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Rental Housing Recommendation System Model Based on Multi-Criteria Decision Making and Machine Learning with Technology Acceptance Model Integration

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Abstract

The selection of rental housing is a multi-criteria decision-making problem involving factors such as price, location, facilities, security, and environment, making it difficult for prospective tenants to determine the option that best suits their needs. This study aims to develop a rental housing recommendation system model by integrating Multi-Criteria Decision Making (MCDM), Machine Learning, and Technology Acceptance Model (TAM). The Analytical Hierarchy Process (AHP) is used to determine the criteria weights. In contrast, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is used to rank rental housing alternatives. Furthermore, a Machine Learning approach using the Random Forest algorithm is applied to predict user preferences from historical data. System evaluation is carried out by comparing recommendation performance between AHP–TOPSIS and Simple Additive Weighting (SAW), testing the performance of the Machine Learning model, and analysing user acceptance using Structural Equation Modelling based on Partial Least Squares (SEM-PLS) within the Technology Acceptance Model framework. The results show that the AHP–TOPSIS model outperforms SAW in recommendation performance, achieving 89.4% compared to 84.7%. The Random Forest-based Machine Learning model also demonstrated good performance in predicting user preferences. The SEM results showed that perceived ease of use significantly influenced perceived usefulness and behavioural intention; perceived usefulness significantly influenced behavioural intention; and behavioural intention significantly influenced actual use, with p-values < 0.05. The R-square value of 0.67 indicated that the model had strong explanatory power for user acceptance. This study developed a rental housing recommendation system model that not only objectively provides the best alternative but also adjusts its recommendations to user preferences, achieving high acceptance. This model has the potential to be applied in the development of recommendation systems in the housing sector and artificial intelligence-based decision support systems.

Keywords: Recommendation System; Rental Housing; AHP; TOPSIS; Machine Learning.

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Introduction

The development of information and communication technology has brought significant changes to various sectors of life, including the property and housing sector. Digital transformation has driven the emergence of various web-based and mobile platforms that provide online property search, booking, and management services. Digitalisation in the housing sector not only simplifies users' access to information but also changes how they make decisions about their choice of residence. In an information-rich digital environment, users are often presented with various rental housing options with varying characteristics, so a system is needed to assist them in selecting the best option for their preferences and needs. In this context, recommendation systems are widely used tools that assist users in decision-making based on data and user preferences (Jadiga, 2025; Ravi et al., 2025; Roy & Dutta, 2022).

Choosing rental housing is a complex decision-making problem because it involves many criteria, such as price, location, facilities, security, transportation access, and environment. Each prospective tenant has different preferences for each of these criteria, making the decision-making process more complex and multi-criteria. Multi-criteria decision-making problems arise when decision-makers must choose the best alternative from several available options while considering conflicting criteria (Lamrini et al., 2023; Rachman et al., 2024; Sahoo & Goswami, 2023). When choosing rental housing, trade-offs often occur among price and facilities, location and environment, and security and rental costs, so a system is needed to help users objectively and systematically determine the best choice.

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Therefore, to overcome the problem of multi-criteria decision making, various Multi-Criteria Decision Making (MCDM) methods have been developed and used in decision support systems. Some of the widely used MCDM methods include Analytical Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Simple Additive Weighting (SAW), and Weighted Product (WP) (Deta & Bedanaen, 2025; Masudin et al., 2024; Vafaei et al., 2022). The AHP method is used to determine the importance weights of each criterion based on pairwise comparisons, while the TOPSIS method is used to determine the best alternative based on the distances to the positive and negative ideal solutions (Chakraborty, 2022; Ciardiello & Genovese, 2023; Trivedi et al., 2024). The combination of AHP and TOPSIS methods is widely used in decision support systems because it can produce more objective and systematic decisions than other methods.

Several previous studies have used the AHP and TOPSIS methods in various decision-making cases, such as location selection, supplier selection, employee selection, and housing selection (Deepika et al., 2023; Modibbo et al., 2022). Other studies have shown that the TOPSIS method is effective at providing alternative rankings because it considers both positive and negative ideal solutions (Alshamrani et al., 2023; Pandey et al., 2023). However, most previous studies have used MCDM methods without considering user preferences derived from historical data, so the resulting recommendations are not yet personalised or adaptive.

