

Property Recommendation Systems Based On Hybrid Filtering And Profile Matching

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Abstract. Housing is a fundamental need for every individual. However, the abundance of available property options often leads to information overload, complicating decision-making processes. To address this issue, this final project develops a property recommendation system based on Hybrid Filtering that integrates Content-Based Filtering (CBF) and Knowledge-Based Recommender Systems (KBRS) with the Profile Matching method. This system aims to produce more personalized and relevant property recommendations while also mitigating the cold-start problem. During implementation, the system was evaluated using Black-Box Testing with Decision Table Testing, comprising a total of 300 test cases, 100 cases for each of the three user profiles: Single Individuals, Working Couples without Children, and Working Couples with Children. The testing results indicated that the system could classify the Single Individuals profile with an accuracy of approximately 61% and Working Couples with Children at about 75%, but only around 35% for Working Couples without Children. The confusion matrix analysis revealed frequent misclassification of properties, indicating overlapping characteristics among segments. Overall, the system achieved only about 57% classification success. This suggests that although the hybrid approach can be applied by combining the advantages of CBF, KBRS, and profile matching, further refinements are needed, particularly in defining ideal profiles and weighting criteria, to improve the accuracy and relevance of recommendations in future work.

INTRODUCTION

Housing is one of the fundamental needs of every individual, providing not only physical shelter but also fulfilling important psychological and social aspects [1]. Due to its critical role, selecting a property is a highly consequential decision that is typically undertaken with great care [2]. This complexity arises from the significant economic value associated with real estate and the many factors that must be considered, such as location, price, size, facilities, and personal preferences.

In today's digital era, the process of searching for properties has largely shifted to online platforms, which significantly facilitate access to information. However, this ease of access also introduces the challenge of information overload, where the abundance of property options can overwhelm users, making the search process more tiring and potentially reducing satisfaction [3]. Recommendation Systems (RS) have emerged as effective solutions to this problem by filtering out irrelevant options and highlighting properties that are more likely to match a user's preferences [4].

Several studies have laid the groundwork for developing property recommendation systems. One significant work is by Jun et al., who proposed *SeoulHouse2Vec*, a neural network collaborative model leveraging embeddings to capture complex relationships between users and properties, demonstrating promising results for urban real estate markets [5]. Another study by Zhang et al. implemented a two-stage content-based filtering approach that combined item characteristics and user historical preferences for improved recommendation accuracy [6]. Additionally, Badriyah et al. developed a web-based property recommendation system using content-based filtering with TF-IDF to weight keywords in property titles, descriptions, and addresses, complemented by the Apriori algorithm to identify

user browsing patterns and generate similar property recommendations [7]. This study highlighted the effectiveness of combining keyword analysis with pattern mining to improve user satisfaction. Despite these advances, many systems still rely heavily on item features or past interactions, which do not always capture genuine user needs. As noted by Knoll et al., behavioral data may not fully reflect actual user preferences since clicks can be random or influenced by external factors [1].

This highlights the necessity for a more holistic approach that integrates explicit knowledge about user characteristics, such as demographic and lifestyle profiles, to better personalize recommendations and mitigate the cold-start problem [8, 9]. In response, this study develops a property recommendation system using Hybrid Filtering, combining Content-Based Filtering (CBF), Knowledge-Based Recommender Systems (KBRS), and Profile Matching. This approach specifically incorporates profiles such as Single Individuals, Working Couples without Children, and Working Couples with Children, which are derived from studies on millennial housing preferences in urban Indonesia [10, 11].

METHODOLOGY

This section describes the step-by-step process carried out in this research, starting from data collection to the implementation of algorithms and testing. The methodology integrates multiple techniques to develop a property recommendation system capable of providing personalized suggestions while addressing cold-start problems.

Data Collection

The property dataset was collected through web scraping using Selenium in Python, targeting listings from a prominent Indonesian online property platform. The scope included properties in the JABODETABEK area and Surabaya. Attributes extracted covered structured data such as location, price, land and building area, number of bedrooms and bathrooms, ownership certificates, as well as unstructured textual descriptions provided by property sellers.

