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A SYSTEMATIC REVIEW OF MOVIE RECOMMENDER SYSTEMS

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ABSTRACT

Recommender systems are vital to everyone's information selection. Managing massive amounts of data is common with recommendation system technology. Annual film releases are rising, and currently films are released within months. With movie releases, apps like Netflix, Viu, Amazon Prime Video, Disney+, etc. have emerged. Thus, Movie Recommender Systems (MRS) are essential to simplify and improve user experience. This research gives a systematic literature review (SLR) of MRS's current condition. Our comprehensive review addresses recommendation algorithms, data processing, and evaluation approaches. In SLR MRS, content-based filtering, collaborative filtering, knowledge-based recommender systems, and hybrid approaches are employed. To achieve this, 66 high-quality studies were selected from 27,187 2019-2023 studies using strict quality criteria. The study found that most MRSs use content-based filtering and machine learning to deliver non-personalized movie suggestions in various domains. The review helps researchers choose MRS development strategies. This study can assist MRS development catch up to other recommendation systems by improving efficiency. The MRS investigation found accuracy, sparsity, scalability, cold start, and operating time issues. Future study will examine how temporal and demographic data affect movie recommendation system relevancy and customization.

I. INTRODUCTION

With the current abundance of information, accessing essential information quickly is becoming more challenging [1]. In order to address this issue, Recommendation Systems (RS) have been developed and implemented [2]. RS, short for Recommender System, is a software solution that uses data filtering techniques to provide users with personalized recommendations for the most suitable items and services [3]. Recommendation systems are gaining popularity and are utilized in several domains, including music, movies, news, comedy, health, and article recommendations.

Consumers are presented with many options as the Netflix movie supplier service gives a diverse range of things tailored to their individual tastes [4]. Optimizing the alignment between customers and the most suitable items is crucial for enhancing customer happiness and fostering loyalty [5]. As a result, recommendation systems (RS) are gaining popularity on e-commerce platforms due to their ability to analyze user interest patterns and provide personalized suggestions based on user preferences [6]. Companies at the forefront of e-commerce, such as Netflix, Amazon, Flipkart, and YouTube, have effectively incorporated RS (Recommendation Systems) into their online platforms to improve the customer experience [7]. Content-based filtering (CB) and collaborative filtering (CF) are two elements of the recommendation system (RS) approach. Nevertheless, CB techniques necessitate the involvement of multiple experts to gather knowledge that is not accessible through external sources [8]. Conversely, collaborative filtering approaches depend on users' previous actions without a distinct profile. CF uncovers novel connections by analyzing user interactions and interdependencies across items [9]. The primary benefit of the CF strategy is its domain independence, making it more precise than the CB approach [10].

System recommender tasks can be broadly classified into two basic categories: item recommendation and ranking prediction [11]. Item recommendation predicts the collection of products that users are likely to utilize [12]. Rating prediction is a method used to estimate ratings for products that users have not provided, typically employed on movie-sharing platforms [13]. Collaborative filtering (CF) is widely recognized as a prominent method for implementing recommendation systems [14]. The underlying principle is that consumers with comparable tastes have a tendency to select the same products. The often-employed CF model is matrix factorization (MF) [15]. In order to express the ranking matrix and complete the missing values in the matrix [16], Matrix Factorization (MF) employs the multiplication of two feature matrices with low ranks [17]. Nevertheless, most collaborative filtering (CF) techniques suffer from a shared limitation: the precision of the anticipated outcomes may diminish when ranking data is scarce [18]. Recommendation systems [19] manage three entities: users, things, and explicit item ratings.

Movie Recommendation Systems are autonomous machine learning algorithms that utilize big movie libraries like Netflix and Amazon to filter movies according to customer preferences [20]. The primary objective of this study piece is to enhance the user and movie environment factors by adjusting the number of row and column clusters in co-clustering [21].

Recommendation systems are highly effective solutions for addressing the challenges of the modern digital environment, and movie recommendation systems, in particular, have reached a high level of sophistication [22]. Regression-based methods are primarily employed to forecast rating values as preference scores for user-movie pairs. Movies can be presented in numerous modalities, including text, video, and audio. To assess the efficiency of multimodal models, researchers have employed different combinations of display modalities. Consequently, numerous experiments have been conducted to create real-time systems specifically for this objective [23].

