Bibliometric Mapping and Systematic Review of Deep Learning Approaches in Film and Multimedia Recommendation Systems within New Media

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***Abstract*—The rapid growth of film, video, and multimedia content on new media platforms has intensified information overload, increasing the importance of effective recommender systems. Traditional recommendation approaches face limitations in modeling complex content semantics and dynamic user preferences. Deep learning techniques have been widely adopted to enhance film and multimedia recommendation performance. This study presents a bibliometric mapping and systematic literature review of deep learning film and multimedia recommendation systems in new media. Scopus was used as the primary data source, yielding 679 peer-reviewed studies following a structured screening and inclusion process. The research methodology, search strategy, and selection criteria are explicitly documented. Bibliometric techniques, including citation analysis, keyword co-occurrence, and thematic clustering, are applied to identify influential publications, dominant research streams, and emerging trends. The reviewed literature is synthesized into major thematic areas, including multimodal representation learning, graph-based recommendation, multimedia feature extraction, personalization and cold-start mitigation, fairness and bias, emotion-aware recommendation, and explainability. The findings reveal a strong dominance of multimodal and graph-based deep learning models, particularly those integrating visual, audio, textual, and interaction data. However, many existing approaches rely on shallow feature fusion and demonstrate limited capability in capturing fine-grained semantic relationships, user attraction mechanisms, and contextual meaning. Challenges related to cold-start, sparse feedback, fairness, transparency, and user experience remain insufficiently addressed. This study identifies critical research gaps and outlines future research directions, emphasizing the need for semantically rich, explainable, fair, and human-centered multimedia recommender systems capable of supporting the evolving complexity of new media ecosystems.**

Keywords*—Deep learning; multimedia recommendation systems; film recommendation; new media platforms; multimodal learning; graph-based recommender systems

I. Introduction

The rapid expansion of new media platforms, including film streaming services, short-video applications, and multimedia social networks, has led to an unprecedented growth in audiovisual content [1]. While this abundance enhances user choice, it simultaneously intensifies information overload, making effective recommendation systems indispensable for personalized content discovery [2]. Deep learning-based recommender systems have emerged as a dominant solution, demonstrating superior performance in capturing complex user item interactions and multimodal content representations compared with traditional collaborative and content-based approaches [3], [4], [5]. Recent advances in film and multimedia recommendation increasingly use deep neural architectures such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), graph neural networks (GNNs), and multimodal representation learning. Multimodal graph-based models, including the Multimodal Graph Convolution Network (MMGCN), have shown strong capability in integrating visual, acoustic, and textual features within unified recommendation frameworks [6]. Self-supervised and contrastive learning techniques have been introduced to improve representation disentanglement in short-video and micro-video recommendation contexts [7].

Despite these methodological advances, the fast-growing body of literature remains fragmented across domains, media types, and modeling paradigms. A key problem in current research is the lack of a systematic and quantitative synthesis of deep learning approaches applied specifically to film and multimedia recommendation within new media ecosystems [8], [9]. Existing studies predominantly focus on algorithmic taxonomies or specific media modalities, without offering a bibliometric perspective on research evolution, influential themes, and intellectual structures shaping the field [5]. It remains unclear how research trends have evolved over time, which deep learning paradigms dominate high-impact studies, and where critical knowledge gaps persist. Several substantive research gaps emerge from highly cited works. First, although multimodal deep learning has improved recommendation accuracy, most models rely on feature-level fusion and fail to incorporate semantic and relational knowledge underlying film and video content, limiting interpretability and fine-grained reasoning [6] [10]. Second, issues such as cold-start, fairness, emotional engagement, and sustainable user experience are often addressed in isolation, rather than through unified deep learning frameworks suitable for complex new media environments [1] [11]. Third, explainability and attraction modeling remain underexplored, even though understanding why content appeals to users is crucial when explicit feedback is sparse or unavailable [10]. To address these limitations, this study conducts a bibliometric mapping and systematic literature review of deep learning-based film and multimedia recommendation systems within new media. By analyzing highly cited publications, keyword co-occurrence networks, and thematic clusters, this research identifies dominant methodologies, emerging trends, and underdeveloped research directions. Unlike prior narrative reviews, the bibliometric approach provides an evidence-based overview of the intellectual structure of the field, enabling objective identification of research concentrations and gaps [4], [9], [12]. The contributions of this study are threefold. First, it provides a comprehensive bibliometric analysis that maps the evolution of deep learning approaches in film and multimedia recommendation. Second, it synthesizes major thematic streams. Third, it highlights critical research gaps and outlines future directions.