Along with the development of artificial intelligence, machine learning has been widely used in recommendation systems to predict user preferences from historical data. Machine learning is a branch of artificial intelligence that allows systems to learn from data and make predictions or decisions without explicit programming (W. M. Ahmed et al., 2025; Shafik, 2024; Taye, 2023). In recommendation systems, machine learning can be used to learn user preference patterns and provide more personalised recommendations. Some machine learning algorithms frequently used in recommendation systems include decision trees, naive Bayes, support vector machines, and random forests (Matias & Latip, 2025; Pathak et al., 2023; Rustam et al., 2022). Previous research has shown that the random forest algorithm achieves high classification and prediction accuracy by combining multiple decision trees, thereby reducing overfitting (Rimal et al., 2025; Sun et al., 2024).

Although Multi-Criteria Decision Making and Machine Learning methods have been widely used in recommendation systems, most studies still employ them separately. The integration of Multi-Criteria Decision Making and Machine Learning methods into a single recommendation system remains rare, especially in the context of selecting rental housing. The integration of these two methods can improve the quality of the recommendation system, as Multi-Criteria Decision Making is used to objectively determine criterion weights and rank alternatives. In contrast, Machine Learning is used to predict user preferences from historical data. In addition to system accuracy, another important factor in information system development is user acceptance of the developed system. Many information systems fail to be implemented, not because they are not functional, but because users do not accept or use them (Singun, 2025; Vössing et al., 2022). Therefore, in developing a recommendation system, it is important to analyse the factors that influence user acceptance of the developed system.

One model widely used to analyse user acceptance of information systems is the Technology Acceptance Model (TAM). The TAM model states that user acceptance of information systems is influenced by two main factors: perceived usefulness and perceived ease of use (Park et al., 2025; Wu & Yu, 2024). Perceived usefulness is the user's perception that the system can improve their performance, while perceived ease of use is the user's perception that the system is easy to use. The TAM model has been widely used in various information systems studies to analyse user acceptance of information systems (Legramante et al., 2023; Natasia et al., 2022).

Based on previous research, most studies on recommendation systems still focus on using Multi-Criteria Decision Making or Machine Learning methods in isolation. On the other hand, research that integrates multi-criteria decision-making methods, historical data-based user preference prediction, and user acceptance analysis within a single, cohesive research framework remains relatively limited, particularly in the context of rental housing selection. This condition indicates a research gap: the lack of research integrating MCDM, Machine Learning, and Technology Acceptance Models in the development of rental housing recommendation systems.

Based on this gap, this study proposes a rental housing recommendation system model that integrates AHP for criteria weighting, TOPSIS for alternative ranking, Machine Learning with the Random Forest algorithm for user preference prediction, and a Technology Acceptance Model to analyse user acceptance of the system. This approach is expected to produce not only objective recommendations but also more personalised and adaptive to user needs. Thus, the main contribution of this research is the development of a hybrid recommendation system model that integrates multi-criteria decision-making, machine-learning-based preference prediction, and technology acceptance evaluation within a single, comprehensive research framework. The proposed model is expected to provide theoretical contributions to the development of intelligent recommendation systems, as well as practical contributions to helping users choose rental housing more effectively, objectively, and in line with their preferences.

Method

Research Design

This study uses a Design Science Research (DSR) approach to design, develop, and evaluate a rental housing recommendation system model. This approach was chosen because it is oriented towards developing technological artefacts that can be used to solve real-world problems systematically (Şenyüzlüler & Baykasoglu, 2026; Zeng et al., 2025). In this study, the developed artefact is a hybrid recommendation system model that integrates Multi-Criteria Decision Making, Machine Learning, and the Technology Acceptance Model. The stages of Design Science Research include problem identification, solution goal setting, artefact design, system development, demonstration, evaluation, and communication of research results.

Conceptual Model

This research's conceptual model integrates three main components: Multi-Criteria Decision Making, Machine Learning, and Technology Acceptance Model, into a single framework for a rental housing recommendation system. In the initial stage, the Analytical Hierarchy Process (AHP) is used to determine the weight of each decision criterion. In contrast, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is used to rank rental housing alternatives based on their proximity to the ideal solution. Furthermore, a Machine Learning approach with the Random Forest algorithm is used to predict user preferences based on historical data. To evaluate user acceptance of the system, this study uses the Technology Acceptance Model, which includes perceived ease of use, perceived usefulness, behavioural intention, and actual use. The relationships between variables are analysed using SEM-PLS (Papakostas et al., 2023; Zhu et al., 2025). The conceptual model of the proposed system is shown in Figure 1.

