ADVANCEMENTS IN NEWS RECOMMENDATION SYSTEMS: THE ROLE AND IMPACT OF ARTIFICIAL INTELLIGENCE AND LARGE LANGUAGE MODELS

CEYHUN KAZANÇ, NAZIM TAŞKIN
Boğaziçi University, Department of Management Information Systems, Istanbul, Turkiye
ceyhun.kazanc@std.bogazici.edu.tr, nazim.taskin@bogazici.edu.tr

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The rapid evolution of artificial intelligence (AI) and large language models (LLMs) significantly advanced the news recommendation systems (NRS). However, comprehensive analyses evaluating recent advancements and practical implications of integrating AI and LLMs into NRS remain scarce in existing literature. This study systematically examines AI and LLMs' effects and usage methods on NRS and analyzes 42 studies using the Prisma methodology It emphasizes the features of collaborative filtering (CF), content-based filtering (CB), hybrid systems, AI based systems including LLM-based models like BERT. While these technologies offer advanced semantic analysis and real-time adaptability opportunities, they are still partially affected by traditional challenges, such as cold-start and data sparseness, though less so than traditional methods. This study emphasizes innovations in AI-driven NRS, focusing on hybrid approaches, session-based and multi-interest models and efficient use of LLM. The findings provide actionable insights for researchers and practitioners seeking to optimize NRSs in an increasingly dynamic digital landscape.

Keywords:
news recommendation systems,
artificial intelligence (AI),
large language models (LLMS),
personalization,
hybrid systems

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1 Introduction

In an age of overloading information, personalized news recommendation systems (NRSs) play a critical role in providing content compatible with user preferences and behaviors. NRSs are algorithms that provide personalized news content based on users' interests and reading habits. These systems work using a variety of techniques, including content-based filtering CB recommending items based on the features of the items themselves and a user's past preferences (Symeonidis, Chaltsev, et al., 2021), collaborative filtering CF, recommending items based on the preferences of similar users or the similarity between items (Han, 2024), and deep learning (Karimi et al., 2018). In recent years, deep learning-based models have made great progress in NRS (Mahesh et al., 2022). Additionally, integrating editorial feedback into recommendation systems is an important step toward improving the accuracy and quality of news (Mahmood et al., 2024).

The rapid evolution of AI technologies, especially LLMs, provides features that can provide significant breakthroughs in this field by making systems better understand user behavior, news content semantics, and context (Amir et al., 2023). LLMs are AI models trained on large amounts of text data to perform natural language processing (NLP) tasks. These models excel at tasks, such as text generation, summarization, translation, and question-answering (Pahune & Chandrasekharan, 2023). Developments in LLMs and NLPs have significantly enhanced the accuracy and efficiency of digital news platforms in providing personalized news suggestions.

In spite of this progress, new problems can arise with new technologies while some challenge in the field continues. Previous approaches, such as CF and CB often struggled with problems, such as cold-start problem, which refers toa difficulty that occurs in recommendation systems when there is not enough data about new users or new products, preventing the system from making accurate predictions and reducing the quality of recommendations (Moghaddam & Elahi, 2019). Another issue is the risk of filter bubbles where personalized algorithms showing content aligned with users' interests. This limits exposure to different perspectives and reduces information diversity (Flaxman et al., 2016). Although hybrid systems offer improvements regarding some of these problems, the dynamic structure of user interest and the complexity of news data requires more sophisticated methods. The latest developments in LLMs, such as Bert and GPT models offer new opportunities by improving their semantic understanding and contextual suggestion skills (Zhang et al., 2021). However, calculation costs and sustainability concerns show that more research is needed.

The motivation for this study stems from the gap in understanding the full scope of AI on NRS, especially the role of LLMs. While the existing investigations provide valuable insights (Raza & Ding, 2022) on previous methods, such as CB, CF, hybrid approaches, and deep learning-based models, the effects of the latest LLM and Generative AI progress are omitted (Amir et al., 2023) with the rapid development of these technologies. While some previous studies (Hou et al., 2023) have addressed the impact of LLMs and Generative AI, a study conducted after the development of these technologies will better explain and compare current methods Although previous studies (Zhang et al., 2021) examined the impact of LLMs and generative AI, further research conducted following recent advancements in these technologies is needed to better understand and comparatively evaluate current methods. This study addresses this gap by systematically examining the integration of AI and LLMs into NRS, focusing on system performance, user personalization and contribution to contextual understanding.

To guide this exploration, the study addresses two central research questions:

1. What are the approaches used in news recommendation systems (NRS) in the literature after the development of large language models (LLMs), and what are their advantages, limitations, and the role of artificial intelligence in these approaches?

2. How have LLMs influenced the development and performance of NRS?

By systematically analyzing the 42 studies published after 2021, this research aims to provide a comprehensive understanding of progress, difficulties and future aspects in the field and to provide valuable insights for researchers and practitioners.

