Exploring the Evolution of Recommender Systems Through Social Network Analysis

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Abstract. This study leverages social network analysis to examine the evolution of recommender systems research from 2007 to 2024, focusing on influential research categories and scholarly communities. By constructing a social graph linking highly cited papers to extracted categories, we applied centrality measures such as degree, betweenness, and PageRank along with Louvain community detection to uncover structural patterns and temporal dynamics often missed by traditional methods. Each link represents a paper–category association identified by the IBM NLP Cloud service. The findings suggest that analyzing trends in this field can reveal broader societal and technological shifts. For instance, the rising prominence of categories like Power and Energy aligns with Industry 4.0, where recommender systems optimize energy usage and personalize resource allocation. Detected communities demonstrate dynamic, period-specific clustering, reflecting maturing subfields and emerging applications. This network-based perspective offers insights into the shifting knowledge structure in recommender systems and supports anticipating future directions shaped by societal needs.

Keywords: social network analysis, recommender systems, Community detection

1 Introduction

Social networks are complex structures representing relationships among social entities, such as individuals, groups, or organizations, and are characterized by homophily, community structure, the small-world property, and scale-free topology. Social Network Analysis (SNA) uses graph and network theory to uncover underlying patterns, with major applications in community detection, link prediction, and recommender systems [15].

In recent years, recommender systems have played a key role in artificial intelligence (AI) and are used in various applications in daily life. Over time, recommender systems have evolved from classic approaches to more advanced, AI-driven models. This surge has been driven by advancements in AI and deep learning, as well as a shift toward addressing new challenges and societal concerns [52]. Studying this evolution offers insights into how recommender systems have co-evolved with societal and technological shifts, revealing emerging trends and guiding future research.

But what exactly is a recommender system, and why is it so important? Recommender systems were introduced in the 1990s to help people effectively manage and navigate the increasingly vast amounts of information available. In simple terms, a recommender system's main job is to guess how much someone might like something she hasn't seen before, and suggest things she probably likes. These systems play a vital role in domains like e-commerce, advertising, and academic retrieval [55], with companies such as Amazon, Google, and YouTube relying on them to recommend products, content, or connections. Given their significant societal impact and rapid development, recommender systems are facing a range of challenges, driving numerous research efforts to make these systems more reliable and accurate for various applications. Some of the key challenges include fairness, bias, explainability, security, and privacy [55].

At a high level, a recommender system connects users with items to provide personalized suggestions. It uses a utility function u to assess how valuable an item $s \in S$ is to a user $c \in C$, where $u : C \times S \to R$, and R is an ordered set, such as positive numbers or a range of real numbers. Typically, a recommender system uses ratings to express how much a user likes an item. However, in some cases, the system ranks items relative to each other, suggesting the item with the highest relevance ranks to the user [1].

Over the past two decades, a wide range of recommendation approaches have been developed, evolving from traditional methods like content-based filtering to modern techniques that continue to shape the field of recommender systems. In this paper, we explore the evolution of recommender systems from 2007 to 2024, dividing the timeline into four distinct periods: 2007-2010, 2011-2015, 2016-2020, and 2021-2024. Using social network analysis, this study identifies key research categories and their interconnections, uncovering structural and temporal patterns in the field.

The remainder of the paper is organized as follows: Section 2 reviews prior work and key challenges; Section 3 presents our methodology; Section 4 discusses the results; and the final section concludes with key findings and directions for future research.

2 Literature review

This section provides a brief overview of the evolution of recommender system approaches from early techniques to current advancements. Fig.1 summarizes the main categories. Many systems are hybrid, combining methods to improve accuracy and user satisfaction through model integration, feature blending, or joint architectures [59][9][64][45].

One of the **classic** approaches in this field is content-based filtering, which generates recommendations by evaluating item attributes and aligning them with the user's historical behaviors, preferences, and interactions [1]. Techniques such as Jaccard similarity, Cosine similarity, and more recently, deep learning-based embeddings and metric learning, have improved their accuracy [47].

