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Research article

Housing fuzzy recommender system: A systematic literature review

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A R T I C L E I N F O

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A B S T R A C T

In recent years, significant attention has been paid to fuzzy recommender systems for housing, highlighting their ability to effectively handle the imprecision and uncertainty inherent in the real estate market. With the objective of improving the filtering of recommendations in the real estate sector, the PRISMA 2020 methodology was applied to perform new systematic reviews using its checklist on six academic databases from 1985 to 2024. RawGraph, Orange Data Minig, Jamovi and R software were used for document classification and data visualization. After classification, 1003 articles were obtained, of which 46.36% were in Scopus, and 57.82% were articles. At the end of the type, 50 articles were identified as primary, subjecting them to six research questions. It was found that 65% of the algorithms used fuzzy logic, 60% used spatial data, and 80% evaluated performance. The main difficulties were related to the integration of various sources of information. Although incorporating reclusive methods is anticipated in future systems, the need remains to address challenging areas to improve the overall performance of fuzzy recommender systems. The reviewed articles focus on enhancing fuzzy data-based recommendation systems by proposing flexible and less intrusive techniques. The significance of incorporating contextual information and exploring hybrid approaches is emphasized, along with the evaluation in real world environments, averaging artificial intelligence.

1. Introduction

Due to the large amount of existing data, obtaining valid data has become highly complex; distinguishing between accurate and inaccurate reasoning in-creases the difficulty of managing the desired information. For these reasons, new practical tools have been generated to find adequate information on time and improve the efficiency in the use of data, such as clustering techniques, biclustering, matrix factorization, graph theory and fuzzy techniques in data systems recommendation that have been mentioned by Cassidy [1] and Goldberg et al. [2].

However, there are some drawbacks to RS, such as recommending items that a customer buys less frequently, and this action may need more information to support the earlier recommendation, or insufficient customer ratings and inaccurate data. Therefore, a practical request cannot be made the difficulties of recommender systems.

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1.1. Difficulties have been registered, among which we have

1.1.1. The habituation

Chao et al. [3] refers to the phenomenon in which users become less receptive to recommendations as they interact more with the system. This typically occurs when users identify repetitive patterns in recommendations and become weary of encountering the same choices repeatedly, in addressing this matter, recommender systems can employ exploration and mining techniques, as proposed by alternatives, to balance popular recommendations and less-known and undiscovered.

1.1.2. Cold start

Refers to the lack of information about new or unknown users. Recommender systems must provide accurate recommendations even with little information about users. One viable solution is to employ recommendation techniques rooted in content popularity, as proposed by Lika et al. [4].

1.1.3. Data sparseness

Is a common problem in recommender systems, especially when the number of users or products is small. In such circumstances, recommender systems can employ collaborative filtering techniques, leveraging data from akin users to formulate recommendations, as elucidated by Massa and Bhattachar-jee [5].

1.1.4. The scalability

Refers to the system's ability to handle large data sets and users. Recommender systems must be able to process large amounts of data in real-time to provide accurate and relevant recommendations. To this issue, recommender systems can employ distributed and scalable machine learning techniques, as proposed Singh [6].

1.1.5. The diversity

Refers to the system's ability to offer varied and diverse recommendations, and recommender systems must be able to recommend relevant options but also unknown or less popular options that may interest users. In addressing this challenge, recommender systems can employ recommendation diversification techniques. Alternatively, if additional information is accessible, such as the user's social network activity, incorporating such data is advisable to enhance the recommender system's overall effectiveness, as suggested by Wasid and Ali [7].

Zadeh [8], to improve the effectiveness and solve the difficulties of there commender system, soft computing techniques are used, which have provento be effective in various fields and have significant potential to improve performance, this techniques refers to a group of methodologies that offer practical solutions for problems that cannot be easily modelled mathematically or that are not modelled at all; other techniques that are used are the following:

The term fuzzy sets that were established in 1965, encompasses the clear group and is suitable for handling incomplete or imprecise information, giving way to fuzzy logic; this has experienced significant growth in the field of recommender systems, such as product recommendations, song semantics, etc, how it was mentioned by Zadeh [8]. In the pursuit of efficiency, collaborative filtering (CF), as discussed by Thorat et al. [9], stands out as a widely adopted technique in recommendation system design. It adopts a personalized approach by comparing new user's preferences with those of other users who have evaluated similar products. This process leads to tailored recommendations, drawing from the user's historical choices, item descriptions, and targeting profile. Furthermore, CF seeks to suggest items based on their similarity to the user's past selections, or it can recommend items based on their descriptions, the user's targeting profile, and items previously chosen by the user.

1.2. The following characteristics are evaluated to assess the performance of the recommender systems

1.2.1. Evaluation metrics

Recommender systems are widely used in various fields to help users find relevant information and products more efficiently. A range of evaluation metrics is utilized to enhance the effectiveness of recommender systems. These standard metrics encompass recall, precision, accuracy, ROC curves, and F-measures. Recall and precision measure the proportion of relevant items that were recommended and the proportion of appropriate recommendations that were made, respectively. Accuracy measures the overall effectiveness of the recommendations. The ROC curve is a graphical measure that plots the actual positive rate versus the false positive rate. Finally, F measurements are a measure that combines recall and precision into a single metric. These are important to measure the effectiveness of recommender systems and allow their continuous improvement.Nevertheless, combining multiple metrics to achieve a comprehensive evaluation is advisable, as Jirvelin and Keklinen [10] recommended. Moreover, there is a need for developing new metrics for enhancing the accuracy of existing ones.

1.2.2. Accuracy and interpretability

The fuzzy rules-based system successfully enhanced accuracy while maintaining low interpretability, thus improving the utilization of customer behaviour information. Furthermore, it considers various factors, including mouse movement distance, page scrolling, mouse clicks, and user activity time, to predict purchase intent, as demonstrated by Sulikowski et al. [11]. Due to the aforementioned, recommender systems have become one of the most relevant research areas; for this reason, recommender systems have.

1.2.3. Undergone different approaches

Kim and Chen [12], to study the current situation, reviewed featured articles and recommender systems keywords from 1992 to 2019, condensed into three groups: 1) confirming results that align with previous survey articles, 2) emerging trends and patterns that have been recently identified, and3) unresolved challenges and suggestions for future research, on the other hand, Sinha and Dhanalakshmi [13] present an analysis of various recommender systems based on content, hybrid recommendation techniques, based on metaheuristic collaboration and approaches biological, waiting for the improvement in efficiency when recommending a suggestion, for this they explored 125 articles published from 1992 to 2019, where they present various results among the most prominent we have that, most of the time the recommendation system fails to recommend the least popular elements to the user, in addition, they suggest that you should focus on a few measures such as performance, novelty, chance, coverage and privacy.

Additionally, there are the emotions were had integrated into the item selection process to enhance the accuracy of product recommendations; this enabled the creation of a specific evaluation matrix encompassing both tested and untested products tailored to the buyers preferences and emotions associated with the development, as proposed by Poirson and Cunha [14].

Nonetheless, most recommender systems leverage textual data by applying content-based image retrieval (CBIR) and artificial intelligence techniques. These systems can visually identify products and contrast consumers' purchasing preferences with factors such as product value, complexity, and durability. Price comparison, frequently employed for comprehensive search descriptions, plays a pivotal role in this process. These advancements promise to enhance the efficacy of online product recommendations, as highlighted by Salman and Varaprasad [15] and Deldjoo et al. [16].

Recommender systems (RS) are currently incorporated into all search areas, which is why the real estate sector is no exception, (RS) are an efficient tool, allowing users to tailor their preferences using overload information. Nevertheless, uncertainty is an inherent aspect of human nature, continually posing new challenges, as Hosseini et al. [17] noted. The real estate industry tends to have unstructured metadata such as explanations, designs, images, and geospatial data that contain valuable information for recommender systems, even with specific fuzzy properties like neighbourhood range and quietness. These factors contribute to the processing problem from these data; therefore, the problem that (RS) presents in housing due to these aspects is striking.

That is why one of the unusual alternatives in recommender systems is the application of fuzzy soft computing, which, in one way or another, produces an easy adaptation to the preferences and uncertainties of users when making decisions. In general, fuzzy recommendation systems for homes promise to improve the decision-making process for buyers and sellers in the real estate market. However, more research is needed to address challenges such as handling large and complex data sets, image-based processing, and improving the accuracy and reliability of recommendations.

By the considerations above, identifying variables influencing recommendation systems and applying fuzzy logic in the real estate sector have facilitated effective data handling. However, in regions with limited real estate platforms, using social networks such as TikTok, X, Instagram and Face-book through the Marketplace platform has optimized the search process. Although this platform has experienced a significant increase in users, unfortunately, it has also been the scene of incidents such as scams, thefts, and threats.

For this reason, designing a fuzzy recommendation system that integrates social media comments, videos, user relationships, geographical location, and crime levels could significantly contribute to minimizing these adverse effects. It would improve the security and trust of users and enhance the quality of recommendations by providing valuable information based on real community experiences.

This innovative approach represents a proactive and effective response to current challenges in using real estate search platforms while contributing to developing safer and more efficient strategies in the sector.

For this reason, the purpose of this study is to carry out a comprehensive review of the literature aimed at identifying the current state of research in the field of fuzzy recommendation systems for housing suggestions, to investigate which algorithms and data sets are used in fuzzy recommendation systems, the results obtained and challenges encountered in housing recommendation.The Research Questions (RQ) were defined as follows: (RQ)1. What algorithms are used in fuzzy recommendation systems for homes? (RQ)2. What data sets are used to model fuzzy recommender systems to present housing? (RQ)3. What have been the results of the recommendation for selecting accommodation using fuzzy recommendation systems? (RQ)4. What difficulties are found in using fuzzy recommendation systems to suggest homes? (RQ)5. What is the approach or method proposed in recommender systems? (RQ)6. What are some possible future research directions to improve fuzzy-based recommender systems? Section II describes the paper's methodology, detailing the

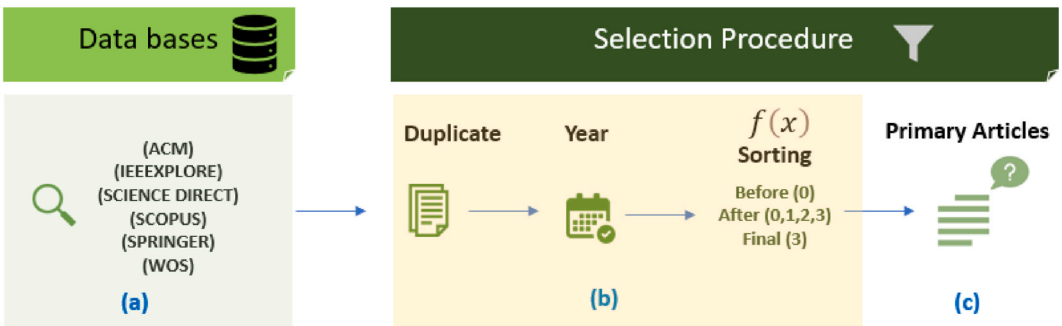

Fig. 1. Search flow and item selection.

systematic literature review based on the PRISMA Tugwell and Tovey [18] model. Section III presents the results, Section IV discusses, and Section V presents the conclusions.