II. Related Work

Existing literature reviews on recommender systems demonstrate substantial breadth and technical depth; however, they largely adopt horizontal cataloging approaches that organize studies by algorithms, applications, or datasets without critically integrating media specificity, deep learning evolution, and new media contexts. As reflected in Table I, most reviews provide valuable taxonomies but stop short of synthesizing how deep learning paradigms reshape film and multimedia recommendation systems in structurally distinct ways. The study of [8] provides broad algorithmic taxonomies across application domains, yet treats movies, videos, and multimedia content as interchangeable recommendation targets. This idea hides the unique multimodal complexity inherent in film and new media content, where visual, acoustic, textual, emotional, and social signals interact nonlinearly. In [13], the authors emphasize deep learning–based collaborative filtering but focus primarily on neural architectures rather than media-aware representation learning. More recent reviews address emerging paradigms but remain method-centric rather than domain-centric. The study of [9] advances the field by contrasting traditional AI with generative AI. However, its scope spans heterogeneous domains and does not examine how generative or deep models specifically transform film and multimedia recommendation workflows. In [14] and [4], the authors further classify deep learning techniques but emphasize algorithm families over content modality integration, leaving unanswered questions about how deep learning handles narrative structure, emotion, attraction, and temporal dynamics in media content.

Video-specific reviews, such as [12], provide applied insights into platforms like Netflix but rely on platform-centric narrative discussion rather than systematic bibliometric evidence. Meanwhile, [15] delivers a macro-level trend analysis linking recommendation research with business growth, yet does not isolate deep learning driven transformations in multimedia recommendation. In contrast, the present study makes a distinctive and complementary contribution in three critical ways. First, it employs bibliometric mapping to quantitatively reveal intellectual structures, influential works, and thematic evolution of deep learning approaches in film and multimedia recommendation, an approach limited from prior reviews. Second, it explicitly situates recommendation models within new media ecosystems, including streaming platforms, short-video services, and social multimedia environments, rather than treating recommendation as a domain-agnostic problem. Third, by synthesizing highly cited studies, this review critically identifies systemic research gaps, including limited multimodal knowledge integration, weak attraction modeling, insufficient explainability, and fragmented treatment of user experience, fairness, and emotion. Therefore, rather than functioning as another annotated inventory, this study advances the literature by providing a theory-informed, evidence-driven synthesis that clarifies how deep learning has reshaped and continues to challenge film and multimedia recommendation systems within new media.

TABLE I. Related Work

Source	Type	Included Studies	Aim / Focus
[8]	Systematic Review	60	General taxonomy of recommender systems across applications (books, movies, products); algorithmic comparison, datasets, metrics
[9]	Systematic Review	52	Comparative analysis of traditional AI vs generative AI (GANs, VAEs) in recommender systems
[14]	Systematic Review	787	Classification-based review of deep learning techniques (CNN, RNN, GNN) across multiple domains
[4]	Systematic Review	46	Taxonomy of deep learning algorithms for social recommendation systems
[13].	Systematic Review	102	Deep learning–based collaborative filtering; neural architectures, tools, applications
[12]	Narrative Review	189	Video recommendation systems with emphasis on Netflix and hybrid filtering approaches
[15]	Trend Analysis Review	135	Longitudinal analysis of recommendation technologies and business applications

III. Methodology

The systematic bibliometric review method is used in this research to examine the deep learning-based film and multimedia recommendation system research landscape within the new media settings. The research methodology was planned specifically to provide a sense of transparency, reproducibility and methodological rigor [16], [17].

A. Data Source

Bibliographic information was searched in the Scopus database only because it has a wide collection of peer-reviewed journals, conference proceedings, and book series related to the computer science domain, artificial intelligence, and multimedia, and information systems [18]. Scopus also offers extensive indexing of citation and superior analysis features; thus, it has been appropriate towards bibliometric mapping and trend analysis [19]. Bibliometric analysis, as emphasized by prior scholars, serves as a systematic method for uncovering research patterns and intellectual structures within a specific knowledge domain [20].

B. Search Strategy and Search String

A systematic procedure was adopted to identify and compile the most relevant literature for this study, as illustrated in Fig. 1. The search strategy incorporated a wide range of terms to capture all possible research related to deep learning applications in film and multimedia recommendation systems within new media environments. The final search string included: ("deep learning" OR "machine learning" OR "artificial intelligence" OR AI OR "neural network*" OR "convolutional neural network*" OR CNN OR "recurrent neural network*" OR RNN OR "transformer model*" OR "deep neural network*" OR DNN) AND (film OR movie* OR cinema* OR video* OR "media content" OR "digital content" OR multimedia*) AND ("recommender system*" OR "recommendation system*" OR "content recommendation" OR "personalized recommendation" OR "content-based" OR "collaborative filtering" OR "hybrid recommendation" OR "media recommendation") AND ("new media" OR "digital media" OR "online media" OR platform* OR "social media" OR "streaming" OR "OTT" OR "web-based" OR "internet media" OR "digital platform*"). This systematic search approach ensured broad coverage of studies addressing deep learning-driven recommendation technologies across film, multimedia, and new media platforms.