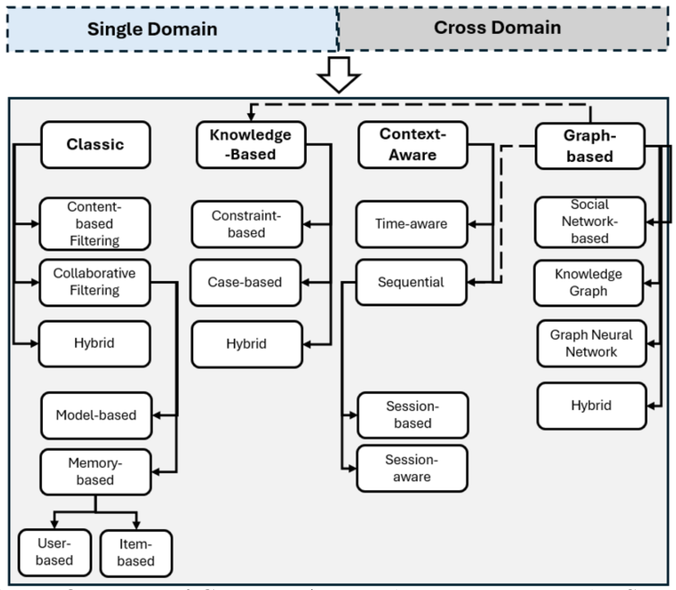

Fig. 1. Overview of Common Approaches in Recommender Systems

Another important and widely adopted approach is collaborative filtering, which recommends items to a person based on the preferences and ratings of similar users. Collaborative filtering can struggle with data sparsity (insufficient user-item interaction) and the cold-start problem (where the system encounters difficulties in recommending items due to insufficient data for new users or items) [1]. To mitigate these, matrix factorization methods like Singular Value Decomposition (SVD), Non-Negative Matrix Factorization (NMF), and Alternating Least Squares (ALS) have been developed [31], along with neural approaches like autoencoders and neural collaborative filtering (NCF) [20][56]. These methods collectively improve the ability to predict user preferences and generate accurate recommendations.

Knowledge-based recommenders integrate domain knowledge, rules, or case-based reasoning, often using knowledge graphs to enhance transparency and personalization [61]. These models are increasingly popular due to their explainability and adaptability in conversational settings.

In recent years, as recommender systems have increasingly emphasized personalization, **context-aware** approaches have emerged, incorporating contextual and situational knowledge. These systems adapt recommendations to align with the user's current situation and preferences, resulting in more personalized results [39]. A real-world application of this is the integration of Internet of Things (IoT) technologies, enabling deeper personalization. Similarly, sequential and session-based recommenders use recent interactions and context to deliver timely and relevant suggestions, leveraging techniques such as convolutional neural networks, recurrent neural networks, graph neural networks, and attention mechanisms [41][51].

With the growing interest in social media platforms, research has increasingly proposed using social network-based approaches to optimize and enhance the quality of recommendations. This approach incorporates social network analysis techniques and characteristics such as homophily, community structure, social conformity, influence, and trust to improve the accuracy and relevance of recommendations [60].

Modeling recommender systems using social graphs and applying techniques like community detection and link prediction are key methods for guiding search direction and improving accuracy [50]. **Graph-based** approaches have gained significant attention, especially with the success of deep learning and graph neural networks, which enhance the modeling of complex relationships and user interactions, leading to more accurate and personalized recommendations [77].

Finally, multi-domain recommendation aims to transfer insights between domains to enhance accuracy, especially in sparse or low-data environments. This area faces multiple challenges related to complexity, privacy, and ethics [49].

Despite progress, major challenges such as data sparsity, cold-start, privacy protection, diversity, bias, and explainability still exist in this field. These issues continue to shape the research agenda as systems aim to become more robust and user-centric. Given the importance and rapid evolution of recommender systems, numerous valuable surveys and systematic reviews have summarized trends and best practices. We believe that examining them through the lens of social network analysis can provide valuable insights into their co-evolution with societal changes and mutual influence over time.

3 Methodology

In order to explore the evolution of recommender systems in the last decade, we have designed and followed a process illustrated in Fig. 2. In this section, we explain each phase in detail.