2. Materials and methods

A thorough exploration was conducted in academic databases, which were analyzed using PRISMA, according to Page et al. [19]. The following text presents one of the methodologies formulated for literature analysis.

2.1. Planning search strategies: analysis and review of documents in the literature

In Fig. 1, the implemented process for obtaining document search can be observed, which consisted of three phases: the first was the search and selection stage, symbolized by the letter (a); the second was Sorting, rep-resented by the letter (b); and the third was the application of research questions, identified by the letter (c).

2.1.1. Search and choice (a)

During the phase of exploration and selection, we commenced by delineating essential terminology sorted into controlled articles and articles related to the recommendation system theme. With these documents, a text analysis was done on the titles and keywords, identifying the most commonly occurring words to construct the most fitting search string for the investigation. In this way, it is possible to identify the algorithms and data sets used in fuzzy recommendation systems with the results and problems found in housing recommendations.

The review began by conducting an exhaustive literature search using a combination of keywords such as "fuzzy recommender systems", "housing market", "appropriate housing", and "real estate". Based on the keywords, the search was carried out in each database, with the detailed format in Table 1. It searched the following databases: ACM Digital Library (ACM), Web of Science (WOS), IEEE Xplore, Scopus, Science Direct and Springer, starting January 3, 2024. Table 1 illustrates the search phrases employed in each database.

In refining the investigations, the procedure outlined in Keele [20] was modified and structured as follows: 1) removal of duplicated studies, 2) evaluation of the titles, abstracts, and keywords of the studies, dismissing those that do not fulfil the exclusion criteria, 3) assessment of the introduction and conclusion segments of the studies chosen in step 2, eliminating those that do not comply with the inclusion standards and lastly, and evaluation of the quality of the studies. This search yielded a total of 50 relevant articles, these were carefully examined and selected based on relevance, as described below.

2.1.2. Sorting (b)

The primary objective of the information retrieval process is to establish the standards for eligibility. The inclusion criteria category was subsequently included: studies focused on fuzzy recommendation systems in the context of housing selection, scientific articles and conference papers, focusing on user preference based housing recommendations, identifying data sets, and artificial intelligence techniques. Lastly, the goal is to discover verified computational models in published works that integrate housing with recommendation systems and exhibit outcomes and challenges. Conversely, investigations documented in reports, undergraduate and graduate dissertations, and research on sustainable housing, energy conservation, real estate market analyses, property value forecasting, and recommendation models that are not directly related to housing recommendations are excluded.

Table 2 displays the inclusion and exclusion standards arranged with their explanations and overall rationale.

One thousand two hundred ninety-nine articles were gathered from various databases, then refined by applying the Prisma methodology, as depicted in Fig. 1. It carried out a detailed record and precise classification; the process was divided into three stages: 'Before Sorting,' 'After Sorting,' and 'Final Sorting' of primary articles.

In the 'Before Sorting' stage, articles were encoded by the number '0'. In the next phase, an R function was applied to analyze titles and classify articles into four segments: the '0' segment included articles that did not meet any requirements for the research; those

Table 1
Application of the search string to information sources.

Database	Research strings format
ACM	(TITLE-ABS-KEY ("recommender system" OR "decision support system" OR "collaborative filtering") AND (fuzzy) AND ("housing market" OR "real estate" OR "appropriate housing"))
IEEExplore	("All Metadata":"recommendation sys- tem"OR"recommender system") AND ("All Meta- data":"housing" OR "All Metadata":"house" OR "All Metadata":"home" OR "All Metadata":"Real Estate")
Science Direct	("recommender system" OR "decision support system" OR "collaborative filtering") AND(fuzzy) AND ("housing market" OR "real estate" OR"appropriate housing")
Scopus	(TITLE-ABS-KEY ("recommender system" OR"decision support system" OR "collaborative filtering") AND (fuzzy) AND("housing market"OR "real estate" OR "appropriate housing"))
Springer	("recommender system" OR "decision support system" OR "collaborative filtering") AND("fuzzy") AND ("housing market" OR "real estate" OR"appropriate housing")
WOS	"recommender system" OR "decision support system" OR "collaborative filtering" (All Fields) and fuzzy (All Fields) and "housing market" OR "real estate" OR "real estate"OR"appropriate housing" (All Fields)

Table 2
Description and rationale for eligibility criteria.

Criteria	Description/Motivation
Inclusion: 1. Articles of any language. 2. Publications from the year 1985. 3. Scientific and conference articles. 4. Focus on housing recommendation. 5. Publications that include evaluation and optimization of models focused on housing recommendation. 6. Focus on housing recommendation based on user preferences, including artificial intelligence techniques, data set, results and difficulties of fuzzy recommendation systems. 7. Selecting Relevant Articles on Fuzzy Recommendation Systems. 8. Highly Cited Housing Recommender System Articles Regardless of Publication Date	The standards for inclusion were established based on present-day significance, a broad range of languages, and a concentrated emphasis on housing recommendations, as well as data mining methods employed for this in- tent. Furthermore, research that evaluates data individually and collectively considers the number of citations and has the potential to assist users in formulating housing recommendations is also incorporated.
Exclusion: 1. Reports on essential service con text in housing, algorithms unrelated to the context of housing recommendation. 2. Publications before the year 1985. 3. Reports, doctoral or master's the- ses. 4. Publications with algorithms un- related to the context of housing recommendation.	Articles incorporating other scenarios, different from the recommendation of Housing according to the user's preferences, were excluded. Any other forms of literature besides articles and conference papers are not considered. In addition, it excluded studies that focus exclusively on essential services in the home and prediction algorithms of the cost of the house.

numbered '1' met one requirement; those with '2' met both criteria and required further analysis, while those numbered '3' met all three conditions, achieving the ideal score. This process occurred in the 'After Sorting' stage.

In the 'Final Sorting' stage, an analysis function of abstracts, titles, and keywords was applied to articles previously classified with the number '2'. They were divided into two groups: those with a score of '0,' not meeting any requirements, including those that previously had scores '0 and '1'; and those with a score of '3', meeting all three requirements.

2.1.3. Application of research questions (c)

Articles that received a score of '3' in the 'Final Sorting' stage under-went a set of detailed questions that were applied during the information extraction phase, standards set for problem analysis, contribution, applica tion scenarios, analysis of results and conclusions, input and output data, artificial intelligence-based approaches, technologies employed, advantages and drawbacks, and prospective applications were considered.

Table 3 displays the research inquiries and their corresponding explana ions and rationale.

The information extraction phase, established standards for problem analysis, contribution, application scenarios, results analysis, and conclusions were taken into account, as shown in Table 4.

2.2. Data processing and visualization

2.2.1. R function

The function defined in R was responsible for reading the abstracts of the articles. A vector containing keywords associated with research variables, such as "logic," "Recommender," "System," "recommendation," "Real," and "estate," was generated. Subsequently, a matrix of zeros was created with dimensions $n * m$, where n represented the number of articles and m the number of words in the vector. To ensure consistency, the function converted all text to lowercase before comparing each word in the vector with the content of the abstract. In case of a match, a value of one was assigned; otherwise, zero was assigned.

A nested for loop was used to traverse the articles' abstract table, the matrix of zeros, and the keyword vector. During this process, zeros were replaced with ones when a similarity was found. Then, the values of the entire row were calculated by summing the first

Table 3
Systematic literature review research questions.

Research questions	**Motivation and expected** results
RQ1. What algorithms are used in fuzzy recommendation systems for housing?	To identify the use of artificial intelligence techniques focused on housing recommendation systems.
RQ2. What are the data sets that are used to model fuzzy recommendation systems for presenting housing?	To identify the data sets focused on housing recommendation systems.
RQ3. What have been the results of the recommendation for selecting housing using fuzzy recommendation systems?	To pinpoint contributions closely associated with using recommendation systems for proposing housing alternatives.
RQ4. What difficulties are found in the use of fuzzy recommendation systems for suggesting housing?	To identify challenges directly related to recommendation systems for suggesting housing.
RQ5. What is the proposed approach or method in recommendation systems?	Identify the proposed methods in fuzzy recommendation systems.
RQ6. What are some potential future research directions for improving fuzzy based recommender systems?	Identify future research directions to improve fuzzy recommendation systems.

Table 4
Criteria description for information extraction.

Specifictions	Explanation
C1.Artificial intelligence methods	To identify artificial intelligence techniques used in recommendation systems.
C2. Input	To identify data types, samples, and significant aspects of data processing and obtaining results from them.
C3.Performance of the recommendation system	The aim was to examine the findings and conclusions to identify suggestions to help analyze the study variables.
C4. Advantages and limitations	To recognize the advantages of the contribution and de- fine the shortcomings or restrictions of the research studies.
C5. Aproach	Identify the proposed approaches in recommendation systems.
C6.Future research directions.	Identify future research directions in fuzzy recommendation systems.

column and multiplying

the second with the third columns, multiplication of the third and fourth columns, and finally, the sum of the expansion of the fifth and sixth columns of the updated matrix.

Subsequently, a vector 'words to search' with some keywords was defined. A matrix 'Mt1' with dimensions $n * 6$ was created, where n is the number of rows in the data object. Then, a nested loop was used to apply the 'search word' function to each element of data and each word in 'words to search', the results were stored in the 'Mt1' matrix.

Finally, a series of operations were performed to calculate the 'results' variable, and a frequency table was displayed.

2.2.2. Alluvial diagram

This graph was generated in RAWGraphs Mauri et al. [21] using the variables Before Sorting, Document Type, Language, Year, Source, After Sorting, and Final Sorting. The aim is to provide a clearer understanding of the data flow.

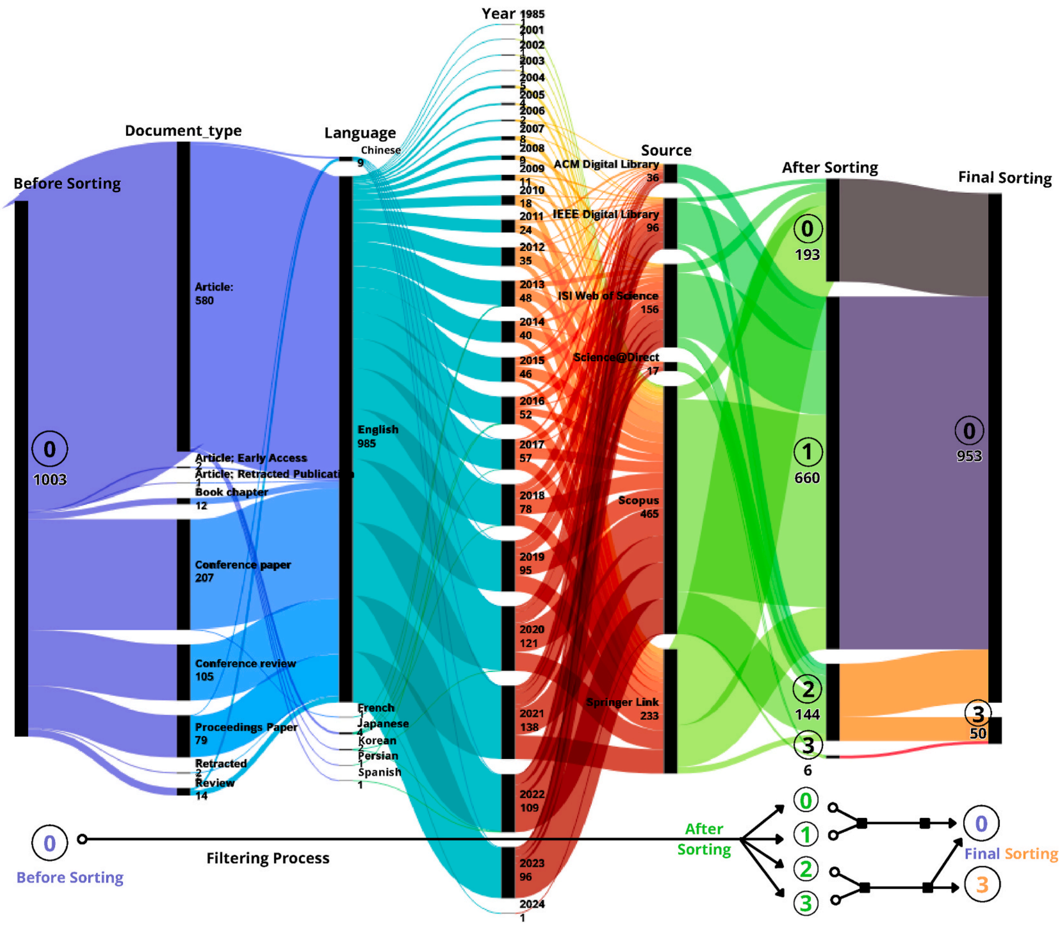

Fig. 2. Procedures and results of article analysis.