2 Methodology

This study uses the PRISMA guidelines to systematically review the existing literature on the integration of NRSs with AI and LLM (Moher et al., 2009). The PRISMA guidelines provide rigorous and transparent framework for identifying, screening, and selecting studies relevant to the research questions, ensuring the reliability and reproducibility of the review process.

To collect relevant studies, we conducted a comprehensive search of two academic databases, Web of Science and Scopus, due to their worldwide importance (Mongeon & Paul-Hus, 2016). In the search, we used the following query strings to capture a wide range of research in the field:

"news recommendation" and "artificial intelligence", "news personalization" and "artificial intelligence", "news recommendation" and "large language models", "news personalization" and "large language models".

This search yielded a total of 129 studies. Of these, 23 were eliminated due to duplicate records, leaving 106 studies for further evaluation. We excluded 42 studies conducted before 2021, since the release of ChatGPT-3.5 that year has irrevocably changed the landscape of AI-based recommendation systems (Myers et al., 2024). The rationale for this decision was to be able to investigate the impact of LLMs and AI on NRS methods with these revolutionary developments in AI technology. We then screened each study based on the availability of title, abstract, and full text to determine its relevance to the research questions. Studies that were unrelated to the role of AI or LLMs in NRS or did not have full-text access were excluded, resulting in the elimination of 22 studies. Details can be examined on the flow diagram in Figure 1 (see Appendix A).

Considering that content-based, collaborative and hybrid filtering are definitions that have been used long without AI technologies (Aboutorab et al., 2023), we have explained the advantages and limitations of models that are based on AI and can be used with AI in Tables 1, 3, 5, and 6. Although the studies on the subject are limited for now, we meticulously compiled the information about the use of LLMs in NRSs in the existing literature. The last part included the results by interpreting the impact of AI on NRSs, the comparison of AI approaches, the impact of LLMs and their future according to the inferences we made from the literature.

The final selection included 42 studies that met the inclusion criteria. We analyzed these studies to address the research questions and focused on the impact of AI on NRS and the impact of LLMs on their development and performance. Through this process, we aimed to provide a comprehensive and unbiased review of the latest developments in the field.

3 Common Approaches in News Recommendation Systems

3.1 Collaborative Filtering

Collaborative filtering (CF) is a recommendation system that analyzes user behavior and makes predictions about possible future behaviors of users (Shichang, 2021). CF methods are based on the idea that users who have made similar choices in the past will make similar choices in the future (Feng & Lv(U), 2022).

We can examine CF models under two headings: User-Based CF identifies users with similar tastes and recommends items that these users have liked in the past to others (Ludwig et al., 2023). For example, if user 1 and user 2 both showed interest in news x and y, the system predicts that these users' preferences are similar. If user 1 shows interest in news z, the system recommends news z to user 2 (X. Liu, 2022). Item-Based CF focuses on similarities between items and recommends items that are similar to items the user has liked before (Ludwig et al., 2023). For example, if a user is reading a news article, the recommendation system shows related articles in a news feed component (Lucas & de Figueiredo, 2023).

Although CF is one of the most prominent methods used by sources, such as Google News among NRSs, it inherently suffers from a cold-start problem when it comes to new users and new items (Lv et al., 2024). To overcome such difficulties, hybrid approaches are preferred by using models such as CB (Zhu et al., 2022) and session-based (Pourashraf & Mobasher, 2023).

3.2 Content-Based Filtering

Content-based (CB) NRSs use the content of news articles to make recommendations (Fieiras-Ceide et al., 2023). These systems analyze features, such as news topics or content and suggest news similar to what the user has previously been interested in (Ludwig et al., 2023). CB methods are widely used in news recommendations because users usually do not have long-term profiles on news sites (Alam et al., 2022).

CB NRSs represent news articles using feature vectors (Ludwig et al., 2023), which can include information like topics discussed in an article, the news outlet that published it, or other relevant metadata (Manh Nguyen et al., 2022). Similarity calculation in CB calculates the similarity between news articles based on their feature vectors (Alam et al., 2022). Term frequency-inverse document frequency (TF-IDF) is the most widely used method for numerically representing text. This technique converts the similarities between news items into values between 0 and 1 using cosine similarity, allowing for accurate recommendations (Ludwig et al., 2023).

CB methods build user profiles based on their past interactions with news articles. These profiles represent a user's interests and preferences (Lv et al., 2024). They do not rely on the behavior of other users (Ludwig et al., 2023). They expand user profiles using personal information and address the cold-start problem (J. Yang et al., 2023). With these features, they are useful at utilizing the rich textual content of news articles (Fu, 2023).