C. Inclusion and Exclusion Criteria

In order to generate a high-quality dataset that will be of use in deep learning applications in film and multimedia recommendation systems under new media, there were clear inclusion and exclusion criteria. Research papers were considered provided that they were focused directly on the application of deep learning to the improvement of film or multimedia recommendation, and covered such topics as content-based filtering, collaborative filtering, hybrid recommendation systems, user profiling, and the multimodality of data integration. Publications in English that were published after 2016 and before 2025 were regarded only to preserve their accessibility and reflect the latest advances in technology. Research that was not directly related, like hardware design, purely social sciences, environmental science or mathematics, was not counted. No non-research articles, such as editorials, opinion pieces, and general reviews, were also included in order to give priority to empirical and application-oriented articles, as presented in Table II.

TABLE II. INCLUSION AND EXCLUSION

Criteria	Inclusion	Exclusion
Topic	Deep learning based film/multimedia recommendation systems within new media.	Non deep-learning studies; unrelated multimedia topics.
Document Type	Journal articles and conference papers.	Reviews, editorials, letters, notes, book chapters.
Language	English.	Non-English.
Years	2016-2025.	Before 2016 or after 2025.
Subject Area	Computer science, decision sciences, information systems, multimedia, AI.	Fields unrelated to media/AI (e.g., materials science, medicine).
Database	Scopus-indexed documents.	Non-Scopus sources.
Quality	Clear methodological relevance to deep learning and recommendation systems.	Low methodological clarity or irrelevant focus.

D. Study Selection Process

The Scopus database was used in November 2025 for data extraction, the search limit to sources available in 2016-2025, aiming to obtain the latest research in deep learning-based film and multimedia recommendation systems in new media. The selection of the data was based on the systematic multi-stage strategy, as seen in Fig. 1. A preliminary search had found 962 documents. A provided filtering based on computer science, decision sciences, social sciences, multidisciplinary, and arts and humanities to refine the dataset was the first screening that narrowed the dataset to 842 studies to include the relevant ones. Then, the results were restricted to English-language articles, which produced 825 studies, which guaranteed the accessibility and uniformity. In the next step, only articles and conference papers were included, and the reviews, editorials, and opinion articles were excluded, leading to a final sample of 679 articles. The resulting dataset of high-quality, after this multi-stage filtering process, that included meaningful contributions to deep learning applications in a film and multimedia recommendation system were of good quality and offered a solid basis of bibliometric mapping, thematic analysis, and discovery of new trends and research opportunities in this area.

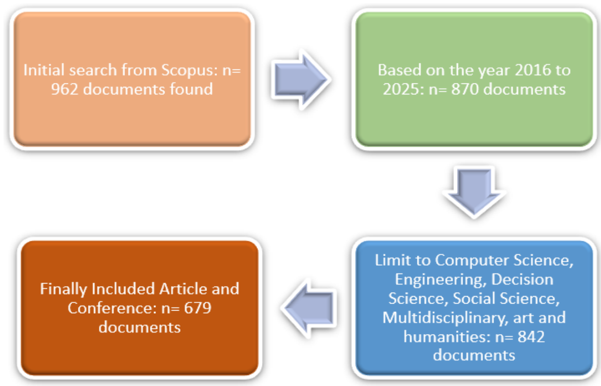

Fig. 1. Study selection process.

IV. Results and Discussion

This section provides a discussion of the results. Citation counts serve as an important indicator for identifying influential studies and mapping prevailing research trends within a scholarly domain. Accordingly, this bibliometric analysis seeks to offer a systematic and transparent overview of impactful research in deep learning–based film and multimedia recommendation systems within new media, by highlighting key publications, dominant themes, and emerging research directions shaping this field.

A. Annual Distribution

The annual publication distribution reveals a clear and sustained growth direction in research on deep learning approaches for film and multimedia recommendation systems within new media environments. As shown by the publication frequencies in Fig. 2, scholarly output increased steadily from 2016 (10 publications) to 2025 (139 publications), reflecting the maturation and expanding relevance of this research domain. Between 2016 and 2018, publication activity remained relatively modest (10–17 studies per year). During this formative phase, research primarily focused on traditional collaborative filtering, early deep learning architectures, and basic content-based multimedia recommendation methods. Foundational works during this period laid the groundwork for incorporating deep neural networks, sentiment analysis, and early multimodal representations into recommendation systems.

