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Book Recommendation Systems: A Survey of Approaches, Techniques, Datasets, Evaluation Metrics, Challenges and Future Directions

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Abstract— Book recommendation systems (BRSs) play a vital role in digital libraries, online bookstores, and e-learning platforms by assisting users in discovering relevant content from vast collections. Traditional methods, such as collaborative filtering (CF), content-based filtering (CBF), and hybrid techniques, have historically formed the foundation of BRSs; however, they suffer from limitations including the cold-start problem, data sparsity, and overspecialization. In recent years, deep learning–based approaches have emerged as powerful alternatives, leveraging architectures such as CNNs, RNNs, BERT, and Neural Collaborative Filtering (NCF) to capture complex user–item interactions and support multimodal integration. This survey is the first to systematically review book recommendation systems published between 2020 and February 2025, filling a critical gap left by earlier studies that did not comprehensively examine this recent period of accelerated research. The paper introduces a novel taxonomy of BRSs that classifies systems according to methodological foundations, approaches, datasets, and evaluation metrics, while also identifying recurring challenges and emerging trends. The findings reveal a clear methodological transition from similarity-driven approaches to neural representation learning, reflecting the increasing demand for intelligent, scalable, and adaptive solutions. Traditional methods, however, remain essential as baseline models for benchmarking and comparative evaluation.

Keywords— Book recommendation Systems, Deep Learning Approach, Traditional Approaches.

I. INTRODUCTION

A recommender system (RS) is generally defined as an intelligent information filtering tool designed to suggest relevant content, products, or services to users based on their preferences, behaviours, past interactions, or content similarities [1]. The primary goal of a recommender system is to reduce the time and effort users spend searching for suitable content online, thereby improving user satisfaction and minimize information overload [2]. Within domains such as digital libraries and online bookstores, RSs play a critical role in enhancing user experience, increasing engagement, and facilitating the discovery of relevant materials. The concept of a recommendation system originated in the early 1990s. Belkin and Croft [3] distinguished between information filtering and information retrieval, thereby laying the theoretical foundation for recommender technology. In the same year, Goldberg, et al. [4] introduced Tapestry, the first information filtering model, which employed collaborative filtering supported by user evaluations.

Techniques used for building BRSs initially relied on traditional approaches such as collaborative filtering (CF) and content-based filtering (CBF). Although widely adopted, these approaches suffer from persistent challenges, including the cold-start problem, data sparsity, and overspecialization. To mitigate these limitations, hybrid recommender systems emerged by combining CF and CBF to exploit the strengths of both. While such hybrid systems offered partial improvements, they remained constrained by their reliance on manually engineered features or linear models, which limited their ability to capture the complex, non-linear interactions between users and items, particularly in data-rich environments[5].

In recent years, deep learning (DL) models have emerged as powerful tools for modelling complex user-item interactions and extracting semantic features from items (e,g book metadata and textual descriptions). These models have opened new frontiers for developing book recommendation systems, enabling richer representation learning and personalization. On the other hand, the rapid growth of studies in this field makes it increasingly difficult for researchers and practitioners to maintain a clear understanding of state-of-the-art methods, their limitations, and their applicability across different contexts. Motivated by this challenge, this survey seeks to provide a unified and updated overview of recommendation techniques, spanning from traditional methods to cutting-edge deep learning approaches. By addressing these needs, the primary objectives of this survey are:

- To investigate the evolution and current state of book recommendation systems, emphasizing advanced methods introduced in the last five years.
- To highlight emerging research trends and future directions to guide future advancements in the field.
- To analyze the methodological approaches employed in book recommendation systems.
- To classify the techniques applied in book recommendation systems and their applications, according to the terminologies adopted in the selected studies.
- To review the commonly used datasets and evaluation metrics reported in the selected studies, thereby assisting researchers in identifying appropriate resources and measures for future work in the field.

Overall, this survey provides a comprehensive, structured review of modern book recommender systems (BRSs), with a focus on the evolution from traditional algorithms to deep learning-based approaches from 2020 to February 2025. Accordingly, this review provides novel contributions to the field, which can be summarized as follows:

- Focused domain scope: This survey is the first to exclusively examine the evolution of research activity in book recommendation systems between 2020 and February 2025, setting it apart from broader reviews of general recommender systems.
- Systematic taxonomy: It introduces a structured classification of recommendation system types, methodological approaches, methods used, datasets, and evaluation metrics employed in book recommendation research.
- Datasets and evaluation metrics: It provides a comprehensive analysis of commonly used datasets and performance metrics, highlighting their suitability for different scenarios.
- Domain-specific challenges: It examines the unique challenges of book recommendation systems, such as cold-start, data sparsity and overspecialization
- Emerging trends and research directions: It identifies key future directions, including hybridization, multimodal integration, and contrastive/self-supervised learning.

The overall structure of this paper consists of six sections. Section I introduces the article, outlining the motivation, objectives, contributions and the paper's structure. Section II presents the background, providing an overview of a recommendation system. Section III related work, reviewing existing surveys and prior work on book recommendation systems. Section IV describes the research methodology. Section V provides the results and discussion, covering methodological approaches, applied techniques, datasets, evaluation metrics, research challenges, and trends. Finally, Section VI concludes the paper by summarizing the key findings and outlining future research directions.

II. BACKGROUND

2.1 Recommendation Systems overview

In the digital era, the overwhelming abundance of information and content choices poses a significant challenge for users in finding relevant content. Recommender systems have emerged as essential tools for addressing this challenge by filtering information and providing users with suggestions aligned with their interests [2] These systems play a crucial role in digital libraries and online bookstores by enhancing user experience, increasing engagement, and improving discovery of relevant content. The most used methods in recommendation systems are Collaborative Filtering (CF), Content-Based Filtering (CBF) and hybrid filtering. A schematic illustration of these three types of recommendation systems is presented in Figure 1.

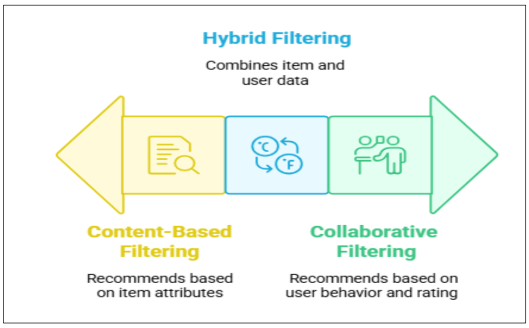

Figure 1: Types of recommendation systems.

1) Content-Based Filtering (CBF)

CBF is a recommendation method that emerged in the early 1990s, fundamentally relies on analyzing item attributes to generate recommendations. It recommends items by com paring the features of products a user has previously liked with those of other available items [2, 6]. This approach analyzes the content of items that a user has interacted with and recommends similar ones accordingly [7]. Figure 2 illustrates content-based filtering:

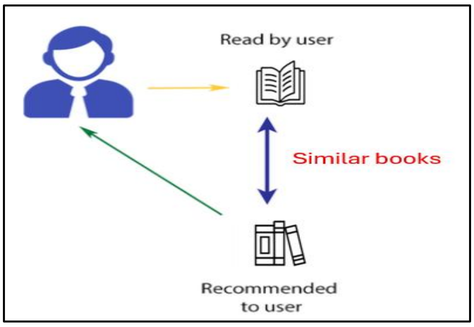

Figure 2: Content-Based Filtering (CBF).

2) Collaborative Filtering (CF)

CF methods are an approach of recommendation systems that first emerged in the 1990s [6] and provide personalized suggestions to users based on their preferences and the behaviours of other users. The main idea of this approach is that users with similar preferences are likely to exhibit comparable interests and, consequently, enjoy similar items. By leveraging the collective behaviours and preferences of users, CF can generate tailored recommendations that closely align with individual tastes [8]. It operates by collecting user data, identifying similarities among users, generating personalized recommendations, and continuously learning from user interactions. Collaborative filtering generally can be classified into two main categories: memory-based methods and model-based methods[6]. Firstly, memory-based Collaborative Filtering employs techniques such as Pearson Correlation, Vector Cosine Similarity, and K-Nearest Neighbours (KNN) to identify similar user groups, or neighbourhoods, and subsequently recommend items to users within these groups.

This approach is categorized into two types: user-based collaborative filtering and item-based collaborative filtering[6]. User-based collaborative filtering operates by measuring the similarity between users through the comparison of their ratings for common items. Based on the ratings from similar user groups, the model then generates and recommends a list of the top N items that best align with the target user's preferences [2, 6]. In contrast, item-based collaborative filtering predicts a user's preference for an item by assessing the similarity between that item and others previously selected by the user, based on the user-item rating matrix [9].The model-based collaborative filtering methods utilize various data mining and machine learning algorithms to construct predictive models capable of estimating a user's rating for unrated items. Secondly, the model-based collaborative filtering methods utilize various data mining and machine learning algorithms to construct predictive models capable of estimating a user's rating for unrated items[6]. Figure 3 presents a collaborative filtering recommendation system.

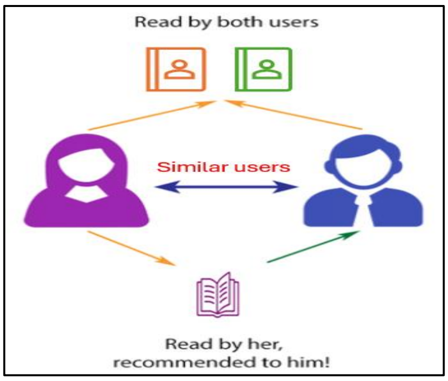

Figure 3: collaborative filtering (CF).

3) Hybrid filtering

It was first introduced by [10]. in 1997, marking a significant development in the field of recommendation systems. Several studies have explored a hybrid method to take the strengths of different methods and integrate them to get better results. In the following years, hybrid recommendation systems have become one of the three most popular methods for making suggestions.[11]This popularity is due to their ability to combine two or more different recommendation techniques, allowing for a more comprehensive approach to user preferences. This hybridization can mitigate the weaknesses of each method, providing a more robust recommendation framework[11]. Figure 4 illustrates the concept of a hybrid method that combines collaborative filtering and content-based Filtering.