Several recommendation systems employ hybrid filtering techniques that integrate characteristics from both content-based filtering (CBF) and collaborative filtering (CF) methodologies [24]. Collaborative filtering (CF) addresses certain drawbacks of content-based filtering (CBF) by generating suggestions based on the comparison of user-item similarities [25]. The system leverages information about past user preferences and the preferences of comparable users to provide recommendations.

A knowledge graph representing human emotions in movies can enhance the movie recommendation process by considering the user's emotional state and decision-making influenced by this element [13]. Emotions extracted from prior movie reviews are utilized in a knowledge graph [26].

Contemporary collaborative recommendation models prioritize user preferences in the context of multimodal information while disregarding user aversions. Nevertheless, integrating user dislikes into user modeling is crucial for a comprehensive understanding of user profiles. Therefore, while constructing collaborative recommendation models, it is essential to incorporate user dislikes [27].

The recommender system comprises a content-based system, a collaborative filtering system employing the SVD algorithm [28], and a fuzzy expert system [29]. The recommender algorithm utilizes the user's preferred and less preferred genres to generate a conclusive compilation of suggested movies. The fuzzy expert system evaluates the significance of movies by considering multiple characteristics [30], including the average rating, number of ratings, and degree of similarity [31].

SLR and a detailed study of all the latest MRS domains contribute to this paper. Several crucial elements must be considered during system development to achieve this. This review covers movie recommendation methods, data and preprocessing, assessment and metrics, and pros and cons. The availability of data sets and codebases also affects research replication. To gather data on these components, 66 high-quality research from 27187 were selected using strict quality standards. Table 1 shows 66 MRS use in this work. These five research questions summarized MRS now.

This paper follows this structure. Section 2 describes movie recommender system research materials and methodology. Section 3 presents the results, explains the movie recommender system, and suggests future research. Section 4 outlines this study's result.

Table 1: Research Question.

No	Research Question	
1	RQ1	What methods do movie recommendation systems use?
2	RQ2	What data and preprocessing methods do Movie Recommendation Systems use?
3	RQ3	Movie recommendation systems: how are they assessed?
4	RQ4	How current is movie recommendation system research?
5	RQ5	What are the pros and cons of movie recommendation systems?

Source: Authors, (2024).

II. MATERIALS AND METHODS

II.1 MOVIE RECOMMENDER SYSTEM (MRS)

The exponential growth of the film industry and its establishment in multiple nations has elevated movie-watching to a prominent leisure pursuit for the general populace [32]. Nevertheless, the ongoing advancement of films, coupled with the swift evolution of technology, is progressively shifting the paradigm of movie consumption. It is transitioning from the conventional practice of seeing movies in theaters to the convenience of online streaming platforms, enabling consumers to enjoy films from the comfort of their own homes. Online media streaming platforms have enhanced and implemented numerous features by integrating new technologies and prioritizing the trends of the substantial data era [33]. These functionalities enable users to evaluate films and exchange their experiences with peers. Furthermore, this platform utilizes user score data to establish a recommendation engine capable of forecasting the choices made by each user [34]. The assessment of MRS recommendations involves using objective or subjective ground truth values. This is done by gathering data and comparing it with the item database. The diagram in Figure 1 below illustrates the overall framework and methodology for conducting a comprehensive investigation of the MRS literature in order to address a specific research question (RQ).

Is an e-learning platform designed to provide educators, students, and administrators with one integrated system [23]. E-learning is the principle of direct learning, and in its application, it promotes independent learning, namely web-based distance learning that can be accessed via the Internet network [24]. Moodle provides digital classrooms to access material or anything related to learning that is freely accessible to anyone, anytime, anywhere [25]. The advantage of using Moodle is that it is open source, so someone with programming skills can adjust and develop existing features according to their needs and desires [26].

