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# Recommender systems in real estate: a systematic review

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**ABSTRACT**

The constant growth of online real estate information has emphasized the need for the creation and improvement of intelligent recommendation systems to help mitigate the difficulties associated with user decision-making. This systematic review, following the preferred reporting items for systematic reviews and meta-analyses (PRISMA) guidelines and criteria, investigates current approaches and models used in real estate recommendation systems, with a focus on papers published in 2019 and 2024. The review identifies four main techniques: content-based filtering, collaborative filtering, knowledge-based systems, and hybrid approaches. Key findings indicate a preference for deep learning models, specifically convolutional neural network and long-short term memory (CNN-LSTM) architectures, and highlight the most used property characteristics: price, number of rooms, size, and location. The research addresses several important challenges, including the cold start problem, data sparsity, and the importance of adaptive learning in dynamic markets. Potential future research fields are outlined, with a focus on hybrid model architectures, attention mechanisms, and explainable artificial intelligence (AI). This review provides a comprehensive overview of the field, enabling scholars and practitioners to improve the accuracy and user experience of real estate recommendation systems.



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## 1. INTRODUCTION

In the current era, the exponential growth of information on the Internet has led to the development of advanced tools such as big data and machine learning, which are essential for analyzing and processing vast amounts of data [1]. This field has gained relevance by developing models to identify hidden patterns in complex systems, thereby improving organizational decision-making [2]. The analysis and processing of large amounts of data generated by various devices is crucial. To implement big data, the data must be abundant, varied, and quickly processable, ensuring effective results [3]. Within this context, recommendation systems have emerged, utilizing algorithms and artificial intelligence techniques to provide personalized recommendations for products, services, or content, based on data analysis, machine learning, and information theory [4].

In the real estate sector, where users must navigate an overwhelming amount of information, these tools become critical in helping them make informed decisions. As the data in the real estate sector increases, it becomes more complex for users to choose whether to buy or rent a property on these websites. They spend significant time filtering through this information, making the process intimidating for the average user [5].

The importance of studying recommender systems in this context lies in their ability to streamline the decision-making process, providing personalized and efficient solutions that can significantly impact user satisfaction and industry success.

Various studies have explored recommender systems across different sectors, including e-commerce, healthcare, and real estate [6], [7]. In the real estate industry, the application of these systems is still emerging. Researchers [8]-[10] have investigated collaborative filtering approaches, while [11]-[13] has focused on content-based filtering. Despite these advances, research by [14], [15] indicates that significant challenges remain, particularly in addressing the cold-start problem and enhancing user interaction with these systems. Additionally, studies such as those by [16], [17] highlight the limitations in fully integrating diverse property features and personalizing recommendations in the real estate domain. Given these gaps in the literature, this study seeks to consolidate existing research by providing a comprehensive analysis of current techniques, thereby offering insights into potential solutions, and highlighting opportunities for further exploration. Recommendation systems are intelligent models that use statistical methods and machine learning to provide personalized suggestions to users based on their interests, automatically filtering a large amount of information [9], [18]. In 2012, a study collected 210 articles related to recommendation system applications, with a significant portion related to movies and shopping, but fewer in real estate [9]. Of these, 53 were associated with movies (25.2%), 42 with shopping (20%), 7 related to recommendation systems in the field of images (3.3%), and 9 in each of the fields of music and TV programs (4.2%).

In the real estate sector, advances in information technologies have been rapidly presented [19]. Furthermore, real estate agents often use these sites to reduce information costs and increase sales [20], [21]. However, despite these developments, these recommendation systems are less studied compared to other industries [7]. Some authors have attempted to address the problem using different methods, such as collaborative filtering (model-based or memory-based), content-based filtering, knowledge-based filtering, hybrid systems, reinforcement learning, deep learning, among others [6], [7], [22]-[24]; leveraging various property features such as price, size, number of rooms, neighborhood, location, and proximity [6], [7], [22], [25], [26]. Nonetheless, existing studies often fall short in tackling the integration of diverse property features and in personalizing recommendations to the specific needs of real estate users. This systematic review aims to address these shortcomings by providing a comprehensive overview of current methodologies and identifying areas for future research.

To guide this systematic review, the following research questions are posed:

- What are the predominant techniques in real estate recommendation systems?
- What are the most used features in real estate recommendation systems?

Recommendation systems are increasingly covering more areas, and their importance lies in reducing the time it takes for users to make choices. These tools are necessary and important in the real estate sector, as the decision-making process for choosing a property becomes highly personalized. This paper contributes to the field by analyzing the limitations of traditional models and proposing directions for future research.

The remainder of this paper is structured as: section 2 outlines the methodology and protocol for data extraction. Section 3 presents the systematic literature review results, addressing the research questions. Finally, section 4 summarizes the main conclusions and suggests future research directions based on the findings.

## 2. METHOD

In this systematic literature review, we employed the preferred reporting items for systematic reviews and meta-analyses (PRISMA) method for the collection, filtering, and selection of relevant articles for this study [27]. The choice of a systematic review approach is particularly crucial in software engineering, where empirical studies often employ diverse experimental forms and contexts, making objective summaries of available research evidence essential for informed decision-making and research direction [28]. The PRISMA method was selected due to its systematic approach and its wide acceptance in the scientific community for conducting high-quality systematic reviews [29]. Furthermore, this methodology builds upon the experiences and recommendations of software engineering researchers who have critically examined the systematic review process in this field [30].

### 2.1. Information sources

For the search process it used two of the most important digital libraries that specialize in technology and engineering [31]. These chosen information repositories, detailed in Table 1, were selected based on their reputation, the quality of their holdings in the field of interest, and their comprehensive coverage of scientific literature in the areas of recommendation systems and real estate.

Table 1. Information sources used for the literature review process

| Information source | Type | URL |
|---|---|---|
| Web of Science | Digital library | [32] |
| Scopus | Digital library | [33] |

The selection of these specific digital libraries was based on several factors: both Web of Science and Scopus are known for their extensive coverage of peer reviewed literature across various scientific disciplines, including computer science and real estate [34]. These databases primarily index peer reviewed journals and conference proceedings, ensuring a high standard of scientific consistency in the included studies [35]. They offer sophisticated search features, including the ability to construct complex queries using Boolean operators and filters [36]. Additionally, Web of Science and Scopus provide robust citation tracking and analysis features, which can be valuable for identifying seminal works and understanding the impact of specific studies in the field. Finally, the interdisciplinary coverage offering appropriate coverage across relevant disciplines [37].

While other databases such as IEEE Xplore and ACM Digital Library are also valuable resources in computer science, we chose Web of Science and Scopus for their broader interdisciplinary coverage, which is particularly important given the cross-domain nature of our research topic. It's worth noting that the use of only two databases might be seen as a limitation. In our case, given the interdisciplinary nature of our topic, we believe that Web of Science and Scopus provide the most comprehensive coverage.

### 2.2. Search strategy

The search strategy phase aimed to identify search terms that would effectively retrieve all relevant information from the chosen scientific databases, facilitating the process of answering the research questions. To accomplish this, two distinct keyword categories were established, as outlined in Table 2.