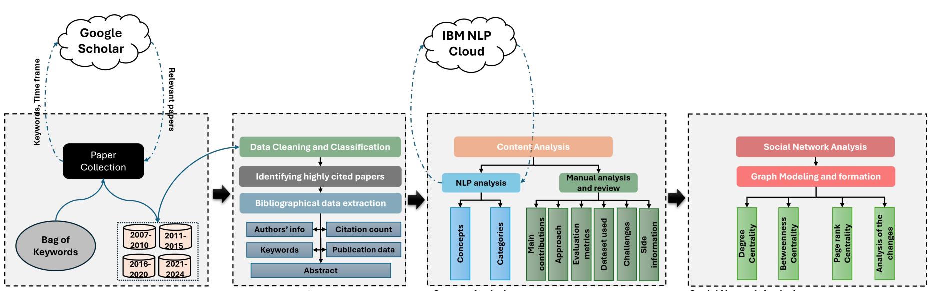

Fig. 2. Overview of Our Research Process Workflow

Data Collection: We used Google Scholar to search and identify related papers. Our query was based on keywords related to recommender systems, including *recommendation system*, *recommender*, *recommendation*, *learn to rank*, *Netflix*, *matrix factorization*, *factorization machine*, *collaborative filtering*, *content-based*, *context-aware*, *sequential*, *session-based*, and *graph-based recommender systems*. The collected papers were manually reviewed to verify their relevance to the topic and were stored in our dataset according to their publication dates. By the end of this phase, we compiled a list of approximately 1,500 papers across different time spans from 2007 to 2024.

Pre-processing: In this stage, we filtered and organized the collected data for analysis. First, we excluded irrelevant materials such as surveys and books to focus on research papers with original contributions. We then categorized the selected papers into four time periods: 2007–2010, 2011–2015, 2016–2020, and 2021–2024. For each period, we identified highly cited papers, 10 with over 700 citations (2007–2010), 10 with over 500 (2011–2015), 20 with over 100 (2016–2020), and 20 with over 20 (2021–2024).

The differences in citation thresholds reflect both the growth in research output and the time available for citations to accumulate. The full list of papers is shown in Table 1.

Content Analysis: In this phase, we conducted a brief bibliometric analysis of the selected papers by extracting metadata such as the number of authors, publication venue, year, and citation count.

The core of our analysis, relied on the IBM NLP Cloud service [22], which we used to automatically mine the content and extract key categories from the selected papers. We retrieved the list of categories whose estimated scores were above the 0.65 threshold.

Table 1. List of the Selected Papers in Different Categories

Period	**Description**	**References**
2007-2010	Foundational years with the introduction and adoption of key concepts and algorithms.	[76], [44], [5], [29], [57], [42], [30], [10], [54], [75]
2011-2015	Growth in scalability, big data techniques, and practical applications influenced by industry challenges like the Netflix Prize.	[13], [35], [56], [66], [16], [38], [26], [46], [43], [62]
2016-2020	The rise of deep learning and neural networks, leading to more sophisticated and complex models.	[8], [20], [18], [69], [6], [27], [65], [67], [70], [12], [58], [7], [37], [19], [74], [33], [4], [72], [28], [77]
2021-2024	Innovations in reinforcement learning, conversational AI, privacy-preserving techniques, real-time and on-device systems.	[41], [59], [25], [32], [9], [24], [11], [64], [63], [23], [73], [34], [14], [21], [53], [17], [40], [71], [45], [36]

Social Network Analysis: Next, we used social network analysis techniques to identify key categories and uncover patterns and trends in the dataset. A social graph was created by linking each paper to its extracted categories, and community detection was applied to identify groups of papers with similar topic focus. This helped us explore how the research community evolved over time and which areas attracted increasing attention.

We also applied various centrality metrics to assess the relative importance of papers within the network for each period:

- **Degree centrality** measures the number of direct connections a paper has.
- **Betweenness centrality** reflects a paper's role as a bridge between other papers.
- **PageRank** evaluates a paper's importance based on both direct links and the influence of linked papers.

These metrics helped us determine the prominence and influence of different categories across time. Finally, we conducted statistical analyses to extract patterns from the results.

4 Findings

We followed our proposed methodology to gather information from 2007 to 2024. Using Python and its libraries, we processed and analyzed the data, created visualizations, and constructed a social graph to perform social network analysis.

To further analyze the graph, we identified the main communities in each period and studied their evolution over time. For this purpose, we used Gephi [2] and applied the Louvain method [3] through its built-in modularity function to detect communities.