2.2.3. Wordcount

Orange Data Mining software, version 3.36.2, was used to create this graph. The titles and abstracts of the main articles were used as input data. The 'File' widget was applied to read the database, 'Corpus' to transform the summaries into text format, 'Preprocess text' to configure and remove stop words, and 'Word Count' to display, apply the algorithm and configure the colours.

2.2.4. Multiple correspondence analysis (MCA)

Jamovi Software version 2.4.11.0 was used to perform this analysis. Various variables such as source, document type, publication year, language, and keywords were employed to investigate the association between different categories applied to the articles. The aim was to identify the relationship between thematic categories assigned to scientific papers, explore aspects such as authors' institutional affiliation, country, and area of specialization, and examine the relationship between keywords used in articles and assigned categories.

The analysis also delved into how journals cluster based on categories assigned to published articles, and comparisons were made between groups of compositions according to different criteria, such as publication year, language, and study type. This approach allowed for identifying meaningful patterns and relationships among the analyzed variables. Additionally, variables that did not contribute to the model were removed to increase the percentage of the dimensions.

2.2.5. Results visualization with ggplot

Bar and doughnut charts were created with the results obtained in the last stage.

3. Results

According to the planning phase, the following results were presented.

3.1. Before sorting

In Fig. 2, the flow of the article filtration process was presented, leading to the acquisition of the 50 primary articles. Out of the 1003 articles obtained after removing duplicates and applying coding, 580 (57.82%) were identified as scientific articles, 207 as Conference papers (20.62%), 106 as conference reviews (10.57%), 79 as proceeding papers (7.88%), 14 as Reviews (1.4%), 12 as book chapters (1.2%), and three as articles in early access and retracted publications (0.3%). Additionally, it was observed that 985 documents were written in English (98.20%), 4 in Japanese (0.4%), 2 in Korean (0.2%), and one (0.1%) in Spanish, French, and Persian. The years with the highest publication rates were 2021 with 138 documents (13.75%), 2020 with 121.

(12.06%), 2022 with 109 (10.87%), 2019 with 95 (9.47%), and up to the date of 2024, one (0.1%). The majority of these documents were found published in the Scopus database with 465 (46.36%), followed by Springer Link with 233 (23.23%), Web of Science with 156 (15.55%), and to a lesser extent ACM with 36 (3.6%).

After applying the R function to the titles and abstracts of the documents before sorting (Before Sorting) and subsequently to the

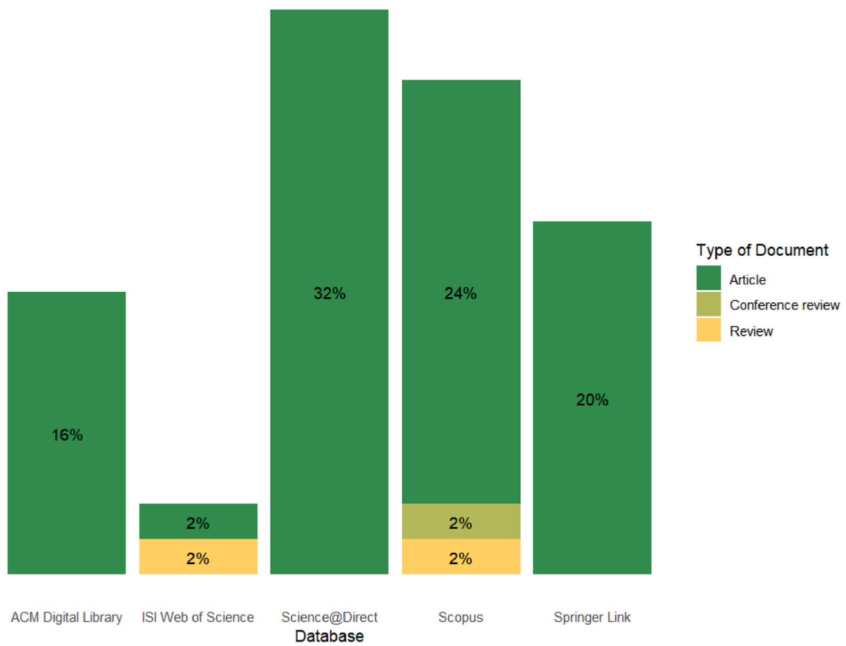

Fig. 3. Histogram of primary articles by database.

sorting process (After Sorting), scores were distributed as follows: 193 papers with a score of 0 (19.24%), 660 with a score of 1 (65.80%), 144 with a score of 2 (14.36%), and 6 with a score of 3 (0.6%). After reapplying the R function, considering titles, abstracts, and keywords for those documents with a score of 2 in the After Sorting, 50 articles with coding of 3 were obtained, representing 5% of the documents obtained.

3.2. Final Sorting of the primary articles

The descriptive statistical analysis has reflected the process of searching, filtering, refining, applying criteria, duplicates, and selecting primary articles. This stage was assigned to gathering information that could answer the research inquiries.

Of the 50 articles compiled for our study, 98% are written in English, and 2% are in Korean; a diverse distribution was observed in the publication sources. 20% of these articles originated from Springer Link, 28% from Scopus, 32% from Science@Direct, 4% from Web of Science, and 16% from the ACM Digital Library. Upon analyzing the documents obtained, it was iden tified that 94% corre-sponded to articles, 4% to reviews, and 2% to conference reviews. Within the category of articles, a specific distribution was evident: 20% came from Springer Link, 24% from Scopus, 32% from Science@Direct, 2% from Web of Science, and 16% from the ACM Digital Library. Regarding conference reviews, 2% was attributed to Scopus. In the reviews category, it was found that both ISI Web of Science and Scopus contributed 2% each, as seen in Fig. 3.

Upon examining Fig. 4, the most frequent words in the abstracts and titles of the analyzed primary articles were identified as recommendation, housing, system, social, data, network, and urban. On the other hand, words.

like algorithm, fuzzy, rental, and Airbnb were found less frequently.

In the Multiple Correspondence Analyses of primary articles, as depicted in Fig. 5, ISI Web of Science was predominantly associated with Dimension 1, while Scopus showed an association in the opposite direction. Regarding Document Types, 'article' exhibited a positive association, whereas 'Conference paper' and 'Conference review' were negatively associated. Notably, 'Proceedings Paper' and 'Review' showed a strong positive association.

For Dimension 2, ISI Web of Science was primarily associated, while Scopus exhibited an association in the opposite direction. Document Types 'Article' and 'Review' were positively associated, whereas 'Conference paper' and 'Conference review' showed a negative association.General Interpretation: In both Dimension 1 and Dimension 2, the cate-gories of 'ISI Web of Science' and 'Scopus' played a pivotal role in differentiation. Document Type categories also displayed distinctive associations in the dimensions.

On the other hand, language and publication years exhibited a weak association among the variables.

3.3. Information obtained from research questions in primary articles

table 5 (review appendix) presents the summary information extracted from the primary articles about each research question, which relate to the algorithms, data sets used, approach, and the results and challenges encountered, in addition, the number of ci-tations reached until the end of this research.

3.3.1. Algorithms used in recommendation systems (RQ1)

Most housing recommendation systems utilize hybrid algorithms that amalgamate various techniques to enhance the precision of their suggestions. As per the scrutinized articles, about 51% of recommendation systems employ fuzzy logic, 21.5% utilize spatial

Fig. 4. Word count of abstracts in the 50 articles.

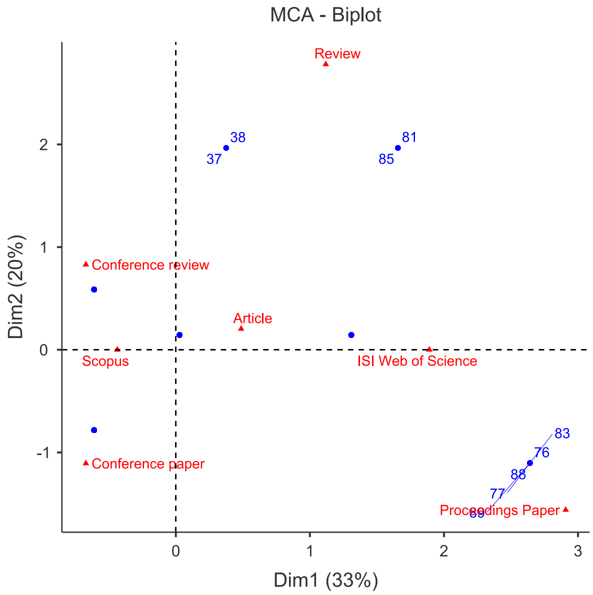

Fig. 5. Multiple correspondence analysis of primary articles.

statistics, and 27.5% use multiple cri teria, along with additional techniques such as Natural Language Processing (NLP), Markov, and Monte Carlo (Fig. 6).

3.3.2. Dataset used in recommendation systems (RQ2)

According to the reviewed articles, the data sets used in housing recommendations are organized into 25% housing market data, 60% spatial data, and 15% simulated data (Fig. 7). Housing market data includes information about the price, location, and features of available housing on the market. Spatial data includes geographic and cartographic valuable information for recommending accommodation in specific areas. Simulated data are artificially created to test and evaluate housing recommendation systems.

3.3.3. Performance in recommendation systems (RQ3)

The results obtained from the review of articles indicate that more than 80% of housing recommendation algorithms have been evaluated in terms of performance, pressure, correlation, and satisfaction indices.

3.3.4. Difficulties in recommendation systems (RQ4)

The reviewed articles on housing recommendations may present various challenges in their research and analysis. One of these is the existence of multiple criteria to consider when making recommendations (40%) and the need for accurate data (35%). In addition, it may be necessary to integrate different sources of data (25%) to have a more comprehensive view of the environment and make informed decisions (Fig. 8).