Table 2. Categories and keywords selection

| Category | Keywords |
|---|---|
| Recommendation system techniques | Recommender system*, recommend system*, collaborative filtering, recommendation algorithm*, personalized recommendation |
| Real estate domain | Real estate, immovable, house, dwelling, residence, edifice, apartment |

The first category, *recommendation system techniques*, encompasses a range of keywords that are specifically related to the core concepts and methodologies employed in developing and implementing recommender systems. This category covers the essential techniques and approaches used in creating personalized recommendations for users.

The second category, *real estate domain*, consists of keywords that are directly associated with the real estate industry and its various subdomains. This group ensures that the search results are focused on studies that apply recommendation systems within the context of real estate.

By combining these two categories using logical and Boolean operators, we created a comprehensive search query that aims to retrieve studies that explore the application of recommendation system techniques in the real estate domain. This search query, as described in Table 3, ensures that the returned results contain at least one keyword from each of the two categories, effectively narrowing down the scope of the search to the most relevant and pertinent studies for our research objectives.

Table 3. Search equations for using in selected information sources

| Information source | Search equation |
|---|---|
| Web of Science | TS=(("recommender system*" OR "recommend* system*" OR "collaborative filtering" OR "recommendation algorithm*" OR "personalized recommendation") AND ("real estate" OR "immovable" OR "house" OR "dwelling" OR "residence" OR "edifice" OR "apartment")) |
| Scopus | (TITLE-ABS-KEY("recommender system*" OR "recommend* system*" OR "collaborative filtering" OR "recommendation algorithm*" OR "personalized recommendation") AND TITLE-ABS-KEY("real estate" OR "immovable" OR "house" OR "dwelling" OR "residence" OR "edifice" OR "apartment")) |

This strategy aligns with established guidelines for systematic reviews in software engineering [30], balancing sensitivity (finding all relevant studies) and precision (avoiding excessive irrelevant results). We refined our search strings through iterative testing and consultation with a librarian experienced in systematic reviews.

### 2.3. Inclusion criteria

We established the following inclusion criteria to ensure the relevance and quality of the studies in our review:
- Language of publication: all publications reported in English.
- Type of publication: only peer reviewed journal articles, conference papers, and systematic reviews.
- Date of publication: papers related to recommender systems in the real estate sector published between 2019 and 2024.
- Subject areas: studies conducted in the fields of computer science, information technology, artificial intelligence, engineering, and real estate.
- Methodology: studies utilize statistical analysis, predictive modeling, or machine learning techniques.

These criteria were chosen to capture recent, high-quality research directly relevant to our research questions. The five-year time frame (2019-2024) ensures we focus on the most current developments in this rapidly evolving field. We applied these criteria in two stages: first during the initial screening of titles and abstracts, and then during the full-text review. This two-stage process, recommended by [30], helps to efficiently manage the review process.

### 2.4. Exclusion criteria

The exclusion process was conducted in two steps to ensure that only the most relevant and high-quality articles were included in the review. In the first step, articles were analyzed based on their title, abstract, and keywords. Studies that did not align with the research questions or were not directly related to recommendation systems in the real estate sector were excluded at this stage. The second step involved a thorough examination of the full text of the remaining articles. The following exclusion criteria were applied:
- Duplicate articles: duplicate articles were excluded to ensure unique contributions.
- Abstract only articles: articles that were retrieved based solely on their abstract and did not provide full text access were discarded.
- Non-peer-reviewed publications: exclude non-peer-reviewed publications, such as these, technical reports, and book chapters.
- Irrelevant subject areas: exclude studies not conducted within the fields of computer science, information technology, artificial intelligence, engineering, or real estate.
- Insufficient methodological rigor: exclude studies that do not utilize statistical analysis, predictive modeling, or machine learning techniques.

This two-stage approach, recommended by [38] maintaining academic rigor.

## 3. RESULTS AND DISCUSSION

This section presents the results of our systematic review on recommendation systems in the real estate sector. The analysis showed the next key findings:
- A total of 16 articles directly related to real estate recommendation systems were identified after the screening process.
- Content-based filtering, collaborative filtering, knowledge-based systems, and hybrid approaches emerge as the primary techniques used in this domain.
- Property price, number of rooms, property size, and location are the most frequently used characteristics in real estate recommendation systems.
- There is a growing trend towards the use of advanced machine learning techniques, particularly deep learning models, in real estate recommendation systems.

These findings provide insights into the current state of recommendation systems in this sector and identified areas for potential future research.

### 3.1. Screening results

After a query was performed in the Web of Science and Scopus databases using the search equation detailed in Table 3, yielded the following results (see Figure 1):
- Initial search: 334 articles (Web of Science: 67, Scopus: 267)
- After duplicate removal: 278 articles (56 duplicates removed)
- After applying inclusion criteria: 144 articles
- After full text review: 16 articles

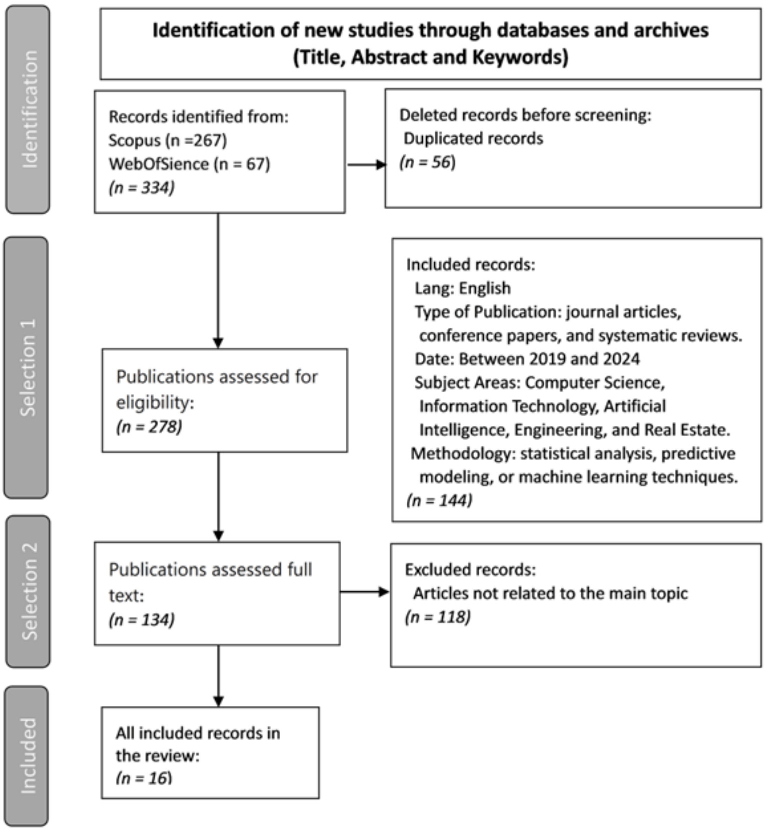


Figure 1. Selection of the scientific articles using PRISMA methodology

## 3.2. Recommender systems in the real estate

Recommendation systems are intelligent models that leverage data mining methods and machine learning to learn about the user's historical interactions with the system and provide them with a more personalized experience. Specifically, the task of recommendation systems is to convert data about users and their preferences into predictions of their possible future tastes and interests [4]. Currently, there are various techniques for creating this type of technology, among the most prominent are: collaborative filtering, content-based filtering, knowledge-based filtering, multi-criteria decision making, hybrid approach, deep learning, reinforcement learning, so on [7].