Fig. 3 illustrates the visual representation of highly cited paper communities from 2007 to 2015, while Fig. 4 shows the visual representation of highly cited paper communities from 2016 to 2024. The results are presented below.

4.1 2007-2010

During 2007–2010, recommender systems mainly relied on collaborative and content-based filtering due to their simplicity and effectiveness. Hybrid methods began to emerge, though broader adoption came later.

Results and Observations: In this period, the most influential categories by degree centrality were *AI* (0.4154), *Information Security* (0.3231), and *Software Applications* (0.3231). Betweenness centrality also highlighted *AI* (0.2945) and *Information Security* (0.1595) as key connectors.

PageRank confirmed the dominance of *AI* (0.1167) and *Information Security* (0.0910). Emerging categories with moderate influence included *Computing & General Technology* and *Internet & Networking*, while areas like *Mobile Games* and *Online Education* began to grow but remained less central.

Three main communities were detected: the first on *AI* and *Information Security* (4 papers), the second on *Computing & General Technology* (3 papers), and the third on *Internet & Networking*, *Software & Applications*, and others including *Online Education*, *TV*, and *Mobile Games* (3 papers).

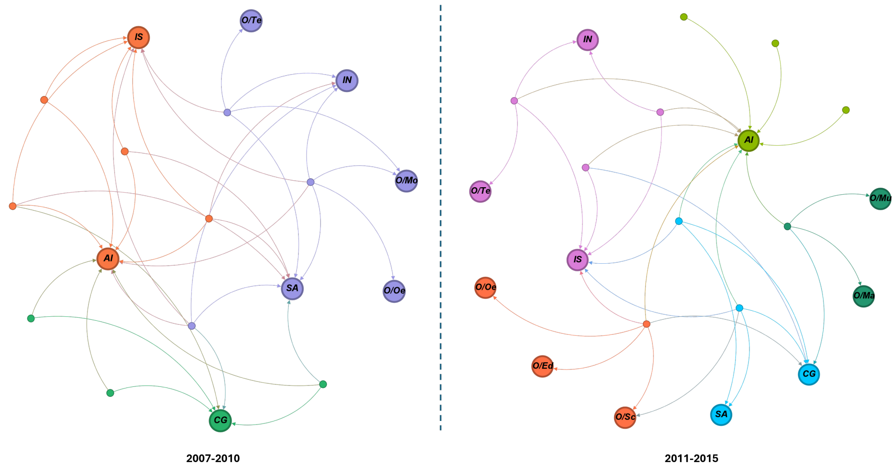

Fig. 3. Community Detection on the Graphs of Papers and Their Categories (2007-2010 and 2011-2015). The smaller nodes represent the papers, and the bigger ones denote the categories. Abbreviations: AI: Artificial Intelligence; IS: Information Security; CG: Computing & General Technology; IN: Internet & Networking; SA: Software & Applications; O/Te: Other/Television; O/Mo: Other/Mobile Games; O/Oe: Other/Online Education; O/Ed: Other/Education; O/Sc: Other/science; O/Mu: Other/Music; O/MA: Other/Variety Audio.

4.2 2011–2015

From 2011 to 2015, hybrid systems, context-aware recommender systems, and social network-based systems gained traction. Integration of multiple techniques and contextual information such as time and location became common to improve accuracy and address the cold start problem. Social connections were also leveraged to enhance recommendations.

Results and Observations: *AI* (0.3846) and *Information Security* (0.2308) remained dominant in degree centrality, with *Computing & General Technologies* (0.1923) also influential. Betweenness centrality showed *AI* (0.5482) and *Information Security* (0.1259) as key bridges.

PageRank ranked *AI* (0.1475) highest, followed by *Information Security* (0.0827) and *Computing & General Technology* (0.0710). New areas like *Education*, *Online Learning*, and *Music and Audio* (including *Comedy* and *Variety*) gained attention, marking their initial integration into the research network despite lower centrality.

Five communities emerged: the first around *AI* (3 papers), the second on *Information Security*, *Internet & Networking*, and *TV* (3 papers), the third on *Computing & General Technologies* and *Software & Applications* (2 papers), the fourth on *Science*, *Education*, and *Online Education* (1 paper), and the fifth on *Music and Audio*, including *Comedy* and *Variety* (1 paper).