A noticeable acceleration begins in 2019 (37 publications) and continues through 2020 (50 publications) and 2021 (57 publications). This growth coincides with the widespread adoption of deep learning models such as CNNs, RNNs, and matrix factorization enhanced with neural networks alongside the increasing availability of large-scale multimedia datasets from platforms like Netflix, YouTube, TikTok, and Spotify. Research during this phase increasingly addressed challenges such as cold-start problems, data sparsity, and sentiment-aware personalization. The period from 2022 to 2024 marks a significant expansion phase. Publications rose sharply from 76 studies in 2022 to 113 in 2023, peaking at 167 studies in 2024. This surge aligns with the emergence of graph neural networks, multimodal contrastive learning, hypergraph embeddings, and self-supervised learning frameworks, which enabled more sophisticated modeling of complex relationships among users, films, videos, audio, and textual metadata. Growing concerns over algorithmic fairness, explainability, user experience, and sustainable engagement in new media platforms further fueled scholarly interest. The strong publication count observed in 2025 (139 studies), despite the year being potentially incomplete, indicates that research momentum remains high. Current studies increasingly emphasize fine-grained multimodal representation learning, emotion- and attraction-aware recommendation, cross-domain and cross-platform modeling, and human-centered AI approaches. This trend suggests a shift from purely accuracy-driven systems toward more holistic, interpretable, and socially responsible recommendation frameworks.

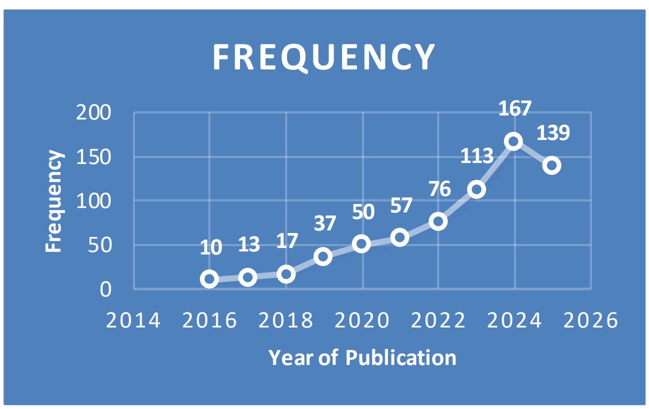

Fig. 2. Annual publication.

B. Evaluation of Journal Bibliometrics

The journal bibliometric analysis provides insights into the intellectual outlets. The selected sources meet the high citation impact criterion with a minimum of 50 citations, highlighting journals and proceedings that play a central role in shaping this research area, as in Table III. The findings reveal a strong dominance of computer science, artificial intelligence, multimedia, and information systems venues. Journals such as Artificial Intelligence Review, Journal of Big Data, ACM Computing Surveys, and IEEE Transactions on Neural Networks and Learning Systems exhibit high citation-to-document ratios, indicating that although they publish fewer papers, their contributions show substantial publication influence. This pattern is consistent with the review-oriented and theory-building focus of these outlets, which frequently publish highly cited surveys and conceptual studies. In contrast, conference proceedings and book series, particularly Lecture Notes in Computer Science (LNCS) and Lecture Notes in Networks and Systems, account for a large share of publications. This reflects the fast-evolving and technically driven nature of multimedia recommendation research, where early dissemination of deep learning models, graph-based techniques, and multimodal frameworks is commonly achieved through conferences. Although these venues show moderate citation density, they remain essential for methodological innovation and rapid knowledge diffusion. Application-oriented journals, including Multimedia Tools and Applications, Expert Systems with Applications, IEEE Access, and Electronics (Switzerland), display a balanced profile combining relatively high publication volumes with solid citation performance. These outlets serve as key platforms for applied deep learning solutions in video, film, music, and social media recommendations.

TABLE III. SOURCES CITATION

Source Name	Documents	Citations	Impact Factor
Journal of Big Data	2	425	6.4
Artificial Intelligence Review	3	373	13.9
ACM SIGMOD Conference Proceedings	1	235	NA
ACM Computing Surveys	1	220	23.8
Lecture Notes in Computer Science	32	220	NA
IEEE Transactions on Industrial Informatics	2	189	9.9
Multimedia Tools and Applications	8	167	NA
Expert Systems with Applications	5	157	7.5
IEEE Access	16	148	3.6
ACM CIKM Proceedings	6	145	NA
Electronics (Switzerland)	8	135	2.6
Symmetry	3	123	2.2
Scientific Programming	2	105	1.025
IEEE Transactions on Neural Networks and Learning Systems	1	87	8.9
Mathematics	2	86	2.3
International Journal of Information Management	1	78	27.0
Applied Sciences (Switzerland)	3	74	2.5
Lecture Notes in Networks and Systems	24	62	NA
Computers, Environment and Urban Systems	1	57	8.3
IJCAI International Joint Conference on Artificial Intelligence	2	55	NA

C. Country Analysis

The country collaboration network shows a hierarchical and organized international research environment with well-defined knowledge centers within the country, regionally integrated groups, or clusters, and gradually embracing the peripheral contributors, which are shown in Fig. 3. The visual topology shows that there is a definite hub-and-bridge structure, with the United States placed in an intermediary position between various regional research communities. The high-level of collaboration with China, India, the United Kingdom and some partners in the Asia-Pacific revealed that it has big part to play in the process of knowledge exchange and methodological diffusing across culture among deep learning-based multimedia recommendation studies. China and India are high-productivity ends of innovation as demonstrated by the large node size and multiple foreign connections. The fact that they are immensely connected to developed and emerging research systems implies sustained institutional investment in artificial intelligence, digital media analytics, and scale data infrastructures. The European countries, in contrast, have a networked regional ecosystem in the collaboration pattern, and the European nations (Germany, France, Spain, Italy, Austria, Norway, Switzerland, etc.) have their close-knit clusters. Regardless of its relatively moderate amount of publications, the concentration of intra-European connections speaks in favor of methodologically sophisticated and citation-influencing works with collaborative studies and cross-border initiatives to finance their activities.