Data Preprocessing and Feature Engineering

Data cleaning involved handling missing values, removing duplicate records, and standardizing data types. Additional features were extracted from the textual descriptions using regular expressions, for instance, identifying electricity capacity (in Watts), orientation (facing North, South, etc.), and the number of floors. Beyond these intrinsic features, the presence of surrounding facilities (Points of Interest - POI) such as schools, hospitals, or shopping centers serves as an extrinsic factor that significantly influences the value and attractiveness of a property. Since this information is often narratively embedded by sellers within description fields, a systematic extraction was performed using a Named Entity Recognition (NER) approach. Considering the domain-specific nature of property listings and informal language with frequent typos, a hybrid model was employed, combining rule-based NER with fuzzy string matching. This approach was chosen for its ability to maintain high precision on common terms while providing the flexibility needed to handle spelling variations and textual inconsistencies.

Implementation of Algorithms

The approach adopts Hybrid Filtering with Feature Augmentation, integrating three sequential modules. First, the Knowledge-Based Recommender System (KBRS) augments the feature set by assigning a profile label to each property in the dataset. These labels then serve as additional input features for the Content-Based Recommender System (CBRS), which transforms property attributes into vector space and calculates similarity scores against user preference vectors, producing a shortlist of the top-N most relevant properties. Finally, this shortlist is processed by the Profile Matching module, which performs gap analysis to rank properties based on their alignment with the user's ideal profile.

Knowledge-Based Recommender System (KBRS)

In the KBRS module, properties were labeled into three distinct user profiles—Single Individuals, Working Couples without Children, and Working Couples with Children—based on predefined as shown in the **Table 1**. This knowledge base was built on findings from Indonesian millennial housing preference studies, which highlighted that

millennials prioritize attributes such as comfort, accessibility, and cost efficiency. A study conducted in Bekasi by Puspitasari et al. [10] involving 436 respondents aged 20–39 revealed that millennials in this satellite city of Jakarta value environmental quality factors like safety, cleanliness, and flood-free locations. Meanwhile, research by Yustika et al. [11] in DKI Jakarta, using literature analysis on 369 samples, showed that millennials in the capital emphasize proximity to public transportation, urban activity centers, and educational facilities, driven by the city’s land constraints and high property prices. These insights informed the formulation of the KBRS rule base to ensure relevance to millennial buyer characteristics in Indonesian urban contexts.

Table 1. User Profile

Profile	Property Type	Land Area (m ²)	Building Area (m ²)	Bedrooms	Bathrooms	Nearby Facilities
Single	Apartment	22 – 50	22 – 50	1 – 2	1 – 2	Mall, Transportation, Market
Working Couples without Children	Apartment or House	22 – 70	22 – 70	2	2	Mall, Transportation
Working Couples with Children	House	200 – 600	200 – 600	3	2	School, Hospital, Transportation, Market

Content-Based Filtering (CBF)

Next, the system applied Content-Based Filtering. In this module, the augmented features and profile labels produced by the KBRS were utilized to transform both qualitative and quantitative property descriptions into unified numerical vector representation. The transformation was performed using the Term Frequency-Inverse Document Frequency (TF-IDF) technique, calculated as follows:

$$tfidf_{t,d} = tf_{t,d} \times idf_t \quad (1)$$

With:

$$tf_{t,d} = \frac{f_{t,d}}{\sum_k f_{k,d}} \quad (2)$$

$$idf_t = \log\left(\frac{1+N}{1+n_t}\right) + 1 \quad (3)$$

where $f_{t,d}$ is the frequency of term t in document d , N is the total number of documents, and n_t is the number of documents containing. Then, cosine similarity was used to compute the similarity between the user's preference vector Q and each property vector D :

$$\cos(\theta) = \frac{Q \cdot D}{\|Q\| \times \|D\|} \quad (4)$$

yielding values between 0 and 1, where higher scores indicate greater similarity.

Profile Matching

This stage represents the final step in the workflow of the Hybrid System Recommender algorithm. After the CBRs produced a shortlist of properties relevant to the user's input, the Profile Matching method was implemented to provide a more personalized assessment. The objective here was to match each candidate property against the specifically defined user profiles, ensuring the recommendations were not only similar in features but also qualitatively aligned with the user’s lifestyle and needs. This approach was adapted from decision support system (DSS) frameworks, which use comparisons between ideal and actual profiles to derive the best-ranked alternatives.