3.3.5. Approach in recommendation systems (RQ5)

From the reviewed articles, 65% employed collaborative methods, implementing the preferences of multiple users to generate

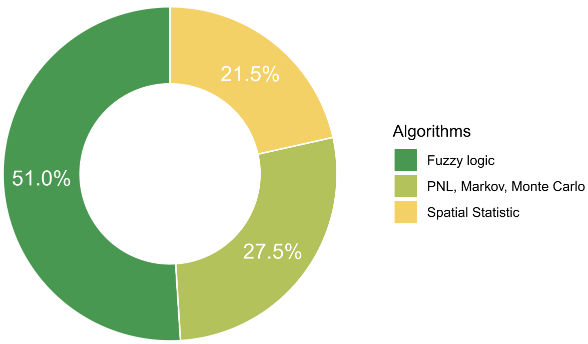

Fig. 6. Artificial intelligence algorithms used in the articles reviewed.

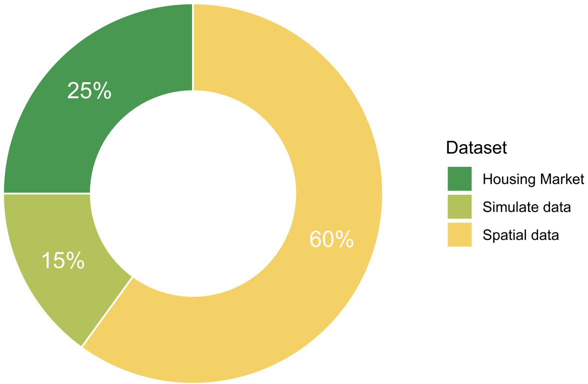

Fig. 7. Data set, used in the articles reviewed.

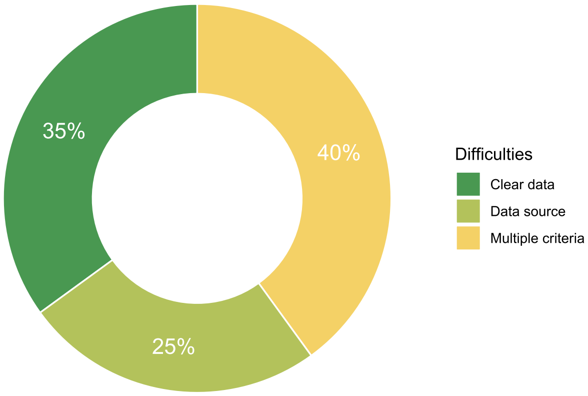

Fig. 8. Difficulties in the articles reviewed.

recommendations, while 35% used exclusive methods based on individual preferences without considering the choices of others. Various techniques, such as fuzzy sets, machine learning, and fuzzy clustering, were applied to address the challenges associated with representing the subjective, imprecise, and vague characteristics of articles and user comments.

3.3.6. Future research in recommendation systems (RQ6)

The contributions suggest future research directions enhance recommendation systems, including improved representation of user behaviour, advanced modelling techniques, and integration of contextual information. Other areas involve leveraging multicriteria ratings, creating adaptable recommendation methods, considering social networks, and establishing specific effec tiveness metrics.

4. Discussion

Fuzzy housing recommendation systems have the potential to provide consumers with personalized and transparent recommendations based on their preferences and requirements. Between 2019 and 2024, 46.16% of a total of 1003 articles addressing topics such as recommendation systems, algorithms, and optimizations were published. However, combining fuzzy algorithms in recommendation systems applied to the real estate sector represented only 5% (50 primary articles) from 1985 to 2023. Below is an analysis of the questions used to the primary articles.

4.1. Algorithms (RQ1)

Algorithms play a pivotal role in housing recommendations, serving as a cornerstone within recommendation systems and exerting a profound impact on the accuracy and effectiveness of the suggestions. This review of articles shows that hybrid algorithms, amalgamating multiple techniques, are the most prevalent choice for housing recommendations.

Fuzzy logic, a technique that utilizes imprecise concepts and variables to model and solve problems, facilitates the prediction of user preferences and the generation of appropriate housing recommendations. It is prominent in 51% of the analyzed housing recommendation systems. However, in a prior analysis of titles and abstracts, it is found less frequently due to its integration with other techniques. Spatial statistics were applied in 21.5% of housing recommendation systems and proved to be very useful for identifying patterns and trends related to the location and price of homes through the analysis and processing of geographical and spatial data.

Additional techniques, collectively constituting 25% of the reviewed articles, encompass Multiple Criteria Analysis (MCA), Natural Language Processing (NLP), Markov, and Monte Carlo methods. These techniques entail the evaluation of diverse criteria and weightings to inform decision making, enabling the analysis and processing of review information and user preferences. It's essential to underscore that each algorithm possesses unique advantages and limitations concerning housing recommendations. For the most optimal recommendations, it is imperative to employ a blend of multi-ple algorithms and techniques.

Conducting thorough testing and evaluations is crucial to determining the most suitable algorithm or combination of algorithms for a specific scenario. Monti et al. [22] conducted a comprehensive study that analyzes existing literature on recommendation systems utilizing multiple criteria for decision-making.

Furthermore, Pelissari et al. [23] highlighted that most recommenda tion systems rely on classification approaches, suggesting that future research could explore integrating preference learning methods with Multiple Criteria Decision Making (MCDA) techniques. This integration aims to enhance the prediction and recommendation phase and improve overall quality and processing time.

Idrissi and Zellou [24] also presented a systematic literature review concerning proposed solutions for mitigating data scarcity in recommendation systems. Their study covered various aspects, including similarity measures, proposed approaches, types of secondary information, and criteria to enhance recommendation accuracy.

In this research, the works of Monti et al. [22], Pelissari et al. [23], and Idrissi and Zellou [24] coincide with the work carried out in this review. On the other hand, Cano and Morisio [25] mention that hybrid recommenders, which are recommendation systems that combine different algorithms and techniques, can help address issues such as personalized recommendations based on the context in which they are presented and handling large datasets. In the article by Cano and Morisio [25], it has been ev idenced in the literature review that these have yet to be explored for this recommendation area.

4.2. Datasets (RQ2)

The datasets employed in housing recommendation are a critical component of recommendation systems and significantly impact the accuracy and effectiveness of the submissions. According to the reviewed articles, the datasets used in housing recommendations are organized into 25% housing market data, 60% spatial data, and 15% simulated data. Housing market data includes information on the price, location, and features of available housing in the market. The data is crucial in comprehending trends and patterns in the real estate market, and it can aid in recommending appropriate housing options to users. Spatial data includes geographic and mapping information that guides housing in specific areas. For example, if a user is looking for accommodations near their workplace, spatial data can help identify available housing. Simulated data are artificially created to test and evaluate housing recommendation systems.

These data can help evaluate the performance of algorithms and adjust systems in consequence. It is essential to note the quality and quantity of the data sets used in housing recommendations. Similarly, Amig et al. [26] demonstrate that synthetic data metrics designed to measure equity are compelling and show the expected characteristics of system results. However, Eili et al. [27] mention that synthetic data do not necessarily reflect the complexity and variability of accurate records, so evaluating algorithms on both synthetic and precise data is essential. Similarly, Martins et al. [28] mention that researchers using real-world public data sets in their experiments obtained better results than synthetic data and various evaluation metrics. In this sense, the works mentioned in references Amig et al. [26], Eili et al. [27], and Martins et al. [28] share similarities with the work carried out in the current review. Both pieces address similar methods or approaches to analyze or solve the problem.

In other circumstances, According to reference Guruge et al. [29], student enrollment data is the predominant source of information utilized to evaluate course recommendation systems, although certain systems address the "cold start" problem by incorporating alternative data sources like synthetic data, LinkedIn profiles, WordNet, and survey data. However, some articles should have included information on the data used, and not just be based on the system design.

4.3. Performance (RQ3)

The evaluation of algorithms for housing recommendation is an integral part of implementing and improving these systems. It is crucial to assess the performance of the algorithms to determine their precision and efficiency and ensure that they deliver the most optimal recommendations to users. According to the reviewed articles, some algorithms for housing recommendation have been evaluated in 80% or more in terms of performance, pres-sure, correlation, and satisfaction rates. These criteria are used to measure the quality of recommendations and the degree to which they meet the needs and preferences of users. For example, performance refers to the accuracy of submissions, pressure measures the grade to which the algorithm is overloaded, and correlation measures the relationship between recommendations and user preferences.

Other articles, have found significant differences in variables such as proximity to recreational facilities, suggesting that this variable may be necessary for some users when choosing a home. However, other articles have compared different models and have yet to find significant differences in terms of performance. Villegas et al. [30] Typically, the primary objective of a The recommendation system is to enhance the user experience.

The system's efficacy and various characteristics have been put forth and employed, each accompanied by a set of metrics dating back to the early days of the field. These characteristics aid in assessing the pertinence of the recommendations proposed by the system. Several properties, including predictive power, confidence, diversity, learning rate, reach, scalability, and user evaluation, help determine the relevancy of the suggestions provided. Similarly, Freire and de Castro [31] found that the most commonly used metrics to evaluate recommendation systems are precision, recall, AUC, ROC curve, and F measure, which represents 41.67% of the reviewed works. In addition, expert validation and comparison with other approaches were used in 20.83% of the results.

Villegas et al. [30] and Freire and de Castro [31] share similarities with the current review as they employ comparable methods and approaches for model validation. Conversely, Cunha et al. [32] take a different perspective by scrutinizing pertinent studies across critical dimensions for addressing algorithm selection challenges. Their paper provides an in-depth exploration of the research conducted within each size and suggests avenues for future studies. Additionally, they conduct experimental evaluations to determine the most effective strategies for algorithm selection in collaborative filtering.

4.4. Difficult (RQ4)

Research on housing environments can present several difficulties that can affect the quality of recommendations. The 40% represent the implementation of Multiple criteria to consider when making recommendations, making it complicated to choose between different options and make informed decisions. For example, when selecting a home, it is essential to consider factors such as location, size, price, and quality. However, this can be particularly complicated when choosing between options that present different combinations of these factors, and it is necessary to weigh them properly.

Another area for improvement is the need for more straightforward or precise data 35%, making it harder to make decisions and more complicated to evaluate the environment and its characteristics. For example, updated or detailed data on air quality, traffic, or safety in a particular area are unavailable. In that case, it may be more challenging to evaluate if it is a suitable place to live. Additionally, it may be necessary to integrate different data sources 25% to have a more complete view of the environment and make informed decisions. Collecting and analysing data from other sources can be tedious and require time and effort. For example, it may be necessary to compare data on housing prices in an area with information on employment and cost of living to have a more complete view and make an informed decision.

Overall, the literature indicates that fuzzy recommendation systems in the housing domain can enhance the decision-making process for real estate buyers and sellers. However, it is necessary to continue researching to address challenges such as dealing with large and complex data sets and improving recommendations' precision and reliability. According to Murillo et al. [33], the main challenges identified in the area of recommendations include starting from cold, precision, data scarcity, integration of data sources, scalability, lack of personalization, lack of novelty in submissions, lack of explanations for recommendations, transparency and interpretability, session-based recommendations, and the need to use parallel algorithms to improve efficiency.

All of these issues must be addressed to improve the effectiveness and usefulness of recommendations. In summary, da Silva et al. [34] state that if more sets of data were available to the public, researchers would have more opportunities to find those that fit their needs and, as a result, increase the size of their experiments. It could benefit them by making obtaining data more accessible and less costly. Moreover, the scientific community could gain access to data from users in unfamiliar settings and conduct experiments based on diverse data.