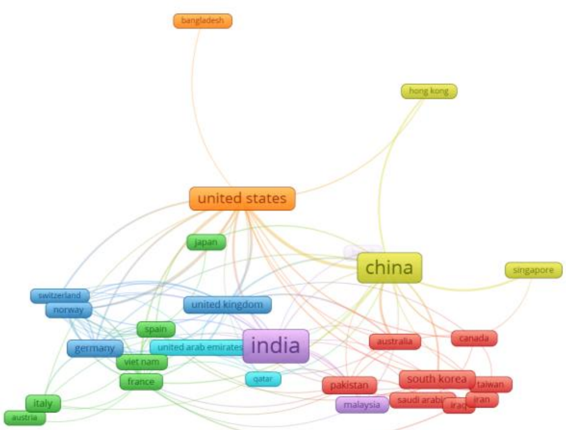

Fig. 3. Country analysis.

The Asia-Pacific region makes a manifestation of a bridging and diffusion position in the global network. South Korea, Singapore, Malaysia, Pakistan, Hong Kong, and Australia demonstrate the strategic positioning between the major knowledge centers, which indicates their increased involvement in the international research consortia and technology-based innovation ecosystems. Canada also has been helping in the integration of regions by consistently maintaining alliances with both its North American and Asian partners. In addition, there are new contributions of the Middle East and developing research systems like Saudi Arabia, Iran, Iraq, Qatar, and Bangladesh, which does indicate a progressive increase in the geographical coverage of the field. Their comparatively peripheral network positioning, however, means that the intensity of collaboration and the impact of citation is not evenly distributed. Generally, the visualized structure can be defined as a core-periphery model of knowledge diffusion, where core nations spearhead theoretical and technological development whereas peripheral regions are progressively transformed into converged capacity by neural network development. This trend highlights the significance of global collaborations in rapidly enhancing the global development of smart multimedia recommendation studies.

D. Co-occurrence Keyword Analysis

The co-occurrence network keyword indicates a hub-and-cluster intellectual structure indicative of the maturity and current diversification of deep learning-based multimedia recommendations research. Fig. 4 shows that recommender systems is the central node, highly linked to deep learning and machine learning as well as collaborative filtering, which validates the fact that current studies are still based on the performance-oriented algorithm optimization. This high centralization is a sign of methodological convergence, with deep representation learning becoming the mainstream paradigm to overcome the old methods of similarity-based recommendation. In addition to the main center, the network also features clear but connected themes clusters that are indicative of the conceptual development of the field. One of the key methodological clusters connects convolutional neural networks, graph neural networks, knowledge graphs, and personalized recommendation, which emphasizes learning representations in a relational and multimodal form. According to this trend, the intelligence of recommendations is more and more determined by the possibility to represent the complicated semantic interactions between heterogeneous media content, individual behavior, and context.

A second stream was focused around the social media, data mining, user profiling, and online systems; this change in focus towards more platforms signals the increasing platform-driven nature of recommendation research. The high-density proximity of these terms suggests that deep learning recommender innovations are being empirically tested on large-scale digital ecosystems especially streaming and social networking environments. Such structural connection proves the fact that technological development is strictly correlated with the growth of data-intensive media consumption space. Another thematic category is related to natural language processing, sentiment analysis, behavioral research, and user experience, which is indicative of a new direction towards cognitive- and affect-aware design of recommendation. The incorporation of semantic comprehension and emotional modeling is a possible indication that the latest research is now shifting the focus past accuracy measures to the levels of engagement, interpretability, and user-focused intelligence. Nevertheless, the relative peripheral stance of fairness and privacy words suggests that ethical and responsible AI are taken into account, being more and more intense, but are not yet deeply established in the popular recommendation structures. The co-occurrence structure shows a gradual evolution of algorithm-driven optimization approach into context-enriching, multimodal, and human-conscious paradigms of recommendation. Meanwhile, the discontinuity between the clusters of technical performance and the growing socio-cognitive comes out as a research gap, there are no single comprehensive paradigms that incorporate deep semantic modelling, scalable personalization and ethical system design simultaneously in multimedia recommendation contexts.

Fig. 4. Keywords occurrence.

