

Using AI to Recommend Books: A Review of Current Methods

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Abstract - The growth of digital libraries, online bookstores and electronic reading platforms has increased the number of books available to readers and, consequently, the difficulty of selecting relevant titles. Book recommendation systems address this information-overload problem by using item content, user preferences, ratings and historical interactions to generate personalized suggestions. This focused review examines research supplied for the study, with primary attention to publications from 2021 to 2026. The reviewed literature covers content-based filtering, collaborative filtering, clustering, nearest-neighbor methods, matrix factorization, deep-learning embeddings, natural language processing and language-model-assisted recommendation. The evidence shows that traditional representations such as TF-IDF and cosine similarity remain common, while hybrid systems increasingly combine content and interaction signals. Reported evaluation practices include precision, recall, F1, RMSE, MAE, confusion-matrix analysis and user testing. Because the reviewed studies use different datasets, tasks and evaluation protocols, their numerical results should not be interpreted as a direct ranking of algorithms. Recurring challenges include cold-start conditions, data sparsity, metadata limitations, personalization, diversity, privacy, explainability and inconsistent evaluation. The review identifies opportunities for richer book representations, hybrid architectures, NLP and transformer-based semantic modeling, explainable recommendations, context-aware personalization and privacy-conscious evaluation.

Key Words: Book Recommendation System; Artificial Intelligence; Machine Learning; Deep Learning; Natural Language Processing; Content-Based Filtering; Collaborative Filtering; Hybrid Recommendation.

1. INTRODUCTION

Recommendation systems are information-filtering systems designed to help users select relevant items from a large collection. In the book domain, the recommendation task can involve books in public or academic libraries, online bookstores, digital reading platforms and educational collections. The problem is not simply to identify popular books; a useful system should account for differences among users and, where possible, represent the characteristics of individual books. The literature supplied for this review shows that these requirements have led researchers to combine information such as titles, authors, genres, descriptions, ratings, user histories and textual reviews.

Recent book-recommendation research continues to use established filtering approaches while incorporating machine learning and deep learning. Sarma, Mittra and Hossain (2021) investigated clustering, K-means and cosine-distance based recommendation. Other reviewed studies use content-based filtering with TF-IDF and cosine similarity, collaborative filtering based on user-item interactions, and hybrid systems that combine complementary signals. A 2022 study explored GPT-3 together with the Google Books API, illustrating an early language-model-assisted workflow. More recent work includes embedding-based hybrid recommendation and systematic review research examining the broader book-recommendation literature.

The central objective of this article is therefore to organize the recent evidence rather than to present a new experimental system. The review emphasizes how the reviewed studies represent books and users, which algorithms they apply, how they evaluate recommendations, and which limitations recur across approaches. The article also separates reported findings from proposed future directions so that claims from individual papers are not presented as general performance guarantees.

1.1 Motivation and Problem Definition

A book recommendation task can be represented as the generation of a ranked list of candidate books for a user. The input may include a user profile, previous ratings, reading history, a selected book, or a textual query. The system then estimates relevance using one or more signals. In a content-based system, relevance is derived mainly from similarity between book representations. In collaborative filtering, relevance is inferred from relationships among users and items. Hybrid systems combine these sources.

1.2 Objectives of the Review

The objectives are: (i) to summarize AI and machine-learning techniques used for book recommendation; (ii) to compare the information and evaluation practices reported by the supplied studies; (iii) to identify recurring technical and user-centered challenges; and (iv) to organize research gaps and future directions supported by the reviewed literature.

2. REVIEW METHODOLOGY

This article is a focused literature review based on the research papers supplied for the study. Primary attention is given to publications dated 2021-2026, while older references appearing in the supplied papers are used only when they provide foundational context. The review does not claim exhaustive coverage of every book-recommendation publication or every database. Instead, the supplied studies are grouped by recommendation paradigm, learning technique, data representation, evaluation practice and reported limitation.

2.1 Review Questions

The synthesis is organized around five questions:

- RQ1: What AI and machine-learning techniques are used for book recommendation?
- RQ2: How are content-based, collaborative and hybrid approaches applied?
- RQ3: What datasets, representations and evaluation measures are reported?
- RQ4: What recurring limitations affect personalization and recommendation quality?
- RQ5: What future research directions are indicated by the reviewed literature?