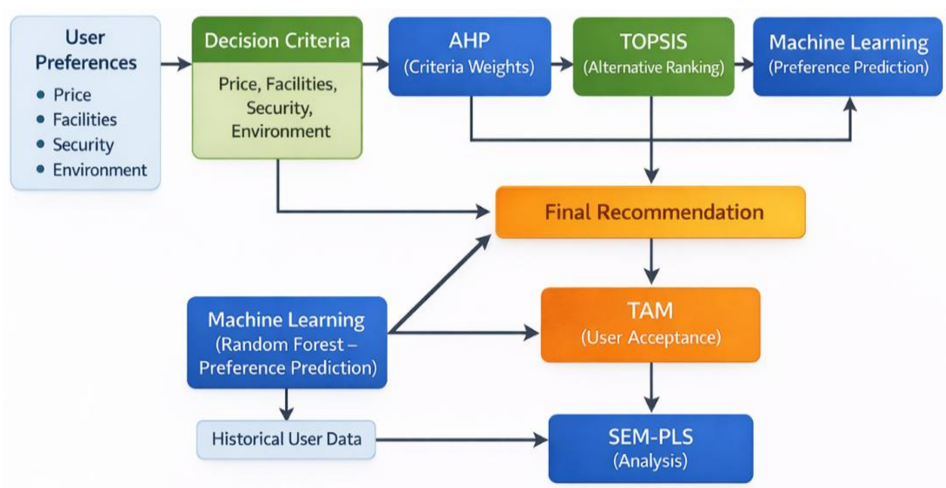

Figure 1. Conceptual Model of Recommendation System

System Architecture

The system architecture consists of four main components: users, a recommendation system, a database, and a recommendation processing module. Users input their preferences, such as price, location, amenities, security, and environment, through the system interface. The preference data is stored in the database and processed using the Analytical Hierarchy Process (AHP) to determine criteria weights. The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method is then used to rank rental housing alternatives. The system also uses machine learning algorithms to predict user preferences and generate personalised recommendations. The system architecture is illustrated in Figure 2.

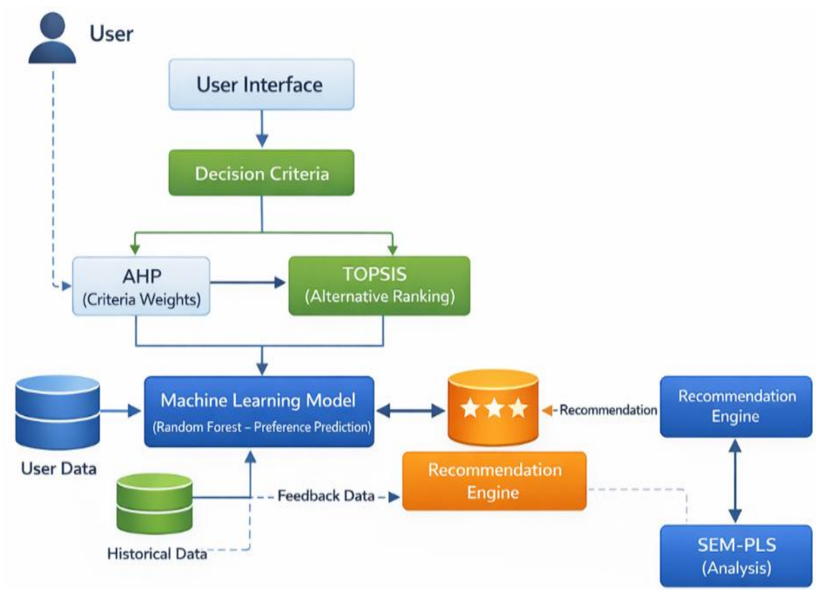

Figure 2. Recommendation System Architecture

Respondents and Data Collection

The data in this study consists of primary and secondary data. Primary data were collected by distributing questionnaires to 120 prospective users of rental housing. Respondents were selected using purposive sampling, with the criterion that they had previously searched for or considered rental housing as a place to live. The questionnaire was compiled using a Likert scale of 1 to 5 to measure the variables of perceived ease of use, perceived usefulness, behavioural intention, and actual use within the Technology Acceptance Model framework. Meanwhile, secondary data consisted of rental housing alternative data covering attributes of price, location, facilities, security, and environment. This data was used in the alternative weighting and ranking process at the MCDM stage and as a basis for compiling historical data for predicting user preferences.

Multicriteria Decision-Making Method

The multicriteria decision-making methods used in this study are the Analytical Hierarchy Process (AHP) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). AHP is used to determine the weight of each criterion through pairwise comparisons (F. Ahmed & Kilic, 2024; Winarno & Riezky, 2023). The AHP stages include compiling a pairwise comparison matrix, calculating eigenvector values, and testing consistency using the Consistency Ratio (CR). If the CR value is less than 0.1, the pairwise comparison matrix is considered consistent. After obtaining the criteria weights using the Analytical Hierarchy Process, the next step is to rank the alternatives using the Technique for Order Preference by Similarity to Ideal Solution. This method ranks alternatives based on their distances from the positive and negative ideal solutions (Das & Kumar, 2023; Vahidnia et al., 2022; Wang & Luo, 2009). The alternative with the highest preference value is considered the best alternative.