E. Citation Analysis of the Top-Most Articles

The reviewed literature demonstrates a clear thematic and methodological evolution in multimedia recommendation research, moving from early multimodal feature fusion toward more structured and semantically grounded models, as shown in Table IV. Early influential works on multimodal graph learning established the feasibility of integrating visual, audio, textual, and interaction signals, but they largely treated modalities as parallel inputs [6], [21], [22]. Subsequent advances introduced contrastive and hypergraph learning to better disentangle modality-specific preferences [5]. However, these approaches still fall short in modeling fine-grained semantic relationships within multimedia content [6]. This direction reveals a persistent limitation in current graph-based multimodal recommenders rich content signals are incorporated, yet their semantic interdependencies remain weakly represented, motivating the growing interest in multimodal knowledge graphs [23].

Research on multimedia content understanding has progressed rapidly in feature extraction and spatiotemporal modeling, particularly through deep CNNs and large-scale distributed learning [24], [25]. While these studies significantly enhance retrieval accuracy and system efficiency, they remain largely decoupled from personalization objectives. Survey evidence further indicates that most systems rely on fragmented, media-specific pipelines, highlighting a structural gap between low-level content understanding and high-level recommendation intelligence, especially in film and video platforms [5], [15]. Across themes, personalization challenges, most notably cold-start and sparsity, persist despite the adoption of multimodal deep learning [8], [12], [13], [26]. Although content-aware models improve performance for new items, their reliance on feature concatenation limits interpretability and weakens their ability to explain user attraction [13]. Scalability-oriented solutions similarly prioritize efficiency over nuanced preference modeling, reinforcing the trade-off between accuracy and explanatory depth [27].

More recent studies foreground fairness, bias, and human-centered considerations, highlighting that recommender systems can amplify structural inequalities if left unchecked [28]. However, fairness-aware methods are rarely integrated with multimodal or graph-based architectures, particularly in video-centric domains [29]. This separation suggests that ethical considerations have evolved as a parallel stream rather than being embedded into core recommendation design. Emerging work on emotion, sentiment, and attraction modeling points to a shift toward experience-oriented recommendation [10], [24], [26].

TABLE IV. DOCUMENT CITATIONS

Ref	Keywords	Method & System	Research Gap	No. of Cite.
[6]	Computing, Recommender systems; Information systems, Personalization, Multimedia and multimodal retrieval	Multimodal Graph Convolution Network (MMGCN)	Limited multimodal knowledge integration in MMGCN	592
[5]	Recommender systems, Information systems, Multimodal and Multimedia retrieval, User models, Human-centered computing	Multimedia content–based recommendation framework	Limited unified frameworks across media types	220
[30]	Video advertising, in-video ads, Content based, optimization, object level	deep convolutional neural network	Need to conduct a large-scale user study on more videos in future work	174
[29]	Music recommendation, Algorithmic fairness, Popularity bias, Item popularity, Recommender systems, Reproducibility	recommender systems	we plan to adapt this GAP metric in order to make it more robust for various domains.	128
[31]	Social media Sentiment analysis Sentiment prediction Sentimental trajectory	Convolutional Neural Networks	Lack of real-time sentiment trajectory prediction	126
[7]	Multimodal Learning, Micro-Video Recommendation, Social Media Platforms, Self-Supervised Learning, Graph Contrastive Learning	Multi-Modal Graph Contrastive Learning recommender framework	Insufficient disentanglement of user modality preferences	123
[32]	User Experience Optimization, Recommendation Systems, Reinforcement Learning, Deep Q-Network, Online Advertising	RL-based	User experience ignored in RL advertising	105
[33]	Recommender systems, graph embedding, information filtering, hypergraph	Graph Machine Learning	Limited hypergraph-based models in music recommendation	87
[28]	deep learning; recommendation system; multimodal technique MSC: 68T07; matrix factorization	Deep Learning	Limited multimodal deep-learning solutions for cold-start	84