The top-N properties from CBF were then passed to the Profile Matching module for final personalization. Each property's attributes were compared against ideal profile values to compute a gap, formulated as:

$$Gap = Actual Value - Target Value \quad (5)$$

These gaps were then weighted using a standard gap scale, e.g., Gap = 0 mapped to a score of 5, ± 1 mapped to 4, etc. The final score was calculated by prioritizing Core Factors (CF) over Secondary Factors (SF):

$$Total Score = (0.6 \times NCF) + (0.4 \times NSF) \quad (6)$$

where NCF and NSF are the normalized scores for Core and Secondary Factors respectively

Testing and Evaluation

The system was evaluated using Black-Box Testing with Decision Table Testing, applying 300 test cases evenly divided among the three user profiles and designed with varying levels of similarity to ideal profiles. System outputs were compared to expected classifications.

Actual	Single	FAC	FAB	TA
	Working Couple without Children	FBC	TB	FBA
	Working Couple with Children	TC	FCB	FCA
		Working Couple with Children	Working Couple without Children	Single
Prediction				

Figure 1. Confusion Matrix

Evaluation metrics included:

- Accuracy:

$$Accuracy = \frac{TA+TB+TC}{Total Data} \quad (7)$$

- Precision and Recall:

$$Precision = \frac{TA}{TA+FBA+FCA} \quad (8)$$

$$Recall = \frac{TA}{TA+FAB+FAC} \quad (9)$$

- F1-Score:

$$F1 - Score = 2 \times \frac{precision \times recall}{precision + recall} \quad (10)$$

Where A is for “Single”, B “Working Couple without Children” and C “Working Couple with Children as shown in the Figure 1. Additionally, a confusion matrix was constructed to visualize the distribution of predictions across actual vs predicted user profiles.

RESULTS AND DISCUSSION

This section presents the outcomes from applying the proposed methodology, including data insights, performance of the hybrid algorithm, and quantitative evaluations.

Data Collection and Exploratory Analysis

Data scraping and cleaning processes resulted in approximately 16,000 high-quality property records ready for analysis. Exploratory Data Analysis revealed that Surabaya had the highest number of property listings with 2,364

advertisements, followed by Bekasi with 1,831, and Depok with 1,771 listings. Other urban areas such as South Jakarta, South Tangerang, and Tangerang also showed substantial volumes. This distribution is clearly illustrated in the bar chart in Fig. 2, which visualizes the comparative listing counts across the top urban regions in the dataset.

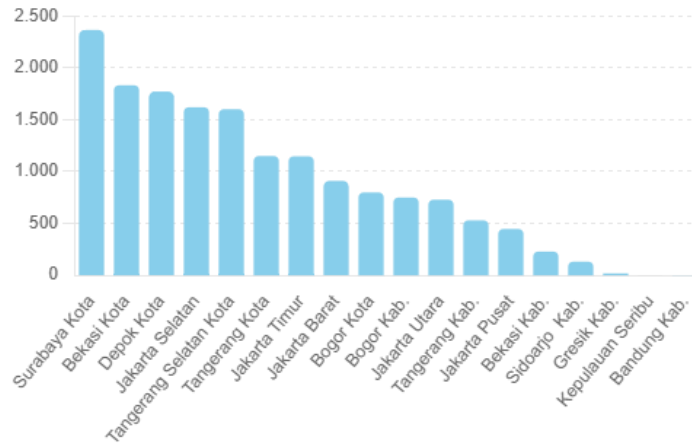


Figure 2. Distribution of Listing Region

Further analysis was conducted to determine the relationship between the number of properties registered in each sub-district and population density in the Surabaya City area. A correlation analysis method was used by calculating the Pearson Correlation Coefficient (PCC) between the number of property advertisements and population density data from BPS Surabaya for the City of Surabaya. The result of PCC is a weak negative correlation of -0.33 between population density and the number of property listings suggested that more densely populated sub-districts in Surabaya tend to have fewer new properties listed for sale, possibly due to market saturation. This relationship is visually illustrated in Fig. 3, which shows a downward trendline across the data points for Surabaya's sub-districts.