### 3.2.1. Techniques

In recommendation systems, various techniques can be employed under different circumstances. Based on this, the following taxonomy outlines the most important techniques: content-based filtering, collaborative filtering (both model-based and memory-based), knowledge-based systems, and hybrid systems. Refer to Figure 2 for a visual representation.

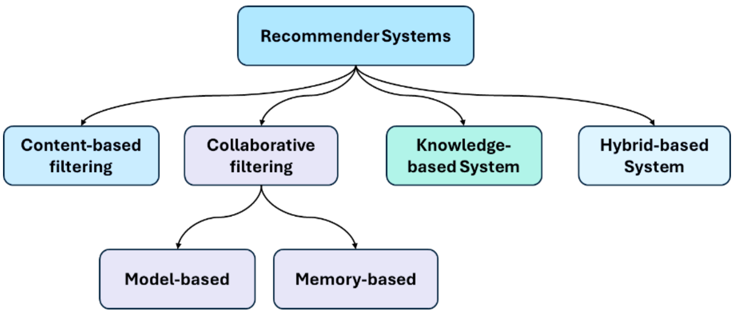


Figure 2. A recommender systems techniques taxonomy

a. Content-based filtering

In this technique, the features are matched to the user's profile (without inferring user preferences from collaborative information), leading to issues with specification and generating obvious recommendations. Current work has utilized structured, semi-structured, and unstructured data such as comments and reviews. One study highlights recent trends for available data (linked open data, user-generated content, multimedia features, and heterogeneous information) [11]. Furthermore, content-based (CB) methods depend on user behavior, including descriptions, information, and operational behavior [39]. Moreover, using the content-based approach, which includes a learning profile and a filtering component, mitigates the cold-start problem. This recommendation system employs an attention mechanism within a session-based framework, leveraging contextual data and click sequences [25].

Kabir *et al.* [23] adapted the neural tensor network (NTN) [40] to calculate similarity scores between recommended properties and items viewed by users, then ranked the properties for each user. They also captured user preferences through a chat box. This study employed a two-stage process [14]: first, they calculated similarity scores between the target user and items using the cosine similarity measure, representing users and items in the same space. Users have different interactions (clicking, checking, viewing details, booking, and inquiries), each receiving different weights. In the second stage, they used XGBOOST to predict the probabilities of users liking the items based on preliminary recommendations generated in the first stage. Each item was then ranked based on these relevant scores. Another study applied term frequency-inverse document frequency (TF-IDF) based on words in the titles, descriptions, and addresses reviewed by the user, suggesting similar properties [14]. Some authors use simple cosine similarity in content-based recommender systems to provide ranked information about properties from the user's session; for new users, they propose using the average of vectors from all users [41].

In deep learning, Shen *et al.* [42] applied the model a text-based price recommendation (TAPE) system which utilizes deep learning techniques such as feedforward network, long short-term memory, and mean shift to implement this system. The root-mean square error (RMSE) metrics achieved were 33.73 in Boston, 20.50 in London, 34.68 in Los Angeles, and 26.31 in New York City. Shi and Jiang [43] used a model called CNN_LSTM that combines convolutional neural network (CNN) and long-short term memory (LSTM) to calculate recommendations between users and properties, achieving an accuracy of 94%. Additionally, they implemented a text-based CNN model which achieved an accuracy of 90%.

b. Collaborative filtering

In this technique, a user's preferences are inferred using the preferences of other users in the system. Users with similar histories will have similar tastes. It is worth noting that recommendations from this method are not obvious. There are two types of collaborative filtering: model-based and memory-based. It is widely used in various applications and is also common in the real estate sector [10], [17], [44]-[48]. Moreover, collaborative filtering reduces computational costs by suggesting properties similar to those favored by a similar group of users [6].

- Model-based collaborative filtering

These types of models utilize user feedback for training through ratings, clicks, and interactions. In [46], two real estate CF models were created based on geographical proximity, utilizing two geography-based regularization terms in weighted regularized matrix factorization (WRMF). Jun *et al.* [47], propose SeoulHouse2Vec, a property recommendation system based on embeddings using a collaborative neural network model that connects users and properties. Milkovich *et al.* [44], a CNN model is used to suggest to user a property based on building Images, comparing Adam and stochastic gradient descent (SGD) optimizers; as well as L1, L2, and ElasticNet regularizes to prevent overfitting, with SGD and L1 demonstrating superior performance; they used accuracy as a metric. Rehman *et al.* [17], the focus is on predicting the next recommended item given previous items (session-based recommendation). In the first stage, they used gated orthogonal recurrent unit (GORU) and the Top1 loss function, with the final ranking based on cosine similarity, their metrics were recall, user coverage mean reciprocal rank (MRR), their method shows better performance than GRU4REC [49], [50], BPR, and K-nearest neighbors (KNN). Knoll *et al.* [45], item information is incorporated into NeuMF and factorization machines (FM); they also used deep neural network (DNN), all models were measured with AUC where euMF demonstrates better performance than FM in both scenarios (cold-start problem user vs no cold-start problem user), however, the DNN model was the best model in this study.

- Memory-based collaborative filtering

This approach relies on using user-based K-nearest neighbors (UKNN) and item-based K-nearest neighbors (IKNN). These heuristic methods do not learn parameters but determine the shape of the neighborhoods based on similarities to generate recommendations [7]. Wang *et al.* [10], the Pearson similarity measure in UKNN is modified to enhance the similarity between users with similar preferences, they used the algorithm named collaborative filtering based personalized top-k recommender for housing (CFP-TR4H). Liu and Guo [48], the authors propose using a cosine similarity measure to recalculate scores between users and attributes such as area, price, location, patterns, and traffic. Subsequently, they employ UKNN to identify users with similar preferences. However, they do not provide a performance evaluation of their approach.

c. Knowledge-based

In this method, preferences are inferred based on knowledge, and specific items are matched to specific needs. The RentMe study [26], is one of the earliest examples and falls into the knowledge-based category. The knowledge base for recommendations includes the quality of neighbors, the relative position of neighbors, and the apartment's characteristics with their relative quality.

In another study, a user's query helps recommend their desired property by checking prior information and retrieving a relevant solution [30]. Pranckutė [31] uses a method called "methontology" [51] to represent semantic relationships between nodes in an ontology based on knowledge gained from user studies and real estate experts. Malczewski and Jelokhani-Niaraki [52] developed an ontological domain called "analytic hierarchy process" (AHP), which contains semantic relationships between different elements such as criteria, objectives, attributes, weights, and geographic units. The user selects the geographic area and the criteria weights to receive recommendations on the website.

d. Hybrid-based systems

Hybrid methods combine two or more techniques to address this problem. There are different hybridization methods such as weighted, switching, mixed, feature combination, cascading, and meta-level [53]. Batet *et al.* [54], a hybrid recommendation system agent is proposed, which combines CB and CF information to overcome the limitations of individual strategies. Rehman *et al.* [17] focus on user context (e.g., time, neighborhood, season), as these data play a crucial role in hybrid systems. Logesh and Subramaniyaswamy [51], a context-aware hybrid travel recommendation system called personalized context-aware hybrid travel recommender system (PCAHTRS) is proposed in this survey, they used expectation maximization (EM) algorithm to predict personalized recommendations and they also used RMSE, Coverage and F-Measure to evaluate the model.

e. Others

This issue has been addressed using less commonly employed approaches such as multi-criteria decision making (MCDM) [52],[55]-[57], reinforcement learning (RL) [58], [59], among others [56], [60], [61]. Table 4 provides a summary of this section, detailing the techniques, models, metrics, and references for each approach.