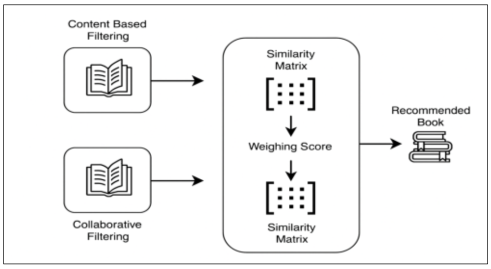

Figure 4: Hybrid Filtering Method.
Source : [12]

2.2 Deep learning techniques

Deep Learning (DL) is a subfield of machine learning that employs multi-layered artificial neural networks to mimic human cognitive processes [13]. It can automatically extract complex patterns from large-scale, high-dimensional, and unstructured data sources without relying on manual feature engineering [14, 15].

Deep learning models are typically categorized into three primary types based on their learning approach: supervised learning, unsupervised learning, and reinforcement learning [16]. A deep learning model is structured with several layers stacked one after another, as shown in Figure 5. It starts with an input layer, which holds values sent to each neuron in the first hidden layer. The model then produces its final predictions through the output layer, which contains as many units as there are desired output categories. Between the input and output layers are hidden layers, which assign weights to the inputs and use activation functions to introduce non-linearity, enabling the model to learn complex patterns and relationships in the data [17].

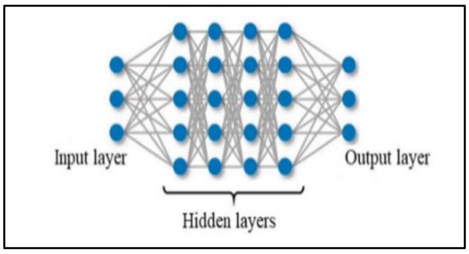

Figure 5: Deep learning neural network.
Source : [17].

In the context of recommender systems, deep learning techniques have significantly advanced the field by enabling more accurate, scalable, and personalized recommendations. Unlike traditional methods, which rely heavily on similarity metrics or linear factorization, deep learning models capture high-level abstract features from user–item interactions, textual descriptions, images, and other side information.

The most prominent deep learning techniques in recommendation research, such as CNN, RNN, Autoencoders (AEs), and Neural Collaborative Filtering (NCF), not only improve predictive accuracy but also extend the functionality of recommender systems by incorporating multimodal inputs (e.g., text, images, reviews) and enabling dynamic personalization, thereby marking a methodological shift from similarity-driven methods to neural representation learning. Their application in book recommendation systems reflects a clear methodological shift from traditional similarity-driven approaches to representation learning and neural modelling. A more detailed description of these techniques is presented in the Results and Discussion section, specifically in the subsection
(techniques commonly applied in BRSs).

III. RELATED WORK

Several studies have attempted to review or survey the field of recommendation systems, but very few have focused specifically on book recommendation systems using deep learning. For example, [18] published the first survey dedicated to book recommendation systems, categorizing them into six classes: collaborative filtering, content-based, demographic, social, context-aware, and association rule–based systems. They also highlighted common datasets (Book-Crossing, LitRec) and challenges such as sparsity, cold start, overspecialization, and evaluation inconsistencies. [19] extended this line of work by presenting a survey of book recommendation systems, with a comparative study of algorithms employed. They focused on CF, CBF, and hybrid models, emphasizing that item-based collaborative filtering enhanced with opinion mining offered the most effective strategy for improving accuracy and personalization in book recommendation systems. Moreover, [20] reviewed methods applied to book recommendation systems, emphasizing applications in libraries, e-learning, and e-commerce, and noting the growing adoption of ML to address sparsity and cold-start issues.

Most recently, [21] conducted a state-of-the-art survey covering book recommendation techniques from 2012 to 2023. Their review classified systems into six categories, discussed datasets (Book-Crossing, Goodreads, Amazon), and reported evaluation metrics (precision, recall, RMSE). They also introduced a taxonomy of book recommendation systems and highlighted persistent challenges such as sparsity, scalability, cold start, and grey sheep. Importantly, while the paper acknowledged the growing role of deep learning, it did not systematically categorize advanced neural architectures.

3.1 Comparison with This Study

While these prior surveys (2018–2024) have provided valuable contributions, several gaps remain:

- **Scope and Focus:**

Prior surveys (2018–2024) provided general overviews of book recommendation systems, focusing essentially on traditional methods. For example, [18] mainly focused on traditional CF and CB approaches without integrating modern deep learning architectures, while [19] only briefly mention books in broader contexts or emphasize classical ML rather than advanced neural models. In contrast, this study is the first to exclusively examine the evolution of book recommendation system research from traditional algorithms to deep learning–based approaches between 2020 and February 2025, thereby addressing a critical research gap.

- **Lack of Deep Learning Emphasis:**

Recent surveys only mentioned deep learning briefly, for example[20] discussed machine learning applications but provided limited analysis of deep learning frameworks like CNNs, RNNs, GNNs, or BERT. Similarly, [21]mentioned RNNs and LSTMs but focused on broad categories without systematically classifying deep learning architectures or evaluating their performance on book data. In contrast, this survey explicitly categorizes these deep learning models and explains their application in the book RS.

- **Novelty:**

Previous surveys [18-21] established foundations but remained generalized or ML-centric. This survey is the first study that includes a deep learning-focused survey of book recommendation systems, traditional methods, datasets, metrics, challenges, and emerging research directions (e.g., hybridization, multimodal integration, explainability, contrastive/self-supervised learning).

3.2 Research Gap

From this analysis, it is evident that none of the earlier surveys (2018–2024) systematically reviewed the evolution of research in book recommendation systems (BRSs) between 2020 and February 2025. In particular, prior works do not comprehensively address methodological foundations, traditional and deep learning approaches, techniques employed, datasets, evaluation metrics, challenges, and future research directions. The current survey addresses this gap by analyzing recent architectures, providing a dedicated and up-to-date review of BRSs, and introducing a novel taxonomy that classifies systems into types, approaches, datasets, and evaluation metrics. Moreover, it highlights emerging challenges and outlines future directions, thereby offering a unique and structured perspective on the evolution and current state of BRS research.

IV. LITERATURE SURVEY METHODOLOGY

This section outlines the methodology adopted for conducting the literature survey. It includes the formulation of research questions, the search procedure for identifying relevant studies, the classification framework used to organize the selected literature, and data extraction and documentation. The overall structure of this methodology is illustrated in Figure 6.

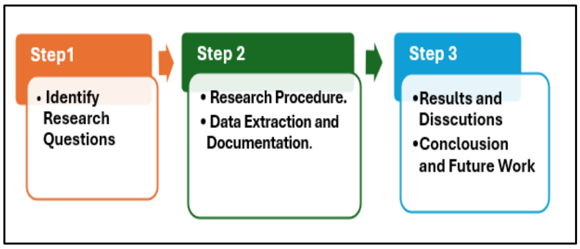

Figure 6: Literature Survey Methodology.

4.1 Research Questions

The purpose of this survey is guided by a set of research questions designed to structure the review process and synthesize insights from the selected studies. By the conclusion of this survey, the findings are expected to answer the following key questions:

RQ1: *What types of approaches are utilized in existing book recommendation systems research?*

RQ2: *What techniques are commonly applied to book recommendation systems?*

RQ3: *Which datasets and evaluation metrics are mostly used?*

RQ4: *What challenges and future directions exist in BRSs?*

4.2 Search Procedure:

The survey reviews literature on book recommendation systems, highlighting the methodological shift from traditional approaches to advanced deep learning techniques. Relevant literature was gathered from leading digital libraries and academic databases, including IEEE Xplore, ACM Digital Library, SpringerLink, Elsevier, and Google Scholar. The scope of this survey encompasses studies published between 2020 and February 2025, with publication dates verified via Google Scholar and includes both traditional recommendation approaches, such as collaborative filtering and content-based methods, as well as advanced deep learning techniques, including CNNs, RNNs, Transformers, and hybrid models. The identified studies were analyzed and classified based on methodological foundations, types, approaches, datasets, evaluation metrics, challenges, and future research directions.

4.3 Data Extraction and Documentation

For this survey, a structured data extraction process was adopted to ensure consistency, transparency, and replicability. Each selected study was carefully reviewed, and relevant information was documented in a predefined Excel spreadsheet template. The extraction sheet was designed to capture comprehensive bibliographic and methodological details, including:

- Paper ID and Bibliographic Information (title, authors, year, publication type).
- Methodological Approach (traditional vs. deep learning–based methods)
- Techniques Used (e.g.,CF,CBF CNN, RNN, Transformers, Hybrid filtering).
- Datasets (e.g., Book-Crossing, Amazon Books, Goodreads).
- Evaluation Metrics (e.g., RMSE, MAE, Precision, Recall, NDCG).
- Challenges Reported (e.g. sparsity, cold-start, scalability).
- Future Work Suggested (e.g., multimodal integration, explainability).
- Application Type/Domain (e.g., library systems, e-commerce, education platforms)

The use of an Excel spreadsheet facilitated a structured and comparative analysis of the surveyed studies. Each row corresponded to an individual paper, allowing patterns and trends to be identified across multiple dimensions such as techniques applied, dataset utilization frequency, evaluation practices, and emerging research directions. This documentation process not only enhanced the clarity and reliability of the survey but also provided a foundation for generating the tables, charts, and taxonomy presented in later sections. By employing this systematic extraction framework, the survey ensures reproducibility and allows future researchers to expand the dataset with newly published works.

V. RESULTS AND DISCUSSION

This section introduces the proposed taxonomy of book recommendation systems, as depicted in Figure 7. Complementing this, Table 1 presents the selected studies reviewed in this survey, classifying them according to their methodological foundations. Moreover, it provides a comprehensive analysis of the findings derived from these primary studies. To ensure clarity and coherence, the results are systematically organized and discussed in the following subsections.