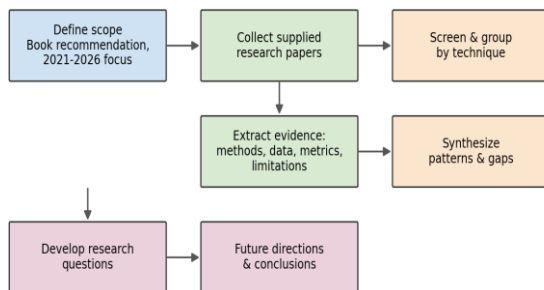


Fig -1: Focused review methodology used in this article

2.2 Evidence Extraction

For each selected paper, the review records the publication year, recommendation approach, input information, algorithmic technique, dataset or application context, reported evaluation method and stated limitations. This makes it possible to compare the structure of the research without treating unlike metrics as if they were measured under the same conditions.

2.3 Scope and Interpretation

The review uses a descriptive synthesis. For example, a paper reporting RMSE is not placed numerically above a paper reporting Precision@10 because these metrics

answer different evaluation questions. Likewise, results from different datasets cannot automatically be interpreted as evidence that one algorithm is universally superior. The comparison table later in this paper is therefore intended to show methodological diversity rather than provide a ranking.

3. CONCEPTUAL FOUNDATIONS OF BOOK RECOMMENDATION

3.1 Recommendation Signals

The supplied literature identifies several types of evidence. Item-side information includes title, author, genre, description, synopsis, publication information and other metadata. User-side information includes ratings, reading history, interactions and profile attributes. Textual information includes descriptions and reviews that can be processed with NLP. Interaction information captures relationships between users and books and is especially important for collaborative filtering.

3.2 General Recommendation Pipeline

A typical AI-based book recommender contains stages for data collection, preprocessing, representation, model learning or similarity computation, candidate generation, ranking and user feedback. The exact pipeline varies by approach. Content-based systems may not require a large user-item matrix, whereas collaborative systems depend strongly on interaction data. Hybrid systems introduce an additional fusion or ranking stage.

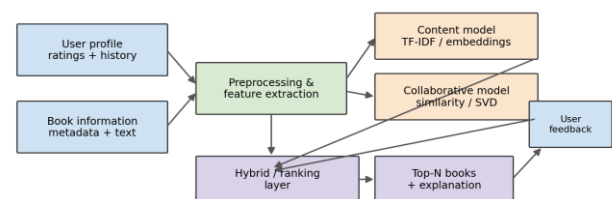


Fig -2: Conceptual architecture of an AI-based book recommendation system

4. AI TECHNIQUES IN BOOK RECOMMENDATION SYSTEMS

4.1 Content-Based Filtering

Content-based filtering recommends books whose attributes are similar to the attributes of books or topics preferred by the user. In the reviewed literature, book title,

author, genre and description are common features. A frequent text-processing pipeline converts the descriptive fields into numerical vectors using TF-IDF and then calculates similarity using cosine similarity. The approach is attractive for library settings because it can operate from book metadata without requiring a large community of users.

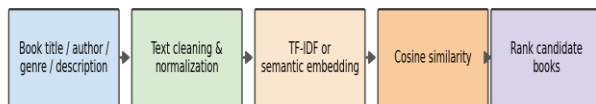


Fig -3: Typical content-based filtering pipeline

Saputri and Suryati (2025) describe a content-based application using TF-IDF and cosine similarity and report Precision@10 of 70%, Recall@10 of 58% and F1@10 of 63% in their evaluation. Rosidah and Dellia (2024) similarly apply TF-IDF and cosine similarity in a library setting. These studies also illustrate a limitation: recommendation quality is dependent on the completeness and informativeness of the metadata. If descriptions are short or inconsistent, textual similarity may not represent the user's actual interest.

4.2 Collaborative Filtering

Collaborative filtering infers preference from interactions among users and items. A basic intuition is that users with similar rating or reading patterns may be interested in similar books. The supplied studies include clustering, K-means, cosine distance, nearest-neighbor approaches and matrix-factorization techniques. Collaborative methods can capture relationships that are difficult to express through metadata alone, but they are sensitive to sparse interaction matrices and the cold-start problem.

4.3 Matrix Factorization and SVD

Matrix-factorization approaches represent users and books in a lower-dimensional latent space. Singular Value Decomposition (SVD) is one such approach appearing in the reviewed literature. Harahap's hybrid study combines TF-IDF-based content filtering with SVD-based collaborative filtering on the Goodbooks-10k dataset. The reported dataset contains 10,000 books, 981,756 ratings and 53,424 unique users. The study reports RMSE and MAE for its collaborative component and diversity and coverage measures for the content-based component.