Table 4. Recommender systems model approaches based on techniques and metrics

| Model | Techniques | Metrics | References |
|---|---|---|---|
| TAPE | Content-based filtering | RMSE | [42] |
| NTN | Content-based filtering | Accuracy | [23] |
| Regression Tree | Content-based filtering | Recall@K, MRR@K | [25] |
| Linear Regression | Content-based filtering | Recall@K, MRR@K | [22] |
| CNN_LSTM | Content-based filtering | Accuracy | [43] |
| Text-based CNN | Content-based filtering | Accuracy | [43] |
| Boosting Tree | Content-based filtering | Precision@K, Recall@K | [14] |
| WRFM | Model-based collaborative filtering knowledge-based | Precision@K, Recall@K | [46] |
| DNN | Model-based collaborative filtering knowledge-based | Precision, recall, F1_Score, AUC | [45], [47] |
| CNN | Model-based collaborative filtering | Accuracy | [44] |
| GORU | Model-based collaborative filtering | Recall, user coverage, MRR | [17] |
| FM | Model-based collaborative filtering knowledge-based | AUC | [45] |
| CFP-TR4H | Memory-based collaborative filtering | Precision | [10] |
| UKNN | Memory-based collaborative filtering | Accuracy | [48] |
| Apt Decision | Knowledge-based reinforcement learning | X | [26], [59] |
| Tourist@ | Hybrid-based system | X | [54] |
| PCAHTRS | Hybrid-based system | RMSE, coverage, F-Measure | [51] |
| MC-SDSS | Multi-criteria decision making | (User satisfaction) | [52] |
| JOURA | Multi-criteria decision making | (User satisfaction) | [55] |
| PRM | Multi-criteria decision making | Precision, recall, F-Measure | [56] |
| FGP | Multi-criteria decision making | (User satisfaction) | [56] |
| PROMETHEE II | Multi-criteria decision making | x | [57] |
| HumanE | Reinforcement learning | (User satisfaction) | [58] |
| GAN | Others | RMS, CORR, EMD, RMSE | [61] |

X: it means the survey didn’t report this field.

The diverse range of techniques reflects the complexity and multifaceted nature of the domain. Content-based filtering and collaborative filtering emerge as the most prevalent approaches, with increasing adoption of deep learning models like CNN and LSTM. This trend suggests a move towards more specialized analysis of property features and user behavior. The presence of knowledge-based systems shows the importance of domain expertise in real estate recommendations, while hybrid systems demonstrate efforts to combine multiple techniques for improved performance. The exploration of less common approaches like MCDM and reinforcement learning indicates ongoing innovation in the field. The metrics used to evaluate these systems vary widely, from accuracy and precision/recall to user satisfaction. This diversity in evaluation metrics suggests a need for standardization in the field to enable more direct comparisons between different approaches. Future research may focus on further refinement of hybrid systems and the integration of advanced machine learning techniques to improve recommendation accuracy and personalization.

f. Relevant techniques from other domains

While our primary focus is on recommender systems designed for the real estate sector, innovative techniques from other domains offer valuable insights for potential adaptation. Addressing the cold-start problem in real estate, where new properties often lack rating data, [62] present a singular value decomposition approach for predicting ratings based on user and item characteristics without relying on available ratings. Rrmoku *et al.* [63] incorporate social network analysis and data provenance, offering potential applications in factoring property seller or agency reputations into recommendations.

### 3.2.2. Characteristics

In artificial intelligence and recommendation systems, features become a determining factor for decision-making. A study identified the 7 best decision factors for buying and selling real estate: price, number of bedrooms, number of bathrooms, location, built area, total area, and house certification [16]. Other authors identified additional data such as property type (house, plot, flat), purpose of the house (sale or rental), location (city, longitude, latitude) [17].

Various studies have presented different features when creating a recommendation system in the real estate sector. Currently, there is no standard for selecting these features. Table 5 shows the most relevant studies with the features used: price, number of bed-rooms, number of bathrooms, number of floors, property size, property age, location, and user interactions. The most used variable in the studies was the property price, being used in 18 out of 19 studies reviewed, followed by the number of rooms, the size of the property area, and its location. The least used characteristic was the age of the property, being used in only 1 out of 19 studies reviewed, followed by the number of floors in the property and the number of bathrooms (see Figure 3).

Table 5. Real estate characteristics in relevant surveys

| Survey | Price | Number of rooms | Number of bathrooms | Number of floors | Property size | Property antique | Location | User interactions |
|---|---|---|---|---|---|---|---|---|
| [6] | x | ? | ? | | ? | ? | x | X |
| [17] | x | x | x | | x | | x | X |
| [22] | x | x | | x | x | x | | |
| [25] | x | x | x | x | x | | x | x |
| [26], [45] | x | x | | | x | | x | x |
| [42] | x | x | x | ? | ? | ? | x | |
| [43] | x | | | | x | | x | |
| [14] | x | x | x | | x | | | x |
| [46] | x | | | | | | x | |
| [47] | x | x | x | | x | | | |
| [44] | | | | | | | | x |
| [48] | x | x | | x | x | | x | x |
| [56] | x | x | | x | x | | x | |
| [56] | x | x | | | | | x | x |
| [58] | x | ? | ? | ? | ? | ? | ? | x |
| [59] | x | x | | | | | x | x |
| [57] | x | x | | | x | | x | x |

?: it is not clear if they used this variable.
x: the survey used this variable.

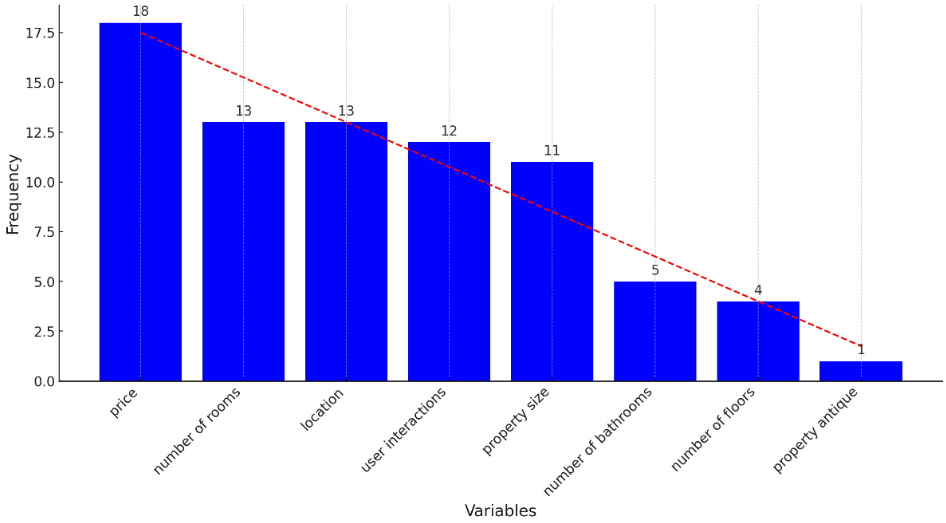


Figure 3. Frequency of variables used in survey

The review of characteristics used in real estate recommendation systems reveals several key insights:

- Prevalence of core features: price, number of rooms, property size, and location emerge as the most frequently used characteristics across studies. This consistency suggests a consensus on the primary factors influencing real estate decisions.
- Variability in feature selection: the lack of a standardized set of features across studies highlights the complex and multifaceted nature of real estate recommendation. It also indicates potential opportunities for research into optimal feature selection for different contexts or user groups.
- Underutilized characteristics: the limited use of features such as property age and number of floors suggests these may be undervalued in current systems. Future research could explore the potential impact of these less used characteristics on recommendation accuracy.
- User interactions: the inclusion of user interaction data in many studies indicates a trend towards more personalized, behavior-driven recommendations. This aligns with the broader trend in recommendation systems towards leveraging user behavior for improved accuracy.
- Contextual factors: the consideration of factors like house certification and property purpose (sale or rental) in some studies suggests an emerging focus on contextual aspects of real estate decisions.

These aspects appear to reveal the complexity of real estate recommendation systems and highlight the need for a balanced approach that considers both traditional property characteristics and user-specific factors. We consider that future research could benefit from exploring the optimal combination of features for different types of real estate markets or user segments, as well as investigating the potential of incorporating more diverse or novel characteristics into recommendation models.

The field of recommendation systems in the real estate sector, while growing, remains less extensively researched compared to other domains [7], [64]. This review has revealed several critical gaps and technical challenges that suggest further investigation.

### 3.3. Technical analysis of key findings

After a critical review, we can highlight a panorama of possibilities related to recommendation techniques applied to the real estate sector, each with its own strengths and limitations.

#### 3.3.1. Content-based filtering techniques

Content-based filtering methods have shown promise in mitigating the cold-start problem, a persistent challenge in recommendation systems. However, these methods often suffer from over-specification and the generation of obvious recommendations. The TAPE model [42], utilizing deep learning techniques such as feedforward networks and LSTM, demonstrated varying performance across different cities RMSE ranging from 20.50 in London to 34.68 in Los Angeles), highlighting the impact of local market characteristics on model performance.

The CNN_LSTM model proposed in [43] achieved a high level of 94% accuracy, outperforming a text-based CNN model (90% accuracy). This suggests that the combination of convolutional and recurrent neural network architectures can effectively capture both spatial and temporal features of real estate data.

#### 3.3.2. Collaborative filtering approaches

Collaborative filtering techniques, while widely used, have shown mixed results in the real estate domain. Some studies report that these methods only marginally outperform matrix factorization approaches [65], [66]. The CFP-TR4H algorithm [10], which modifies the Pearson similarity measure in user-based K-nearest neighbors (UKNN), represents an attempt to enhance similarity calculations between users with similar preferences. However, the lack of standardized performance metrics across studies makes direct comparisons challenging.

#### 3.3.3. Machine learning models-based approaches

The integration of deep learning and factorization machines has shown promising improvements in accuracy [45]. The GORU model [17] demonstrated faster training and better performance compared to GRU and URNN models, particularly in session-based recommendations. This suggests that orthogonal recurrent units may be particularly well-suited for capturing the temporal aspects of user preferences in real estate browsing.

### 3.4. Estimation of model performance

A critical examination of the reported performance metrics exhibits significant variability across studies. For instance:

- Accuracy-based metrics: models like CNN_LSTM report high accuracy (94%), but this metric alone may not fully capture the nuanced performance required in real estate recommendations.
- Ranking-based metrics: the use of mean reciprocal rank (MRR) and recall in studies like [17] and [25] provides insight into the models' ability to rank relevant properties, which is crucial in real-world applications.
- Error-based metrics: RMSE, used in studies like [42] and [51], offers a more granular view of prediction errors, especially important in price recommendation systems.
- The diversity in evaluation metrics (e.g., precision, recall, F1-score, AUC) used across studies [45], [47] indicates the multifaceted nature of performance evaluation in real estate recommendation systems. This variability establishes the need for a more standardized approach to model evaluation in this domain.

### 3.5. Feature analysis and selection

While certain features like price, number of rooms, property size, and location are consistently used across studies (see Table 5), there is significant variability in feature selection. This lack of standardization poses challenges for cross-study comparisons and model generalization. The underutilization of features such as property age and number of floors, represents a potential area for improvement. Future research could benefit from a more comprehensive exploration of feature importance, potentially employing techniques like shapley additive explanations (SHAP) [67] values to quantify the impact of each feature on model predictions.

### 3.6. Technical challenges and limitations

Several key technical challenges emerge from our analysis:

- Cold-start problem: while some studies [7], [25] report progress in addressing this issue, it remains a significant challenge, particularly for properties with limited viewing history [17].
- Data sparsity: these systems often suffer from sparse user item interaction data, which can impact the performance of collaborative filtering approaches.
- Temporal dynamics: from our point of view, the main challenge to be face up is the dynamic nature of the sector. it makes difficult to get model stability, what it requires adaptive learning approaches.
- Heterogeneous data integration: combining structured (e.g., property features) and unstructured data (e.g., property descriptions, user reviews) remains a technical challenge.

### 3.7. Adapting techniques from other domains

The analysis of techniques from other domains reveals both promise and challenges for real estate recommender systems. NLP techniques could significantly enhance the utilization of textual data in property listings and reviews, but may have difficulties with the highly localized and specialized vocabulary of real estate. The clustering approach could effectively segment the diverse real estate market, but might oversimplify complex, multi-faceted property preferences. SVD techniques show potential for addressing data sparsity and scalability issues common in real estate databases, but may lose interpretability, which is crucial in high-risk real state decisions. Social network analysis could introduce valuable trust metrics, but must be carefully implemented to avoid bias and ensure fair housing practices. In general, while these techniques offer possibilities, their adaptation to real estate will require careful consideration of the domain's unique characteristics, including its high-value transactions, regulatory environment, and the deeply personal nature of home selection.

### 3.8. Future research directions

Based on our findings, we propose the following directions for future research:

- Hybrid model architectures: develop advanced hybrid models that can effectively combine content-based, collaborative, and knowledge-based approaches to leverage the strengths of each method.
- Attention mechanisms: investigate the use of attention mechanisms in neural network architectures to better capture user preferences and property relevance.
- Transfer learning: explore transfer learning techniques to address the cold-start problem and improve model performance in markets with limited data.
- Explainable artificial intelligence (AI): develop interpretable models that can provide reasoning for property recommendations, enhancing user trust and system transparency.
- Spatiotemporal modeling: incorporate advanced spatiotemporal modeling techniques to capture the geographic and time-dependent aspects of real estate markets.
- Multi-modal learning: investigate techniques for integrating diverse data types, including text, images, and geospatial data, to create more comprehensive property representations.