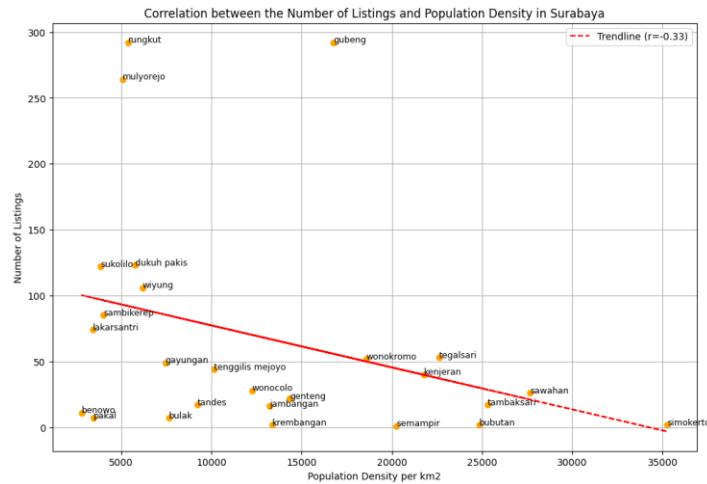


Figure 3. visualization of the distribution of the correlation between the number of listings and population density in Surabaya

Algorithm Performance

KBRS and Content-Based Filtering

The KBRS implemented in this study used a rule-based approach, where a set of explicit knowledge base rules defined the ideal preferences for each user profile. These rules, as shown in the Table 1, as acted logical constraints against which property attributes were evaluated. The system iteratively matched each property's features to all three ideal profiles, assigning points whenever a criterion was met. Each profile's score was then normalized by the total

number of evaluated rules, and the profile with the highest score was selected as the representative label for that property.

Table 2. KBRS Labeling

...	type	land_area	building_area	...	best_profile_match	match_score
...	House	112.0	109.0	...	Working Couples with Children	0.6
...	House	75.0	50.0	...	Working Couples with Children	0.8
...	House	40.0	30.0	...	Working Couples without Children	0.8
...	House	40.0	30.0	...	Working Couples without Children	0.6
...	Apartment	17.0	17.0	...	Single	0.6

The KBRS successfully labeled properties into three user profiles using explicit rules based on area size, number of bedrooms, and proximity to educational facilities [8]. A snippet of these labeling results is presented in Table 2, which illustrates how each property was tagged according to its strongest profile alignment.

After all properties in the dataset are labeled, the next step is to apply CBF. An initial data filtering step was performed to narrow the search space and focus on the most relevant set of properties. First, the dataset was filtered based on the geographical location specified by the user. This was followed by a contextual filtering that leveraged the profile determined from the Profile Matching calculation on the user's input. Properties were restricted to those matching the user's profile; for instance, if the profile matching results classified the user as a "Single," then at the CBRS stage, only properties labeled under this category were considered.

The property data were transformed into numerical vector representations to facilitate mathematical comparison with user preferences. Each property's feature set combined both structured attributes—such as building area, number of bedrooms, and property type—which were encoded and standardized—and unstructured textual elements. Textual descriptions, including facility information and named entities extracted via NER (such as nearby POIs), were vectorized using TF-IDF, with separate vectorizers applied for facilities and entity mentions. These were then horizontally stacked with the structured features to form the final property matrix *property_matrix*. A similar transformation process was applied to the user input: structured preferences were encoded and standardized, while user-desired facilities and POIs were transformed with the same TF-IDF vectorizers to ensure consistency in the feature space, resulting in a consolidated *user_vector*.