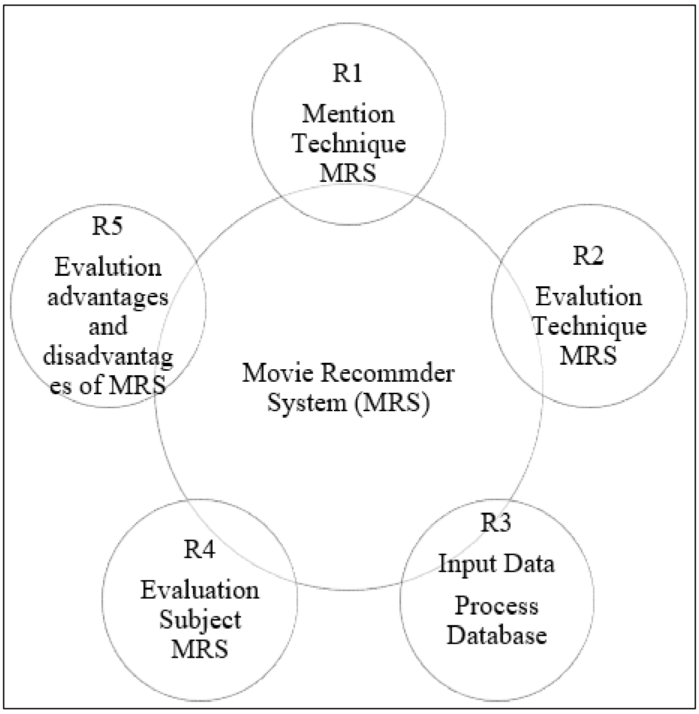

Figure 1: The general architecture used in MRS and RQ relates to the system's relevant aspects.
Source: Authors, (2024).

II.2 RECOMMENDATION METHODS

The MRS recommendation approach elucidates the rationales and characteristics employed in generating movie selection suggestions. The classification of these methods is based on the components utilized for making suggestions. The designs are categorized into four distinct groups: content-based filtering, collaborative filtering, knowledge-based recommender systems, and hybrid approaches recommender systems [35].

1) Content-Based Filtering (CBF)

Content-based filtering (CBF) systems primarily depend on two types of data: a) the description and structure of data attributes and b) user profiles derived from their feedback on different items [36]. An advantage of this system is its capability to address cold start issues related to new users [37]. The system operates at a somewhat basic level since it generates recommendations by considering users' ratings of goods [38]. The primary determinant of the system's quality and accuracy is its capacity to extract and analyze the content of things in order to measure their resemblance to other items [39].

2) Collaborative Filtering

Collaborative filtering (CF) is one of the most suggested and successful algorithms [40]. CF approaches can be classified into model-based and memory-based [41]. A learning approach based on a ranking pattern model acquires a model and generates predictions [42]. Memory-based collaborative filtering (CF) algorithms determine the similarity between users or products [43] by analyzing their current ranks. This allows them to identify neighbors who share similar tastes [44]. User-based or item similarity is the foundation for creating suitable surroundings, anticipating evaluations of unfamiliar items, and producing suggestions for specific users [33].

3) Knowledge-Based Recommender Systems

This system employs user profiles to ascertain the correlation between user preferences and various forms of content, such as products, information, services, and others [45]. Unlike content-based or collaborative recommendation systems, these systems utilize information about movies and user interests to offer suitable recommendations [46]. It provides personalized recommendations by directly correlating movie attributes with user preferences. The primary constraints include the challenge of accurately recording user preferences and the reliance on data quality [47].

4) Hybrid Methods Recommender Systems

As implied by its name, this strategy can amalgamate multiple methodologies to leverage their respective capabilities [24]. Hybrid methods enable the combination of multiple approaches to address the limitations of each other, resulting in enhanced recommendation accuracy and performance. Nevertheless, the enhancement of performance relies on how the approaches are integrated [48], as these methods can offer thorough and precise recommendations to users [49].

The systematic literature review (SLR) approach categorizes published research and its findings in an organized manner by thoroughly examining the primary material, methodology, and results. This process aims to minimize bias and draw conclusions based on statistical meta-analysis, which is supported by empirical data [50]. We employed a methodical methodology to gather, categorize, and scrutinize the most up-to-date data on MRS [51], given the limited number of thorough studies that have endeavored to assess MRS research [52]. Therefore, we relied on recognized methodologies for conducting Systematic Literature Reviews (SLR) in this investigation.

The SLR review process has multiple steps: 1. Determining research goals and questions; 2. Choose a database and gather data for the initial investigation; 3, define extraction and extraction points; 4, analyze, synthesize, and report results.