## 4. CONCLUSION

This systematic review showed the complex and rapidly evolving of the recommendation systems in the real estate sector, offering concrete insights into current methodologies and future directions. Our analysis reveals a field characterized by diverse techniques, each with unique strengths and challenges, used to improve the way users interact with property listings and make decisions in the real estate market.

The trend towards hybrid systems emerges as a dominant direction. By combining content-based, collaborative, and knowledge-based approaches, these systems address the limitations of individual methods and offer more robust recommendations, considering simultaneously various factors, from property features to user preferences and market trends. Parallel to this trend, the increasing adoption of deep learning models, particularly CNN-LSTM architectures, marks an important shift towards more complex analysis. Mainly, due to these models have shown ability to capture complex patterns in other domains, potentially leading to more accurate and personalized recommendations. However, related challenges are in terms of interpretability and the need for large, high-quality datasets.

Feature selection play a critical role in the effectiveness of recommendation systems. While traditional features such as price, location, and property size remain crucial, the underutilization of factors like property age and market trends presents untapped potential for enhancing recommendation accuracy. Future research could benefit from a more comprehensive exploration of feature importance, employing techniques like SHAP.

In the context of make comparison, the diversity of evaluation metrics used across studies underscores the varied nature of recommendation quality. This variability, points to the need for a more standardized evaluation framework. Establishing common benchmarks and metrics could facilitate more meaningful comparisons between different approaches.

Looking ahead, several key areas emerge as critical for future research and development. The integration of contextual and temporal dynamics presents a significant opportunity. Real estate markets are inherently dynamic, influenced by seasonal trends, economic factors, and rapid shifts in buyer preferences. Developing models that can effectively capture and adapt to these dynamics could greatly enhance the relevance and timeliness of recommendations. Another direction is the exploration of multi-modal learning techniques. By integrating diverse data types, including text, images, and geospatial data. This approach could be particularly valuable in capturing the nuanced attributes of properties that are difficult to quantify through traditional features alone.

The development of explainable AI models could not only enhance user trust but also provide valuable insights to real estate professionals and policymakers. The advancement of these systems has the potential to bring about fundamental changes in how real estate markets operate, leading to more efficient and transparent transactions maintaining a balance between technological advancement and ethical considerations.

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This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

| Name of Author | C | M | So | Va | Fo | I | R | D | O | E | Vi | Su | P | Fu |
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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

## CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

## INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

## DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

## REFERENCES


[1] "Data growth worldwide 2010-2025," Statista. [Online]. Available: https://www.statista.com/statistics/871513/worldwide-data-created/, (Accessed: May. 23, 2024).

[2] M. Salehi, I. N. Kamalabadi, and M. B. G. Ghoushchi, "Personalized recommendation of learning material using sequential pattern mining and attribute based collaborative filtering," *Education and Information Technologies*, vol. 19, no. 4, pp. 713–735, 2014, doi: 10.1007/s10639-012-9245-5.

[3] H. E. Pence, "What is Big Data and Why is it Important?," *Journal of Educational Technology Systems*, vol. 43, no. 2, pp. 159-171, 2014, doi: 10.2190/ET.43.2.d.

[4] L. Lü, M. Medo, C. H. Yeung, Y.-C. Zhang, Z.-K. Zhang, and T. Zhou, "Recommender systems," *Physics Reports*, vol. 519, no. 1, pp. 1–49, Oct. 2012, doi: 10.1016/j.physrep.2012.02.006.

[5] L. Chen and P. Pu, "Preference-Based Organization Interfaces: Aiding User Critiques in Recommender Systems," in *User Modeling 2007*, C. Conati, K. McCoy, and G. Paliouras, *Eds., Berlin, Heidelberg: Springer*, 2007, pp. 77–86, doi: 10.1007/978-3-540-73078-1_11.

[6] M. Mubarak *et al*., "A Map-Based Recommendation System and House Price Prediction Model for Real Estate," *ISPRS International Journal of Geo-Information*, vol. 11, no. 3, no. 3, 2022, doi: 10.3390/ijgi11030178.

[7] A. Gharahighehi, K. Pliakos, and C. Vens, "Recommender Systems in the Real Estate Market—A Survey," *Applied Sciences*, vol. 11, no. 16, no. 16, 2021, doi: 10.3390/app11167502.

[8] J. S. Breese, D. Heckerman, and C. Kadie, "Empirical analysis of predictive algorithms for collaborative filtering," *in Proceedings of the Fourteenth Conference on Uncertainty in Artificial Intelligence, in UAI'98. San Francisco, CA, USA: Morgan Kaufmann Publishers Inc*., 1998, pp. 43–52.

[9] M. K. Najafabadi and M. N. Mahrin, "A systematic literature review on the state of research and practice of collab-orative filtering technique and implicit feedback," *Artificial Intelligence Review*, vol. 45, no. 2, pp. 167–201, 2016, doi: 10.1007/s10462-