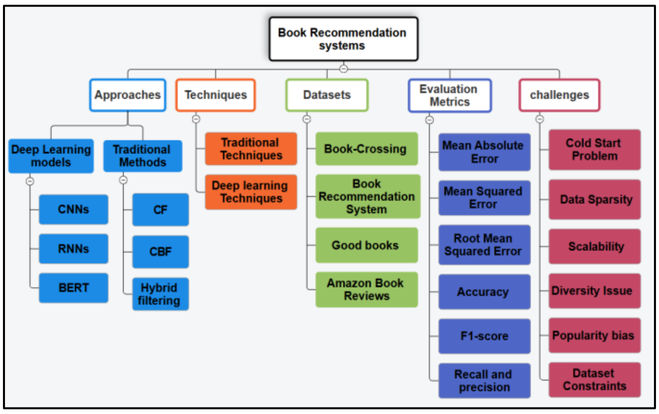

Figure 7: Taxonomy of Book Recommendation Systems.

Table 1: Selected studies

	Ref. NO	Year	Approach Type	Method Used	Techniques Used
1	[24]	2021	Traditional Approach	CF	Matrix Factorization (SVD), KNN
2	[22]	2020			Cosine similarity, KNN.
3	[25]	2022			Cosine similarity, Pearson correlation
4	[26]	2023			Matrix Factorization (SVD), KNN
5	[23]	2021			Pearson correlation, KNN, Cosine Similarity
6	[27]	2023			Matrix Factorization (SVD)
7	[29]	2024			Matrix Factorization (SVD)
8	[28]	2023			KNN, Cosine Similarity, Matrix Factorization (SVD)
9	[31]	2024		CBF	TF-IDF , cosine similarity.
10	[30]	2024			TF-IDF , cosine similarity.
11	[37]	2024		Hybrid Filtering	CBF+CF
12	[36]	2023			CBF+CF
13	[34]	2023			CBF+CF
14	[35]	2023			CBF+CF
15	[32]	2022			CBF+CF
16	[33]	2023			CBF, CF, clustering
17	[39]	2020	Deep Learning–Based Approach	Deep learning Models	CNN
18	[48]	2025			BERT + CNN, LSTM, BiLSTM, GRU
19	[40]	2022			CNN
20	[38]	2020			DNN
21	[43]	2024			Wide and Deep Learning Models
22	[45]	2024			Neural Collaborative Filtering,
23	[42]	2023			VGG16 (CNN-based model), LSTM.
24	[41]	2022			LSTM, Autoencoder
25	[46]	2024			Graph Convolutional Network (GCN)
26	[47]	2025			Embedding-Based Deep Learning (word embeddings)
27	[44]	2024			RNNs, ,LSTM.

5.1 Types of Methodological Approaches in BRSs

Book Recommendation Systems (BRSs) employ a diverse range of methodological approaches to generate personalized suggestions for users. In the selected studies, the employed approaches are broadly categorized into two principal methodological groups: the traditional approach and the deep learning–based approach, with each group relying on distinct sets of techniques.

5.1.1 Traditional Approach

A substantial number of earlier studies employed traditional approaches, including Collaborative Filtering (CF), Content-Based Filtering (CBF), and hybrid filtering (more details on these approaches in the background section). The reviewed studies are organized according to these methodological categories and are summarized as follows:

- **Collaborative filtering (CF):**

Several studies have designed book recommendation systems, with the majority relying on the CF method. [22] designed a university library recommender system, applying user-based collaborative filtering using cosine similarity and KNN. By leveraging user lending patterns and subject categorizations, the system provided personalized recommendations ranked according to relevance. Similarly, [23]employed user-based CF utilizing Pearson correlation, KNN, and cosine similarity on a combined dataset of books, ratings, and users, achieving moderate accuracy (RMSE 1.72, MAE 0.998) but facing scalability issues with larger datasets. In addition , [24]examined user-based, item-based and SVD approaches using the Arabic BRAD dataset, contains over 500,000 Arabic-language reviews. Their results showed that matrix factorization (SVD) achieved higher accuracy, while user- and item-based methods were faster for training and testing. This study is notable for expanding recommender system research into Arabic-language datasets. Furthermore, [25] proposed an item-based collaborative filtering system that employed cosine similarity and Pearson correlation to identify relationships between books and generate personalized suggestions. While the implementation effectively demonstrated the practicality of memory-based CF, the study did not report predictive accuracy metrics, focusing instead on system-level functionality and the feasibility of applying CF techniques in book recommendation.

Next year, [26] conducted a study using library data from the University of Gondar, this work compared memory-based CF with model-based approaches. Experiments applied KNN and SVD, with cross-validation. The findings indicated that SVD significantly outperformed KNN (RMSE 0.162 vs. 1.053), underscoring the robustness of matrix factorization in designing collaborative filtering recommendation. Moreover, [27] presents a book recommendation system that employs matrix factorization with Singular Value Decomposition (SVD) to tackle the problem of information overload in online book platforms. By examining user–item rating data, the system uncovers latent features that represent both reader preferences and book characteristics. The SVD technique strengthens this decomposition by capturing the most significant hidden factors, enabling the generation of personalized recommendations derived from users' past behaviours and predicted ratings. Experimental results showed improved accuracy and diversity in capturing reader preferences. Furthermore, [28] developed a web application for book recommendations, using K-Nearest Neighbors (KNN), matrix factorization (SVD) and cosine similarity to identify user–item relationships and capture latent user–item factors, providing personalized suggestions based on historical ratings. While the system effectively demonstrated usability and practical deployment, it did not report detailed quantitative metrics (e.g., RMSE, MAE), focusing instead on system design and implementation. Lastly, [29] conducted a comprehensive study aiming to develop a personalized book recommendation system using matrix factorization with SVD. The study focused on generating Top-n recommendations using user-item interaction data from the Book-Crossing dataset. It employed data preprocessing, matrix decomposition, and evaluation via recall@5 and recall@10, achieving scores at recall@5 of 0.1721 and recall@10 of 0.2784.

- **Content-Based Filtering (CF):**

While various studies have been conducted on different types of recommendation systems methods, only a few have specifically explored the application of Content-Based Filtering (CBF) in book recommendation systems, with a focus on enhancing personalization and improving user satisfaction. For instance, [30] developed a Library Book Recommendation System aiming to improve digital library services at Darul Mustofa Vocational School , using TF-IDF and cosine similarity to match book descriptions with user queries. User testing showed a 91.4% satisfaction score, confirming the system's feasibility. Similarly, [31]

introduced a study focused on developing a recommendation feature to support academic material discovery on the PNJ Press website. The objective was to enhance the efficiency of user searches by leveraging TF-IDF and cosine similarity to match queries with book titles and abstracts. The methodology included standard text preprocessing techniques such as case folding, tokenizing, stop word removal, and stemming. The system showed high performance, achieving a precision of 91.84%, a recall of 97.83%, and an overall accuracy of 90%.

- **Traditional Hybrid Filtering:**

Hybrid filtering, which integrates CB and CBF methods, is widely adopted in book recommendation systems studies to mitigate individual methods limitations. For example, [32], presented an online book recommendation system that compared multiple models, including item-based CF, content-based approaches (using features such as title, author, and summary), and a custom recommender. The study highlighted the role of feature-rich metadata in improving recommendation accuracy. In addition, [33]. proposed a pattern-based hybrid system that employs semantic relationships and clustering to enhance recommendations for new users. By combining CF and CBF with semantic similarity, the system achieved superior performance in precision, recall, and F-measure compared to state-of-the-art methods. In the same year, [34], introduced an improved hybrid CF–CBF framework, demonstrating that combining collaborative insights with content-based item attributes enhanced both accuracy and diversity. Their study confirmed that the hybrid model mitigates limitations like cold-start and lack of diversity, outperforming individual techniques. Extending this direction, [35]. integrated sentiment analysis with hybrid filtering using the DBSCAN clustering algorithm, aiming to improve recommendations through integrating user sentiment and demographic attributes into CF and CBF. By extracting sentiment scores from book reviews and leveraging demographic data for incomplete ratings, the system improved precision and recall while reducing RMSE and MSE on the Amazon dataset. Similarly, [36]proposed a hybrid book recommendation system for library management, combining content-based filtering and collaborative filtering. A switching hybrid technique was applied, dynamically choosing between the two methods depending on user context (e.g., cold-start vs. historical ratings). Experiments on Good Books datasets showed that the hybrid approach outperformed individual methods in recommendation accuracy and adaptability.

Finally, [37] developed a hybrid recommender model for digital libraries that links multiple online e-book sources via APIs. Their system integrates collaborative filtering (80%) and content-based filtering (20%) and was assessed using NDCG and precision, demonstrated superior efficiency compared to traditional approaches.

5.1.2 Deep Learning–Based Approach

In recent years, an increasing number of studies employed deep learning models to address the shortcomings of traditional methods. The reviewed studies are summarized below:

[38] introduced DNNRec, a deep learning–based hybrid recommender system that employed user and item embeddings alongside side information to learn non-linear latent features. By applying cyclical learning rates and weight decay within a deep neural network framework, DNNRec achieved state-of-the-art results across MovieLens, FilmTrust, and Book-Crossing datasets, particularly excelling in cold-start scenarios. Similarly, [39] introduced a book recommendation platform using deep learning that combines text-based similarity and image-based CNN classification. Their system processed subject names using cosine similarity with datasets from Amazon and Flipkart, while CNNs were applied to Kaggle book cover images to recommend visually similar books. Expanding the use of CNNs, [40] developed a CNN-based recommender system using Kaggle's book ratings dataset. Their model achieved strong results (MAE = 1.345, MSE = 3.034), highlighting

CNN's ability to handle large-scale, sparse data. Around the same period, [41] proposed an LSTM-enhanced autoencoder for personalized university library recommendations, which leveraged borrowing sequences to model temporal behavior. Although later retracted, this study illustrated the growing role of sequential modeling in book recommendations. The shift toward more sophisticated hybrid and personalized solutions became more prominent from 2023 onwards. [42] introduced a multimodal deep learning framework combining VGG16 for image features and Word2Vec with LSTM for textual analysis, further enhanced with CBAM attention. Their model improved precision by dynamically weighing visual and textual features. In 2024, research advanced toward scalability and real-time personalization. [43] evaluated Wide & Deep Learning models on the Book-Crossing dataset, demonstrating superior performance in handling sparse and large-scale data compared to Random Forest, GBDT, and MLP. [44] proposed HSBRS (Hybrid Sentiment-based Collaborative Architecture), which integrates item-based Collaborative Filtering with a hybrid sentiment analysis framework that combines Lexicon-based methods and a Long Short-Term Memory (LSTM) Recurrent Neural Network. Using the Amazon book review dataset, their model outperformed ML-based baselines such as SVM, Logistic Regression, and LDA, achieving an accuracy of 80.95%. This work underscored the effectiveness of combining deep learning–based sentiment modelling with collaborative filtering to enhance personalization in book recommendation systems.