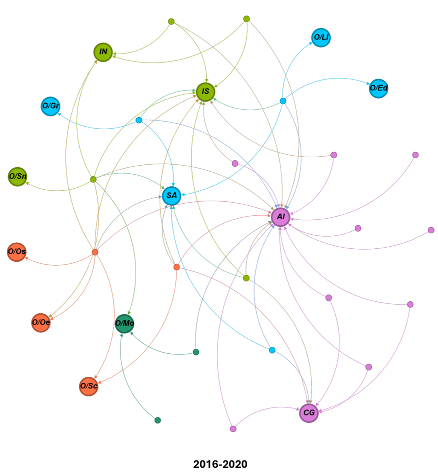

Fig. 4. Community Detection on the Graphs of Papers and Their Categories (2016-2020 and 2021-2024). The smaller nodes represent the papers, and the bigger ones denote the categories. **Abbreviations:** AI: Artificial Intelligence, IS: Information Security, CG: Computing & General Technology, IN: Internet & Networking, SA: Software & Applications, O/Mo: Other/Mobile Games, O/Oe: Other/Online Education, O/Ed: Other/Education, O/Ll: Other/Education/Language Learning, O/Ce: Other/Education/College Education, O/Gr: Other/3D Graphics, O/Sn: Other/Social Networking, O/Os: Other/Operating Systems, O/Sc: Other/science. O/Mu: Other/Music, O/MA: Other/Variety Audio, O/Ds: Other/Data Storage and Warehousing, O/Is: Other/Information Service, O/En: Other/Energy.

4.2 2016-2020

From 2016 to 2020, there were major advancements in recommender systems, with a strong trend toward hybrid models combining multiple techniques for improved accuracy and performance. Deep learning, attention mechanisms, and graph-based methods became particularly prominent. Sequential recommenders using RNNs and transformers emerged, along with growing interest in explainability and the use of social and cross-domain data to better capture user behavior and relationships.

Results and Observations: *AI* (0.6552) and *Information Security* (0.3448) led in degree centrality, followed by *Computing & General Technologies* (0.2414) and *Software & Applications* (0.1379). Betweenness centrality showed *AI* (0.6183) as the main bridge, with *Information Security* (0.1212) and *Computing & General Technologies* (0.0356) also serving connecting roles.

PageRank emphasized *AI* (0.1620) and *Information Security* (0.0808) as central. New fields such as *Biological Sciences*, *3D Graphics*, and *Language Learning* emerged, while *Online Education* and *Mobile Games* showed continued growth.

Five communities were observed: (1) *AI* and *Computing & General Technologies* (9 papers); (2) *Information Security*, *Internet & Networking*, and *Social Networking* (4 papers); (3) *Software & Applications*, *Education*, *3D Graphics*, and *Language Learning* (3 papers); (4) *Operating Systems*, *Online Education*, and *Science* (2 papers); and (5) *Video* and *Mobile Games* (2 papers).

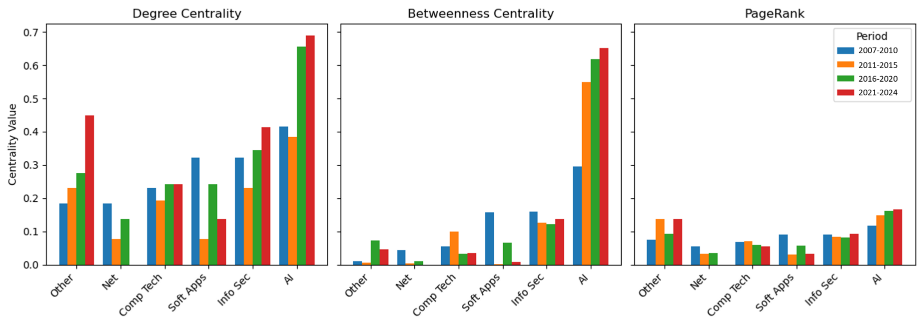

Fig. 5. Evolution of Categories over Time using Different Centrality Measures

4.4 2021–2024

From 2021 to 2024, recommender systems advanced with the emergence of conversational, cross-domain, and social network-based systems, along with a continued emphasis on explainable AI. NLP breakthroughs enabled natural language interactions in conversational systems. Cross-domain systems used knowledge from multiple domains to enhance recommendations. On-device systems began to offer real-time personalization without constant internet access, though this trend is still evolving.