The main challenges identified in the reviewed studies to generate accurate recommendations include the absence of semantic information, the intricacy of item information, reliance on user data, starting from scratch, data quality, computational complexity, data dispersion, domain dependence, and limited domain specificity Figueroa et al. [35]. These problems must bead dressed to make accurate and useful recommendations. These difficulties include multiple criteria to consider, the need for clear and precise data, and the need to integrate different data sources. These factors can make it harder to make decisions and make choosing between different housing options more complicated. Additionally, spending time and effort collecting and analyzing data from other sources may be necessary to have a more complete view of the environment and make informed decisions.

4.5. Approach (RQ5)

In general, recommendation system approaches encompass both exclusive and collaborative methods. Exclusive methods are based on individual preferences and do not consider the choices of others (35%), while collaborative processes leverage the tastes of multiple users to generate recommendations (65%). Additionally, various techniques, such as fuzzy sets, machine learning, and fuzzy clustering, address the challenges posed by representing the subjective, imprecise, and vague characteristics of articles and user comments.

Overall, the approaches aim to improve the accuracy of recommendations and address problems such as data scarcity and cold start. These concepts can be found in articles by Yager [36], Zenebe and Norcio [37], Ghavipour and Meybodi [38], Cheng and Wang [39], Son [40], Yera and Martnez [41] and Tern and Meier [42].

4.6. Future research (RQ6)

"The proposals made by the authors Yager [36], Zenebe and Norcio [37], Ghavipour and Meybodi [38], Cheng and Wang [39], Son [40], Yera and Martnez [41], and Tern and Meier [42] notably enhance the discourse surrounding fuzzy recommendation systems."

These contributions shed light on potential avenues for future research to strengthen such systems' accuracy and effectiveness. Some of the suggested areas for further exploration include.

- Developing improved methods for representing user behaviour and item information.
- Advancing recommendation modelling techniques.
- Integrating contextual information into the recommendation process.
- Leveraging multicriteria ratings for more comprehensive recommendations.

- Creating less intrusive and more adaptable recommendation methods.
- Establishing effectiveness metrics specific to recommender systems.
- Use of social media.

The articles also suggest exploring hybrid approaches, investigating context-awareness, and evaluating the usability and effectiveness of fuzzy based recommender systems in real-world settings. Additionally, future recommender systems will likely incorporate collaborative filtering and reclusive methods. Finally, the articles identify four challenging areas that should be expanded to improve the performance of fuzzy based recommender systems, including developing a fuzzy common framework, integrating different sources of infor mation, adapting to other contexts, and effectively evaluating the system`s performance. In addition, adopting node selection approaches based on fuzzy logic and TOPSIS for efficient data management in IoT with blockchain and edge computing how they mention it Gardas et al. [43], Yan et al. [44], and Asad et al. [45], would allow more accurate and personalized housing recommendations, use federated recommendation systems to protect user privacy while Collaboration in big data is encouraged, thus improving the quality and security of housing recommendations.

5. Conclusions

The presented literature review provides a complete overview of the current state of fuzzy recommendation systems for housing. While these systems can potentially improve decision-making in the real estate sector, obstacles and areas still require further investigation.

The fuzzy recommendation systems for housing presenting significant potential by offering personalized and transparent recommendations tailored to consumers' preferences and requirements. From 2019 to 2024, research in this field stood out with the publication of 46.16% of 1003 articles, covering various aspects related to recommendation systems, algorithms, and optimizations. Despite these advancements, it is essential to note that the integration of fuzzy algorithms into recommendation systems applied to the real estate sector showed more modest growth, representing only 5% (50 articles) over the extended period from 1985 to 2023. This observation underscores the need for further exploration and development in implementing fuzzy approaches in the specific realm of real estate recommendations, aiming to fully harness the potential of this technology for the benefit of personalization and transparency in housing recommendations.

Most recommender systems identified in the review use hybrid algorithms that combine several techniques, including fuzzy logic, spatial statistics, multiple criteria, and NLP, Markov, and Monte Carlo methods. Different housing data sets, such as housing market data, spatial data, and simulated data, are also used.

Evaluation criteria for these systems may include performance, accuracy, correlation, and satisfaction rates. Some studies have found significant differences in variables such as proximity to places of recreation, which indicates that this factor may be necessary for some users when selecting a home. However, the literature review also highlighted several challenges in living environment research that may affect the quality of recommendations.

Future research should focus on overcoming these challenges and enhancing the performance of fuzzy recommendation systems. It may entail integrating diverse structured and unstructured information sources, including user opinions related to scams, thefts, identity theft, or impersonation, and images of properties and videos, using deep learning techniques. Furthermore, developing a practical methodology for representing and modelling user preferences concerning housing attributes is essential. It should incorporate geographical location, green spaces, crime levels in the sector, and high-risk areas.

Overall, the articles reviewed offer valuable information on improving fuzzy-based recommender systems in the future, such as enhancing user and item representations, developing flexible and less intrusive techniques, and incorporating contextual information. Exploring hybrid approaches, context awareness, and evaluating the effectiveness of fuzzy method-based recommender systems in real-world settings and the employment of artificial intelligence is recommended.

In conclusion, optimization methods can be implemented to enhance future systems; nevertheless, there are still outstanding challenges, such as developing a common framework, integrating diverse sources of information, adapting to different contexts modelled with graphs and game theory, and ensuring a practical performance evaluation. On the other hand, improving the technique for classifying articles by analyzing only titles, abstracts, and keywords can result in biases in the results, as many authors combine algorithms without mentioning them individually.

Data availability statement

The data included in this article have been gathered from various sources, including Scopus, IEEE Xplore, Web of Science (WoS), ACM, and Springer. These data are available in both the main article and supplementary material and have been referenced to ensure the results' transparency and reproducibility.

CRediT authorship contribution statement

Emanuel G. Muñoz: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **Jorge Parraga-Alava:** Supervision, Methodology. **Jaime Meza:** Validation, Supervision, Project administration. **Jonathan Josue Proaño Morales:** Writing – review & editing, Visualization, Supervision, Conceptualization. **Sebastian Ventura:** Supervision, Project administration.

Declaration of generative AI and AI-assisted technologies in the writing process

While preparing this work, the author or authors used ChatGPT to improve the writing along with Grammarly. After using this tool/ service, the author or authors reviewed and edited the content as needed and assumed full responsibility for the publication's content.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix. 8

Table 5
Summary of information extracted from the articles and number of cites.

N°	Article	Summary	Cites
1.	Yager [36]	The text is about fuzzy logic methods in recommendation systems, where fuzzy set methods are used to build justifications and recommendation rules based on each user's preferences. Reclusive methods differ from collaborative filtering by not requiring the representation of objects and only relying on the user's preferences. In general, it is recommended to combine both approaches to take advantage of all available information.	282
2.	Zenebe and Norcio [37]	This article proposes using fuzzy sets to address the challenges of representing subjective characteristics in content-based recommendation systems. Different similarity measures and aggregation strategies are described, and several algorithms are designed to evaluate the accuracy and performance of the proposed recommendation systems, using precision and recall metrics combined in the F1 measure.	220
3.	Yera and Martnez [41]	The article analyzes the use of fuzzy tools in recommendation systems to detect common research topics and gaps in research to suggest future lines of research to improve current developments in fuzzy tool-based recommendation systems. The analysis is done through a comprehensive review of works indexed in Thomson Reuters' Web of Science database. The article identi fies four challenging areas that need to be expanded in the future for better exploitation of fuzzy tools to enhance the performance of recommendation systems.	168
4.	Clark and Onaka [46]	The nested multinomial logit model was used to analyze the Housing Assistance Supply Experiment data. The model had limited success in predicting neighbourhood choice, with likelihood ratio indices of 0.08–0.1. The main area for improvement was the specification of neighbourhood choice, and more effort is needed to identify factors that influence the household choice between neighbourhoods.	135
5.	Biancalana et al. [47]	The study used GPS data and a Relational Markov Network to create personal maps and link activities with contexts. A dataset of 1612 entries was collected, and 30 restaurants in New York were randomly selected. The classification accuracy for the entire dataset was 94.97%, but integrating information from different sources could lead to inconsistency in the combined data.	129
6.	Yuan et al. [48]	The article discusses a user-oriented recommendation system for real estate websites that combines case-based reasoning and an ontological structure. The system uses semantic and numeric measurements to compare user queries and database cases to provide recommendations. Using an ontological form improves information management efficiency, while case-based reasoning improves recommendation accuracy. The system employs semantic matching to provide more flexible alternatives for home buyers.	120
7.	Yuan et al. [49]	The housing recommendation system employs a case-based reasoning algorithm and an ontological structure to enhance information management efficiency, based on over 200 sets of apartments and 300 environmental cases in Yuseong-gu, Daejeon, South Korea. The system optimizes real estate searches and has demonstrated its effectiveness in user tests. A combination of case-based reasoning and ontological structure is proposed for improved recommendation accuracy and information management efficiency, with future suggestions including incorporating similarity measurement of additional environmental factors and making adjustments in the research.	120
8.	Son [40]	The article describes the HU-FCF method, a hybrid user-based fuzzy collaborative filtering approach for recommendation systems. It uses degrees of vague similarity to improve the accuracy of the recommendation system and provides a mathematical definition of fuzzy recommendation systems. Accuracy is measured using mean absolute error (MAE) and root mean squared error (RMSE). Limitations include the need for more precise and com plete data and the need to address other important aspects of recommendation.	112
9.	Cheng and Wang [39]	The article uses a fuzzy linguistic model to describe a collaborative filtering framework that integrates subjective preferences and objective information. The Simple Aggregated algorithm (SA) and the Aggregated Subjective and Objective Viewpoint algorithm (ASOV) are used to generate recommendations, which perform better than traditional methods. Although the proposed methods work well, limitations must be addressed before they can be applied in practice.	76
10.	Azadeh et al. [50]	The text describes a hybrid fuzzy regression-fuzzy cognitive mapping algorithm used for forecasting and optimizing real estate market fluctuations based on a dataset of 16 periods of data related to the housing market in Iran. However, the ANOVA analysis yielded insignificant differences, indicating that data is inadequate for predicting and optimizing the housing market due to its uncertainty and noise.	68
11.	Tern and Meier [42]	The article presents a recommendation system architecture for elections that uses fuzzy clustering methods to assist voters in making decisions. The proposed approach differs from collaborative filtering methods and is based on past experiences.	65

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Table 5 (*continued*)