Machine Learning Methods

This study uses a Machine Learning approach with the Random Forest algorithm to predict user preferences based on historical data. Random Forest was chosen because it can handle multidimensional data, reduces the risk of overfitting, and achieves good classification performance (Bhagat & Kumar, 2023; Yaqoob et al., 2025). The analysis stages include data preprocessing, dividing the dataset into 80% for training and 20% for testing, model training, model testing, and performance evaluation using accuracy, precision, recall, and F1-score. Through this approach, the system not only produces criteria-based recommendations but also learns user preference patterns from previous data (Afzal et al., 2024; Gao et al., 2025; Shrivastava et al., 2024).

Integration of Methods in Systems

The integration of methods in this study was carried out in stages. AHP was used to determine the relative importance of each criterion, then TOPSIS was used to generate a ranking of rental housing alternatives based on these weights. Next, a Random Forest-based Machine Learning model was used to predict user preference tendencies based on historical data (Du & Zhai, 2024; Lakshmi Yerrabolu et al., 2024; Outay et al., 2023). The results of these two approaches were used to support more objective and personalised recommendations. After the system was implemented, user acceptance was analysed using the Technology Acceptance Model with SEM-PLS.

System Flowchart

The system flowchart illustrates the system process, starting with user input, criteria weighting using the Analytical Hierarchy Process, alternative ranking using the Technique for Order Preference by Similarity to Ideal Solution, preference prediction using Machine Learning, and the generation of the best rental housing recommendations. The system flowchart is shown in Figure 3.

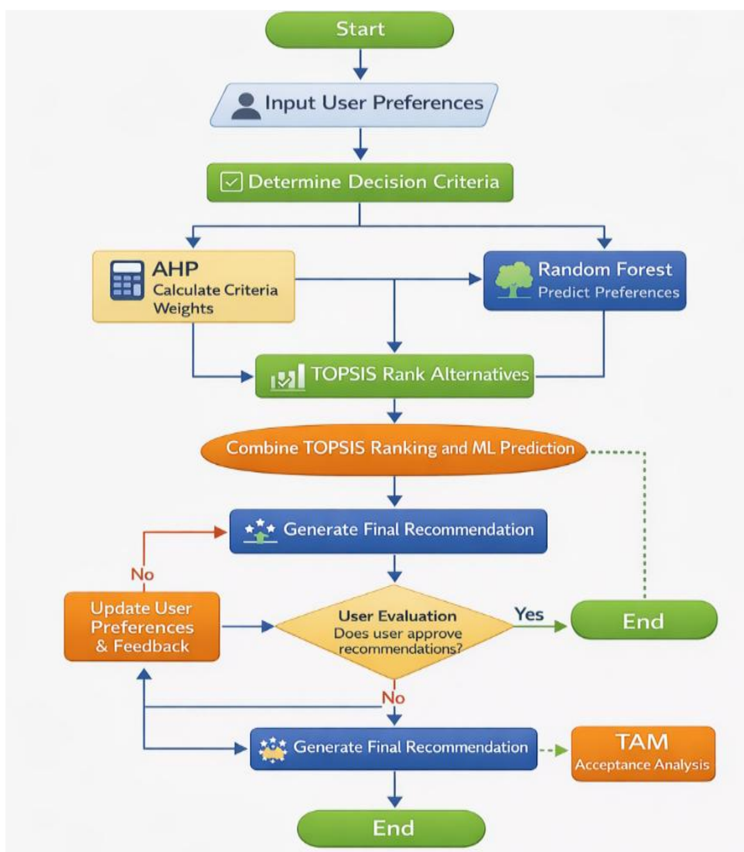

Figure 3. System flow diagram

Data Analysis Techniques

The data analysis techniques used in this study include multicriteria decision-making analysis using Analytical Hierarchy Process and Technique for Order Preference by Similarity to Ideal Solution to determine rental housing rankings, machine learning analysis using Random Forest to predict user preferences, descriptive statistical analysis to analyze respondent data, and Structural Equation Modeling analysis using Partial Least Squares to analyze the relationship between variables in the Technology Acceptance Model. The integration of Multicriteria Decision-Making, Machine Learning, and the Technology Acceptance Model in this study is expected to produce an accurate recommendation system and achieve high user acceptance.