The purpose of this SLR is to investigate and evaluate the present condition of MRS [37]. To accomplish this objective, we employed the review process outlined in Table 2. This study examines five primary facets of Magnetic Resonance Spectroscopy (MRS). The initial part examines the methodologies employed in MRS, encompassing diverse potential amalgamations of recommendation systems and algorithms while leveraging individual traits. The second component of MRS pertains to the data employed for generating movie suggestions. The data encompasses several attributes such as source, format, size, characteristics, pre-processing, and representation. The third aspect of this research pertains to MRS evaluation, encompassing the assessment techniques and metrics that are employed and computed.

The fourth aspect pertains to the study conducted on movie recommendation systems. Subsequently, it is employed for conducting essential experiments aimed at reproducing the experiments and achieving desired learning outcomes; the feasibility of this component relies on the presence of relevant data. Lastly, the scope encompasses the advantages and disadvantages of MRS. In order to guarantee that this systematic literature review (SLR) includes only recent articles, we establish restrictions based on publication dates. Hence, the data utilized for conducting this research comprised literature studies on movie recommendation systems that were published between 2019 and 2023.

III. RESULTS AND DISCUSSIONS

In order to accomplish the objectives of this Systematic Literature Review (SLR), we employed the summary review standards presented in Table 2 to investigate and evaluate the present condition of the MRS. This study examines five primary facets of Magnetic Resonance Spectroscopy (MRS). The initial part examines the methodologies employed in MRS, encompassing many potential amalgamations of recommendation systems and algorithms while also leveraging human qualities. Another crucial element of MRS is the data utilized for movie suggestions. The data includes information on its source, format, size, features, pre-processing, and representation. The third aspect of this study pertains to the assessment of MRS, encompassing both evaluation techniques and the quantifiable metrics obtained through measurement and calculation. The fourth component pertains to the regression of research in the domain of movie suggestions. The replication of the experiment and the achievement of learning results rely on the availability of the code used in the experiment. The benefits and drawbacks of MRS are the ultimate element of the scope. In order to ensure that recent studies are included in this systematic literature review (SLR), we have established certain criteria for the publication date. Hence, we exclusively examined studies that were published between 2019 and 2023.

Table 2: Summary Review Guidelines (SRG).

No	Research Question	
1	Research Question	RQ1 What methods do movie recommendation systems use?
		RQ2 What Movie Recommendation Systems employ what data and pre-processing methods?
		RQ3 How do you evaluate movie recommendation systems?
2	Search string	RQ4 How recent is movie recommendation system research?
		RQ5 What are the pros and cons of movie recommendation systems?
		Existing movie suggestions
		Movie recommendation system
		Movie collaboration filtering
3	Search strategy	Database search: ScienceDirect, LinkSpringer, IEEExplore, Tandfonline
4	Paper inclusion standards	SRG1 Full text.
		SRG2 Paper is English.
		SRG3 Paper describes a movie recommendation system.

Source: Authors, (2024).

The research question serves as the primary driver for the comprehensive systematic review, guiding the search for publications that pertain to the fundamental elements of each systematic review. This is because the entire research methodology is founded upon this inquiry. Determining research questions follows establishing the research's goal and scope, a suggested starting step to mitigate bias throughout the research process. To ensure the dependability of this approach, the research question must be stated in a manner that encompasses the entirety of the study issue.

We created precise and detailed research questions by following criteria and drawing from prior SLRs. Interventions are different suggestion methods in MRS investigations. The advantages and downsides of MRS emerge from this approach. These findings enable this research to uncover significant MRS information. Table 1 shows key research question topics. Figure 1 shows the research question and the MRS architecture relationship. We searched all four journal databases using search strings. Vary database standards make search strings vary. Searches change the paper's title, abstract, and keywords. The research objectives are usually brief to identify just relevant studies to the search phrase. Data from 27,187 papers from various databases in December 2023 is displayed in Table 3.

Table 3: The Total Number of Literature That Was Obtained from The Various Databases.

No	Literature Database	Result
1	ScienceDirect	6825
2	LinkSpringer	6389
3	IEEExplore	68
4	Tandfonline	13.905
	Total	**27187**

Source: Authors, (2024).