N°	Article	Summary	Cites
12.	Ghavipour and Meybodi [38]	The article presents a new approach to improving the accuracy of collaborative recommendation systems by incorporating information on trust and distrust using fuzzy linguistic models and membership function optimization. The proposed method is an adaptive fuzzy recommendation system based on machine learning that addresses data scarcity and cold start. However, it does not specify some technical details and discusses some limitations.	50
13.	Renigier-Bilozor et al. [51]	The study used geoscience and fuzzy logic methods to analyzea dataset of apartment sales in Gdynia, Poland, from 2016 to 2018. The results showed that proximity to the sea is a crucial factor in determining property prices, with properties in the first zone being 35% more expensive than those in the second zone. Spatial analysis techniques are necessary to improve precision and decrease uncertainty in real estate market analysis.	36
14.	Ho et al [52]	The Fuzzy Goal Programming (FGP) method with an S-hapedutility function was used to evaluate the satisfaction rate of 250middle-aged employees who have purchased homes in central Taiwan. The utility value k2 was 0.9829, indicating a high satisfaction rate of 98.29%. The complexity of evaluating various factors simultaneously, such as emotional preferences, financial situations, and subjective preferences, may hinder home buyers from shortening their search duration despite the availability of Internet search tools.	35
15.	Tajani et al. [53]	The study used Evolutionary Polynomial Regression (EPR) and Artificial Neural Networks (ANN) to estimate property prices in the Madonnella neighbourhood in Bari, Italy. The results showed an RMSE value of 1.0723, an R2 value of 0.9998, a MAPE value of 3.3172, and a MaxAPE value of 8.8689. The EPR model provided a precise mathematical expression to determine the significance of explanatory variables in determining property prices.	34
16.	Lau et al. [54]	The article discusses the use of a Monte Carlo simulation forsensitivity analysis in assessing disability inclusion in construction. The study focuses on the Physical Disability Inclusion Secondary Score (PDIS) and the Visual Disability Inclusion Secondary Score (VIIS) in 48 university buildings across four Hong Kong universities. The Building Inclusion Assessment Score (BIAS) was used to evaluate the extent to which construction considerations are inclusive of people with disabilities.	33
17.	Kizielewicz and Bczkiewicz [55]	The article discusses multi-criteria decision-making methods based on fuzzy logic for apartment selection. Seven criteria were identified: cost, number of rooms, and distance from work. Four MCDA methods were used, but no clear best housing alternative was determined.	33
18.	Aydinoglu et al. [56]	A randomized forest algorithm created a soil valuation data model for a 190 square kilometre area in Turkey's Istanbul province. The dataset used for training had 1021 samples, and the evaluation metrics were RMSE, MAE, and CC, which were determined to be 0.080, 0.050, and 0.850, respectively. The heterogeneity of data structures from multiple sources has made analysis difficult for government organizations.	27
19.	Lousada et al. [57]	The article discusses the use of fuzzy cognitive mapping and system dynamics approach in modeling urban decay. The models consist of stock and rate variables, and simulations were conducted to test their reliability. To improve the study, the authors suggest repeating the process with another group of experts, replicating the study in other areas, and investigating methods for preventing and combating urban decay.	25
20.	Kaklauskas et al. [58]	NEAR is an integrated recommendation system for housing selection, utilizing biometric, statistical, and recommender methods. It employs a neuro-decision matrix based on housing attributes and buyer emotions, aiming to enhance decision accuracy by analyzing user preferences and reducing information overload.	25
21.	Attardi et al. [59]	The study uses multidimensional evaluation techniques, multi-group analysis, and Geographic Information Systems to simulate scenarios for improving the landscape in the National Park of Cilento, Vallo di Diano and Alburni. The CLS assessment method organises hierarchical and network connections among municipalities in the area, and social group preferences are introduced to define a multigroup decision problem for simulating landscape improvement scenarios.	21
22.	Jun et al. [60]	SeoulHouse2Vec is an embedding-based collaborative filtering recommender system trained and validated using supervised learning. The system's embedding values become significant after training, reflecting outlier preferences. The model proposed in this study aims to solve problems in the housing market caused by imbalanced information and biased decision-making.	16
23.	Fu et al. [61]	A simplified fuzzy system with single input and single outputmodules (SFS-SISOM) was used to analyze a dataset of 441 apartments developed by Kingston in 2005. Both the SISOM and SFS systems showed high performance levels, achieving test accuracies between 92.64% and 98.28%. The study focused on price negotiation in high-dimensional problems.	15
24.	Daly et al. [62]	The article discusses a multi-modal trip planning system thatuses a multi-objective tension optimization engine to recommend available housing based on user preferences. The system reduces the recommended homes to an average of 50, ensuring that each filtered-out house is dominated by at least one place in the preserved subset. In 77.77% of cases, the user's original selection was included in the final recommendations.	15
25.	Kaklauskas et al. [63]	The article introduces a model for effectively managing real estate market crises, accompanied by a corresponding gauge. The primary objective of this study was to establish a correlation between the temperature of the housing market and critical housing market indicators. The calculations reveal a strong positive correlation between the housing market temperature and indicators such as the housing price-to-income ratio, buyer's income, construction activities, and investments in the construction sector.	13
26.	Bottero et al.[64]	The article discusses the use of Multiple Criteria Decision Analysis (MCDA) and Multiple Attribute Value Theory (MAVT) in evaluating alternative projects for urban regeneration in Turin, Italy. The evaluation considers various criteria and attributes, resulting in a ranking of sustainable solutions. Sustainable development is acknowledged as a complex idea with multiple dimensions and challenges.	13
27.	Wang et al. [65]	The CFP-TR4H collaborative filtering system is based on customized TOP-K home recommendations and uses data collected through questionnaires. The system extracts data from 3 groups of consumers randomly selected from a pool of 5000. The algorithm improves traditional collaborative filtering by addressing data scarcity issues through effective data collection.	12
28.	Nakano and Washizu [66]	The study used a multivariate probit model to analyze factorsaffecting satisfaction with energy-efficient homes. The survey included 619 respondents, with 309 living in condominiums and 310 living in detached houses. The	12

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Table 5 (*continued*)

N°	Article	Summary	Cites
		satisfaction probability was higher in detached houses when respondents actively utilized advanced systems and devices.	
29.	Gharahighehi et al. [67]	The text reviews concepts such as Neural Tensor Network andXGBOOST in recommendation systems, addressing issues like”cold-start” and proposing future directions such as incorporating user feedback and exploring deep learning. The importance of improving the explainability and efficiency of algorithms is emphasized, along with designing systems to handle large real estate datasets and including social network analysis for socially connected recommendations.	12
30.	Alexeev et al. [68]	The article discusses the development of a unique, self adaptive neural network system that distinguishes itself from existing methods, eliminating the need for frequent updates. This system dynamically adjusts to the changing economic state and regional specifics, facilitating scenario forecasting for real estate markets. It considers dynamic economic parameters such as the dollar rate, oil prices, gross domestic product, regional gross product, housing construction volume, and state credit policy parameters.	12
31.	Zeydan et al. [69]	The study used a combination of MCDM, EA, and GIS to identify 29 priority criteria and transform positional data for 160 houses into pixelated raster data. The target population was around 2000 residential units sold in Kayseri within the last month. The study achieved maximization values for 104 alternatives with a 65% performance using CMA-ES-WLC and 56 options with a 35% performance using FDEMATEL-WLC.	10
32.	Zheng et al. [70]	Collaborative filtering with historical data such as consumer ratings, purchases, and browsing can lead to solid profitability in a quantitative investment strategy with an average annualized return of 11.42%. Further exploring the algorithm’s effectiveness in investigating stock volatility transmission effects in other emerging and global markets would be an exciting study area.	9
33.	Liu et al. [71]	The article proposes a new hybrid recommendation method that combines the analysis of social influences and the virtual house bandwagon phenomenon to predict users’ preferences. The dataset used in the study includes 1577 item groups, 41,310 users, and 17,207 items. The method outperforms conventional recommendation methods and highlights the importance of considering both factors.	9
34.	Mosallaeipour et al. [72]	The article discusses the use of fuzzy logic and uncertainty theory in making multi-criteria decisions for real estate location analysis.The decision-making process considers factors such as future performance, tax disadvantages, costs, accessibility, and potential profits, while dealing with risk and uncertainty. Identified 11 localities, among which district 26 already has a facility in operation.	7
35.	Schaller [73]	The text describes a hybrid recommender system that combines collaborative and content-based filtering algorithms. It also mentions an application that includes metadata for 100 landmarks in and around Nuremberg, grouped into 14 categories. Finally, it discusses the Orienteering Problem, which involves finding the most favorable path that includes feasible destinations with assigned scores and travel duration information.	7
36.	Rehman et al. [74]	The research proposes a real-estate recommendation approachusing Gated Orthogonal Recurrent Unit and Weighted Cosine Similarity, utilizing data from AARZ.PK. The system outperformed comparison methods in all evaluation metrics, with a user coverage of 58.5, a recall rate 59.9, and an MRR of 29.3. The ranking module requires manual weights but can incorpo rate business requirements such as recommendation diversity and priority for earlier advertisement submissions.	7
37.	Marsal-Llacuna and Rosa-Esteva [75]	The article discusses a model of recommending agents that extract citizens’ opinions, using the redesign of Avenida Diagonal in Barcelona as an example. This approach allows planners to create proposals that consider citizens’ concerns and predict their reactions more accurately. However, due to its popularity-based process, the model’s efficiency may be limited for rarely accessed items.	7
38.	Li et al. [76]	Real-time log processors, scalable API for recommendations,and machine learning modules are used with data from Suumo, Japan’s largest real estate portal. Suumo’s system responds to over 99.9% of API requests, resulting in a 250% increase in conversion rates compared to their previous recommendation system; this allows data scientists to focus on improving algorithms and core functions, achieving a weekly release cycle in a production environment.	6
39.	Liu and Guo [77]	The article discusses using cosine similarity in deep learning to establish a mathematical housing recommendation model using primary housing data samples and user feedback information. The proposed model recommends housing resources that meet the user’s characteristic information, improving resource retrieval efficiency. To achieve accurate recommendations, the model should consider the grid environment platform, depth training, and similarity.	6
40.	Belaid and Razmak [78]	The literature review highlights the use of Multi-Criteria Decision Support Systems in diverse fields, including Production and Operation Management, Finance, Education, Human Resources, Real Estate, and Multi-Media. The research emphasizes the heavy reliance on decision support systems and user-friendly software for aggregation techniques. These systems are beneficial for making decisions that involve conflicting and incommensurable criteria.	5
41.	Ginevičius et al. [79]	The text explores real estate management methods such as Nearest Neighbourhood and Collaborative Filtering, highlighting challenges in evaluating strengths and suggesting improvements. Common recommendation approaches include content-based and collaborative methods, with the desire for more flexible and less intrusive recommendations.	5
42.	Solans et al. [80]	The article discusses using Collaborative Filtering, Matrix Factorization, and XG-Boost in recommendation systems. The evaluation of recommendations is done using the Discounted Cumulative Gain metric. The study shows that while these algorithms improve finding a suitable tenant or room, they also reinforce performance inequalities between different demographic groups, making it harder for certain minorities to find rentals.	5
43.	Kabir et al. [81]	The article proposes a Neural Tensor Network to sort real estate properties based on their resemblance, using a dataset of over 100,000 properties from Pakistan. The approach achieves an accuracy rate of 86.6% and aims to provide personalized suggestions for users based on their previous interactions with the system.	4
44.	Zhang et al. [82]	The article introduces the elementary notions and aggregation operations of sv-NPCFHSS. The model is applied to a real estate scenario to select a housing project while considering various risk factors. The suggested model	3

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Table 5 (*continued*)