Since CB systems tend to show users news that is similar to news they have seen before, there is a possibility that they will present the same or very similar news to the reader again (Ludwig et al., 2023). These systems can increase the risk of locking users into "filter bubbles" by focusing on similar content, where users are constantly presented with news that is similar to their preferences or to news they have previously engaged with, potentially isolating users from different perspectives (Sun et al., 2021; Vrijenhoek, 2023). Some CF algorithms use only news headlines as input, and headlines often carry a significant bias (Ruan et al., 2023). In order overcome the problems in these systems or to reduce their effects, CB systems are used together with systems, such as CF to form Hybrid Systems (Q. Zhao et al., 2024).

3.3 Hybrid Systems

Hybrid NRSs combine different approaches to improve the accuracy and effectiveness of recommendations (Manh Nguyen et al., 2022). Besides demographic and knowledge-based filtering models, which are beyond the scope of this article as they do not rely on AI (Ludwig et al., 2023), hybrid systems combining models like CB and CF aim to overcome limitations of single-model approaches (Song et al., 2021).

Common hybrid approaches and techniques include CB and CF combining user profiles, news content, and user behavior gives recommendations based on user's interests and past actions (Manh Nguyen et al., 2022). Hybrid Deep Learning Models utilize neural networks to integrate content and user data. For example, ACCM (2018) uses Cold-Sampling strategy that can recommend items even if the user or item is new to the system (Shi et al., 2021). Multi-faceted Hybrid Systems combine content, CF and knowledge graphs (Xu & Gu, 2022). Similarly, Multi-Objective Approaches consider multiple objectives, such as accuracy and diversity, in their recommendations (M. Zhao et al., 2023).

Hybrid systems overcome the cold-start problem, increase diversity (Ludwig et al., 2023), accuracy (X. Liu, 2022) and stability (Song et al., 2021). Additionally, they provide a better user experience (Cui et al., 2021), reduce information overload (X. Liu, 2022), and create more robust systems (Shi et al., 2021).

4 Ai Driven Techniques in News Recommendation Systems

4.1 Session-Based Systems

Session-based NRSs focus on providing recommendations based on a user's current, short-term interactions with the news platform, rather than relying on long-term user profiles (Symeonidis, Chaltsev, et al., 2021). These systems are particularly effective in the news domain, as users' interests vary on a session-by-session basis and most users are anonymous (Lucas & de Figueiredo, 2023).

Session-based systems analyze the sequence of articles users interact with, in a single session to understand their immediate interests (Sheu et al., 2022). A session is defined as a series of interactions within a short time (Symeonidis, Kirjackaja, et al., 2021). These systems aim to capture short-term user preferences, as opposed to long-term interests (Sheu et al., 2022), as user interests can change quickly (Pourashraf & Mobasher, 2023).

Session-based methods can effectively deal with anonymous users since they do not require past user history or profiles (Lucas & de Figueiredo, 2023). The sequential order of articles viewed within a session plays a crucial role, as click order provides valuable insights into users' evolving interests within a given session (Sheu et al., 2022). Some advanced models consider both intra-session element transitions and inter-session transitions to address the problem of insufficient information at the beginning of the session (Symeonidis, Chaltsev, et al., 2021). Table 1 briefly overviews session-based systems, highlighting their strength in capturing short-term behavior and limitation in reflecting long-term preferences(see Appendix B) .

4.2 Graph-Based Systems

Graph-based systems for news recommendation leverage the relationships between different entities, such as users, news articles, topics, to improve the accuracy and relevance of recommendations (Li et al., 2023). In other words, these systems can work with other recommendation systems that keep users, content, products(items), etc. in the form of graphics and control their relationships with each other (Sheu et al., 2022).

Table 2 provides a concise overview of various graph-based approaches currently employed in NRS, emphasizing how each leverages AI to capture and analyze relationships among entities. It highlights key characteristics and research insights, illustrating both their contributions and limitations within the domain (see Appendix C).

Table 3 provides a summary of the advantages and limitations of graph-based systems in news recommendation, highlighting their effectiveness in modeling relationships and their key challenges, such as computational complexity and scalability (Li et al., 2023) (see Appendix D).

4.3 Deep Learning Based Systems

Deep learning (DL) algorithms work in a way similar to the way the human brain works and can automatically be trained with large amounts of data to produce high-quality semantic inferences. Thanks to their ability to be trained continuously, they can optimize their recommendations up to date (Han, 2024). While DL-based methods have shown their effectiveness in different domains, such as image recognition and NLP, extensive experiments have been conducted in NRSs (Lim et al., 2022).

The approaches summarized in Table 4 represent significant advancements in applying Deep Neural Networks (DNNs) within NRS. These methods utilize AI's capability to handle complex user interactions, semantic contexts, and sequential data, directly addressing challenges such as data sparsity and personalization (see Appendix E). This aligns with the research questions by highlighting how various DNN architectures, including CNNs, RNNs, Transformers, and attention mechanisms, influence the performance and development of NRS, particularly in the context of recent advancements in AI and LLMs.