Table 3. Top 10 Property Recommendations from CBF

ads_id	...	type	building_area	bedrooms	bathrooms	...	similarity_score
930793021	...	House	188.0	3	2	...	0.96
932338250	...	House	230.0	3	3	...	0.96
926326098	...	House	90.0	3	2	...	0.95
932272358	...	House	106.0	3	2	...	0.95
930830770	...	House	113.0	4	2	...	0.94
930609799	...	House	54.0	3	2	...	0.94
932386527	...	House	375.0	5	3	...	0.94
932308510	...	House	58.0	3	1	...	0.94
932308650	...	House	100.0	3	1	...	0.94
930581846	...	House	70.0	3	1	...	0.94

Finally, cosine similarity was computed between the *user_vector* and each property vector in *property_matrix* to measure directional alignment in the high-dimensional space, independent of vector magnitude. This process produced a shortlist of properties most similar to the user's specified preferences, as detailed in Table 3, which lists the top-ranked recommendations generated by the CBRS module.

Profile Matching Personalization

The initial step in the Profile Matching method involved constructing ideal profiles to represent different property market segments: "Single," "Working Couple without Children," and "Working Couple with Children." These profiles were formulated based on literature studies on millennial housing preferences in urban areas, as previously summarized in Table 1. Each ideal profile encapsulated preferences for property characteristics grouped into three main criteria: Housing Characteristics, Property Facilities, and Location Facilities. These criteria comprised several sub-criteria, each assessed on an ordinal scale ranging from 1 to 5.

To ensure that the assessment accurately reflects user preferences, this method applies a structured weighting scheme. At the factor level, weights are assigned with Core Factors (CF) set at 60% and Secondary Factors (SF) at 40%, following the fundamental principle of Profile Matching where primary attributes contribute more significantly to the final score than supplementary ones. At the criteria level, weights are normalized to sum to 100% for balanced influence. Housing Characteristics receive the highest weight at 40%, as they directly represent essential user needs regarding property type and specifications. Meanwhile, Location Facilities and Property Facilities are each weighted at 30%, capturing access to public amenities and internal property features, respectively.

The Profile Matching method was implemented in two main stages. In the first stage, it classified the user's profile based on the provided input data, producing a profile label that most closely matched the user's characteristics. This label was then used as a filter within the CBRS module, ensuring that only properties aligned with the user's profile were considered. The second stage occurred after the CBRS generated the top 10 property recommendations; here, Profile Matching was reapplied to evaluate and rank each shortlisted property according to its suitability for the previously determined user profile. Both stages employed similar algorithmic logic, differing only in the input data utilized.

Table 4. Final Recommendation Property

ads_id	...	type	building_area	bedrooms	bathrooms	...	final_score
930609799	...	House	188.0	3	2	...	3.68
930581846	...	House	230.0	3	3	...	3.52
932338250	...	House	90.0	3	2	...	3.36
930793021	...	House	106.0	3	2	...	3.36
932386527	...	House	113.0	4	2	...	3.36
930830770	...	House	54.0	3	2	...	3.36
926326098	...	House	375.0	5	3	...	3.2
932272358	...	House	58.0	3	1	...	3.2
932308510	...	House	100.0	3	1	...	3.2
932308650	...	House	70.0	3	1	...	3.2

As an example of this implementation, the CBRS recommendation results presented in Table 3 were used as input for the Profile Matching algorithm to generate more personalized rankings based on the predefined weights. Interestingly, the property with the highest initial similarity score (ads_id 930793021, similarity_score = 0.96) dropped to fourth place with a final_score of 3.36. Meanwhile, the property with ads_id 930609799, previously ranked sixth with a similarity_score of 0.94, rose to the top position with a final_score of 3.68, as shown in Table 4. This demonstrates how applying Profile Matching effectively produces recommendations that are not only similar in content attributes but also aligned with the user's primary preferences. By emphasizing the most critical aspects for each user profile, this approach enhances the relevance of the final results and potentially offers a more satisfying recommendation experience.

Testing and Evaluation Results

After implementation, the algorithm needed to be tested to ensure it functioned as intended. This study employed Black-Box Testing, as previously outlined in the methodology section and consistent with approaches demonstrated by Sasongko et al. [12]. The advantage of this method is that it does not require insight into the algorithm's internal workings, focusing solely on the correspondence between given inputs and produced outputs [12]. Specifically, Decision Table Testing was used, wherein a set of test cases was prepared based on the three predefined ideal profiles. Each test case was designed with specific input values and an expected output, allowing the algorithm's results to be compared against these expectations as a benchmark for success. For each ideal profile, test cases were divided into four groups reflecting proximity to the maximum score (5): 100% ideal, 75% ideal, 50% ideal, and 25% ideal. This test helps determine whether the system is capable of correctly classifying user profiles. A total of 100 test cases were prepared for each profile, with randomized inputs constrained within ranges that adhered to the designated ideal proportions.