[3]	music recommendation; deep learning; contentbased filtering; collaborative filtering	deep learning	Efficiency drops when multiple variables increase	78
[27]	Collaborative filtering; recommendation engine; filtering; RMSE; Spark machine learning	ALS-based collaborative filtering recommender system	Limited hybrid personalization in large-scale systems	77
[1]	behavioral sciences, Collaborative filtering, Law, Neural networks, social	Neural fair collaborative filtering framework	Gender bias insufficiently addressed in recommenders	76
[34]	Video understanding, metric learning, triplet learning, recommendation, classification, collaborative filtering	deep network	Incorporation of modern neural architectures for extracting input features like LSTMs, modern metric learning techniques,	61
[35]	Social media, Big data fairness, Bias analysis, Disaster informatics	machine-learning	future studies can look into the causal effects between societal characteristics and social media attention in disaster-affected areas.	57
[36]	Personalization, Information systems, Collaborative filtering, Recommender systems.	Graph Neural Networks	Unified modeling of time, context, social noise	51
[37]	Recommender System; Factorization Machines; Deep Neural Networks, deep factorizations machine, Novelty, Diversity	Deep Neural Networks	Lack of advanced models in gaming	47
[23]	Graph Denoising, Graph Neural Network, Micro-video Recommendation	graph neural network	Noise-aware concept modeling underexplored in micro-videos	46
[38]	movie recommendation; deep learning; collaborative filtering	deep learning	Limited accuracy of traditional recommendation methods	43
[11]	habit formation; post-acceptance behavior; mobile short-video platform; ECT-IS theory	ECT-IS–based structural equation modeling framework	Limited focus on sustainable post-acceptance behavior	42
[39]	Feature compression, autoencoders, Multimedia information retrieval systems, recommender systems, deep learning, popularity prediction, music information retrieval	Deep Learning	Future work integrates CNNs and embeddings	38
[40]	Image Clustering, Metaheuristic Optimization, Content-Based Image Retrieval, Feature Fusion, Deep Neural Networks	Deep Neural Networks	Limited optimization-driven deep CBIR frameworks	33
[10]	Attraction modeling, Multilevel Attraction Model (MLAM), Content-based recommendation, User attractiveness interpretation, New media content selection	multilevel attraction model (MLAM)	Recommenders fail to capture attractive new-content features	30
[41]	big data, OSNs, machine learning, online social networks, multimedia, fake profile	machine learning	future work is to apply different neural network-based feature analysis for identifying malicious content in different profiles.	29
[42]	Facebook; Movie recommendation; deep learning; deep belief network; monarch butterfly optimization; movie lens	Deep Belief Network	Limited exploration of hybrid optimization–deep learning models	29
[43]	Encrypted traffic, YouTube, HTTPS, Quality of Experience (QoE), Video streaming, Bitrate estimation	machine learning based bitrate estimation (MBE)	QoE evaluation hindered by unavailable bitrate data	29
[44]	Ant Colony Optimization, Machine Learning, Recommendation Systems, Random Forest, Web Usage Mining	Random Forest	Limited personalization and real-time adaptability	27
[45]	triplet loss; video retrieval; supervised hashing; 3D CNN	Deep supervised video hashing retrieval framework	Limited spatiotemporal modeling in video retrieval	27
[24]	BiLSTM, Emotion classification, EEG, Chinese music	Deep Learning	Limited EEG-driven emotion models for Chinese music	27
[22]	big data; video retrieval; spark; content-based video big data; deep learning; video content extraction	Deep Learning	Inefficient large-scale multimodal video processing	26
[46]	Natural language processing; emotion analysis; graph neural networks; sentiment analysis; recommender system; BERT	Graph Neural Networks	Sentiment–emotion fusion underutilized in movie recommendation	26
[47]	Cold start problem, Off-topic content, Cross-platform information, Matrix Factorization (MF), Collaborative Filtering (CF)	MF based algorithms	Off-topic user content is ignored	25
[48]	Sentiment analysis, Movie recommendation, Multivariate data integration, Deep learning (RNN/LSTM), Big data analytics (Hadoop)	recurrent neural network	Traditional recommendations ignore multivariate user emotions	25
[26]	streaming services recommendation; deep learning; sentiment analysis; genre similarity; natural language processing	Deep learning	Limited integration of sentiment and content	24
[49]	Recommendation System, Book, Machine Learning, Movie, Clustering	NLP-based cross-content recommendation system	Lack of cross-domain recommendation frameworks	23
[25]	Convolutional neural network, Machine learning, Recommender system, Interpretable AI, Multimedia, User-generated content	Convolutional Neural Networks	Lack of explainable multimedia video tag recommenders	23
[50]	e-Learning; data mining; personalized recommendation; collaborative filtering algorithm	Hybrid recommendation system for video learning	Cold-start learners lack personalized recommendations	22
[51]	View propagation, Video popularity, Recommendation system, Keyword suggestion	Recommendation System	Limited understanding of recommendation-triggered view growth.	20

F. Streams of Topological Research and Thematic Evolution

Besides bibliometric performance measures, the literature review demonstrates that the research on deep learning-based multimedia recommendation systems is clearly organized intellectually. The field has four streams. Stream one is focused on models of neural recommendation that are accuracy-oriented and works which focus on performance as deep neural network, graph learning, and hybrid collaborative-content architecture. The initial research primarily focused on enhancing the level of prediction and extended to a big scale, which is an algorithm-based bias in adviser composing studies. The second stream is a transition towards multimodal learning of semantic representation. The distribution of video streaming and social media platforms further indicates adoption of visual, textual, acoustic, and behavioral signs to better depict the content semantics by study. This evolution is an indicator of a broader paradigm shift, where interaction-based filtering is no longer relevant; content-sensitive intelligent recommendation is. The third stream, which is emerging, is user cognition, emotion and experience recommendation. Recent studies indicate that sentiment-aware personalization, attraction modeling and human AI design is under growing interest. This tendency points to the fact that the shift in RS in favor of sustainability in engagement and psychological relevance is becoming more pronounced, instead of utility maximization. The fourth stream is related to ethical, fair, and explainable recommendation frames. Issues of popularity bias, transparency, algorithmic accountability, and so forth, are increasingly being discussed, particularly within and adjacent to large-scale digital media ecosystems. However, it has been found in the review that the fairness mechanisms are loosely related to the multimodal deep learning models, thus there is a significant research gap. The thematic development is a progressive movement towards system-based optimization and socially deliberated, tactically-constrained, and cognitively-directed recommendation intelligence. This shift is an extension of AI into digital media economics and human behavior analytics.