We filter articles from four journal databases using MRS. Direct study selection yielded 66 high-quality MRS-compatible primary publications. Table 4 summarizes each source's main research.

Table 4: The Latest Collection of Primary Research Conducted.

No	Literature Database	Result	Percentage of Studies
1	ScienceDirect	22	33
2	LinkSpringer	27	41
3	IEEExplore	3	5
4	Tandfonline	24	21
	Total	**66**	**100**

Source: Authors, (2024).

Metadata collection follows primary study collection and evaluation. After determining the extraction point, Table 5 shows the extraction form based on Table 2's research questions.

Table 5: Data Extraction.

No	Research Field	Input type	Research Question
1	Filename	Free text	-
2	Paper title	Free text	-
3	Authors	Free text	-
4	Publication year	Numeric year	-
5	Publication venue	Category Search	-
6	Paper type	Category Search	-
7	Aim	Free text	-
8	Recommendation method	Category Search	RQ1
9	Recommendation algorithm	Category Search	RQ1
10	Dataset used	Category Search	RQ2
11	Evaluation method	Category Search	RQ3
12	Repository	Free text	RQ4
13	Advantages	Free text	RQ5
14	Limitations research	Free text	RQ5

Source: Authors, (2024).

After collecting the main study data, analysis began. Data includes category frequencies and percentages. A qualitative study is needed to determine MRS pros and cons. Summaries and categories of pros and cons. Each category is reported beyond its primary study.

As shown in Figure 2, there is a steady growth in the number of paper publications on movie recommendation systems (MRS) from 2019 to 2023. However, it is more probable that this rise is attributable to the date of collecting of these sea level records.

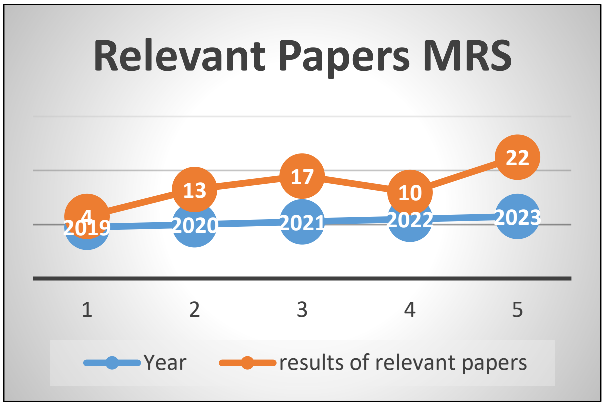

Figure 2: Relevant MRS Papers from 2019 to 2023.
Source: Authors, (2024).

Many movie recommendation algorithms have major issues. The sparsity problem [53] occurs when large data sets have numerous empty items. This makes pattern recognition and recommendation accuracy harder. Scalability is the ability to handle more users and items without sacrificing performance. A cold start occurs when the system lacks historical data to provide relevant offers for new customers or products. Complex systems take longer to create recommendations, which might hurt user experience. MRS experiments are used to test recommendation system algorithms to calculate data accuracy, as shown in Figure 3.

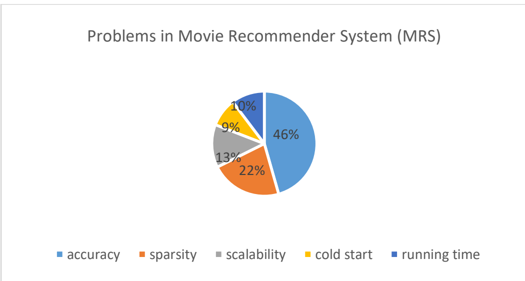

Figure 3: Problems in MRS.
Source: Authors, (2024).

Commonly utilized datasets in film recommendation research include MovieLens, IMDb, Netflix, and TMDB Movie Dataset [54]. The MovieLens dataset, offered by GroupLens Research, encompasses a range of movie ratings, user data, and movie metadata that is accessible in different dimensions [55]. The IMDb dataset provides comprehensive data on movies, including their title, genre, rating, and description. This dataset is well-suited for content analysis and developing content-based recommendation systems [56]. The Netflix Dataset contains more than 100 million reviews provided by Netflix users [57] and plays a crucial role in the development of recommendation systems. Concurrently, the TMDB film dataset offers comprehensive information regarding movies, including a summary, genre, and popularity [36]. This dataset is valuable for conducting research on audience preferences and analyzing the sentiment of films. The MRS literature study included a total of 66 works that focused on film recommendations using public datasets in the field of data, as shown in Figure 4.