Results and Discussion

Results

Implementation of Recommendation System

The rental housing recommendation system developed in this study is implemented as a web-based application that integrates Multi-Criteria Decision Making, Machine Learning, and the Technology Acceptance Model. The system implementation was carried out to validate the conceptual model designed in the method stage and to test the system's performance in generating rental housing recommendations based on user preferences. The developed system serves as a decision support tool that helps users objectively select rental housing based on several predetermined criteria.

The recommendation system consists of several main modules: the login module, user preference input module, criteria weight calculation module using the Analytical Hierarchy Process, alternative ranking module using the Technique for Order Preference by Similarity to Ideal Solution, user preference prediction module using Machine Learning, and recommendation result module. The system interface is designed with a simple, easy-to-use display to increase the system's perceived ease of use, in accordance with the Technology Acceptance Model, as shown in Figure 4.

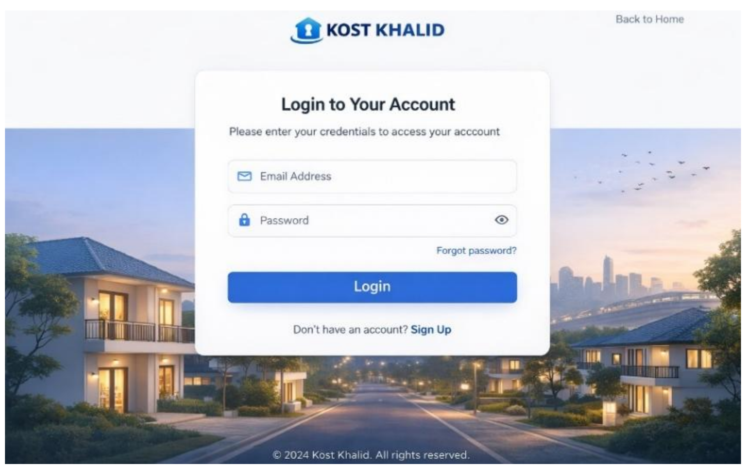

Figure 4. System Login Page

The login page is the initial page used for user authentication before accessing the recommendation system. Users are asked to enter their registered username and password. If the entered data matches the data stored in the database, the user can log in to the system. The login page is designed with a simple interface to facilitate user access. Furthermore, Figure 5 shows the user-preference input page, used to enter preferences for rental housing criteria such as price, location, amenities, security, and environment. The user-entered preference data is then processed by the system using the Analytical Hierarchy Process to determine the importance of each criterion. This page is designed as an input form, allowing users to enter preferences based on their needs easily.

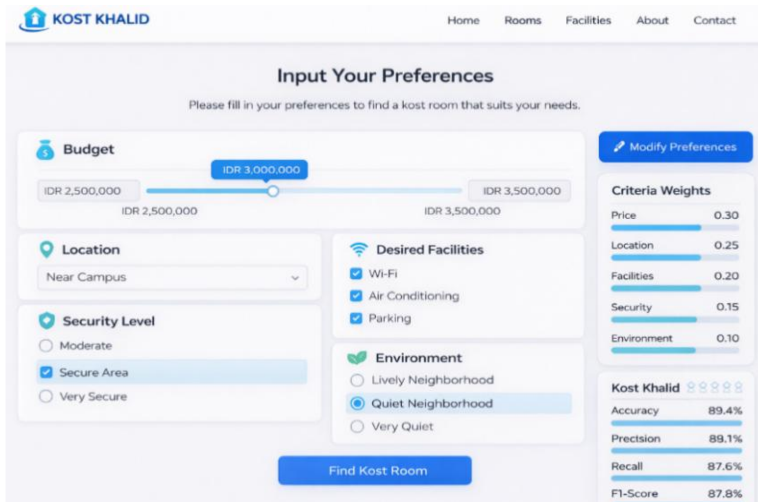

Figure 5. User preference input page

Next, the recommendation results page displays the rankings of rental housing alternatives based on the TOPSIS method and predicted user preferences from Machine Learning, as shown in Figure 6. This page displays the preference scores and rankings for each rental housing alternative. The alternative with the highest preference score is displayed as the primary recommendation to the user.