Table 5 summarizes the advantages and limitations of deep learning-based systems in NRS, emphasizing their strengths in modeling complex user interactions, semantic understanding, and addressing sparsity, but also highlighting their challenges, such as computational complexity and data requirements (see Appendix F).

4.4 Multi-Interest Based Systems

Instead of single-interest models in NRSs, multi-interest based models that aim to capture diverse and varied interests of users, overcome the limitations of single-interest based models (P. Zhao et al., 2023). These systems observe that users generally have multiple areas of interest that can change over time (Hou et al., 2023). Instead of fitting a user's interests into a single mold, multi-interest systems attempt to create several different interest profiles for each user (P. Zhao et al., 2023).

Multi-interest systems learn multiple representation vectors for each user, with each vector representing a different interest (Hou et al., 2023). Some models create interest prototypes that serve as the basis for learning multiple user representations. These prototypes may reflect different topics or interests (S. Wang et al., 2023). Multi-head self-attention models can be used to detect potential interest areas in each clicked news. Each title vector represents an interest area (R. Wang et al., 2022).

Graph Neural Networks (GNNs) are used to model user interests using information collected from user neighbors in a user-news graph. Some models leverage personalized graphs to capture more nuanced relationships between user behaviors (Wu et al., 2021). GNNs can also be used to improve user representations by evaluating the relationships between users and news on graphs containing different types of nodes and relationships (S. Wang et al., 2023).

Multi-channel information fusion involves modeling user interests and capturing diversity by combining news content from different sources, at different levels of detail, and using different types of information, such as text and assets (Z. Yang et al., 2023).

As shown in Table 6, multi-interest models capture diverse, multi-grained user preferences, from low-level keywords to high-level topics, and track both short- and long-term dynamics to enhance recommendation accuracy and adaptability. However, as detailed in Table 6, they may misinterpret curiosity-driven clicks, introduce noise and redundancy when the number of interests grows, and oversimplify news by overlooking key events and stylistic nuances (see Appendix G).

4.5 LLMs In NRSs

Despite the limited research on the topic, important insights have emerged from the use of LLMs particularly models like BERT and other PLMs in NRSs.

BERT (Bidirectional Encoder Representations from Transformers) is a pre-trained language model (PLM) that can capture contextual information and semantic meaning of words. BERT-based models improve the understanding of news content by learning richer semantic information (Hou et al., 2023). It is used to initialize the word-level module of some news recommendation models and enables the development of textual representations. It further helps to alleviate the cold-start problem by taking advantage of rich grammar. Pre-trained models like BERT are used to create contextual word embeddings. These embeddings help models capture the meaning of words based on how they are used in a sentence (Zhang et al., 2021).

Using BERT or other PLMs such as RoBERTa and GPT often leads to significant performance improvements in NRSs (S. Wang et al., 2023). For example, one study showed that a model using BERT outperformed other models, with a 2.81% improvement in AUC (area under the curve) on a large dataset (Zhang et al., 2021).

Although PLMs are effective, they often require high computational resources. Traditional end-to-end training paradigms also face efficiency challenges, particularly due to the repeated encoding of the same news content. To address this, Q. Liu et al. (2024) introduced the OLEO (Only-Encode-Once) paradigm, which involves pre-training the content encoder before integrating it into the model. This approach has shown comparable accuracy while significantly improving sustainability metrics by up to 2992% compared to state-of-the-art end-to-end methods. (Q. Liu et al., 2024). Beyond BERT, transformer-based models like ELECTRA are also being used for pre-training text encoders as discriminators rather than generators (J. Yang et al., 2023). This shift in pre-training strategy offers a more sample-efficient alternative, which could further reduce computational costs while maintaining or even improving model performance in NRSs.

5 Discussion

This research aims to examine the impact and applications of AI, and especially LLMs, on NRSs. The findings show that AI-driven approaches provide improved results in personalization, accuracy, and efficiency compared to traditional methods. However, challenges such as bias, filter bubbles, and computational costs remain for some methods.

5.1 The Impact of AI

With the advancement in AI, significant advances have been made in NRSs by developing personalized experiences tailored to individual user preferences. CF, which we also encounter in traditional approaches, effectively uses user behavior patterns to predict future interests, although it has a cold-start problem. CB significantly prevents the cold-start problem by analyzing news content, but it carries the risk of creating filter bubbles because it constantly recommends similar content. Similarly, Flaxman et al. (2016) note that CB often narrows exposure by reinforcing user biases, contributing to the filter bubble effect. Hybrid systems combining CF and CB significantly eliminate these limitations by taking advantage of both user behavior and content similarity. X. Liu (2022) also supports that by emphasizing how hybrid models outperform single approaches in terms of accuracy and diversity. Session-based systems, which focus on short-term interactions, make effective recommendations to anonymous users and dynamic interests, and demonstrate the ability to adapt to real-time user behavior thanks to AI-supported systems. Symeonidis et al. (2023) also highlight the value of session-based models in addressing the transient nature of user interests in news domains. Graph-based systems and deep learning-based systems allow complex understanding of user preferences and news content connections by using complex relationships between entities together with traditional methods. Li et al. (2023) and W. Liu et al. (2024) similarly show that graph-based methods capture higher-order interactions, improving recommendation precision.