4.4 Hybrid Recommendation

Hybrid recommendation combines multiple sources of evidence. A common combination is content-based filtering plus collaborative filtering. The motivation is complementary: content can provide information when interaction data are weak, while collaborative patterns can capture relationships that metadata similarity misses.

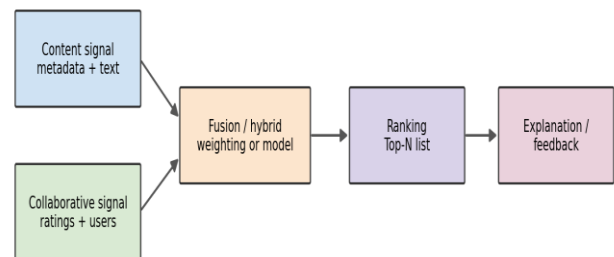


Fig -4: Hybrid recommendation - complementary information sources

Remadnia, Maazouzi and Chefrour (2025) describe a hybrid e-book recommendation mechanism combining collaborative filtering, content-based recommendation and embedding-based deep learning. Their reported evaluation gives MAE 0.51 and RMSE 0.69 on a Book Recommendation Dataset. These values are reported findings from that study and should not be compared directly with Precision@10 or F1@10 from other studies.

4.5 Machine Learning Techniques

Machine learning appears at several levels of the recommendation pipeline. Clustering can group users or books with similar patterns. K-nearest-neighbor methods can retrieve similar books or users. Regression and matrix-factorization methods can estimate ratings or latent preferences. The reviewed work shows that the algorithm alone does not determine recommendation quality: preprocessing, feature construction, data sparsity, hyperparameters and evaluation design also influence results.

4.6 Deep Learning and Embeddings

Deep-learning methods can learn dense representations of books, users or interactions. Embeddings allow semantically related items to occupy nearby positions in a learned representation space. The reviewed literature includes embedding-based hybrid recommendation and studies discussing neural approaches for book-related recommendation. The main potential advantage is richer representation of complex relationships, while the

practical costs include greater computational requirements, model complexity and the need for appropriate training data.

4.7 Natural Language Processing

Book descriptions and reviews contain information about themes, topics, sentiment and narrative characteristics. NLP can transform this unstructured information into features that are more expressive than simple categorical metadata. The reviewed studies and their references point toward word embeddings, LSTM/CNN-based text processing, transformer-based representations and language-model-assisted recommendation. However, semantic richness does not by itself prove better recommendation quality; an NLP-based system still requires suitable evaluation against an explicit recommendation task.

4.8 Language Models and GPT-Based Recommendation

Dubey and Gandhimathi (2022) describe a book recommendation system using GPT-3, Python, Streamlit and the Google Books API. The user enters a book and the language-model component produces similar-book suggestions, while the API provides book information. The study identifies practical limitations including dependence on API data availability and the cost associated with GPT-3 use. This work is relevant because it illustrates a transition from conventional similarity pipelines toward language-model-assisted interaction, although the evaluation approach differs from the numerical offline evaluation used in other reviewed studies.

5. COMPARATIVE ANALYSIS OF SELECTED STUDIES

Table -1: Descriptive comparison of selected studies. Reported metrics are not directly comparable across different datasets and evaluation protocols

Study	Main approach	Data / evaluation reported
Sarma et al. (2021)	Clustering; K-means; cosine distance	Ten datasets; sensitivity, specificity, F-score and ROC
Dubey & Gandhimathi (2022)	GPT-3 + Google Books API	User-entered book; recommendation testing
Bachhav et al. (2022)	Collaborative + content-based;	Book/user information; top-rated recommendations

	cosine similarity	
Rosidah & Dellia (2024)	Content-based; TF-IDF + cosine	Library context; testing and confusion matrix
Shukla et al. (2024)	CF, CBF, hybrid; KNN-oriented	Kaggle data; precision/recall/accuracy/novelty discussed
Saputri & Suryati (2025)	Content-based; TF-IDF + cosine	10,000 books; P@10 70%, R@10 58%, F1@10 63%
Remadnia et al. (2025)	Hybrid CF + content + embeddings	Book Recommendation Dataset; RMSE 0.69, MAE 0.51
Harahap (2025/2026)	TF-IDF CBF + SVD CF	Goodbooks-10k; RMSE/MAE plus diversity/coverage
Malakul & Songmuang (2026)	Systematic review of BRS	PRISMA; 32 studies from 2020-2024; network analysis
Jogar et al. (2026)	Content-based, CF and hybrid	Live user experiments + offline analysis

The comparison demonstrates methodological diversity rather than a single dominant recipe. Content-based approaches are relatively straightforward and can work with limited interaction information. Collaborative methods make stronger use of community behavior but require sufficient interactions. Hybrid approaches explicitly combine these information sources. The 2026 systematic review by Malakul and Songmuang further broadens the perspective by analyzing 32 studies published between 2020 and 2024 and examining technical and reading-engagement themes.