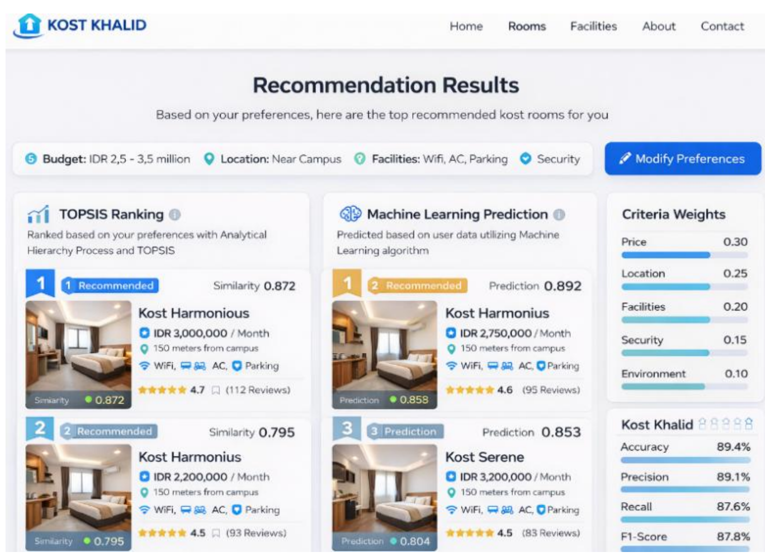

Figure 6. Recommendation Results Page

Results of Criteria Weight Calculation Using Analytical Hierarchy Process

The Analytical Hierarchy Process method is used to determine the importance weight of each criterion in selecting rental housing. The criteria used in this study consist of price, location, facilities, security, and environment. The weight determination is performed using a pairwise comparison matrix of criteria, and normalisation is then applied to obtain the eigenvector values as criterion weights. Based on the calculation results using the Analytical Hierarchy Process (AHP) method, the importance weights for each criterion used in selecting rental housing are obtained. Criteria weights are obtained through pairwise comparisons, matrix normalisation, and eigenvector calculations. The results of the AHP-based criterion weight calculation are shown in Table 1.

Table 1. Criteria Weighting Using AHP

Criteria	Weight
Price	0.30
Location	0.25
Facility	0.20
Security	0.15
Environment	0.10
Total	**1.00**

Based on Table 1, the price criterion has the highest weighting, namely 0.30. This indicates that price is the most important factor for users when choosing rental housing. The second criterion, with the highest weighting, is location (0.25), followed by facilities (0.20), security (0.15), and environment (0.10). The Consistency Ratio is 0.06 (<0.1), so the pairwise comparison matrix is consistent and can be used in further calculations.

Alternative Ranking Results Using TOPSIS

After the criteria weights are obtained using the AHP method, the next step is to rank the rental housing alternatives using the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method. The TOPSIS method is used to determine the best alternative based on its proximity to the positive and negative ideal solutions. The results of the preference value calculation and the alternative ranking using the TOPSIS method are shown in Table 2.

Table 2. Ranking Results Using TOPSIS

Alternative	Preference Value	Ranking
A1	0.82	1
A2	0.76	2
A3	0.65	3
A4	0.58	4
A5	0.49	5

Based on Table 2, alternative A1 has the highest preference score of 0.82, making it the system's recommended alternative. Alternative A2 is ranked second with a preference score of 0.76, while alternative A5 has the lowest preference score of 0.49. These results demonstrate that the TOPSIS method can objectively rank alternatives based on predetermined criteria weights.

Machine Learning Test Results

A machine learning approach using the Random Forest algorithm was used to predict user preferences based on historical data. The dataset was divided into 80% for training and 20% for testing. Model evaluation was performed using a confusion matrix and performance metrics, including accuracy, precision, recall, and F1-score. Test results showed that the Random Forest model performed well with an accuracy of 89.4%, a precision of 88.1%, a recall of 87.6%, and an F1-score of 87.8%. These results indicate that the model can identify user preference patterns with sufficient accuracy and balance. The results of the Machine Learning model testing are shown in Table 3.

Table 3. Machine Learning Test Results

Metric	Mark
Accuracy	89.4%
Precision	88.1%
Recall	87.6%
F1-Score	87.8%

Comparison of Methods

A comparison was conducted between the AHP–TOPSIS and Simple Additive Weighting (SAW) methods to determine which method produces better alternative ranking quality. This comparison was not based on classification accuracy, but on the level of conformity of the ranking results with user preferences. The comparison results showed that the AHP–TOPSIS method had a conformity level of 89.4%, while the SAW method had 84.7%. This indicates that the

TOPSIS method is more effective at ranking alternatives because it considers the distances to the positive and negative ideal solutions, thereby producing more relevant recommendations. The comparison results are shown in Table 4.

Table 4. Comparison of Recommendation Performance

Method	Recommended Performance Value
AHP–TOPSIS	89.4%
SAW	84.7%

Results of the Technology Acceptance Model and SEM-PLS analysis

User acceptance analysis of the system was conducted using the Technology Acceptance Model and tested with the SEM-PLS approach. The test results show that perceived ease of use has a significant effect on perceived usefulness; perceived usefulness has a significant effect on behavioural intention; perceived ease of use also has a significant effect on behavioural intention; and behavioural intention has a significant effect on actual use. All relationships between variables have p-values < 0.05, indicating that all hypotheses are accepted. In addition, the R-square value of 0.67 indicates that the model has strong explanatory power in explaining user acceptance of the developed recommendation system. The SEM-PLS test results are shown in Table 5.

