Neural Networks (CNNs)	Extracts spatial features from content (images/text), used in content-aware recommendation	Excels at visual/textual feature extraction and Good for multimodal inputs	Poor at modeling user history/temporal data ,Needs large labeled datasets and High computational cost
Recurrent Neural Networks (RNNs, LSTM, GRU)	Designed to handle sequential data, capturing time-dependent user behavior	Good for session-based and sequential behavior modeling and GRU and LSTM solve long-term dependency issues	Training/inference is slower due to sequential processing and Suffers from vanishing gradients (in vanilla RNNs)

Synthesis and Interpretation of Key Findings

Based on the review of Machine Learning Algorithms for recommendation systems, Matrix Factorization (MF), specifically using Alternating Least Squares (ALS), is the most dominant algorithm to efficiently analyze data and provide personalized, real-time recommendations [59], [70], [71]. It effectively handles large-scale data, uncovers hidden patterns, and adapts to dynamic user needs.

For building effective recommendation systems, a hybrid approach combining Neural Collaborative Filtering (NCF) [61] with Recurrent Neural Networks (RNNs), particularly Gated Recurrent Units (GRUs) [72], is highly recommended. This combination harnesses the power of NCF to capture complex, non-linear interactions between users and items, while leveraging GRUs to model sequential dependencies and temporal patterns in user behavior.

Such an integration enables the system to adapt and evolve based on past interactions, providing personalized, real-time recommendations. This approach effectively handles challenges like data sparsity and evolving preferences, making it a strong choice for scalable, dynamic recommendation systems in various domains.

Table 3: Comparison between Matrix Factorization (MF) and Hybrid Models (NCF + RNNs/GRUs)

Aspect	Matrix Factorization (MF)	Hybrid Models (NCF + RNNs/GRUs)
Model Complexity	Simple, linear model, easier to implement and interpret	Complex, combining deep learning models (NCF and RNN/GRU)
Handling Non-linearity	Limited; assumes linear user-item interactions	Strong; NCF can model non-linear interactions
Temporal Modeling	Not suitable for sequential or dynamic user preferences	Excellent for modeling sequential data and evolving preferences
Scalability	Highly scalable, efficient for large datasets	Less scalable, computationally expensive for large-scale datasets
Data Requirements	Works well with sparse data	Requires large datasets for training, and can struggle with sparse data

Aspect	Matrix Factorization (MF)	Hybrid Models (NCF + RNNs/GRUs)
Adaptability to Change	Assumes static preferences, struggles with cold-start issues	Adaptable to changing user preferences, suitable for real-time systems
Computational Efficiency	Efficient and relatively fast during both training and inference	Computationally expensive, especially for real-time recommendations
Ideal Use Case	Large-scale, static systems with minimal dynamic changes	Session-based, dynamic, or context-aware recommendation systems

Body of Knowledge on Machine Learning-Based Recommendation Systems

This study employs document co-citation analysis to explore the knowledge structure and future trends in machine learning-based recommendation systems. Using VOSviewer, we visualized a co-citation network where nodes represent cited papers, and links indicate co-citation relationships, with stronger links reflecting shared research themes. A minimum citation threshold of 10 was set to focus on influential works shaping the field. Figure 6 illustrates thematic clusters, revealing key paradigms and interconnections. The network's evolution highlights emerging research in explainable AI, reinforcement learning, and personalized recommendations, while sparsely connected regions indicate research gaps. As the field progresses, greater integration with big data analytics, human-centered AI, and privacy-preserving techniques is expected, driving the next generation of intelligent and trustworthy recommendation systems.