Similarly, [45] integrated Neural Collaborative Filtering (NCF) with Alternating Least Squares (ALS) and real-time personalization through Apache Kafka, enabling dynamic and scalable recommendations that continuously adapted to user interactions. [46]further advanced this trend by proposing a knowledge graph–based digital book recommendation model that integrates an optimized Graph Convolutional Network (GCN), a centrality quantification algorithm, and an attention mechanism. The model simplifies traditional GCNs by removing non-linear components and focusing on domain aggregation over user-book interaction graphs. Simulation experiments using metrics such as Recall@20, NDCG@20, and Precision@20, demonstrate the model's superiority over baselines such as FM, DNN, NFM, CFKG, and KGAT, with results like NDCG@20 = 0.6325. The use of knowledge graphs significantly improved semantic reasoning while alleviating cold-start and data sparsity issues, marking an important contribution to personalized book recommendation research.

Most recently, [47]explored hybrid embedding-based frameworks that combines collaborative and content-based filtering with deep embeddings, achieving strong results (RMSE = 0.69, MAE = 0.51) on educational datasets. In addition , P18 [48]introduced a sentiment-driven ensemble hybrid deep learning model that combined CNN, LSTM, BiLSTM, and GRU architectures with BERT embeddings for contextual understanding. Using the Amazon Books dataset, their ensemble achieved 97.68% accuracy and 98.21% F1-score, significantly outperforming individual hybrid models. By integrating both ratings and review sentiments, their approach provided emotion-aware, highly personalized recommendations, thereby addressing sparsity, cold-start, and linguistic complexity.

5.1.3 Comparative Perspective

The analysis of methodological approaches indicates a noticeable shift in book recommendation system (BRS) research. As shown in Figure 8**,** traditional approaches remain the most widely used, representing 59% of the surveyed studies (16 papers), while deep learning–based methods account for 41% (11 papers).

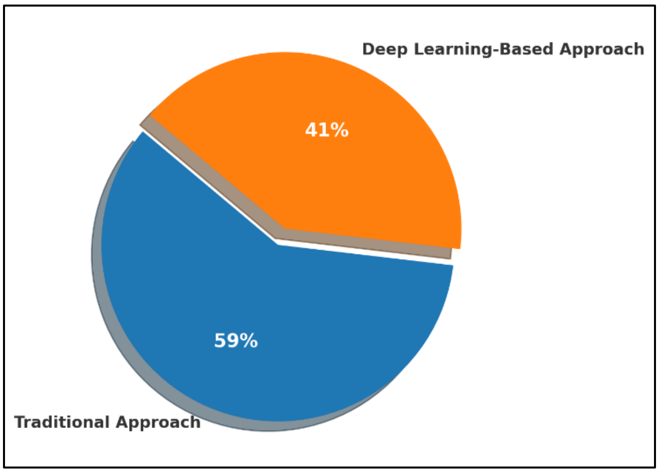

Figure 8: Distribution of Methodological Approach Types

Traditional models have long dominated the field due to their simplicity, interpretability, and relatively low computational cost, making them suitable for academic libraries, school environments, and small-scale platforms. Commonly adopted techniques include collaborative filtering (CF), content-based filtering (CBF), and hybrid extensions that rely on user ratings and item metadata. However, these methods are often constrained by well-known challenges such as the cold-start problem, data sparsity, and scalability issues, which limit their applicability in dynamic or large-scale contexts.

In contrast, deep learning–based approaches have emerged as a growing trend in recent years (2020–2025). Leveraging advanced models such as Neural Collaborative Filtering (NCF), convolutional neural networks (CNNs), recurrent neural networks (RNNs), Transformers (e.g., BERT), and multimodal fusion frameworks, these methods enable the modeling of complex user–item interactions and the integration of diverse data sources, including textual descriptions, reviews, and images. Such techniques have demonstrated superior performance in terms of accuracy, personalization, scalability, and multimodal integration, making them particularly effective in large-scale digital libraries, e-commerce, and online learning platforms.

Overall, this distribution underscores the methodological evolution of BRSs from rule-based, similarity-driven approaches to data-driven, neural network–powered architectures, reflecting the growing demand for intelligent, adaptive, and scalable recommendation systems.

5.2 Techniques Commonly Applied in Book BRSs

The effectiveness of BRSs depends heavily on the underlying techniques applied to model user preferences and item features. Based on the surveyed literature, these techniques can be grouped into traditional techniques and deep learning techniques.

5.2.1 Traditional Techniques

- ***Frequency–Inverse Document Frequency (TF–IDF):***

TF-IDF is one of the most widely used techniques for weighing the importance of terms in a document. It serves as a fundamental weighing scheme that quantifies the importance of words based on their occurrence within documents. TF-IDF is frequently used in tasks such as keyword extraction, document similarity assessment, and relevance ranking [49].

In the techniques presented, three statistical measures, Term Frequency (TF), Inverse Document Frequency (IDF), and their combination TF-IDF, are computed for each word token across both document clusters and individual texts.

Term Frequency (TF) quantifies how often a specific term appears within a document, offering insight into the term's importance in that context. A higher TF score indicates greater significance of the term within the document. TF is formally defined as in equation (1)[49]:

$$TF_{t,d} = \frac{f_{t,d}}{max\{f_{t',d}:t'\in d\}} \quad (1)$$

Where $f_{t,d}$ refers to the frequency of term t in document d, and the denominator represents the maximum frequency of any term in the same document.

- Inverse Document Frequency (IDF), by contrast, measures how uncommon or distinctive a term is across a corpus. Words that appear in fewer documents receive higher IDF values, highlighting their discriminative power. It is defined as in formula (2) [49]:

$$IDF_{t,D} = log\frac{D}{|\{d\in D:t\in d\}|} \quad (2)$$

where D is the total number of documents, and the denominator counts the number of documents in which the term t appears.

- The combined TF-IDF score is obtained by multiplying the TF and IDF values. This score increases when a term appears frequently in a particular document but rarely across the rest of the corpus, thereby indicating its relevance as in equation (3) [49]:

$$TF-IDF = TF_{t,d} \times IDF_{t,D} \quad (3)$$

This weighting scheme effectively balances term frequency with term uniqueness, making it a robust feature for tasks such as content-based recommendation and text classification.TF–IDF, a widely adopted technique in content-based book recommendation systems, is particularly suitable for representing book metadata such as titles, abstracts, and keywords [30] [31].

- ***Cosine Similarity***

In both content-based filtering (CBF) and collaborative filtering (CF), cosine similarity is one of the most widely used techniques for measuring the similarity between items or users. Each item (e.g., a book) is represented as a feature vector derived from descriptive attributes such as keywords, genres, or TF–IDF scores. The cosine of the angle between two such vectors indicate the degree of similarity: a value close to 1 reflects high similarity, while a value close to 0 indicates weak or no similarity [50]. Unlike distance metrics that consider magnitude, cosine similarity focuses on vector orientation, making it well-suited for high-dimensional text and rating data.

In CBF, cosine similarity plays a central role in identifying books similar to those a user has previously engaged with, thereby enabling personalized recommendations. The general formula for cosine similarity between two vectors a and b is expressed as (4) [50]:

$$Cosine\ similarity\ (a,b) = \frac{(\boldsymbol{a}.\boldsymbol{b})}{||\boldsymbol{a}||.||\boldsymbol{b}||} \quad (4)$$

In CF, users and items are represented as rating vectors, where cosine similarity can be applied in two ways:

User-based cosine similarity compares users' rating patterns. The similarity between users u and v is computed as (5) [51]:

- :

$$Cosine\ (u,v) = \frac{\sum_{i\in I_{u\,v}} r_{ui} r_{vi}}{\sqrt{\sum_{u\in I_u} r_{ui}^2}\sqrt{\sum_{u\in I_v} r_{vi}^2}} \quad (5)$$

I_u and I_v represent the sets of items rated by users u and v, while $I_{u\,v}$ refers to the set of items rated by both. The terms r_{ui} and r_{vi} indicate the ratings given by users u and v assigned to item i,

Item-based cosine similarity compares rating patterns across items. The similarity between items i and j is calculated as shown in equation (6)[51]:

:

$$Cosine\ (i,j) = \frac{\sum_{u\in U_{i\,j}} r_{ui} r_{uj}}{\sqrt{\sum_{u\in U_i} r_{ui}^2}\sqrt{\sum_{u\in U_j} r_{uj}^2}} \quad (5)$$

In this case, U_i and U_j refer to the sets of users who have rated items i and j, respectively, while $U_{i\,j}$ indicates the group of users who have rated both items. The values r_{ui} and r_{uj} are the ratings assigned by the same user u to items i and j.

Cosine similarity thus provides a computationally efficient and widely applicable measure for both content-based similarity between books and collaborative similarity between users or items, making it a central technique in traditional recommendation systems [24, 25] .