Table 5. Results of Black Box Testing

Profile	Ideal Percentage	Results
Single	100%	100% as expected
	75%	95.24% as expected
	50%	48.39% as expected
	25%	0% as expected
Working Couple without Children	100%	0% as expected
	75%	61.9% as expected
	50%	63.33% as expected
	25%	0% as expected
Working Couple with Children	100%	100% as expected
	75%	100% as expected
	50%	100% as expected
	25%	0% as expected

From the total of 300 test cases conducted—comprising 100 cases for each user profile—the system’s ability to correctly classify profiles was evaluated, as summarized in Table 5. The "Working Couple with Children" profile proved to be the easiest for the algorithm to classify, achieving 100% accuracy even at 50% and 75% input similarity levels. This underscores the strong influence of the applied rules and gap weights in capturing distinctive characteristics of this segment, such as larger house sizes, more bedrooms, and the presence of amenities like gardens and water heaters. In contrast, the "Working Couple without Children" profile was most frequently misclassified, with 0% accuracy even at the 100% match level, as test cases were often predicted as belonging to the couple-with-children category due to similar attributes like large building areas and comprehensive facilities. Overall, mid-level input variations (50%–75%) led to noticeable drops in accuracy, particularly for the "Single Individual" profile at 50%, which reached only about 48%, and for "Working Couple without Children," which hovered around 60%. These results indicate that the system is highly sensitive to deviations in key variables such as building size, number of rooms, and facility availability. Based on the Black-Box Testing, the system successfully classified "Single Individual" and "Working Couple with Children" profiles at rates of 60.9% and 75%, respectively.

The confusion matrix was employed to visualize the classification results, with the Y-axis (rows) representing the actual target profiles and the X-axis (columns) denoting the predicted profiles generated by the algorithm. Each cell in the matrix indicates the number of test cases from a given target profile that were classified into a particular predicted profile. This visualization provides insights into how often the algorithm correctly identified profiles—reflected by values along the diagonal—as well as the extent of misclassification, shown by the off-diagonal cells.

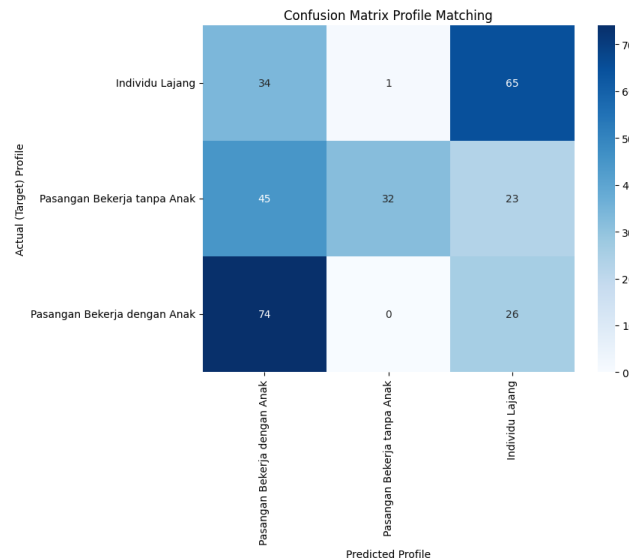


Figure 4. Confusion matrix illustrating the classification performance across user profiles, with diagonal values showing correct classifications

The confusion matrix reveals that the majority of test cases for the "Single Individual" profile were correctly classified, with 65 instances accurately identified. In contrast, many test cases for the "Working Couple without Children" profile were misclassified as "Working Couple with Children," totaling 45 instances. This is primarily due to the profile preferences for couples without children sharing overlapping characteristics with the other two profiles. Specifically, this segment tends to be flexible in property types—favoring both apartments, similar to single individuals, and houses, as with couples with children. In the dataset used, most properties labeled for couples without children were houses, leading to characteristic overlaps with the couple-with-children profile. Consequently, the system frequently misclassified these cases, influenced by shared core features such as property type and number of bedrooms. This distribution of correct and incorrect classifications is clearly illustrated in Figure 4, which shows how predictions align—or diverge—from the actual target profiles.