5.2 Comparing AI-driven Tecniques

Each AI-based NRS we mentioned has its own strengths and weaknesses. While CF is very successful in capturing the behavior of users by grouping them, it struggles when dealing with new users and items. While CB overcomes these problems with its content-focused approach, it fails to direct users to new interests, constantly recommending similar content. Hybrid systems aim to overcome these problems by using the strengths of both. While session-based systems address the dynamic structure of the news domain, graph-based methods exploit complex relationships to provide more sophisticated recommendations. Deep learning models, such as CNNs, RNNs, and attention networks are powerful tools to analyze complex data and provide more accurate and personalized recommendations when used in conjunction with other methods. Multi-interest-based systems increase the performance in personalization by capturing different interests of users. The selection of the most appropriate method depends on the requirements and data characteristics.

5.3 The Influence of LLMs

Although there are few studies on the use of LLMs in NRSs, we can say that LLM models, such as BERT have started a new era with the performance increase, they bring in news recommender systems as well as in many other areas. When we look at CB models before LLMs, LLMs that capture contextual information and meanings provide a more detailed understanding of news content compared to models that measure the frequency of words used. In this way, the increase in recommendation accuracy has been proven numerically by the studies (Zhang et al., 2021). However, when it comes to cost and sustainability, the use of LLMs in NRSs can be a source of concern. LLMs have become more competitive in terms of cost and sustainability with innovative approaches such as the OLEO paradigm. Recent frameworks like OLEO aim to address these concerns, aligning with Hou et al. (2023) who suggest lightweight multi-head attention as a viable cost-efficient alternative.

5.4 The Future of LLMs in News Recommendation

The potential of LLMs in developing NRSs cannot be underestimated. Future research should explore more efficient training paradigms by focusing on reducing costs to increase sustainability. Hybrid use of LLMs with other recommender system methods should also be tried to optimize costs. Combining LLMs with session-based models can help capture the dynamic nature of news and improve accuracy, while using them with multi-interest models may help personalize content and introduce users to new topics. In addition to CB methods, using LLMs together with CF methods, especially with item-based CF methods, is a promising method for developing recommendation systems with semantic similarities of news, and reducing costs.

5.5 Limitations

The study is not without limitations. First of all, since this review focused on AI-driven methods, it ignored studies that examined the possible contributions of other approaches. Although the focus was on recent studies, the rapid development of the field under investigation means that new techniques can emerge rapidly, and potentially some findings can quickly become outdated. Additionally, the inclusion criteria limited the scope to studies published after 2021, which may have excluded foundational works or earlier influential models still relevant today. Another limitation is the variation in evaluation metrics and datasets used across studies, which makes it difficult to directly compare the performance of different models. Finally, the review emphasizes technical and performance-based aspects, while socio-ethical implications, such as user trust, transparency, and fairness in AI-driven news recommendation received limited attention.

6 Conclusion

This study highlights the role of AI and LLMs in the development of NRSs. AI has been effective in improving personalization, scalability, and contextual understanding with hybrid, graph-based, and deep-learning approaches that address limitations such as cold-start problems and data sparsity. Although LLMs such as BERT offer new paradigms for efficiency and sustainability by further improving semantic analysis and recommendation accuracy, more observations are needed as these developments are still very recent.

Despite these developments, challenges remain in terms of computational efficiency, ethical issues, and maintaining diversity in recommendations. Future efforts should focus on energy-efficient systems, cost reduction, sustainability, and integrating multimodal data such as textual, visual, and behavioral.