- ***Pearson Correlation (PCC):***

PCC is a widely used similarity measure in collaborative filtering. It quantifies the linear relationship between the rating patterns of two entities (users or items), producing values in the range –1 to 1 [52]. A value of 1 indicates a strong positive correlation, –1 reflects a strong negative correlation, and 0 denotes the absence of any linear relationship [53] . In user-based collaborative filtering, the similarity between two users u and v is calculated using Equation (6) [51]:

$$PCC(u,v) = \frac{\sum_{i\in I_{u\,v}}(r_{ui}-\bar{r}_u)((r_{vi}-\bar{r}_v)}{\sqrt{\sum_{i\in I_{u\,v}}(r_{u\,i}-\bar{r}_u)^2}\sqrt{\sum_{i\in I_{u\,v}}(r_{vi}-\bar{r}_v)^2}} \quad . \qquad (6)$$

Here, $I_{u\,v}$ represents the set of items that have been rated by both users u and v. The terms $\bar{r}_u$ and $\bar{r}_v$ refer to the average ratings given by users u and v on the items within $I_{u\,v}$ respectively. r_{ui} and r_{vi} are ratings assigned by the users u and v to the same item i. Formula (7) is used to compute the similarity between two items i and j [51]:

$$PCC(i,j) = \frac{\sum_{i\in U_{ij}}(r_{ui}-\bar{r}_i)((r_{uj}-\bar{r}_j)}{\sqrt{\sum_{i\in U_{ij}}(r_{u\,i}-\bar{r}_i)^2}\sqrt{\sum_{i\in U_{ij}}(r_{uj}-\bar{r}_j)^2}} \quad . \qquad (7)$$

Where, U_{ij} refers to the group of users who have rated both items i and j. The symbols $\bar{r}_i$ and $\bar{r}_j$ represent the average ratings for items i and j among these users. r_{ui} and r_{uj} indicate the ratings given by user u to items i and j, respectively.

By centring the ratings around user or item means, PCC accounts for individual rating biases, making it an effective measure for identifying similarity in both user-based and item-based collaborative filtering [22, 23].

- ***K-Nearest Neighbours (KNN):***

After computing similarity scores, the system selects the Top-N or (Top-K) nearest users or items to generate recommendations. A widely adopted method for this task is the K-Nearest Neighbours (KNN) algorithm, which recommends items either by identifying users with similar preferences (UserKNN) or by finding items similar to those a user has previously interacted with (ItemKNN). Originally, these techniques were developed to work with explicit feedback, such as user rating data [54]. In the context of book recommendation systems, KNN has been extensively used in both user-based and item-based collaborative filtering to capture neighbourhood relationships and produce personalized recommendations [24, 26].

- ***Matrix Factorization (MF):***

MF emerged as a prominent recommendation technique following its success in the Netflix Prize competition, where it demonstrated strong effectiveness in addressing the data sparsity problem inherent in collaborative filtering [6]. MF operates by extracting latent factors from user–item interaction data and representing both users and items as vectors in a shared latent space. The key objective is to uncover hidden dimensions that capture user preferences and item characteristics by structuring the evaluation data within a rating matrix framework.

An important advantage of MF lies in its scalability and flexibility, as it can incorporate both explicit feedback (e.g., user ratings) and implicit behavioural signals (e.g., search patterns, clicks, and mouse movements), thus providing a more comprehensive analysis of user interests [6]. There are two widely adopted algorithms illustrate the practical application of MF:

- **Singular Value Decomposition (SVD):** SVD decomposes the original user–item rating matrix into a product of three smaller matrices, thereby uncovering the latent features underlying user and item interactions [55].
- **Alternating Least Squares (ALS):** ALS factorizes the user–item rating matrix into two smaller matrices—a user-to-feature matrix and an item-to-feature matrix. It is particularly effective for sparse data, filling missing values with initial estimates and iteratively minimizing the error term until the product of the matrices approximates the original ratings [55]. MF and its variants, including SVD and ALS, have been widely adopted in book recommendation studies to address sparsity and improve prediction accuracy [26, 27, 29] .

- ***Clustering:***

Clustering is a method used to partition data into a finite number of categories or clusters and has been widely applied in recommender systems, particularly within collaborative filtering–based models. By grouping similar users or items, clustering reduces the dimensionality of the recommendation problem and facilitates the generation of more accurate predictions.

Among the various clustering methods, K-means is the most frequently employed. This algorithm begins by specifying the number of clusters (K) and then groups data points based on their proximity to cluster centroids. It iteratively assigns each data point to the nearest cluster, updates the cluster centres, and repeats the process until convergence [6].

Other methods, such as density-based clustering (e.g., DBSCAN), group users or items into clusters without requiring predefined cluster counts. In book recommendation systems, DBSCAN has been combined with hybrid filtering and sentiment analysis to enhance accuracy and address data sparsity issues [35].

Thus, clustering techniques—whether centroid-based like K-means or density-based like DBSCAN—play an important role in improving scalability, personalization, and robustness in book recommendation systems.

5.2.2 Deep Learning–Based Techniques and models

- ***Convolutional Neural Networks (CNNs)***

CNNs are a class of deep learning models that automatically learn hierarchical feature representations from raw data, thereby reducing the need for manual feature engineering. Initially introduced for tasks such as image classification, object detection, and semantic segmentation in domains including medical imaging, computer vision, and natural language processing [56].

CNNs have subsequently been adapted to recommender systems due to their ability to capture spatial and local dependencies within data. They are particularly effective for extracting semantic representations from both structured attributes (e.g., item metadata) and unstructured sources (e.g., images, textual descriptions, and user-generated reviews). Their capacity to enhance item similarity analysis and user preference modeling has been validated in large-scale domains such as e-commerce and fashion. For instance, [57] developed a CNN-based recommendation framework that outperformed traditional algorithms by capturing complex interaction patterns in the Alibaba dataset.

In the domain of book recommendation systems, Convolutional Neural Networks (CNNs) have been employed in multiple innovative ways to enhance recommendation performance. For instance, they have been applied to image-based similarity analysis of book covers, enabling systems to capture visual patterns and aesthetics that influence user preferences[39]. Additionally, CNNs have been utilized for rating prediction tasks, where their ability to learn hierarchical feature representations contributes to improved predictive accuracy [40]. More recently, CNNs have been integrated into multimodal frameworks that combine textual and visual features, thereby improving the personalization and contextual relevance of recommendations [42] . These applications highlight the versatility of CNNs in managing heterogeneous data modalities. Overall, CNNs play a pivotal role in advancing book recommender systems by exploiting both visual and textual signals to enhance similarity computation, personalization, and predictive performance.

- ***Recurrent Neural Networks (RNNs):***

Recurrent Neural Networks (RNNs) are advanced pattern recognition models derived from the Multilayer Perceptron (MLP) architecture, distinguished by their feedback loop mechanism. Unlike traditional feedforward structures, RNNs map inputs to outputs while simultaneously feeding the output back into the network as input for subsequent steps. This recursive structure enables RNNs to retain contextual information from prior inputs, making them particularly effective for modeling sequential and time-dependent data. One of their notable advantages is the capacity to process input sequences of varying lengths, which is highly beneficial in domains such as load forecasting, where the availability and length of historical data may vary. Furthermore, RNNs excel at learning temporal correlations, such as those between environmental factors and user behavior, thereby improving predictive accuracy in contexts characterized by dynamic and fluctuating conditions [58]. Beyond forecasting, RNNs have demonstrated significant value in recommender systems by effectively modeling sequential user interactions. Their ability to capture both short- and long-term dependencies makes them well-suited for session-based and time-aware recommendation tasks. For example, [59] introduced a hierarchical RNN architecture that incorporates temporal intervals of different lengths in user activity, yielding improved recommendation accuracy across datasets such as MovieLens and Steam. In the context of book recommendation systems, RNNs have been employed within hybrid and multimodal frameworks to capture user dynamics and semantic information from textual reviews, thereby enhancing personalization and recommendation quality [44].

- ***Long Short-Term Memory (LSTM)***

LSTM networks represent a specialized class of Recurrent Neural Networks (RNNs) designed to address the limitations of standard RNNs in capturing long-term dependencies within sequential data [60]. Their gating mechanisms enable the selective retention and forgetting of information, allowing them to learn complex temporal patterns across extended sequences. In the domain of recommendation systems, LSTMs have proven particularly effective for modeling evolving user behaviour, as they capture how preferences shift over time based on the order and context of prior interactions [21]. Within book recommendation systems, LSTMs are frequently applied in sequence-aware models, where users' historical reading behaviours are represented as time-dependent sequences. Such models generally outperform traditional collaborative filtering and content-based methods because they can adapt to dynamic user interest patterns [21]. A common application involves next-item prediction, in which LSTM models forecast the next book a user is likely to read based on previously consumed titles. For instance, when a user repeatedly engages with books from a specific author or genre, LSTMs can recognize these temporal dependencies and recommend subsequent works that align with established preferences. [42]**.** Empirical studies demonstrate that LSTM-based recommender systems achieve superior accuracy and personalization, particularly when datasets include timestamped user–book interactions. Moreover, advanced variants such as Bidirectional LSTMs (Bi-LSTMs) and Attention-enhanced LSTMs further improve performance by capturing bidirectional context and emphasizing the most relevant temporal features, thereby enhancing recommendation quality and user satisfaction [21] [44] [48].

- ***Gated Recurrent Units (GRUs)***

GRUs are a simplified variant of Recurrent Neural Networks (RNNs) developed to efficiently capture sequential dependencies in data while mitigating the vanishing gradient problem commonly observed in traditional RNNs [61] . By employing update and reset gates, GRUs simplify the architecture compared to Long Short-Term Memory (LSTM) networks while maintaining strong performance in modeling temporal patterns. In the context of recommendation systems, GRUs are particularly effective in predicting user preferences by learning from sequences of prior interactions and dynamically adapting to evolving user interests. Several studies have highlighted the potential of GRUs within hybrid frameworks. For instance, [62]integrated GRUs with spectral clustering techniques to address cold-start and data sparsity challenges, demonstrating improvements in both recommendation accuracy and robustness. Within book recommendation systems specifically, GRUs have been applied to enhance personalization and incorporate sentiment-aware modelling. Notably, [48] combined GRUs within hybrid architecture and reported that a GRU-based approach achieved an F1-score of 98.21%, underscoring its effectiveness in aligning recommendations with user emotions and contextual preferences.

By capturing both short- and long-term dependencies in user–item interactions, GRUs significantly enhance the timing and contextual relevance of recommendations. Their adaptability makes them particularly valuable in book recommendation systems, where user interests are often dynamic, emotion-driven, and influenced by both immediate and long-term reading behaviors.