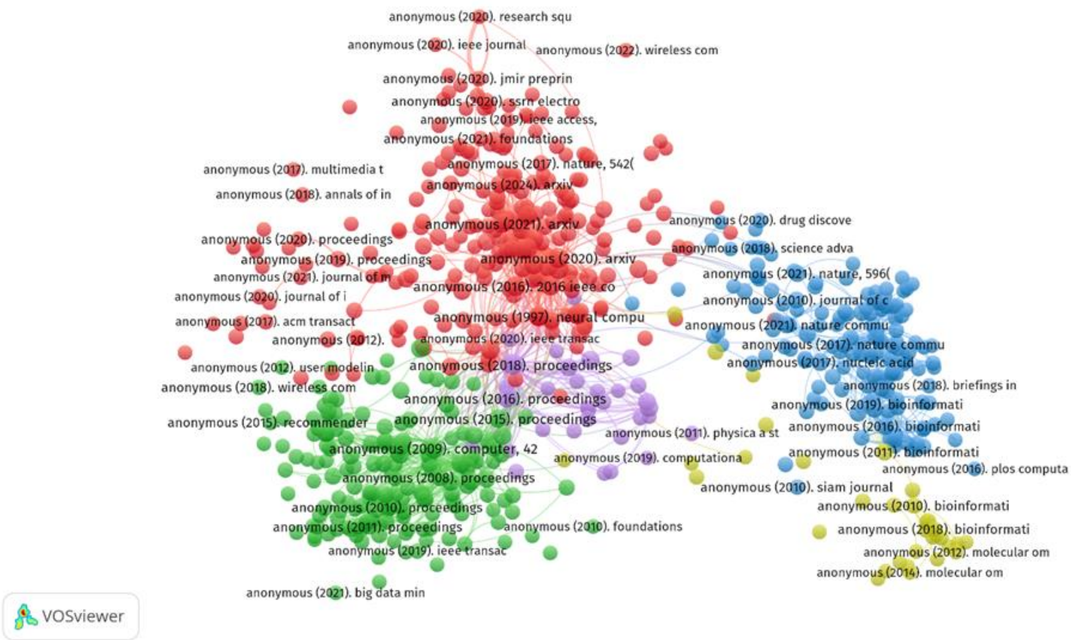

Figure 6: Co-Citation Networks of Documents on Machine Learning and Recommendation Systems

VI. Research Focus on Recommendation Systems

Continuous advancements in technology drive the development of new hypotheses, concepts, and methodologies in machine learning-based recommendation systems. As these innovations emerge, the terminology and research priorities evolve, reflecting shifts in the field. This progression is essential for scientific exploration, allowing researchers to systematically investigate new areas of study. By analyzing bibliographic coupling in machine learning and recommendation system literature, researchers can identify key trends and anticipate the topics that will gain prominence within the field over time.

Bibliographic Coupling and Emerging Trends in Recommendation Systems

By analyzing a bibliographic coupling network of research articles, we identified key clusters shaping machine learning in recommendation systems. Standardizing citation formats and removing duplicates ensured accuracy in visualizing research connections. Figure 7 illustrates the network, where nodes represent papers and edges indicate shared references. Color-coded clusters reveal distinct research themes: the red cluster focuses on probabilistic models and deep learning, the green emphasizes optimization and neural networks, and the yellow explores hybrid recommendation strategies. Foundational works, such as [16], [40] and [2] serve as key influences, linking multiple clusters. A dense central region signifies a strong intellectual core, while smaller, isolated clusters suggest emerging research directions. The strong interconnectivity of core publications highlights the interdisciplinary nature of machine learning, driving both theoretical advancements and practical applications in recommendation systems.