V. Conclusion

This study provides a thematic literature review and bibliometric mapping of the research on deep learning-based film and multimedia recommendation systems in new media settings. The results show that the research landscape is growing very fast and becoming more and more globalized, specifically it begins to grow after 2020 and is supported by the development of multimodal learning, graph-based models, and extensive digital media platforms. Although such strong research centers as China, India and the United States influence the methodological innovations and the intensity of collaboration, European research makes a high citation influence and conceptual refining contribution. In general, the field is experiencing a paradigm shift of the accuracy-based recommendation to context aware, multimodal, and human-centered intelligent systems.

The discussion also indicates that although there have been massive developments in feature extraction, representation learning and scalability of the system, there are still outstanding issues. Current recommender models tend to deploy superficial multimodal combination and provide scant value of interpretability, especially when there is cold-start and sparse-feedback. The new research directions, which deal with fairness, bias reduction, experience-base personalization, and user attraction modelling, indicate a slow shift to socially responsible and experience-centered recommendation design. Nevertheless, these dimensions remain poorly incorporated on mainstream deep learning architectures. The research consequently recommends coherent frameworks that convergingly address semantic multimodal understanding, individual user cognition, as well as ethical system intelligence in the future multimedia recommendation studies.

A. Contribution of the Study

The study is new in the literature, as it presents a systematic bibliometric review offering a concise picture of the intellectual situation, prevailing research trends, and collaborative patterns in multimedia recommendation powered by deep learning across the world. The synthesis of fragmented technical steps into corresponding thematic streams makes the study move forward in the knowledge of the field development, and the necessary research gaps are represented by explainable personalization, multimodal semantic integration research and fairness-conscious design of recommendations. The results provide theoretical understanding and real guidance to scholars and mobile educational content creators that aim at designing the next generation intelligent recommender systems in vibrant new media ecologies.

B. Limitations and Future Research

There are some drawbacks that may be noted. The review is based exclusively on the publications in the Scopus databases and English-language sources over the period of 2016-2025, potentially not including any works in other databases, prior background literature, or local research activities. Secondly, bibliometric methods mostly focus on trends in structure and not specifically on individual models of methodological performance. The future researches can build upon this study by adding multi-database retrieval plan, mixed quantitative-qualitative synthesis plan and longitudinal analysis of the consequences of any recommendation in order to gain a more comprehensive view of intelligent multimedia recommendation systems.

VI. Future Research Agenda

The synthesis of bibliometric and thematic evidence suggests that future research on deep learning film and multimedia recommendation systems should move beyond incremental algorithmic improvements toward integrative, human-centered frameworks. While multimodal and graph-based models dominate current studies, their limited semantic depth highlights the need for richer abstraction through multimodal knowledge graphs capturing objects, scenes, emotions, and narratives. Personalization under cold-start and sparse-feedback conditions remains challenging, calling for causally grounded, attraction-aware models that enhance interpretability. Fairness, bias, and ethical considerations should be embedded within core architectures. Advances in emotion-aware modeling and standardized evaluation protocols are essential to support semantically rich, explainable, and socially responsible recommender systems, as shown in Table V.

TABLE V. FUTURE RESEARCH AGENDA

Research Theme	Suggested Future Research Directions
Semantic understanding of multimedia content.	Develop models that automatically extract and integrate object, scene, narrative, and stylistic features using multimodal deep learning and knowledge graphs to better capture content attractiveness.
Personalization under sparse or missing feedback.	Design attraction-aware and causal recommendation models that infer latent user preferences without relying heavily on explicit user ratings.
Multimodal representation learning.	Propose unified end-to-end architectures that jointly learn from text, audio, visual, and contextual signals to improve recommendation robustness.
Emotion- and experience-aware recommendation.	Incorporate affective computing and emotion recognition techniques to model users' experiential responses to films and multimedia content.
Explainable recommendation systems.	Integrate interpretable deep learning mechanisms (e.g., attention visualization, feature attribution) to enhance transparency and user trust.
Fairness, bias, and ethical AI.	Investigate bias-mitigation strategies and fairness-aware learning frameworks to ensure equitable and responsible recommendation outcomes.
Human-centered recommendation design.	Explore user-centric evaluation metrics that emphasize satisfaction, diversity, and long-term engagement rather than short-term accuracy alone.
Evaluation protocols and benchmarking.	Establish standardized datasets, cross-domain benchmarks, and longitudinal evaluation frameworks to improve result comparability and reproducibility.

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