- ***Autoencoders (AEs)***

AEs are unsupervised deep learning models designed to learn efficient representations of input data by encoding it into a latent space and then reconstructing it [63]. Autoencoders are neural networks that compress data into compact representations while filtering out noise and retaining essential features. In recommendation systems, autoencoders are widely used to model user–item interactions, reduce dimensionality, and alleviate data sparsity, making them particularly effective for collaborative filtering tasks. Recent advancements have further enhanced the role of autoencoders in recommendation systems.For instance, [64] proposed a personalized e-learning recommendation system based on autoencoders, which achieved superior accuracy compared to traditional models such as KNN, SVD, and NMF, demonstrating lower RMSE and MAE by effectively capturing learner preferences in sparse educational datasets [64].

- ***Bidirectional Encoder Representations from Transformers (BERT)***

BERT, introduced by Google in 2018, represents a major breakthrough in natural language processing (NLP) by enabling models to capture deeper contextual understanding of words within sentences [65]. Built upon the transformer architecture, BERT employs multi-layer self-attention mechanisms to model complex word dependencies and relationships. Its tokenizer converts raw text into tokens mapped to unique IDs, allowing the model to generate rich, contextualized embeddings of language [65] [66].

A defining strength of BERT lies in its bidirectional processing capability, which incorporates contextual information from both preceding and succeeding words, thereby providing a more comprehensive semantic representation. Pre-trained on large-scale corpora through unsupervised objectives such as Masked Language Modelling (MLM) and Next Sentence Prediction (NSP), BERT demonstrates strong generalization across a wide range of downstream NLP tasks**[66]**.

BERT has been successfully applied in diverse recommendation-related tasks, particularly those involving textual and semantic analysis. For example, [67] proposed a BERT-enhanced Neural Citation Network that integrates contextual features such as titles and abstracts to improve citation recommendations. Their approach achieved superior accuracy and stability on the arXiv CS dataset by leveraging BERT embeddings in combination with self-attention mechanisms[67].

In the context of book recommendation systems, BERT has been integrated into hybrid and ensemble frameworks to enhance semantic modeling. [48] incorporated BERT embeddings alongside CNN, LSTM, BiLSTM, and GRU within an ensemble-based hybrid architecture, enabling the system to capture nuanced contextual information from user reviews. This integration significantly improved recommendation accuracy and user satisfaction, underscoring the pivotal role of BERT in advancing text-driven personalization in book recommendation systems.

- ***Neural Collaborative Filtering (NCF)***

NCF is a neural-based matrix factorization framework that integrates Generalized Matrix Factorization (GMF) and Multi-Layer Perceptron (MLP) to leverage both linear and nonlinear modeling capabilities for learning user-item interactions [68]. Recent advancements have demonstrated t he effectiveness of NCF in recommendation systems. For ex ample, Dhayanidhi conducted a comparative study using the MovieLens dataset, showing that NCF consistently outperformed Probabilistic Matrix Factorization (PMF) in terms of precision (0.85 vs. 0.78), recall (0.83 vs. 0.75), and F1-score (0.84 vs. 0.76). Their findings confirmed that NCF's ability to capture nonlinear interactions and learn hierarchical user-item representations contributes significantly to improved recommendation accuracy [69]. Within book recommendation systems specifically, NCF has been further extended to hybridized frameworks. [45] introduced an advanced model that integrated NCF with Alternating Least Squares (ALS) and dynamic personalization techniques deployed via real-time streaming platforms such as Apache Kafka. Their findings revealed that combining NCF with real-time personalization mechanisms enhanced scalability, adaptability, and predictive accuracy, demonstrating the potential of NCF-based approaches to advance the efficiency and effectiveness of book recommendation systems.

- ***Deep Neural Networks (DNNs)***

DNNs are a type of machine learning architecture inspired by the human brain. It comprises multiple layers of interconnected neurons, where each layer transforms its input data to uncover deeper patterns and relationships. These networks are powerful due to their depth—typically involving multiple "hidden layers"—which allows them to model highly non-linear and abstract features in data [70]. DNNs have been successfully applied across a wide range of domains, including image recognition, natural language processing, and increasingly, recommendation systems. Their ability to process massive datasets and automatically learn useful feature representations makes them highly effective for personalized decision-making tasks [71] .In the context of recommendation systems, DNNs are utilized to model intricate user–item interactions and uncover latent features that traditional techniques, such as collaborative filtering and matrix factorization, often fail to capture. Unlike linear methods, DNNs can integrate behavioural patterns, content metadata, and auxiliary contextual information to improve recommendation quality [72].

Within book recommendation systems, a notable application of DNNs is the DNNRec model proposed by Kiran et al. in 2020 [38]. This model addresses the cold-start problem by incorporating additional user and item information into a deep neural network framework. Through its hidden layers, DNNRec learns complex, non-linear relationships and generates highly personalized recommendations. Empirical results have shown that it outperforms traditional approaches in terms of precision, recall, and F1-score across benchmark datasets. Overall, the DNNRec demonstrates how deep neural networks can be effectively tailored for domain-specific recommendation tasks, such as book suggestions, where heterogeneous content and sparse user behaviour data must be integrated to deliver accurate and personalized suggestions.

- ***Graph Convolutional Networks (GCNs)***

GCNs are a class of deep learning models specifically designed to operate on graph-structured data. Unlike conventional Convolutional Neural Networks (CNNs), which process Euclidean data such as images, GCNs extend convolution operations to graphs by aggregating information from a node's neighbors and capturing higher-order connectivity patterns [73]**.** This ability to model relationships beyond direct connections makes GCNs particularly well-suited for domains characterized by complex interdependencies among entities.

In the field of recommendation systems, GCNs have demonstrated considerable effectiveness by learning context-aware embeddings that integrate both user–item interactions and auxiliary content information. They excel in capturing high-order connectivity (e.g., a user connected to an item that is also linked to other similar users), thereby addressing common challenges such as data sparsity and cold-start problems through enriched representations derived from neighbour propagation. For example, [74] introduced the LightGCN model, which simplified traditional GCN architectures by eliminating feature transformation and nonlinear activation functions, yet achieved state-of-the-art performance in collaborative filtering tasks .

Book recommendation systems benefit significantly from the flexibility of GCNs, as books and their related entities—such as authors, genres, topics, and readers—can be naturally modeled as graph structures. Edges in such graphs encode semantic and behavioral relationships, including co-reading patterns and thematic similarities. By leveraging these connections, GCNs can integrate heterogeneous data sources (e.g., titles, categories, reviews, and ratings) and capture semantic associations across knowledge graphs. Moreover, attention mechanisms enhance these models by prioritizing the most relevant relationships for generating recommendations. For instance, [46] proposed a digital book recommendation framework that combined knowledge graphs, an optimized GCN, and attention mechanisms to improve recommendation quality. The model achieved Recall@20 = 0.3586 and NDCG@20 = 0.6325, demonstrating its effectiveness in handling sparse, large-scale digital book datasets while modeling user preferences. This contribution highlights the value of GCNs in advancing personalized book recommendation research.

5.3 Datasets Commonly Utilized in BRSs

Datasets play a crucial role in developing and evaluating book recommendation systems. They provide standardized benchmarks containing user ratings, book metadata, and other relevant information. This section outlines key datasets widely used in BRS research to support model training and performance evaluation.

- ***Book-Crossing dataset***

The Book-Crossing Dataset is a widely used benchmark for evaluating book recommendation systems**.** It was originally collected by Cai-Nicolas Ziegler in a 4-week crawl (August–September) from the Book-Crossing community in 2004. The dataset is freely accessible for research and experimental use via Kaggle datasets, where it is presented in three interlinked tables(BX-Users, BX-Books, and BX-Books- Ratings). Specifically, it contains 278,858 user records, 271,360 book entries, and a total of 1,149,780 user ratings, providing a diverse and realistic foundation for developing, training, and evaluating book recommendation system algorithms, particularly for addressing challenges such as data sparsity and cold-start scenarios.

- ***Amazon Book Reviews***

The Amazon Books Reviews dataset, available on Kaggle website, comprises 12,886,488 reviews collected over an 18-year period, making it a valuable resource for researchers and practitioners focused on book recommendation systems, sentiment analysis, and other related fields. Sourced directly from the Amazon book reviews platform, the dataset includes approximately 3M reviews covering 212,404 unique book titles, along with corresponding user information and rating data. It offers rich and comprehensive content, capturing both quantitative ratings and qualitative user feedback in varying lengths and sentiment tones. The dataset is organized into two main CSV files: Books_ratings.csv, which contains user-book interactions, and Books_data.csv, which includes detailed metadata such as book titles, authors, publishers, publication dates, and descriptions. Additionally, over 1 million textual reviews are provided, enabling fine-grained sentiment classification into positive, neutral, and negative categories. In several studies, this dataset has been utilized as a foundational benchmark for assessing proposed models, providing a rich and diverse resource for analyzing user sentiment and behavioral patterns within the scope of book recommendation systems.

- ***Book Recommendation System Dataset***

The Book Recommendation System Dataset, publicly available on Kaggle website , is another widely adopted benchmark for developing and evaluating book recommendation systems. This dataset was selected in several studies due to its comprehensive structure, which includes detailed information on user demographics, book metadata, and explicit user ratings. It is organized into three interrelated CSV files: Books.csv, which contains bibliographic details such as ISBN, title, author, and publisher; Users.csv, which includes user ID, location, and age; and Ratings.csv, which records user–book interactions through rating scores. The dataset contains over 1.1 million ratings from more than 53,000 users on a large corpus of books, offering a robust foundation for collaborative filtering, content-based, and hybrid recommendation approaches. Its well-structured format and the inclusion of demographic data make it particularly useful for modeling personalized recommendations and addressing challenges like user preference modeling and cold-start scenarios.

- ***Good Books dataset***

The Good Books dataset was originally introduced by Zygmunt Zając in 2017[75], and is frequently leveraged in book recommender systems research. The dataset is publicly available via Kaggle as the Goodbooks-10k on Kaggle. This dataset includes real-world user interactions and rich metadata, making it well-suited for both collaborative filtering and content-based recommendation techniques. It presents a well-structured user–item matrix suitable for training and evaluating recommendation models. It comprises approximately 6 million ratings approximately about six ratings across 10,000 of the most highly rated and popular books, provided by a total of 53,424 users. It also includes metadata such as ISBN, title, author, year, and features ratings on a scale from 1 to 5, with a high sparsity level of 98.88%. The dataset has been widely adopted for benchmarking recommendation algorithms due to its balance of size, structure, and metadata richness.