N°	Article	Summary	Cites
		overcomes the limitations of existing fuzzy soft set-type models but has restrictions when dealing with complex intuitionistic fuzzy hyper-soft sets and other comparable models.	
45.	Iikman et al. [83]	The article discusses an adaptive weighted multi-criteria fuzzy query processing system for web-based real estate applications in Turkey. The system generates a higher number of search results until a relevance threshold of 50% is reached, and users can modify the weight or priority assigned to search fields and define the range of search criteria. However, there is a challenge in the usefulness of questions based on fuzziness and weight.	3
46.	Sinha and Dhanalak-shmi [13]	The article discusses using SWRL rules and the GeoSPARQL ontology to facilitate spatial representation and semantically link stored data. The presented taxonomy focuses on neighbourhood concepts and relationships. The GIS engine (ArcGIS) handles spatial information and functions separately from the ontology.	2
47.	Roberto et al. [84]	The article presents a protocol for evaluating effective design alternatives using the Analytic Hierarchy Process and mitigation indicators. Regeneration programs should target high-risk areas with social, building, and urban vulnerability factors to optimize risk reduction measures. Unregulated urban expansion and poverty globally lead to degradation, putting cities at risk of being marginalized.	2
48.	Zhong and Li [85]	The study proposes a Fast FCE model that integrates FCE, NN,and GA to evaluate real estate companies. The model produced consistent results with the Top 10 Study Team, indicating satisfactory outcomes. However, concerns remain regarding subjective index weight determination and slow convergence rates, among other issues.	2
49.	Munoz et al. [86]	The article discusses using neural networks and fuzzy clusters to simulate data from the Municipality of Quito. Forecasting accuracy ranges from 82% to 97%, but more data must be tested to test the models.	0
50.	Yang et al.[87]	The article uses PLS-SEM to establish hypotheses and analyze survey data from 112 cities in China. The study focuses on tenants' perceived value, pleasure, and arousal but acknowledges the complexity of individual rent behaviour and the need for further research. The scale reliability test used the CR coefficient test method.	0

References

[1] R.G. Cassidy, Urban housing selection, Behav. Sci. 20 (4) (1975) 241–250.
[2] D. Goldberg, D. Nichols, B.M. Oki, D. Terry, Using collabo- rative filtering to weave an information tapestry, Commun. ACM 35 (12) (1992) 61–70.
[3] K.-M. Chao, L. Jiang, O.K. Hussain, S.-P. Ma, X. Fei (Eds.), *Advances in E-Business Engineering for Ubiquitous Computing: Proceedings of the 16th International Conference on E-Business Engineer- Ing (ICEBE 2019)*, Volume 41 of *Lecture Notes on Data Engineering and Communications Technologies*, Springer International Publishing, 2020.
[4] B. Lika, K. Kolomvatsos, S. Hadjiefthymiades, Facing the cold start problem in recommender systems, Expert Syst. Appl. 41 (4) (2014) 2065–2073.
[5] P. Massa, B. Bhattacharjee, Using trust in recommender systems: an experimental analysis, in: C. Jensen, S. Poslad, T. Dimitrakos (Eds.), *Trust Management*, Volume 2995 of *Lecture Notes in Computer Science*, Springer Berlin Heidelberg, 2004, pp. 221–235.
[6] M. Singh, Scalability and sparsity issues in recommender datasets: a survey, Knowl. Inf. Syst. 62 (1) (2020) 1–43.
[7] M. Wasid, R. Ali, Use of soft computing techniques for rec- ommender systems: an overview, in: R. Ali, M.S. Beg (Eds.), Applications of Soft Computing for the Web, Springer Singa- pore, 2017, pp. 61–80.
[8] L.A. Zadeh, Fuzzy sets, Inf. Control 8 (3) (1965) 338–353.
[9] P.B. Thorat, R.M. Goudar, S. Barve, Survey on collabora- tive filtering, content-based filtering and hybrid recommendation system, Int. J. Comput. Appl. 110 (4) (2015) 31–36.
[10] K. Jirvelin, J. Keklinen, Ir evaluation methods for retrieving highly relevant documents, ACM SIGIR Forum 51 (2) (2017).
[11] P. Sulikowski, T. Zdziebko, O. Hussain, A. Wilbik, Fuzzy ap- proach to purchase intent modeling based on user tracking for e-commerce recommenders, in: 2021 IEEE International Conference on Fuzzy Systems, FUZZ-IEEE), Luxembourg, Luxembourg, 2021 pages 1–8.
[12] M.C. Kim, C. Chen, A scientometric review of emerging trends and new developments in recommendation systems, Scientometrics 104 (1) (2015) 239–263.
[13] B.B. Sinha, R. Dhanalakshmi, Evolution of recommender paradigm optimization over time, Journal of King Saud University - Com- puter and Information Sciences 34 (4) (2022) 1047–1059.
[14] E. Poirson, C.D. Cunha, A recommender approach based on customer emotions, Expert Syst. Appl. 122 (2019) 281–288.
[15] B.R. Salman, G. Varaprasad, Product recommendation sys- tem using deep learning techniques: cnn and nlp, in: Data Management, Analytics and Innovation, Springer Nature Singapore, 2023, pp. 331–343.
[16] Y. Deldjoo, D. Jannach, A. Bellogin, A. Difonzo, D. Zanzonelli, Fairness in recommender systems: research landscape and future directions, *User Modeling and User-Adapted Interaction* (2023) 1–50.
[17] S.M.A. Hosseini, O. Pons, A. de la Fuente, Suitability of different decision-making methods applied for analysing sustainable post- disaster temporary housing, in: A. Asgary (Ed.), Resettlement Challenges for Displaced Populations and Refugees, Springer Interna- tional Publishing, 2019, pp. 207–220.
[18] P. Tugwell, D. Tovey, Prisma 2020, Journal of Clinical Epidemi- ology 134 (2021) A5–A6.
[19] M.J. Page, et al., Declaracin prisma 2020: una gua actualizada para la publicacin de revisiones sistemticas, Revista Espaola de Cardiologa 74 (9) (2021) 790–799.
[20] S. Keele, Guidelines for Performing Systematic Literature Reviews in Software Engineering, EBSE Technical Report, 2007. Technical report.
[21] Mauri, M., Elli, T., Caviglia, G., Uboldi, G., & Azzi, M. (2017). RAWGraphs: A Visualisation Platform to Create Open Outputs. In Proceedings of the 12th Biannual Conference on Italian SIGCHI Chapter (p. 28:1–28:5). New York, NY, USA: ACM. https://doi.org/10.1145/3125571.3125585.
[22] D. Monti, G. Rizzo, M. Morisio, A systematic literature re- view of multicriteria recommender systems, Artif. Intell. Rev. 54 (1) (2021) 427–468.
[23] R. Pelissari, P.S. Alencar, S.B. Amor, L.T. Duarte, The use of multiple criteria decision aiding methods in recommender systems: a literature review, in: J. C. Xavier-Junior, R.A. Rios (Eds.), *Intelligent Systems*, Volume 11 of *Lecture Notes In Computer Science*, Springer International Publishing, Cham, 2022, pp. 535–549.
[24] N. Idrissi, A. Zellou, A systematic literature review of spar- sity issues in recommender systems, Social Network Analysis and Mining 10 (1) (2020) 15.
[25] E. Cano, M. Morisio, Hybrid recommender systems: a system- atic literature review, Intell. Data Anal. 21 (6) (2017) 1487–1524.
[26] E. Amig, Y. Deldjoo, S. Mizzaro, A. Bellogn, A unifying and general account of fairness measurement in recommender systems, Inf. Process. Manag. 60 (1) (2023) 103115.
[27] M.Y. Eili, J. Rezaeenour, M.F. Sani, A Systematic Lit- Erature Review on Process-Aware Recommender Systems, 2021 *arXiv preprint arXiv:2103.16654*.
[28] G.B. Martins, J.P. Papa, H. Adeli, Deep learning techniques for recommender systems based on collaborative filtering, Expet Syst. 37 (6) (2020).
[29] D.B. Guruge, R. Kadel, S.J. Halder, The state of the art in methodologies of course recommender systemsa review of recent research, Data 6 (2) (2021) 18.
[30] N.M. Villegas, C. Snchez, J. Daz-Cely, G. Tamura, Character- izing context-aware recommender systems: a systematic literature review, Knowl. Base Syst. 140 (2018) 173–200.
[31] M.N. Freire, L.N. de Castro, e-recruitment recommender sys- tems: a systematic review, Knowl. Inf. Syst. 63 (1) (2021) 1–20.