Table 5. Results of SEM-PLS Analysis

Variable Relationship	Path Coefficient	p-value
PEOU → PU	0.62	0,000
PU → BI	0.55	0.001
PEOU → BI	0.41	0.003
BI → AU	0.67	0,000

Based on Table 5, all relationships between variables have p-values < 0.05 and are thus significant. An R-squared value of 0.67 indicates that the model has strong explanatory power for user acceptance of the system.

Discussion

The results of this study indicate that integrating Multi-Criteria Decision Making (MCDM), Machine Learning, and the Technology Acceptance Model (TAM) can significantly improve the quality of rental housing recommendation systems. The hybrid approach used in this study allows the system to provide recommendations not only based on mathematical calculations of decision criteria but also based on user preference patterns learned from historical data. This integrated approach has been shown to improve the quality of recommendations and user satisfaction in recommendation systems and data-driven decision support systems (Champati et al., 2025; Ravi et al., 2025). Therefore, integrating decision-making methods with Machine Learning is a widely used approach for developing intelligent recommendation systems.

Based on calculations using the Analytical Hierarchy Process (AHP) method, price and location were the most influential factors in selecting rental housing. This finding indicates that economic factors and location accessibility are primary considerations for users when choosing a place to live, especially for temporary rental housing. These findings align with previous research, which found that price and location are dominant factors in property and housing recommendation systems because they are directly related to users' financial capabilities and ease of access to public facilities and workplaces (JingFang Liu et al., 2025; Mubarak et al., 2022). Furthermore, facilities and security are also important factors because they relate to user comfort and safety, particularly for students and workers seeking temporary housing (Stemn et al., 2024).

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method was used to rank rental housing alternatives based on their proximity to the positive ideal solution and distance to the negative ideal solution. The results showed that the TOPSIS method provided an objective and consistent ranking of alternatives. Previous research showed that the TOPSIS method outperformed the Simple Additive Weighting method in multi-criteria decision-making cases because it accounted for the relative distances to the ideal and anti-ideal solutions (Al-Sharqi, 2025; Wachowicz & Roszkowska, 2025). This indicates that the TOPSIS method is more suitable for multi-criteria decision-making with many criteria and trade-offs among attributes.

In addition to using the MCDM method, this study also integrates Machine Learning methods to predict user preferences. The Random Forest algorithm was used because it has strong classification capabilities, can handle large amounts of data, and achieves high accuracy in various recommendation systems and data classification tasks (Li et al., 2023; Marcuzzo et al., 2022). Test results show that the Machine Learning model achieves an accuracy of 89.4%, indicating that the system can predict user preferences with high accuracy. Previous research also shows that integrating Machine Learning into recommendation systems can significantly improve recommendation quality compared to conventional methods that rely solely on rule-based approaches or criteria weighting (Benabbes et al., 2022; Garapati & Chakraborty, 2025).

The integration of MCDM and Machine Learning methods in a recommendation system is a hybrid approach that combines the advantages of decision-making methods and data-driven learning. MCDM methods are used to evaluate alternatives based on objectively defined criteria, while Machine Learning is used to learn user preference patterns from historical data. The combination of these two methods enables the system to provide more personalised, adaptive, and accurate recommendations. Previous research has shown that hybrid recommendation systems that combine decision-making and Machine Learning methods can significantly improve recommendation quality and user satisfaction compared to single recommendation systems (He et al., 2024; Li et al., 2023).

In addition, this study also analysed user acceptance of the system using the Technology Acceptance Model (TAM). The results of the SEM-PLS analysis showed that perceived ease of use significantly influenced perceived usefulness, and perceived usefulness significantly influenced behavioural intention. This indicates that the easier the system is to use, the more users will perceive it as useful and the more likely they are to use it. The results of this study are consistent with previous research, indicating that perceived usefulness and perceived ease of use are the primary factors in the acceptance of information technology and computer-based information systems (Alturkustani et al., 2025; Yang et al., 2022).