5.4 Evaluation Metrics Mostly Employed in BRSs

Recommendation Systems Evaluating the performance of book recommendation systems is essential for understanding the effectiveness of different algorithms and techniques. To achieve this, researchers utilize a variety of evaluation metrics that measure prediction accuracy, ranking quality, and user satisfaction. The choice of metric depends on the recommendation task, dataset characteristics, and the underlying filtering approach. This section presents the most commonly used metrics in BRS research.

- ***Mean Absolute Error (MAE)***

MAE is one of the most widely used evaluation metrics in recommender systems. It quantifies the average difference between the predicted ratings and the actual ratings provided by users. A lower MAE value indicates that the recommendation engine is more accurate in predicting user preferences. The MAE is calculated using the formula (8) [76]:

$$\text{MAE} = \frac{1}{N}\sum_{u,i} | p_{u,i} - r_{u,i} | \cdot \qquad (8)$$

Where is $p_{u,i}$ is the predicted rating for user u and item i, $r_{u,i}$ is the actual rating, and N is the total number of predictions.

- ***Mean Squared Error (MSE)***

MSE is a widely used evaluation metric that measures the average of the squared differences between the actual values $(r_{u,i})$ and the predicted values $(\hat{r}_{u,i})$ across all instances in a dataset[18]. It quantifies the prediction accuracy of a model by penalizing larger errors more severely due to the squaring operation. MSE is especially useful during model training and optimization, as it is a smooth, differentiable loss function. However, its output is in squared units of the original values, which may limit interpretability. MSE is calculated as the equation (9):

$$MSE = \frac{1}{N}\sum_{u,i}\left(r_{u,i} - \hat{r}_{u,i}\right)^2 \qquad (9)$$

Where $r_{u,i}$ is the actual rating, $\hat{r}_{u,i}$ is the predicted rating, and N is the total number of user-item pairs evaluated.

- ***Root Mean Squared Error (RMSE)***

Root Mean Squared Error (RMSE) is a widely used statistical metric for assessing the predictive accuracy of recommender systems. Unlike Mean Absolute Error (MAE), RMSE places greater emphasis on larger errors by squaring the residuals before averaging, making it more sensitive to outliers and poor predictions. Consequently, RMSE typically produces higher values than MAE. One of its key advantages is that it retains the same unit as the original values (e.g., rating scale), which enhances interpretability compared to Mean Squared Error (MSE). A lower RMSE value indicates that the recommendation model generates predictions that are closer to the actual ratings, thus reflecting higher accuracy. RMSE is mathematically derived from MSE and is computed as the square root of the mean of the squared differences between actual and predicted values. The RMSE is calculated using the formula (10) [76]:

$$\text{RMSE}=\sqrt{\text{MSE}} = \sqrt{\frac{1}{N}\sum_{u,i}\left(r_{u,i} - \hat{r}_{u,i}\right)^2} \quad . \qquad (10)$$

- ***Accuracy***

Accuracy is one of the most straightforward and commonly used metrics for evaluating the performance of classification and recommendation systems. It is defined as the proportion of correctly predicted instances (both true positives and true negatives) out of the total number of predictions, as presented in Equation (11) or (12):

$$\text{Accuracy} = \frac{\textit{Number of correct recomendations}}{\textit{Total number of recommendations}} \quad . \qquad (11)$$

Or:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad . \qquad (12)$$

Where, TP = True Positives, TN = True Negatives, FP = False Positives, and FN = False Negatives.

- ***Precision and Recall***

Precision and Recall are key evaluation metrics used to assess the performance of recommendation systems, particularly in identifying relevant items and dealing with imbalanced data or binary classification problems **[77]**. Precision measures the proportion of recommended items that are actually relevant to the user, while Recall measures the proportion of relevant items successfully recommended out of all possible relevant items [78]. Precision is calculated using the formula (13):

$$\text{Precision} = \frac{TP}{TP+FP} \quad . \qquad (13)$$

Where TP is True Positive and FP is False Positive. In this case, precision refers to the accuracy of the recommendations by minimising incorrect suggestions. In contrast, Recall measures the system's ability to retrieve all relevant items and is computed as in formula (14):

$$\text{Recall} = \frac{TP}{TP+FN} \quad . \qquad (14)$$

Where TP is True Positive and FN is False Negative.
A high Precision score reflects fewer false recommendations, while a high Recall score indicates the system's effectiveness in covering relevant content for the user. Both metrics are crucial for evaluating the balance between relevance and completeness in book recommendation systems.

- ***F-measure (F1-score)***

F1-score is an evaluation metric that combines Precision and Recall into a single value. While precision indicates the proportion of recommended items that are relevant, and recall reflects the proportion of relevant items that are successfully recommended, the F-measure provides a harmonic mean of the two. This ensures that the score only becomes high if both Precision and Recall are reasonably high [76, 79] . F1-score is particularly useful when both false positives and false negatives need to be minimized, such as in spam detection or personalized content recommendations [79, 80]. It calculates by using formula (15):

$$\text{F1} - \text{score} = \frac{\textit{Precision} \times \textit{Recall}}{\textit{Precision}+\textit{Recall}} \quad . \qquad (15)$$

- ***Normalized Discounted Cumulative Gain (NDCG)***

NDCG is a widely adopted evaluation metric in both recommendation systems and information retrieval, particularly suited for ranking-based tasks. It accounts for not only the graded relevance of items (e.g., user ratings) but also their position in the ranked list. The NDCG evaluates how effectively a recommendation system prioritizes relevant items, assigning greater weight to those that appear earlier in the recommendation list**[81]**. This makes it especially useful when the order of recommendations impacts user experience. The NDCG metric is computed using the formula (16) **[82]**:

$$\text{NDCG@k} = \frac{1}{\text{IDCG@}k}\sum_{i=1}^{k}\frac{2^{rel_i}-1}{log_2(i+1)} \quad . \qquad (16)$$

In this formula, rel_i denotes the graded relevance score (e.g., a user rating) of the item at position i in the recommended list. The numerator represents the Discounted Cumulative Gain (DCG), which accounts for the position of relevant items using a logarithmic discount to prioritize higher-ranked results. The denominator, IDCG@k, represents the Ideal DCG and reflects the maximum possible DCG that can be obtained from a perfectly ranked list. By normalizing DCG with IDCG, the resulting NDCG@k score ranges between 0 and 1, where a value of 1 indicates a perfectly ranked recommendation list.

5.5 Key Challenges in Book Recommendation Systems

Despite the rapid advancements in deep learning and hybrid approaches, book recommendation systems still face several persistent challenges. These include:

- ***Cold Start Problem***

The cold-start problem emerges when the recommendation system encounters new users or items with no historical interaction data, thereby significantly impairing the performance of collaborative filtering (CF) methods [2].

This issue typically manifests in three scenarios: (a) the arrival of a new user, (b) the introduction of a new item, or (c) the formation of a new user group or community. Since CF depends heavily on prior user–item interaction data, it struggles to generate accurate recommendations in the absence of such information [76] .

- ***Data Sparsity***

Data sparsity is one of the most critical challenges in building effective recommendation systems. It occurs when the user-item interaction matrix, used in collaborative filtering (CF), has very few recorded interactions compared to the total number of possible interactions [83] In large-scale systems, users typically engage with only a small subset of items, resulting in a highly sparse matrix that lacks enough information to establish meaningful connections between users and items[84]. This issue significantly impacts the performance of CF algorithms, which depend on historical interactions to measure user-user or item-item similarity. When most matrix entries are empty, it becomes difficult to calculate these similarities accurately, often leading to weak or irrelevant recommendations [85].

- ***Scalability***

Scalability in recommender systems refers to the ability of the system to maintain high levels of efficiency, responsiveness, and accuracy as the volume of users, items, and interactions grows. In large-scale digital environments, such as e-commerce platforms and streaming services, scalability ensures that the system can continue delivering relevant recommendations in real-time without degradation in performance. Traditional algorithms, including those based on matrix factorization and collaborative filtering, often face challenges with scalability due to increased computational load and data sparsity [86].

- ***Over-Specialization Issue***

Over-specialization in recommender systems refers to the problem where a system consistently suggests items that are overly similar to those previously liked by the user, leading to a lack of diversity and novelty in recommendations. Content-Based Filtering (CBF) methods are particularly susceptible to this issue, as they rely heavily on item feature similarities[87].

- ***Diversity Issue***

In many scenarios, recommendation systems may suggest items that are either closely related or intentionally varied. However, the most accurate outcomes often come from recommending items based on similarities between users or items. This leads to the diversity issue, where recommendations tend to emphasize commonalities rather than differences. As a result, users are exposed to a limited range of content, potentially missing out on less popular but highly relevant niche items.

This issue is especially pronounced in collaborative filtering (CF) systems. Because CF heavily relies on historical user-item interactions, it reinforces the popularity of frequently rated or viewed items, often recommending the same popular content to many users. This leads to popularity bias, where niche items or those in the "long tail" of the item distribution are underrepresented or ignored, even if they may be relevant to user interests [88, 89] .As a result, users are frequently exposed to a narrower selection of items, limiting discovery and personalization. This effect can compromise user satisfaction and fairness, particularly for users with unique tastes or those seeking less mainstream content.

- ***Popularity bias***

Popularity bias refers to the tendency of recommendation algorithms to favour items that are already popular (i.e. with many interactions / ratings), over less popular (long-tail) items. This means popular books (or items) get recommended more frequently, which increases their exposure further. The bias comes from data distribution (few items get many ratings, many items get few), collaborative filtering algorithms favouring items with many past interactions, feedback loops (popular items get more exposure, thus more interactions, reinforcing their popularity).