[32] T. Cunha, C. Soares, A.C.P.L.F. de Carvalho, Metalearning and recommender systems: a literature review and empirical study on the algorithm selection problem for collaborative filtering, Inf. Sci. 423 (2018) 128–144.
[33] V.G.M. Murillo, D.E.P. Avendao, F.R. Lopez, J.M.G. Calleros, A systematic literature review on the hybrid approaches for rec- ommender systems, Comput. Sist. 26 (1) (2022).
[34] F.L. da Silva, B.K. Slodkowski, K.K.A. da Silva, S.C. Cazella, A Systematic Literature Review on Educational Recommender Sys- Tems for Teaching and Learning: Research Trends, Limitations and Opportu- Nities, Education and Information Technologies, 2022.
[35] C. Figueroa, I. Vagliano, O.R. Rocha, M. Morisio, A system- atic literature review of linked data-based recommender systems, Concurrency Comput. Pract. Ex. 27 (17) (2015) 4659–4684.
[36] R.R. Yager, Fuzzy logic methods in recommender systems, Fuzzy Set Syst. 136 (2) (2003) 133–149.
[37] A. Zenebe, A.F. Norcio, Representation, similarity measures and aggregation methods using fuzzy sets for content-based recommender systems, Fuzzy Set Syst. 160 (1) (2009) 76–94.
[38] M. Ghavipour, M.R. Meybodi, An adaptive fuzzy recommender system based on learning automata, Electron. Commer. Res. Appl. 20 (2016) 105–115.
[39] L.-C. Cheng, H.-A. Wang, A fuzzy recommender system based on the integration of subjective preferences and objective information, Appl. Soft Comput. 18 (2014) 290–301.
[40] L.H. Son, Hu-fcf: a hybrid user-based fuzzy collaborative filter- ing method in recommender systems, Expert Syst. Appl. 41 (15) (2014) 6861–6870.
[41] R. Yera, L. Martnez, Fuzzy tools in recommender systems: a survey, Int. J. Comput. Intell. Syst. 10 (1) (2017) 776.
[42] L. Tern, A. Meier, A fuzzy recommender system for eelections, in: K.N. Andersen, E. Francesconi, Grnlund, T.M. van Engers (Eds.), *Electronic Government And the Information Systems Perspective*, Volume 6267 of *Lecture Notes in Computer Science*, Springer Berlin Heidelberg, Berlin, Heidelberg, 2010, pp. 62–76.
[43] B.B. Gardas, A. Heidari, N.J. Navimipour, M. Unal, A fuzzy-based method for objects selection in blockchain-enabled edge-iot platforms using a hybrid multi-criteria decision-making model, Appl. Sci. 12 (17) (2022) 8906.
[44] S.-R. Yan, S. Pirooznia, A. Heidari, N.J. Navimipour, M. Unal, Implementation of a product-recommender system in an iot-based smart shopping using fuzzy logic and apriori algorithm, IEEE Trans. Eng. Manag. (2022).
[45] M. Asad, S. Shaukat, E. Javanmardi, J. Nakazato, M. Tsukada, A comprehensive survey on privacy-preserving techniques in fed- erated recommendation systems, Appl. Sci. 13 (10) (2023) 6201.
[46] W. Clark, J.L. Onaka, An empirical test of a joint model of residential mobility and housing choice, Environ. Plann.: Econ. Space 17 (7) (1985) 915–930.
[47] C. Biancalana, F. Gasparetti, A. Micarelli, G. Sansonetti, An approach to social recommendation for context-aware mobile services, ACM Transactions on Intelligent Systems and Technology 4 (1) (2013) 1–31.
[48] X. Yuan, J.-H. Lee, S.-J. Kim, Y.-H. Kim, Toward a user- oriented recommendation system for real estate websites, Information Sys- tems 38 (2) (2013) 231–243.
[49] X. Yuan, J.-H. Lee, S.-J. Kim, Y.-H. Kim, Toward a user- oriented recommendation system for real estate websites, Information sys- tems 38 (2) (2013) 231–243.
[50] A. Azadeh, B. Ziaei, M. Moghaddam, A hybrid fuzzy regression- fuzzy cognitive map algorithm for forecasting and optimization of housing market fluctuations, Expert Syst. Appl. 39 (1) (2012) 298–315.
[51] M. Renigier-Bilozor, A. Janowski, M. Walacik, Geoscience methods in real estate market analyses subjectivity decrease, Geosciences 9 (3) (2019) 130.
[52] H.-P. Ho, C.-T. Chang, C.-Y. Ku, House selection via the internet by considering homebuyers risk attitudes with s-shaped utility functions, Eur. J. Oper. Res. 241 (1) (2015) 188–201.
[53] F. Tajani, P. Morano, M. Locurcio, N. Daddabbo, Property valuations in times of crisis: artificial neural networks and evolutionary algorithms in comparison, in: O. Gervasi, et al. (Eds.), *Computational Science and its Applications – ICCSA 2015*, Volume LNCS 9158 of *Lecture Notes in Computer Science*, Springer International Publishing, Cham, 2015, pp. 194–209.
[54] W.K. Lau, D.C.W. Ho, Y. Yau, Assessing the disability inclusiveness of university buildings in Hong Kong, Int. J. Strat. Property Manag. 20 (2) (2016) 184–197.
[55] B. Kizielewicz, A. Bczkiewicz, Comparison of fuzzy topsis, fuzzy vikor, fuzzy waspas and fuzzy mmoora methods in the housing selection problem, Proc. Comput. Sci. 192 (2021) 4578–4591.
[56] A.C. Aydinoglu, R. Bovkir, I. Colkesen, Implementing a mass valuation application on interoperable land valuation data model designed as an extension of the national gdi, Surv. Rev. 53 (379) (2021) 349–365.
[57] A.L.D. Lousada, F.A.F. Ferreira, I. Meidut-Kavaliauskien, R.W. Spahr, M.A. Sunderman, L.F. Pereira, A sociotechnical approach to causes of urban blight using fuzzy cognitive mapping and system dynamics, Cities 108 (2021) 102963.
[58] A. Kaklauskas, E.K. Zavadskas, A. Banaitis, I. Meidute-Kavaliauskiene, A. Liberman, S. Dzitac, I. Ubarte, A. Binkyte, J. Cerkauskas, A. Kuzminske, et al., A neuro-advertising property video recom- mendation system, Technol. Forecast. Soc. Change 131 (2018) 78–93.
[59] R. Attardi, M. Cerreta, A. Franciosa, A. Gravagnuolo, Valu- ing cultural landscape services: a multidimensional and multi-group sdss for scenario simulations, in: B. Murgante, et al. (Eds.), *Computational Science and its Applications ICCSA 2014*, Volume 8581 of *Lecture Notes in Computer Science*, Springer International Publishing, Cham, 2014, pp. 398–413.
[60] H.J. Jun, J.H. Kim, D.Y. Rhee, S.W. Chang, seoulhouse2vec: an embedding-based collaborative filtering housing recommender system for analyzing housing preference, Sustainability 12 (17) (2020) 6964.
[61] X. Fu, X.-J. Zeng, D. Wang, D. Xu, L. Yang, Fuzzy system approaches to negotiation pricing decision support, J. Intell. Fuzzy Syst. 29 (2) (2015) 685–699.
[62] E.M. Daly, A. Botea, A. Kishimoto, R. Marinescu, Multi- criteria journey aware housing recommender system, in: Proceedings of the 8th ACM Conference on Recommender Systems, ACM, Foster City, Silicon Valley California, USA, 2014, pp. 325–328.
[63] A. Kaklauskas, et al., Crisis thermometer for housing market recom- mendations, Land Use Pol. 48 (2015) 25–37.
[64] M. Bottero, V. Ferretti, G. Mondini, Constructing multi- attribute value functions for sustainability assessment of urban projects, in: B. Murgante, et al. (Eds.), *Computational Science and its Applications ICCSA 2014*, Volume LNCS 8581 of *Lecture Notes in Computer Science*, Springer International Publishing, Cham, 2014, pp. 51–64.
[65] L. Wang, X. Hu, J. Wei, X. Cui, A collaborative filtering based personalized top-k recommender system for housing, in: Z. Du, edi- tor (Eds.), *Proceedings of the 2012 International Conference of Modern Computer Science and Applications*, Volume 191 of *Advances in Intelligent Systems and Computing*, Springer Berlin Heidelberg, Berlin, Heidelberg, 2013, pp. 461–466.
[66] S. Nakano, A. Washizu, Acceptance of energy efficient homes in large Japanese cities: understanding the inner process of home choice and residence satisfaction, J. Environ. Manag. 225 (2018) 84–92.
[67] A. Gharahighehi, K. Pliakos, C. Vens, Recommender systems in the real estate marketa survey, Appl. Sci. 11 (16) (2021) 7502.
[68] A.O. Alexeev, I.E. Alexeeva, L.N. Yasnitsky, V.L. Yasnitsky, Self-adaptive intelligent system for mass evaluation of real estate market in cities, in: Digital Science, Springer, 2019, pp. 81–87.
[69] M. Zeydan, B. Bostanc, B. Oralhan, A new hybrid decision making approach for housing suitability mapping of an urban area, 2018), Math. Probl Eng. (2018) 1–13.
[70] Z. Zheng, Y. Gao, L. Yin, M.K. Rabarison, Modeling and analysis of a stock-based collaborative filtering algorithm for the Chinese stock market, Expert Syst. Appl. 162 (2020) 113006.
[71] D.-R. Liu, Y.-C. Chou, C.-C. Chung, H.-Y. Liao, Recom- mender system based on social influence and the virtual house bandwagon effect in virtual worlds, Kybernetes 47 (3) (2018) 587–604.
[72] S. Mosallaeipour, S.M. Shavarani, C. Steens, A. Eros, A robust expert decision support system for making real estate location decisions, a case of investor-developer-user organization in industry 4.0 era, J. Corp. R. Estate 22 (1) (2019) 21–47.
[73] R. Schaller, Mobile tourist guides: Bridging the gap between au- tomation and users retaining control of their itineraries, in: Proceedings of the 5th Information Interaction in Context Symposium, ACM, Regensburg, Germany, 2014, pp. 320–323.
[74] F. Rehman, H. Masood, A. Ul-Hasan, R. Nawaz, F. Shafait, An intelligent context aware recommender system for real-estate, in: C. Djeddi, A. Jamil, I. Siddiqi (Eds.), *Pattern Recognition and Artificial Intelligence*, Communications in Computer and Information Sci- Ence, Springer International Publishing, Cham, 2020, pp. 177–191.

[75] M.-L. Marsal-Llacuna, J.-L. de la Rosa-Esteva, The representa- tion for all model: an agent-based collaborative method for more meaning- ful citizen participation in urban planning, in: B. Murgante, et al. (Eds.), *Computational Science and its Applications ICCSA 2013*, Volume 7973 of *Lecture Notes in Computer Science*, Springer Berlin Heidelberg, Berlin, Heidelberg, 2013, pp. 324–339.

[76] S. Li, S. Nomura, Y. Kikuta, K. Arino, Web-scale personalized real-time recommender system on suumo, in: J. Kim, et al. (Eds.), *Ad- Vances in Knowledge Discovery and Data Mining*, Volume 10235 of *Lecture Notes in Computer Science*, Springer International Publishing, Cham, 2017, pp. 521–538.

[77] F. Liu, 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), IEEE, Jishou, China, 2019, pp. 121–124.

[78] A. Belaid, J. Razmak, Multi-criteria decision support systems: a glorious history and a promising future, in: *2013 5th International Confer- Ence on Modeling, Simulation and Applied Optimization (ICMSAO)*, Pages 1–9, Hammamet, IEEE, 2013.

[79] T. Ginevicius, A. Kaklauskas, P. Kazokaitis, J. Alchimovienė, Recommender system for real estate management, Bus. Theor. Pract. 12 (3) (2011) 258–267.

[80] D. Solans, F. Fabbri, C. Calsamiglia, C. Castillo, F. Bonchi, Comparing equity and effectiveness of different algorithms in an applica- tion for the room rental market, in: Proceedings of the 2021 AAAI/ACM Conference on AI, Ethics, and Society, ACM, Virtual Event, USA, 2021 pages 978–988.

[81] R.H. Kabir, B. Pervaiz, T.M. Khan, A. Ul-Hasan, R. Nawaz, F. Shafait, Deeprank: adapting neural tensor networks for ranking the rec- ommendations, in: C. Djeddi, A. Jamil, I. Siddiqi (Eds.), *Pattern Recognition and Artificial Intelligence*, Communications in Computer and Information Science, Springer International Pub- lishing, Cham, 2020, pp. 162–176.

[82] H. Zhang, Y. Zhang, A.U. Rahman, M. Saeed, An Intelligent Sv-Neutrosophic Parameterized Mcdm Approach to Risk Evaluation Based on Complex Fuzzy Hypersoft Set for Real Estate Investments, Management Decision, 2022 ahead-of-print(ahead-of-print).

[83] Iikman, B.G. Yalim, M. zdemir, T. zyer, H. Gke, R. Alhajj, Adaptive weighted multi-criteria fuzzy query processing for web- based real estate applications, in: *Proceedings of the 2008 ACM Symposium on Applied Computing*, Page 987, Fortaleza, Ceara, Brazil, ACM Press, 2008.

[84] G. Roberto, N. Antonio, M. Alessandra, C. Maria, A model to mitigate the peripheralization risk at urban scale, in: O. Gervasi, et al. (Eds.), *Computational Science and its Applications ICCSA 2020*, Volume LNCS 12252 of *Lecture Notes in Computer Science*, Springer International Publishing, Cham, 2020, pp. 928–939.

[85] Y. Zhong, B. Li, Design and realization of fce optimized model in dss, in: 2009 WRI Global Congress on Intelligent Systems, 2009, pp. 347–351.

[86] E. Munoz, J. Meza, L. Recalde, L. Teran, Finding the appropri- ate housing: a fuzzy-model-based recommender system, in: *2021 Eighth in- Ternational Conference on eDemocracy & eGovernment (ICEDEG)*, Pages 139–145, Quito, Ecuador, IEEE, 2021.

[87] Z. Yang, W. Zhiruo, C. Chang, D. Xiaoyi, W. Chengliang, N. Yanjie, Impact of web page house listing cues on internet rental, Applied Mathematics and Nonlinear Sciences 6 (2) (2021) 483–498.