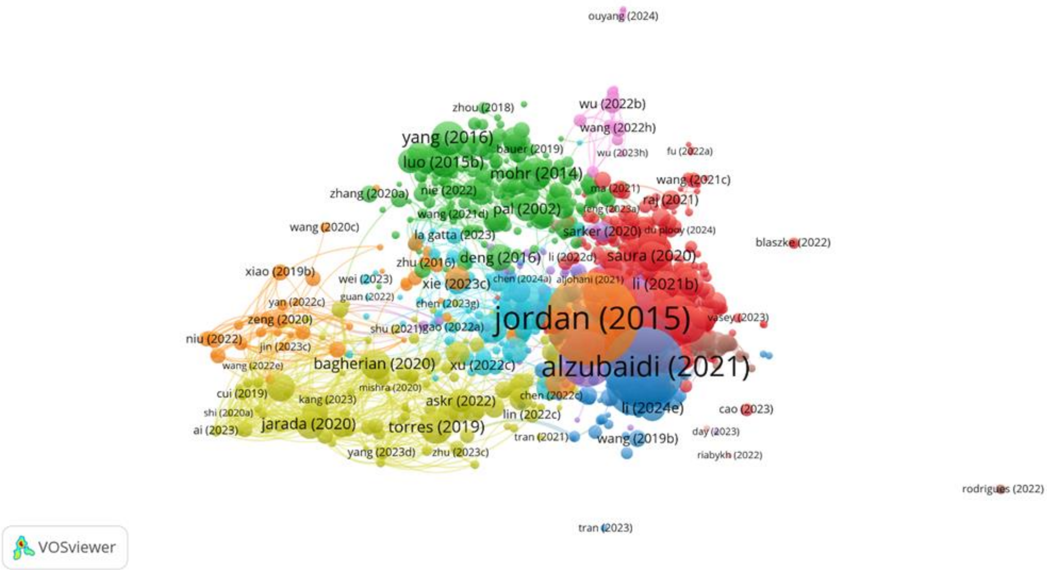

Figure 7: Bibliographic Coupling Network

VII. Conclusion

This bibliometric review provides a comprehensive overview of how machine-learning techniques have been applied in recommendation systems from 2015 to 2025. The analysis categorizes the most commonly used methods into machine learning-based and deep learning-based techniques. For systems with large-scale and stable user preferences involving implicit interactions, matrix factorization remains a widely used technique due to its simplicity, scalability, and low computational cost. In contrast, dynamic, session-based recommendation scenarios benefit more from hybrid models that combine Neural Collaborative Filtering (NCF) with Recurrent Neural Networks (RNNs) or Gated Recurrent Units (GRUs). These models are better suited for capturing evolving user behaviors and complex temporal patterns, though they require higher computational resources and extensive data. Despite the progress made, ongoing challenges related to scalability, real-time responsiveness, interpretability, and bias mitigation highlight the need for further research to develop more robust and equitable recommendation systems.

VIII. Limitations

In recent years, there has been a rapid increase in research on machine learning in recommendation systems, as evident from the growing number of publications. Strong collaborative networks between academic institutions and researchers have contributed to advancements in the field. However, our analysis is limited to the selected dataset, and relying solely on a single bibliometric database may not provide a complete picture of the research landscape. To obtain a more comprehensive overview, future studies should incorporate a wider range of scholarly databases, such as Scopus, Web of Science, and Google Scholar, ensuring a broader dataset for trend analysis. Additionally, integrating insights from industry reports, books, and technical case studies could enhance the scope of research

IX. Future Direction

Our findings indicate that machine learning-based recommendation systems continue to evolve, with significant advancements in deep learning, and hybrid models. One major gap in existing research is the lack of implementation details in many proposed models. Studies often focus on theoretical frameworks without detailing aspects such as algorithm selection, evaluation metrics, computational efficiency, and real-world deployment challenges. Future research should emphasize prototype implementation and real-world validation to bridge this gap. Furthermore, scalability and ethical considerations remain critical challenges in recommendation systems. As machine learning models become increasingly complex, ensuring fairness, transparency, and bias mitigation will be essential for their widespread adoption. Future research should also explore the integration of federated learning, reinforcement learning, and real-time adaptive systems to enhance recommendation accuracy and user satisfaction. As the field continues to expand, it is expected that machine learning techniques in recommendation systems will become even more sophisticated, addressing diverse application needs while ensuring robust, scalable, and ethically responsible solutions.

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