5.1 Dataset and Representation Differences

The reviewed studies use different data sources, including Goodreads/Goodbooks-style collections, Kaggle datasets, library-specific book collections and API-based information. Some studies emphasize ratings, while others emphasize descriptions or metadata. This difference matters because an algorithm that is effective for dense rating data may not be directly transferable to a small library catalog dominated by textual descriptions.

5.2 Evaluation Differences

Evaluation is similarly heterogeneous. Classification-style measures such as precision, recall and F1 are used in some studies; rating-prediction studies report MAE and RMSE; some systems use confusion matrices or user testing; and recommendation quality may also involve novelty, diversity, coverage or engagement. A review should therefore report the metric used by each source rather than merge them into a single score.

6. CHALLENGES AND LIMITATIONS

6.1 Cold-Start Problem

A new user may have no ratings or reading history, while a newly added book may have no interactions. Collaborative filtering has limited evidence in both cases. Content information can provide an alternative signal for new books, while explicit preference collection or hybrid strategies can reduce the new-user problem.

6.2 Data Sparsity

Users normally interact with only a small fraction of a large book catalog. The resulting user-item matrix is sparse, which makes similarity estimation less reliable. Matrix factorization and other representation-learning methods attempt to learn latent relationships, but their effectiveness still depends on the quantity and quality of observed interactions.

6.3 Metadata Quality and Coverage

Content-based systems depend on the fields used to describe a book. Missing descriptions, inconsistent genre labels, duplicate titles, incomplete author information or limited textual detail can weaken the representation. Rosidah and Dellia (2024) and Saputri and Suryati (2025) illustrate the importance of structured book information in their content-based pipelines.

6.4 Personalization and Preference Drift

A user's interests may change over time. A model that relies only on historical similarity may continue to recommend books that match an older preference profile. Dynamic user profiles, temporal weighting and context-aware recommendation are possible directions for addressing this issue, but they require additional behavioral evidence.

6.5 Accuracy Versus Diversity and Serendipity

A system can repeatedly recommend books that are highly similar to a user's previous choices. This may improve perceived relevance but can also reduce exploration of new authors, genres or topics. The reviewed literature therefore points to diversity, novelty and serendipity as important complementary dimensions rather than relying only on accuracy.

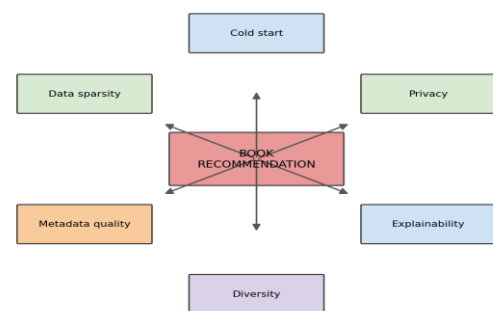


Fig -5: Recurring challenges identified across the reviewed literature

6.6 Privacy and Security

Personalization can require storage of reading histories, ratings, profiles or interaction logs. The 2024 IJSREM study explicitly discusses privacy, secure transmission and protection of user information as quality-assurance considerations. Future systems should minimize unnecessary data collection and make the purpose of personalization clear to users.

6.7 Explainability

Recommendation explanations can help users understand why an item appears in a list. For a content-based system, explanations can be relatively concrete, such as shared author, genre or thematic similarity. For deep or hybrid models, generating faithful explanations is more challenging because the model may combine many latent signals.

6.8 Evaluation Reproducibility

Different papers use different datasets, train-test splits, preprocessing rules, candidate sets and metrics. This limits reproducibility and makes cross-paper numerical comparison difficult. Future studies should describe datasets and evaluation protocols in sufficient detail for independent replication.

7. RESEARCH GAPS IDENTIFIED FROM THE REVIEWED LITERATURE

7.1 Lack of Standardized Evaluation

The most visible gap is the absence of a common evaluation framework. A future benchmark could define standard datasets, fixed train-test protocols, candidate-generation rules and a balanced metric set covering accuracy, ranking quality, diversity, novelty and user satisfaction. Such a framework would make research results easier to interpret without assuming that one metric captures the entire recommendation problem.