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Appendix

Appendix A

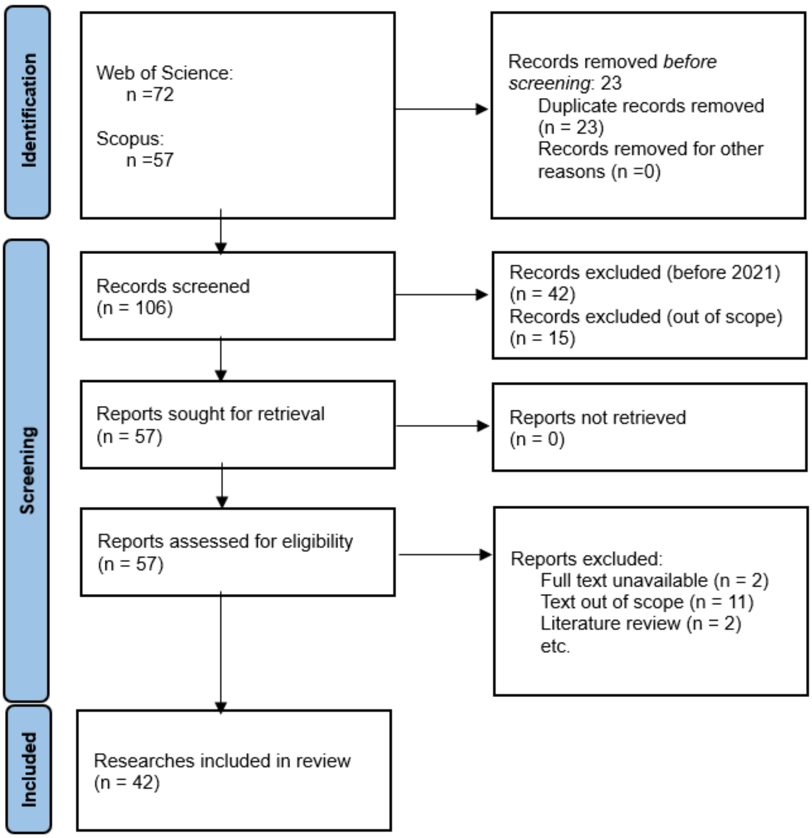

Figure 1: PRISMA Flow Diagram

Appendix B

Table 1: Advantages and Limitations of Session-Based Systems

Session Based Systems			
Adventages		**Limitations**	
Advantage	***Paper***	***Limitation***	***Paper***
Short-Term Preference Modeling: Session-based systems excel at capturing users' short-term interests and intentions by analyzing their interactions within a single session. This is crucial in the news domain, where user interests can change rapidly.	Sheu et al., 2022	*Limited user history*: Session-based systems primarily focus on the current session and often neglect long-term user preferences they may struggle to model or incorporate long-term user interests that span multiple sessions	Pourashraf & Mobasher, 2023
	Symeonidis, Chaltsev, et al., 2021		Symeonidis, Chaltsev, et al., 2021
	Pourashraf & Mobasher, 2023		
Handling Anonymity: Many users browse news websites without logging in. Session-based systems don't require user profiles. They rely on the sequence of items a user interacts with during a session, making them suitable for anonymous users.	Sheu et al., 2022	*Potential for Over-Personalization*: By focusing heavily on the immediate session, these systems may lead to recommendations that are too narrow or repetitive, potentially creating a "filter bubble" effect	Alam et al., 2022
	Alam et al., 2022		
	Lucas & de Figueiredo, 2023		
	Symeonidis, Chaltsev, et al., 2021		
Timeliness: Session-based methods can quickly recommend relevant news stories, reducing the time lag between breaking news and recommendations. These systems are effective at recommending news items due to the importance of recency and freshness.	Lucas & de Figueiredo, 2023	*Data Sparsity*: While session-based systems are good at handling anonymous users and new items, they can still face data sparsity issues, especially with very short sessions or when dealing with new content that has not been viewed by many users	Lucas & de Figueiredo, 2023
	Pourashraf & Mobasher, 2023		Sheu et al., 2022
Reduced Cold-Start Problems: Session-based methods can make recommendations based on a single session.	Lucas & de Figueiredo, 2023	*Contextual Limitations:* While session-based systems consider the immediate context of a user's session, they may not fully account for external factors or broader contexts, such as location, time of day, or current events, which can influence user preferences	Lucas & de Figueiredo, 2023

Session Based Systems			
Adventages		**Limitations**	
Advantage	***Paper***	***Limitation***	***Paper***
Adaptability: Session-based methods adapt to changes in user preferences as they occur, continuously updated with every new user click, making them sensitive to changes in preferences	Symeonidis, Chaltsev, et al., 2021	*Lack of Semantic Understanding*: Some session-based models may not fully exploit the semantic-level structure information of news article. They might focus on the sequence of interactions without capturing deeper semantic relationships between articles.	Sheu et al., 2022
Multi-Interest Capture: Some session-based systems are capable of capturing multiple interests within a single session	R. Wang et al., 2022		
Use of Meta-Paths: Session-based systems can use meta-paths to define relationships between items such as "article-session-article". These paths reveal semantic context and enhance the accuracy and explainability of recommendations	Symeonidis et al., 2023		