Table 6. Recommendation Systems Performance Metrics Results

Profile Name	Accuracy	Precision	Recall	F1-Score
Single	0,57	0.57	0.65	0.60
Working Couples without Children		0.97	0.32	0.48
Working Couples with Children		0.48	0.74	0.58

Table 6 presents the classification performance of the implemented profile matching algorithm. For the "Single Individual" profile, a precision of 0.57 indicates that only 57% of predictions for this category were correct, while a recall of 0.65 shows that the system successfully identified 65% of actual cases, yielding an F1-score of 0.61—reflecting a moderate balance between precision and recall. In contrast, the "Working Couple without Children" profile achieved an exceptionally high precision of 0.97, suggesting nearly all predictions for this category were accurate. However, a low recall of 0.32 reveals that most actual cases were not captured, resulting in a significantly reduced F1-score of 0.48. Meanwhile, for the "Working Couple with Children" profile, a precision of 0.48 demonstrates relatively low prediction accuracy, but a higher recall of 0.74 indicates the system could detect a majority of actual cases, leading to an F1-score of 0.58. With an overall classification accuracy of 57%, the system exhibits limitations in consistently recognizing user profiles, implying that nearly half of the test cases were misclassified—potentially impacting the quality of personalization in the recommendation results.

CONCLUSION

This study successfully developed a property recommendation system using a hybrid filtering approach that integrated KBRS, CBF, and Profile Matching. The system could generate more personalized recommendations and partially overcoming the cold-start problem by leveraging demographic and contextual profiles. Nevertheless, the study revealed notable challenges in clearly distinguishing profiles with overlapping preferences, particularly between households with and without children. Future improvements are suggested, including empirical validation of profile definitions and weights, enhanced text information extraction from property descriptions, and direct user satisfaction studies to further refine recommendation quality. This would ultimately result in a more precise, user-centric recommendation system for digital property platforms.

ACKNOWLEDGMENTS

This study was conducted as part of the requirements for obtaining a bachelor's degree. The author would like to express sincere gratitude to Dr. Retno Aulia Vinarti and Dr. Izzat Aulia Akbar for their invaluable guidance and support throughout this research.

REFERENCES

1. M. Knoll, F. Groß, T. Schwanke, A. Rinn, and F. Schreyer, *Int. J. Housing Policy* 18, 234 (2018).
2. M. Gharahighehi, A. Pliakos, and C. Vens, *J. Property Res.* 38, 145 (2021).
3. L. Yu, Z. Wang, L. Zhang, B. Gao, and Y. Wang, *ACM Trans. Web* 12, 24 (2018).
4. F. O. Isinkaye, Y. O. Folajimi, and B. A. Ojokoh, *Egypt. Inform. J.* 16, 261 (2015).
5. H. J. Jun, J. Kim, W. Rhee, and S. Chang, *IEEE Access* 9, 123456 (2020).

6. X. Zhang, K. Zheng, W. Yang, and H. Hu, Knowl.-Based Syst. 143, 64 (2018).
7. T. Badriyah, S. Azvy, W. Yuwono, and I. Syarif, Proc. ICOIACT 2018, 25 (2018).
8. A. Ameen, Int. J. Comput. Appl. 182, 20 (2019).
9. S. Rahmawati, D. Nurjanah, and R. Rismala, Indo-JC 3, 11 (2018).
10. D. Puspitasari, J. Adianto, and K. Khoirunurrofik, J. Pemb. Wilayah Kota 18, 54 (2022).
11. Y. Yustika, M. Yuliana, and A. N. Sari, J. Perkotaan 2, 72 (2022).
12. B. B. Sasongko, F. Malik, F. Ardiansyah, A. F. Rahmawati, F. D. Adhinata, and D. P. Rakhmadani, J. ICTEE 2, 10 (2021).