Results and Observations: *AI* (0.6897) and *Information Security* (0.4138) remained dominant in degree centrality, with *Computing & General Technologies* (0.2414) and *Science* (0.2580) also showing influence. Betweenness centrality reaffirmed the central role of *AI* (0.6521), followed by *Information Security* (0.1375) and *Computing & General Technologies* (0.0356).

PageRank again emphasized *AI* (0.1658) and *Information Security* (0.0936) as key influencers. Newly emerging categories included *College Education*, *Data Storage & Warehousing*, *Information Services Industry*, *Power & Energy*, *Automotive*, and *Auto Technology*, reflecting expanding research diversity.

Five communities were identified: (1) *AI* and *Information Services Industry* (6 papers); (2) *Information Security*, *Data Storage & Warehousing*, and *College Education* (5 papers); (3) *Computing & General Technology*, *Science*, and *Language Learning* (5 papers); (4) *Software & Applications*, *Education*, and *Online Education* (3 papers); and (5) business and industry topics such as the *Power & Energy Industry* (1 paper).

Fig. 5 provides a visual representation of the evolution of the research categories across four time periods using various centrality measures.

5 Discussion

Social network analysis results demonstrate that the progression of research categories within recommender systems across various timeframes reflects significant changes in society and technology. For instance, the increased attention on education and online learning, which has been ongoing since before 2007 and continued until 2024, corresponds with the growing digital transformation of education. During this period, platforms like Coursera, LinkedIn Learning, and other Massive Open Online Course (MOOC) providers became more prevalent, emphasizing the need for advanced recommender systems to help users manage the abundance of available educational resources. The COVID-19 pandemic amplified this shift, as many traditional schools and universities shut down, prompting students to rely on online platforms, where personalized recommendations became essential to optimize learning experiences [68].

The integration of recommender systems into entertainment genres, such as comedy and variety, aligns with the increasing trend of digital content consumption. As platforms like Spotify and Netflix grew, recommender systems became essential for boosting user engagement and satisfaction. From 2021 to 2024, the emerging research categories—power and energy, automotive, and autotechnology—align with the rise of Industry 4.0. As digital technologies like IoT and AI integrate into industrial processes, the demand for recommender systems to optimize operations has increased, reflecting a shift toward automation and efficiency in modern industry [48].

Based on our community detection results, we can see that the main concepts of research in this field have evolved over time. In the early stages (2007–2010), AI and information security were categorized together, while computing and general technology formed separate communities. As research progressed into the next phase (2011–2015), these topics diversified, with AI maintaining its focus and information security expanding to include internet and networking and TV, reflecting a growing overlap due to societal and technological changes.

In the later stages (2016–2024), research began to consolidate again, with AI merging more closely with computing and general technologies and information security covering areas like social networking and data storage. This maturity phase illustrates the increased integration of AI across domains. By the most recent phase, the field branched out into industry-specific areas such as power and energy, suggesting a new wave of specialization. The evolution can be divided into four phases: inception, growth, maturity, and mitosis, confirming our previous findings regarding the trends and shifts in recommender systems research over these periods.

Overall, the advancement of recommender systems is anticipated to both drive and be driven by societal changes. As digital consumption expands and industries continue to evolve, the demand for personalized recommendations is likely to increase, largely shaped by societal needs.

6 Conclusion

In this paper, we presented a comprehensive study of the evolution of recommender systems from 2007 to 2024. Using social network analysis on a set of highly cited papers, we identified major research trends and developments in the field. Our results highlight the consistent centrality of AI and information security, alongside the growing prominence of areas like education and online learning, reflecting the field's expanding scope and its response to societal changes.

Our analysis suggests a clear link between major societal shifts and emerging research directions. Future research is expected to focus on conversational systems, privacy-preserving techniques, and real-time or on-device recommendations powered by IoT technologies, along with growing interest in fairness, explainability, and ethical concerns, as well as cross-industry applications.

7 Acknowledgment

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