Appendix C

Table 2: Summary of Graph-Based Approaches in NRS

Approach	Description	Role of AI	References
Knowledge Graphs	Capture semantic context but face computational complexity.	Semantic modeling, preference propagation	Y. Wang et al. (2022), Alam et al. (2022)
User-News Graphs	Model detailed user-news interactions; effective yet complex.	User/news embedding, detailed behavior modeling	Wu et al. (2021), Li et al. (2023)
Hypergraphs	Represent complex, higher-order interactions; computationally intensive.	Complex user-news-topic interaction modeling	W. Liu et al. (2024), M. Zhao et al. (2023)
Session Graphs	Track short-term user behaviors dynamically; limited for long-term preferences.	Dynamic behavior analysis, temporal sensitivity	Symeonidis et al. (2021, 2023)
Graph Convolutional Networks	Embed users and news effectively but with high computational requirements.	Node embedding, interest representation	M. Zhao et al. (2023), Zhu et al. (2022)

Appendix D

Table 3: Advantages and Limitations of Graph-Based Systems

Graph Based Systems			
Adventages		**Limitations**	
Advantage	***Paper***	***Limitation***	***Paper***
Improved User and News Representation: GNNs can learn better representations of both users and news by propagating information through the graph structure. Graph structures help to prepare better hybrid systems refining article embeddings and user embeddings.	Li et al., 2023	*Data Sparsity and Cold Start:* While graph structures help alleviate data sparsity issues, they do not completely solve the problem. While GNNs used as CF model, the model can suffer from cold-start problem.	Li et al., 2023
	W. Liu et al., 2024		X. Liu, 2022
	Sheu et al., 2022		Song et al., 2021
	S. Wang et al., 2023		Han, 2024
	Y. Wang et al., 2022		
	Wu et al., 2021		
	Shi et al., 2021		
Capturing High-Order Relationships: Some graph structures like Hypergraph can model relationships beyond simple pairwise connections between users and news, including triadic, tetradic, or higher-order relations	W. Liu et al., 2024	*Over-smoothing:* In graph neural networks (GNNs), increasing the number of propagation layers can lead to over-smoothing, where the node embeddings become too similar and difficult to distinguish.	M. Zhao et al., 2023
Encoding Complex Relationships: Graph-based methods can incorporate various types of relationships, such as semantic similarity, co-occurrence, co-click.	Shi et al., 2021	*Computational Complexity:* Some models, like implicit semantic and matrix decomposition models, suffer from decreased computational performance when the amount of data is large	Lucas & de Figueiredo, 2023
			X. Liu, 2022
Addressing Data Sparsity: By modeling relationships in a graph, GNNs can alleviate the sparsity of user-item interactions. This is particularly helpful for addressing the cold start problem.	Li et al., 2023	*Hyperparameter Sensitivity:* The performance of some graph based systems can be sensitive to the choice of hyper parameters, for example increasing the number of layers in GNNs can improve performance up to a point, after that performance may decrease.	Li et al., 2023
	W. Liu et al., 2024		Y. Wang et al., 2022
	Ludwig et al., 2023		

Graph Based Systems			
Adventages		Limitations	
Advantage	*Paper*	*Limitation*	*Paper*
Utilizing Heterogeneous Information: Graphs can easily incorporate different types of nodes and edges, representing different aspects of news and user behavior like clicked news, topics and entities.	Wu et al., 2021	*Difficulty in capturing complex semantics:* Some methods have difficulty using hypergraphs to capture the potential relationships between news due to the rich textual semantics.	W. Liu et al., 2024
Improved Diversity: Graph-based approaches have shown improvements in the diversity of recommendations, wich is important to awoid filter bubles.	Symeonidis, Kirjackaja, et al., 2021		
	Fieiras-Ceide et al., 2023		
Flexibility: Graph based systems are flexible and can combine information from different sources, including cross-platform data and user interactions	Shi et al., 2021		

Appendix E

Table 4: DNN Approaches and their Roles in NRS

Approach	Description	Role of AI	References
Convolutional Neural Networks (CNN)	Extract features from textual sequences (e.g., news headlines) to improve recommendations.	Semantic feature extraction, sequence modeling	Lu et al. (2022), Manh Nguyen et al. (2022), Pourashraf & Mobasher (2023)
Recurrent Neural Networks (RNN)	Model sequential user interactions; capture dynamic preferences (includes LSTM, GRU).	Sequential modeling, personalization	Manh Nguyen et al. (2022), Lu et al. (2022), Pourashraf & Mobasher (2023)
Deep Matrix Factorization	Uses deep layers to process user-item interactions, enhancing rating prediction.	Non-linear user-item interaction modeling	Li et al. (2023), Zhu et al. (2022)
Transformers	Employ encoder-decoder structures to model contextual relationships in data.	Contextual embedding, semantic understanding	Zhang et al. (2021)