- ***Computational Resources and Cost***

Modern book recommendation systems that leverage deep learning models such as CNN, RNN, and GNNs require substantial computational resources across several dimensions. Training demands high-performance hardware (e.g., GPUs) and memory due to large models and datasets. Real-time inference introduces latency challenges, especially for complex models. Storage requirements are also high due to extensive metadata and precomputed features. Additionally, infrastructure and energy costs increase with scale, and frequent retraining and model updates further contribute to overall system maintenance costs.

- ***Dataset Constraints***

Dataset constraints present substantial challenges in the development of effective book recommendation systems. Many datasets, such as Amazon Books or Goodreads, suffer from limited accessibility due to copyright restrictions or API changes, hindering reproducibility and benchmarking. These datasets are often sparse, with users rating only a few books, leading to poor performance in collaborative filtering models, especially in cold-start scenarios. Additionally, ratings tend to be skewed toward popular titles, creating class imbalance and reducing recommendation diversity. Most datasets also lack multimodal features like images or reviews and often contain noisy or inconsistent data that require extensive cleaning. Moreover, contextual and temporal information, critical for modeling dynamic user preferences, is frequently missing. The absence of standardized datasets and evaluation protocols further complicates fair comparisons across different models and studies.

- ***Evaluation Metric Limitations***

Most book recommendation models are currently evaluated using limited metrics such as Precision, Recall, or RMSE, which primarily capture short-term accuracy. These measures, while useful, fail to account for long-term user satisfaction, interpretability, and trust in recommendations. This narrow focus can result in systems that optimize numerical performance but overlook important dimensions such as diversity, novelty, coverage, and fairness. Addressing this gap requires the adoption of multi-faceted evaluation frameworks that incorporate both accuracy-based and user-centric measures, ensuring sustainable effectiveness and meaningful personalization in book recommendation systems.

5.6 Research Trends and Future Directions

The publication trend in book recommendation systems, from 2020 to February 2025, reveals a steady increase in scholarly interest within this domain. As illustrated in Figure 9, the number of studies has generally increased over the years.

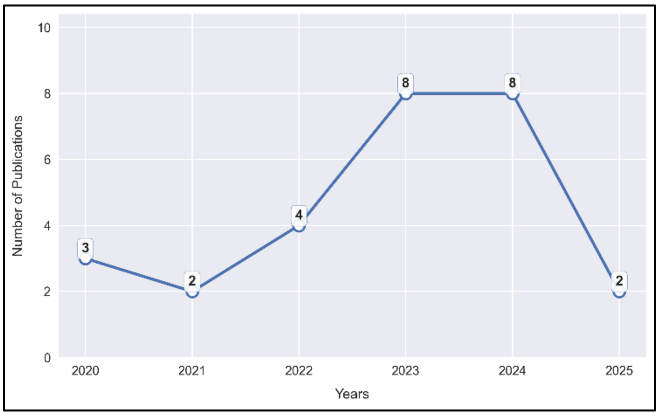

Figure 9: Number of publications on BRSs from 2020 to February 2025

Early contributions In 2020 three publications marked the early stage of this period, followed by a slight decline to two in 2021, reflecting limited activity during that year. Research interest gained momentum in 2022, with four publications, signalling the beginning of a steady upward trend. The field reached its peak in 2023 with eight publications, representing the most productive year within the observed timeframe. This surge coincides with the growing adoption of advanced recommendation frameworks and reflects heightened scholarly attention to addressing persistent challenges in personalization, cold-start issues, and data sparsity. The field maintained this momentum in 2024 with another eight publications, indicating sustained research interest and the consolidation of novel techniques. By early 2025, only two publications had been documented, which is more likely due to the partial coverage of the year rather than an actual decline in research activity.

Figure 10 also illustrates the comparative research trends between traditional approaches and deep learning approaches.

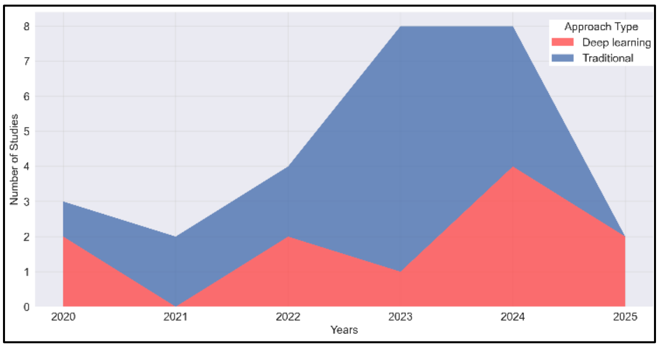

Figure 10 : Comparative research trends in BRSs approaches

In 2020, both approaches were represented, with traditional methods slightly more prominent, while deep learning began to emerge with two publications. By 2021, research relied almost entirely on traditional approaches, as no deep learning studies were recorded that year. In 2022, the field entered a transition phase, with both approaches contributing equally (two papers each), reflecting an exploratory period where researchers began to integrate neural models into book recommendation tasks.

The peak in 2023 was characterized by eight publications, with traditional approaches dominating (seven studies) and only one study adopting deep learning. This indicates that collaborative filtering, content-based filtering, and hybrid similarity-driven frameworks remained the primary methodological foundation, particularly within library and academic contexts. In 2024, the total number of publications remained high at eight; however, the distribution of approaches shifted significantly. Deep learning studies increased to four, while traditional methods declined to four, marking a pivotal turning point in methodological preferences. This balance reflects the growing influence of neural network–based techniques—such as CNNs, RNNs, NCF, and transformer-based architectures like BERT—which have shown superior capacity to overcome the limitations of traditional methods while delivering more adaptive and personalized recommendations. By early 2025, deep learning approaches (two papers) appear to be sustaining their momentum, whereas traditional methods are no longer represented, marking a clear methodological shift in the field.

Overall, the research trend from 2020 to 2025 demonstrates two key insights: (1) a general upward trajectory in the number of studies, with 2023and 2024 marking a turning point for intensified research, (2) a shifts from traditional to deep learning approaches, particularly evident from 2022 onward. While traditional methods dominated the early years (2020–2023), the gradual emergence and consistent rise of deep learning approaches between 2022 and 2025 highlight an ongoing transition toward more effective , scalable, and accurate models.

In context of Future Directions, the observed research trends from 2020 to early 2025 suggest several promising directions for advancing book recommendation systems. The decline of traditional approaches and the corresponding rise of deep learning methods indicate that future research will continue to prioritize neural architectures, with an emphasis on scalability, accuracy, and personalization. In particular, In particular, **hybrid deep learning frameworks**, such as combining Neural Collaborative Filtering (NCF) with transformer-based models like BERT, or integrating CNNs for cover image analysis with RNNs for sequential behaviour modelling, are likely to become more prominent, as they directly address challenges such as data sparsity, cold start, and overspecialization.

Another significant direction is **multimodal integration**, where textual, visual, contextual, and behavioural data are combined to generate richer user and item representations. This approach can substantially improve recommendation accuracy by leveraging diverse information sources, including book reviews, metadata, and cover images. Similarly, the growing adoption of **self-supervised and contrastive learning** presents opportunities to learn robust user–item embeddings without heavy reliance on labelled data, thereby making models more resilient in sparse and imbalanced datasets.

Explainability and transparency are also expected to emerge as central priorities. As models become increasingly complex, interpretable explanations for recommendations will be crucial for fostering user trust, particularly in educational and academic contexts. Alongside this, concerns about **fairness, bias mitigation, and privacy preservation** will become more pressing, ensuring that book recommendation systems deliver equitable and ethical outcomes.

Beyond technical improvements, **domain adaptation and transfer learning** represent valuable opportunities. Leveraging knowledge from related domains such as movies, music, or e-learning can enhance generalization and robustness in book recommendations. Moreover, **personalization and context awareness** will play an essential role, with future systems expected to capture temporal dynamics, reader intent, and contextual signals (e.g., reading environment, device type, or time of day) to generate more adaptive recommendations.

Finally, the **scalability and efficiency** of recommendation models will remain a key research concern. With datasets continuing to expand, optimizing computational costs, inference speed, and deployment strategies for large-scale applications will be critical. In parallel, the expansion of recommendation systems into emerging domains—such as digital libraries, e-learning platforms, and academic publishing—suggests that future research will not only refine predictive performance but also adapt to domain-specific needs. This will involve developing context-aware, cross-domain, and personalized recommendation solutions that extend beyond traditional accuracy metrics to enhance user engagement, satisfaction, and long-term learning outcomes.

In summary, the future of book recommendation systems is likely to be shaped by multimodal, hybrid, explainable, and context-aware models. These advances will not only improve predictive performance but also ensure fairness, inclusivity, and broader applicability across real-world platforms. Traditional approaches, while declining, will remain relevant primarily as baseline methods for benchmarking and comparative evaluation.

VI. CONCLUSION and FUTURE RESEARCH

This survey analyzed the evolution of book recommendation systems from 2020 to February 2025, with a focus on methodological approaches, applied techniques, datasets, evaluation metrics, and research challenges. The review shows that while traditional methods—including CF, CBF, and hybrids—accounted for 59% of the surveyed studies, their dominance has steadily declined as deep learning–based methods have gained momentum. Neural models such as CNNs, RNNs, LSTMs, BERT, and GCNs have demonstrated superior performance in accuracy, scalability, and personalization, particularly in handling multimodal data. This methodological shift highlights the increasing importance of advanced architectures for overcoming limitations such as sparsity, cold start, and overspecialization. At the same time, persistent issues remain, including dataset constraints, high computational costs, limited interpretability, and evaluation practices that focus too narrowly on metrics like Precision, Recall, or RMSE without accounting for long-term user satisfaction. Future research may further explore modern advances in deep learning–based recommendation systems, with a focus on emerging architectures such as transformers, graph neural networks, and self-supervised learning. These approaches can be applied to address persistent challenges in book recommendation systems, including data sparsity, cold-start problems, and the need for improved personalization. In future work, the researchers plan to review studies that apply multimodal frameworks integrating textual, visual, and contextual information, as well as studies that propose the development of explainable and user-centric models aimed at enhancing transparency, fostering trust, and supporting long-term user engagement.

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VIII. Declaration of Computing Interest

The authors declare no competing financial or personal interests influencing this work.

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