015-9443-9.
[10] L. Wang, X. Hu, J. Wei, and X. Cui, "A Collaborative Filtering Based Personalized TOP-K Recommender System for Housing," *Proceedings of the 2012 International Conference of Modern Computer Science and Applications,* 2024, vol. 191, pp. 461-466, doi: 10.1007/978-3-642-33030-8_74.
[11] P. Lops, D. Jannach, C. Musto, T. Bogers, and M. Koolen, "Trends in content-based recommendation," *User Model User-Adap Inter*, vol. 29, no. 2, pp. 239–249, 2019, doi: 10.1007/s11257-019-09231-w.
[12] S. Ayyaz, U. Qamar, and R. Nawaz, "HCF-CRS: A Hybrid Content based Fuzzy Conformal Recommender System for providing recommendations with confidence," *PLoS One*, vol. 13, no. 10, 2018, doi: 10.1371/journal.pone.0204849.
[13] T. Badriyah, S. Azvy, W. Yuwono, and I. Syarif, "Recommendation system for property search using content based filtering method," in *2018 International Conference on Information and Communications Technology (ICOIACT)*, pp. 25–29, 2018, doi: 10.1109/ICOIACT.2018.8350801.
[14] Q. Zhang, D. Zhang, J. Lu, G. Zhang, W. Qu, and M. Cohen, "A Recommender System for Cold-start Items: A Case Study in the Real Estate Industry," in *2019 IEEE 14th International Conference on Intelligent Systems and Knowledge Engineering (ISKE*), pp. 1185–1192, 2019, doi: 10.1109/ISKE47853.2019.9170411.
[15] B. Lika, K. Kolomvatsos, and S. Hadjiefthymiades, "Facing the cold start problem in recommender systems," *Expert Systems with Applications*, vol. 41, no. 4, Part 2, pp. 2065–2073, 2014, doi: 10.1016/j.eswa.2013.09.005.
[16] D. B. Tonara, "Recommender System in Property Business a Case Study from Surabaya, Indonesia," 2014. [Online]. Available: https://www.semanticscholar.org/paper/Recommender-System-in-Property-Business-a-Case-from Tonara/5eb78abab36df5dbc2908aacbb1e551e0bb8ac70. (Accessed: May. 28, 2024).
[17] F. Rehman, H. Masood, A. Ul-Hasan, R. Nawaz, and F. Shafait, "An Intelligent Context Aware Recommender Sys-tem for Real-Estate," *Pattern Recognition and Artificial Intelligence: Third Mediterranean Conference, MedPRAI 2019,* 2020, vol. 1144, pp. 177-191, doi: 10.1007/978-3-030-37548-5_14.
[18] F. Ricci, L. Rokach, and B. Shapira, "Introduction to Recommender Systems Handbook," in *Recommender Systems Handbook, F. Ricci, L. Rokach, B. Shapira, and P. B. Kantor, Eds., Boston, MA: Springer US*, pp. 1–35, 2011, doi: 10.1007/978-0-387-85820-3_1.
[19] B. Kumar, "Impact of digital marketing and e-commerce on the real estate industry," *International Journal of Research in Business Management*, vol. 2, no. 7, pp. 17–22, Jul. 2024.
[20] J. Shaw, "Platform Real Estate: theory and practice of new urban real estate markets," *Urban Geography*, vol. 41, no. 8, pp. 1037–1064, 2020, doi: 10.1080/02723638.2018.1524653.
[21] J. Saginor, "The Real Estate Academic Leadership (REAL) Rankings for 2016–2020," *Journal of Real Estate Literature*, vol. 28, no 2, pp. 150-160, 2021, doi: 10.1080/09277544.2021.1876436.
[22] T.-Y. Ou, G.-Y. Lin, H.-P. Fu, S.-C. Wei, and W.-L. Tsai, "An Intelligent Recommendation System for Real Estate Commodity," *CSSE*, vol. 42, no. 3, pp. 881–897, 2022, doi: 10.32604/csse.2022.022637.
[23] R. H. Kabir, B. Pervaiz, T. M. Khan, A. Ul-Hasan, R. Nawaz, and F. Shafait, "DeepRank: Adapting Neural Tensor Networks for Ranking the Recommendations," in *Pattern Recognition and Artificial Intelligence: Third Mediterranean Conference, MedPRAI 2019*, 2020, pp. 162–176, doi: 10.1007/978-3-030-37548-5_13.
[24] J. Chung, C. Gulcehre, K. Cho, and Y. Bengio, "Empirical evaluation of gated recurrent neural networks on se-quence modeling," *arXiv*, 2014, doi: 10.48550/arXiv.1412.3555.
[25] T. Nguyen, S. Vu, T. Nguyen, V. Pham, and H. Nguyen, "Design a Recommendation System in Real Estate Invest-ment Based on Context Approach:" in *Proceedings of the 15th International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management, Rome, Italy: SCITEPRESS - Science and Technology Publications*, 2023, pp. 255–263, doi: 10.5220/0012210800003598.
[26] R. D. Burke, K. J. Hammond, and B. C. Young, "Knowledge-based navigation of complex information spaces," in *Proceedings of the Thirteenth National Conference on Artificial Intelligence*, 1996, vol. 1, pp. 462–468.
[27] M. J. Page *et al*., "Declaración PRISMA 2020: una guía actualizada para la publicación de revisiones sistemáticas," *Revista Española de Cardiología*, vol. 74, no. 9, pp. 790–799, 2021, doi: 10.1016/j.recesp.2021.06.016.
[28] D. Budgen and P. Brereton, "Performing systematic literature reviews in software engineering," in *Proceedings of the 28th International Conference on Software Engineering, ACM*, 2006, pp. 1051–1052, doi: 10.1145/1134285.1134500.
[29] D. Moher, A. Liberati, J. Tetzlaff, and D. G. Altman, "Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement," *BMJ*, vol. 339, p. b2535, Jul. 2009, doi: 10.1136/bmj.b2535.
[30] B. Kitchenham and P. Brereton, "A systematic review of systematic review process research in software engineering," *Information and Software Technology*, vol. 55, no. 12, pp. 2049–2075, 2013, doi: 10.1016/j.infsof.2013.07.010.
[31] R. Pranckutė, "Web of Science (WoS) and Scopus: The Titans of Bibliographic Information in Today's Academic World," *Publications*, vol. 9, no. 1, 2021, doi: 10.3390/publications9010012.
[32] "Web of Science platform," *Clarivate*. [Online]. Available: https://clarivate.com/products/scientific-and-academic-research/research-discovery-and-workflow-solutions/webofscience-platform/. (Accessed: May. 30, 2024).
[33] "Acerca de Scopus | Base de datos de resúmenes y citas | Elsevier," www.elsevier.com. https://www.elsevier.com/es-es/products/scopus.
[34] M. E. Falagas, E. I. Pitsouni, G. A. Malietzis, and G. Pappas, "Comparison of PubMed, Scopus, Web of Science, and Google Scholar: strengths and weaknesses," *The FASEB journal*, vol. 22, no. 2, pp. 338–342, Feb. 2008, doi: 10.1096/fj.07-9492LSF.
[35] P. Mongeon and A. Paul-Hus, "The journal coverage of Web of Science and Scopus: a comparative analysis," *Scientometrics*, vol. 106, no. 1, pp. 213–228, 2016, doi: 10.1007/s11192-015-1765-5.
[36] W. M. Bramer, G. B. de Jonge, M. L. Rethlefsen, F. Mast, and J. Kleijnen, "A systematic approach to searching: an efficient and complete method to develop literature searches," *Journal of the Medical Library Association: JMLA*, vol. 106, no. 4, pp. 531–541, 2018, doi: 10.5195/jmla.2018.283.
[37] A.-W. Harzing and S. Alakangas, "Google Scholar, Scopus and the Web of Science: a longitudinal and cross-disciplinary comparison," *Scientometrics*, vol. 106, no. 2, pp. 787–804, Feb. 2016, doi: 10.1007/s11192-015-1798-9.
[38] K. Petersen, S. Vakkalanka, and L. Kuzniarz, "Guidelines for conducting systematic mapping studies in software engineering: An update," *Information and Software Technology*, vol. 64, pp. 1–18, 2015, doi: 10.1016/j.infsof.2015.03.007.
[39] R. Mu, "A Survey of Recommender Systems Based on Deep Learning," *IEEE Access*, vol. 6, pp. 69009–69022, 2018, doi: 10.1109/ACCESS.2018.2880197.
[40] R. Socher, D. Chen, C. D. Manning, and A. Y. Ng, "Reasoning with neural tensor networks for knowledge base completion," in *Proceedings of the 26th International Conference on Neural Information Processing Systems*, 2013, vol. 1, pp. 926–934.
[41] Y. Li, S. Gao, W. Wu, P. Xie, and H. Xia, "Research and Development Housing Rental System with Recommendation System