7.2 Integration of Multiple Information Sources

Many systems rely heavily on either ratings or basic metadata. A richer model could combine structured metadata, descriptions, reviews, interaction history and temporal context. The challenge is not simply adding more features; the system must determine which signals are reliable for a particular user and task.

7.3 Better Understanding of Book Text

TF-IDF is useful for lexical matching, but it does not fully represent meaning, narrative themes or relationships expressed through different words. Transformer-based semantic representations provide a possible direction for improving text understanding, particularly when book descriptions and reviews contain sufficient information.

7.4 Diversity, Novelty and Serendipity

Recommendation quality should not be defined only as similarity to previous choices. A useful system may also introduce books that are different but still relevant. Future work should evaluate whether recommendations broaden reading behavior while maintaining acceptable relevance.

7.5 Reading Engagement

Malakul and Songmuang (2026) report that the systematic-review literature is weighted toward technical improvement, while reading engagement is also examined through behavioral, affective, cognitive and social dimensions. This suggests that future recommendation studies can evaluate not only prediction accuracy but also whether recommendations support sustained reading activity.

8. FUTURE DIRECTIONS

8.1 Advanced Hybrid Models

Future systems can combine content, collaborative,

sequential and contextual signals within a single architecture. The goal should be complementary use of information rather than unnecessary model complexity.

8.2 Transformer-Based NLP

Transformer representations can capture semantic relationships between book descriptions and user preferences. They may be used for candidate generation, semantic similarity, review understanding or preference extraction.

8.3 Large Language Models

LLMs can support conversational recommendation, preference elicitation and natural-language explanations. The reviewed GPT-3 study demonstrates the feasibility of language-model-assisted recommendation, while later literature points toward broader language-model applications. Future evaluation should test factuality, consistency, recommendation relevance and computational cost rather than relying only on example outputs.

8.4 Explainable Recommendation

An explainable system could present reasons such as shared author, genre, topic, description similarity or similarity to previously liked books. Explanation quality should be evaluated for faithfulness as well as readability.

8.5 Context-Aware Recommendation

Reading goals may differ by context: leisure reading, academic study, exam preparation, language learning or professional development. Context-aware models could adapt recommendations when such information is voluntarily provided.

8.6 Privacy-Preserving Personalization

Future systems should investigate data minimization, local preference storage, anonymization and privacy-preserving learning where appropriate. The objective is to provide personalization without collecting more personal information than the task requires.

8.7 Multimodal Recommendation

Books have multiple modalities: text, cover images, metadata and sometimes author or publisher information. Multimodal models could combine these signals, although the benefit must be demonstrated using controlled evaluation.

9. DISCUSSION

Across the supplied literature, no single technique solves every recommendation condition. Content-based filtering is relatively transparent and can work when book descriptions and metadata are available. Collaborative filtering can discover patterns that are not explicit in metadata, but it depends on sufficient interactions. Hybrid approaches address this complementarity directly. Deep learning and language models expand the representation space, but they also introduce additional requirements for data, computation, evaluation and explainability.

The most important methodological observation is that algorithm names should not be separated from the data and evaluation context. A TF-IDF system using a small library catalog is solving a different practical problem from an SVD system trained on a large rating matrix. Similarly, a GPT-based conversational recommender and an offline rating-prediction model may produce different types of value. The literature therefore supports a multi-dimensional evaluation approach rather than a single numerical measure.

10. LIMITATIONS OF THIS REVIEW

This paper is a focused review of the supplied literature rather than a fully exhaustive systematic review. The evidence base is constrained by the papers provided for analysis. The article does not perform a new benchmark experiment and does not claim that the reported results from individual studies are directly comparable. Some bibliographic details should be checked against the final publisher versions before journal submission. The review also does not independently reproduce the experiments described in the source papers.

11. CONCLUSION

AI-based book recommendation has developed from conventional similarity and collaborative-filtering techniques toward increasingly hybrid, representation-rich and language-aware systems. The reviewed 2021-2026 literature demonstrates continued use of TF-IDF, cosine similarity, clustering, nearest-neighbor methods and matrix factorization, alongside embedding-based deep learning and language-model-assisted recommendation.

The evidence also shows that recommendation quality depends on more than algorithm choice. Cold-start conditions, sparse interactions, metadata quality, privacy, explainability, diversity and evaluation design remain important. Hybrid architectures offer a practical way to combine complementary signals, while NLP and transformer-based approaches provide opportunities for richer semantic representations. Future work should

therefore emphasize transparent benchmarks, multi-dimensional evaluation and user-centered recommendation objectives, including engagement and diversity.

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