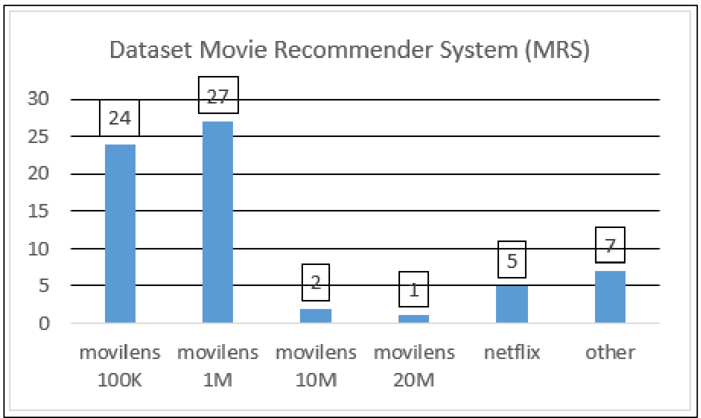

Figure 4: Dataset MRS.
Source: Authors, (2024).

Literature studies on MRS show that MRS can recommend movie-viewing items to users using various methods, algorithms, data sets, pre-processing techniques, and data representation [58]. MRS can also handle information overload by filtering out irrelevant items. This is useful considering the increasing number of film service provider sites [59]. Expanding the e-commerce sector of film service providers is expected to make these systems increasingly important [60]. In addition, MRS has drawbacks, and several limiting factors have been found for various applications. The review shows that content-based filtering and machine learning techniques are used to create most MRSs, which can result in non-personalized recommendations [61]. Non-personalized recommendations are recommendations given without considering a person's characteristics. These recommendations are based on general data or trends rather than personal data, so they are more available to everyone and do not raise privacy issues. This shows that MRS personalization can still be improved. Because movie selection is so diverse and has no common technique, comparing and assessing systems is difficult.

MRS research has become active in the previous five years, as shown by the number of publications. Most research have not examined movie recommendation systems' demographic and timing effects [62]. Demographic and time-based movie recommendation systems will be studied for relevance and customisation [63].

In future research, MRS should use this data to counteract dynamic preference changes with time data, such as watching trends or seasonal popularity. Using demographic data like age, gender, and region, the algorithm can determine group preferences and make more targeted suggestions. Analyzing who and when consumers watch can improve user happiness and suggestion accuracy.

IV. CONCLUSIONS

Movie Recommendation Systems (MRS) use algorithms, datasets, preprocessing methods, and data representations to recommend movies. Multiple evaluation methodologies and indicators are employed to assess recommendation and system quality. This system reduces data overload by filtering unimportant objects. This system becomes increasingly important as more sites provide movie viewing. This system is beneficial, but various limitations can limit its application. This systematic literature evaluation covers several film recommendation topics. The quality of MRS is fully shown here.

Content-based filtering has become the most common movie recommendation approach during the previous five years. As previously said, this greatly diminishes the level of personalization in MRS. Machine learning algorithms are commonly employed to obtain recommendations. The predominant pairing of movie recommendations involves non-personalized content-based machine learning, followed by near-personalized graph-based machine learning. This appears to be the most advanced method. Most of the UCI public film dataset systems are utilized as data sources in MRS.

V. AUTHOR'S CONTRIBUTION

Conceptualization: Yuri Ariyanto and Triyanna Widiyaningtyas.
Methodology: Yuri Ariyanto and Triyanna Widiyaningtyas.
Investigation: Yuri Ariyanto and Triyanna Widiyaningtyas.
Discussion of results: Yuri Ariyanto and Triyanna Widiyaningtyas.
Writing – Original Draft: Yuri Ariyanto and Triyanna Widiyaningtyas.
Writing – Review and Editing: Yuri Ariyanto and Triyanna Widiyaningtyas.
Resources: Yuri Ariyanto and Triyanna Widiyaningtyas.
Supervision: Yuri Ariyanto and Triyanna Widiyaningtyas.
Approval of the final text: Yuri Ariyanto and Triyanna Widiyaningtyas.

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