Based on SpringBoot," in: *Emerging Trends in Intelligent and Interactive Systems and Applications: Proceedings of the 5th International Conference on Intelligent, Interactive Systems and Applications (IISA2020),* 2021, pp. 619–627, doi: 10.1007/978-3-030-63784-2_77.
[42] L. Shen, Q. Liu, G. Chen, and S. Ji, "Text-based price recommendation system for online rental houses," *Big Data Mining and Analytics*, vol. 3, no. 2, pp. 143–152, 2020, doi: 10.26599/BDMA.2019.9020023.
[43] X. Shi and Y. Jiang, "Research on House Rental Recommendation Algorithm Based on Deep Learning," in *2022 3rd International Conference on Big Data Economy and Information Management (BDEIM 2022)*, *Atlantis Press*, pp. 604–613, 2023, doi: 10.2991/978-94-6463-124-1_70.
[44] K. Milkovich, S. Shirur, P. K. Desai, L. Manjunath and W. Wu, "ZenDen - A Personalized House Searching Application," in *2020 IEEE Sixth International Conference on Big Data Computing Service and Applications (BigDataService)*, Oxford, UK, pp. 173-178, 2020, doi: 10.1109/BigDataService49289.2020.00034.
[45] J. Knoll, R. Groß, A. Schwanke, B. Rinn, and M. Schreyer, "Applying Recommender Approaches to the Real Estate e-Commerce Market," in *Innovations for Community Services: 18th International Conference, I4CS 2018*, 2018, pp. 111–126, 2018, doi: 10.1007/978-3-319-93408-2_9.
[46] Y. Yu, C. Wang, L. Zhang, R. Gao, and H. Wang, "Geographical Proximity Boosted Recommendation Algorithms for Real Estate," in *Web Information Systems Engineering–WISE 2018: 19th International Conference*, pp. 51–66, 2018, doi: 10.1007/978-3-030-02925-8_4.
[47] H. J. Jun, J. H. Kim, D. Y. Rhee, and S. W. Chang, "'SeoulHouse2Vec': An Embedding-Based Collaborative Filtering Housing Recommender System for Analyzing Housing Preference," *Sustainability*, vol. 12, no. 17, 2020, doi: 10.3390/su12176964.
[48] F. Liu and W. -W. Guo, "Research on House Recommendation Model Based on Cosine Similarity in Deep Learning Mode in Grid Environment," in *2019 International Conference on Virtual Reality and Intelligent Systems (ICVRIS)*, Jishou, China, 2019, pp. 121-124, doi: 10.1109/ICVRIS.2019.00039.
[49] B. Hidasi, A. Karatzoglou, L. Baltrunas, and D. Tikk, "Session-based Recommendations with Recurrent Neural Networks," *arXiv*, Mar. 29, 2016, doi: 10.48550/arXiv.1511.06939.
[50] B. Hidasi and A. Karatzoglou, "Recurrent Neural Networks with Top-k Gains for Session-based Recommendations," in *Proceedings of the 27th ACM International Conference on Information and Knowledge Management*, 2018, pp. 843–852, doi: 10.1145/3269206.3271761.
[51] R. Logesh and V. Subramaniyaswamy, "Exploring Hybrid Recommender Systems for Personalized Travel Applications," in *Cognitive Informatics and Soft Computing: Proceeding of CISC 2017*, pp. 535–544, 2019, doi: 10.1007/978-981-13-0617-4_52.
[52] J. Malczewski and M. Jelokhani-niaraki, "An ontology-based multicriteria spatial decision support sys-tem: a case study of house selection," *Geo-spatial Information Science*, vol. 15, no. 3, pp. 177-185, 2024, doi: 10.1080/10095020.2012.715900.
[53] R. Burke, "Hybrid Recommender Systems: Survey and Experiments," *User Model User-Adap Inter*, vol. 12, no. 4, pp. 331–370, Nov. 2002, doi: 10.1023/A:1021240730564.
[54] M. Batet, A. Moreno, D. Sánchez, D. Isern, and A. Valls, "Turist@: Agent-based personalised recommendation of tourist activities*," Expert Systems with Applications*, vol. 39, no. 8, pp. 7319–7329, Jun. 2012, doi: 10.1016/j.eswa.2012.01.086.
[55] E. M. Daly, A. Botea, A. Kishimoto, and R. Marinescu, "Multi-criteria journey aware housing recommender system," in *RecSys '14: Proceedings of the 8th ACM Conference on Recommender Systems*, Oct. 2014, pp. 325–328, doi: 10.1145/2645710.2645764.
[56] H.-P. Ho, C.-T. Chang, and C.-Y. Ku, "House selection via the internet by considering homebuyers' risk attitudes with S-shaped utility functions," *European Journal of Operational Researc*h, vol. 241, no. 1, pp. 188–201, Feb. 2015, doi: 10.1016/j.ejor.2014.08.009.
[57] S. Das, S. Ghosh, B. S. P. Mishra, and M. K. Mishra, "A Novel Recommendation System for Housing Search: An MCDM Approach," in *Proceedings of International Conference on Recent Trends in Machine Learning, IoT, Smart Cities and Applications*, 2021, pp. 251–258, doi: 10.1007/978-981-15-7234-0_21.
[58] D. Oh and C. L. Tan, "Making Better Recommendations with Online Profiling Agents," *AI Magazine*, vol. 26, no. 3, 2005, doi: 10.1609/aimag.v26i3.1823.
[59] S. Shearin and H. Lieberman, "Intelligent profiling by example," in *Proceedings of the 6th International Conference on Intelligent User Interfaces*, 2001, pp. 145–151, doi: 10.1145/359784.360325.
[60] S. Li, S. Nomura, Y. Kikuta, and K. Arino, "Web-Scale Personalized Real-Time Recommender System on Suumo," *Advances in Knowledge Discovery and Data Mining*, pp. 521–538, 2017, doi: 10.1007/978-3-319-57529-2_41.
[61] P. Chonwiharnphan, P. Thienprapasith, and E. Chuangsuwanich, "Generating Realistic Users Using Generative Adversarial Network With Recommendation-Based Embedding," *IEEE Access*, vol. 8, pp. 41384–41393, 2020, doi: 10.1109/ACCESS.2020.2976491.
[62] F. Colace *et al*., "Recommender systems: a novel approach based on singular value decomposition," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 12, no. 6, pp.6513-6521, 2022, doi: 10.11591/ijece.v12i6.pp6513-6521.
[63] K. Rrmoku, B. Selimi, and L. Ahmedi, "Provenance and social network analysis for recommender systems: a litera-ture review," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 12, no. 5, pp. 5383-5392, 2022, doi: 10.11591/ijece.v12i5.pp5383-5392.
[64] D. H. Park, H. K. Kim, I. Y. Choi, and J. K. Kim, "A literature review and classification of recommender systems research," *Expert Systems with Applications*, vol. 39, no. 11, pp. 10059–10072, 2012, doi: 10.1016/j.eswa.2012.02.038.
[65] R. Devooght and H. Bersini, "Collaborative Filtering with Recurrent Neural Networks," *arXiv*, 2017, doi: 10.48550/arXiv.1608.07400.
[66] C.-Y. Wu, A. Ahmed, A. Beutel, A. J. Smola, and H. Jing, "Recurrent Recommender Networks," in *Proceedings of the Tenth ACM International Conference on Web Search and Data Mining, in WSDM '17*, 2017, pp. 495–503, doi: 10.1145/3018661.3018689.
[67] S. M. Lundberg and S.-I. Lee, "A unified approach to interpreting model predictions," in *Proceedings of the 31st In-ternational Conference on Neural Information Processing Systems,* 2017, pp. 4768–4777.

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