Approach	Description	Role of AI	References
Attention Mechanisms (Word, News, User Level)	Assign weights to important words/news/user interactions, enhancing relevance.	Context-sensitive modeling, personalization	Manh Nguyen et al. (2022), Z. Yang et al. (2023), Fu (2023), Li et al. (2023)
Multi-Head Attention Networks	Attend multiple input parts simultaneously, capturing diverse contextual aspects.	Multi-aspect representation learning	Hou et al. (2023), Iana et al. (2023), W. Liu et al. (2024)
Deep Reinforcement Learning (DRL)	Optimizes recommendations based on long-term user engagement through interactions.	Adaptive long-term recommendation optimization	Aboutorab et al. (2023), Song et al. (2021)
Deep Knowledge-Aware Networks (DKN)	Integrate semantic and knowledge-level information to enhance recommendation accuracy.	Semantic and knowledge integration	Lim et al. (2022), Lu et al. (2022), Y. Wang et al. (2022), Feng & Lv(U) (2022)
Deep Structured Semantic Models (DSSM)	Rank documents based on semantic similarity using deep neural architectures.	Semantic similarity modeling, ranking	Zhu et al. (2022)

Appendix F

Table 5: Advantages and Limitations of Deep Learning Based Systems

Deep Learning Based			
Adventages		**Limitations**	
Advantage	*Paper*	*Limitation*	*Paper*
Powerful learning ability: Deep learning algorithms can automatically learn features from large datasets and extract high-level semantic expressions.This allows the system to understand complex relationships in data without manual feature engineering.	Han, 2024	Timeliness and Dynamic Nature of News: The rapidly changing nature of news articles, with new articles constantly published and older ones becoming outdated, presents a challenge for deep learning systems.The models need to adapt to the short shelf-life of news and the dynamic nature of user interests. News is highly time-sensitive, requiring models to capture real-time user interests	Lucas & de Figueiredo, 2023
	Z. Yang et al., 2023		Fu, 2023
	Zhu et al., 2022		Zhu et al., 2022
Representation Learning: Deep learning models can produce good representations for news metadata, which is a key component in content-based news recommendation. Traditional methods often rely on categorical features (e.g. news IDs, news categories) or bag-of-words (tokens or n-grams) which do not capture the complexities of language as well as deep learning approaches.	Manh Nguyen et al., 2022		
	Zhang et al., 2021		
Processing multiple data types: Deep learning models can handle various types of input data, such as text, images, audio, and video.	Han, 2024		
Fine-Grained Information: Deep learning methods are capable of capturing fine-grained aspect-level information, leading to more accurate recommendations	Lu et al., 2022		

Deep Learning Based			
Adventages		**Limitations**	
Advantage	***Paper***	***Limitation***	***Paper***
Non-linear relations: Deep learning models are capable of extracting non-linear relationships and dependencies between news articles more effectively than traditional methods	Zhu et al., 2022		
Mitigating Cold-Start and Data Sparsity: Deep learning models can extract valuable features from news and user data to improve user and item profiles, thus alleviating the cold-start and data sparsity issues often encountered in recommender systems	Manh Nguyen et al., 2022		
Improved Accuracy: Deep learning algorithms can enhance the precision and personalization of recommendations by analyzing user behavior and creating user models, making it easier for users to find relevant news	Zhu et al., 2022		
	Han, 2024		

Appendix G

Table 6: Advantages and Limitations of Multi Interest Based Systems

Multi Interest Based			
Adventages		**Limitations**	
Advantage	***Paper***	***Limitation***	***Paper***
Improved User Representation: Multi-interest models capture the diverse and multi-grained nature of user interests. Unlike methods that learn a single interest vector for each user, multi-interest models can represent a user's interest in multiple topics such as sports, movies, and finance.	R. Wang et al., 2022	Relying solely on sequential behavior may not be accurate because users sometimes click on incorrect or unrelated news out of curiosity	Fu, 2023
	Li et al., 2023		
	Hou et al., 2023		
Better Handling of User Dynamics: These models can capture both short-term and long-term user interests, accommodating the evolving nature of user preferences over time	Z. Yang et al., 2023	There is a possibility of introducing noise and redundancy; when the number of interests (K) becomes too large, a lot of interest-level noise information will be introduced while aggregated into the final user representations, which is likely to be detrimental to the recommendation performance	Hou et al., 2023
	Fu, 2023		S. Wang et al., 2023
Enhanced Recommendation Performance: By modeling user interests at multiple granularities (e.g., word-level, news-level, and higher-levels), multi-interest models can more accurately represent diverse user interests, leading to improved recommendation performance.	Hou et al., 2023	They aggregate relevant information of news (e.g., title, content, topic) into a simple and unified news presentation and therefore miss the influence of some important factors such as news event and news style, which are important for guiding users' preferences toward news.	P. Zhao et al., 2023
Capture of Low-Level and High-Level Interests: Multi-interest models can capture both low-level (e.g., specific words or phrases) and high-level user interests, allowing for a more comprehensive understanding of user preferences	Hou et al., 2023		