The R-square value of 0.67 in the SEM-PLS model indicates strong explanatory power for user acceptance of the system. According to (Stemn et al., 2024) An R-square value of 0.67 is considered strong in SEM-PLS-based research. This indicates that the TAM model used in this study can explain user behaviour when using the developed recommendation system. Overall, the main contribution of this research lies in the development of a hybrid recommendation system model that integrates AHP, TOPSIS, Machine Learning, and the Technology Acceptance Model within a single decision-support system framework. Previous research typically uses a single approach, such as MCDM or Machine Learning. In contrast, this research integrates decision-making methods, preference prediction, and user acceptance analysis into a single recommendation system model. This integrated approach is an important scientific contribution in the fields of information systems, decision support systems, and artificial intelligence-based recommendation systems.

In addition to theoretical contributions, this research also has practical implications. The developed system can be used as a decision-support system for selecting rental housing, apartments, or other properties. This system can assist users in objectively selecting rental housing based on their desired criteria and recommendations generated through data analysis and machine learning. Thus, this system not only provides recommendations for the best alternatives but also aligns them with user preferences. The hybrid recommendation system model developed in this research also has the potential to be applied in various other fields, such as product, tourist attraction, job, and education recommendations, thus making theoretical and practical contributions to the development of recommendation systems and artificial intelligence.

Conclusions and Suggestions

Conclusions

This study aims to develop a rental housing recommendation system by integrating Multi-Criteria Decision Making (MCDM), Machine Learning, and the Technology Acceptance Model (TAM) into a single decision-support system framework. The Analytical Hierarchy Process (AHP) method is used to determine the criteria weights, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is used to rank rental housing alternatives, Machine

Learning with the Random Forest algorithm is used to predict user preferences, and the Technology Acceptance Model is analysed using SEM-PLS to measure user acceptance of the system.

The results of the study indicate that the AHP method consistently determines the criteria weights and that price and location are the most influential criteria in the selection of rental housing. The TOPSIS method provides an objective ranking of alternatives based on their proximity to the ideal solution. In addition, the Machine Learning model using the Random Forest algorithm performed well in predicting user preferences, achieving an accuracy of 89.4%. The results of the TAM analysis using SEM-PLS showed that perceived ease of use and perceived usefulness significantly influence behavioural intention and system usage, with an R-square of 0.67, indicating strong explanatory power.

The main contribution of this research is the development of a hybrid recommendation system that integrates multi-criteria decision-making methods, machine-learning-based preference prediction, and user acceptance analysis. The proposed model not only provides objective recommendations for the best alternatives but also offers more personalised, adaptive recommendations based on user preferences, with a good level of user acceptance. Therefore, the model developed in this research can serve as a basis for developing artificial intelligence-based recommendation and decision support systems in the housing sector and other fields.

Suggestions

Future research is recommended to add additional criteria to the rental housing selection process, such as distance to work or campus, access to public transportation, utility costs, and nearby public facilities, to enable the system to generate more comprehensive recommendations. Furthermore, further research could utilise other machine learning methods, such as Support Vector Machines, Gradient Boosting, or Neural Networks, to compare the performance of user preference prediction models. System development can also take the form of a mobile application integrated with a geographic information system (GIS), so that rental housing recommendations can be displayed in a more interactive, location-based way. Furthermore, further research can develop a more complex hybrid-based recommendation model by combining collaborative filtering, content-based filtering, and multi-criteria decision-making to improve the quality of the system's recommendations.

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Contributions

The first author contributed to the research conceptualisation, method design, system development, data collection, data analysis, and writing the initial draft of the manuscript. The second author contributed to the methodology development, machine learning and SEM-PLS analysis, validation of the research results, and review and editing of the manuscript. All authors have read and approved the final version of the manuscript.

Conflict of Interest

The author declares that there is no conflict of interest related to the research, writing, and publication of this article.

References

Afzal, I., Yilmazel, B., & Kaleli, C. (2024). An Approach for Multi-Context-Aware Multi-Criteria Recommender Systems Based on Deep Learning. *IEEE Access*, *12*, 99936–99948. https://doi.org/10.1109/ACCESS.2024.3428630

Ahmed, F., & Kilic, K. (2024). Does fuzzification of pairwise comparisons in analytic hierarchy process add any value? *Soft Computing*, *28*(5), 4267–4284. https://doi.org/10.1007/s00500-023-09593-9

Ahmed, W. M., Azhari, A. A., Fawaz, K. A., Ahmed, H. M., Alsadah, Z. M., Majumdar, A., & Carvalho, R. M. (2025). Artificial intelligence in the detection and classification of dental caries. *The Journal of Prosthetic Dentistry*, *133*(5), 1326–1332. https://doi.org/10.1016/j.prosdent.2023.07.013

Al-Sharqi, N. F. F. M. F. Z. M. R. Z. F. Z. N. M. F. (2025). A New Method for Multi-Criteria Decision-Making: Adaptive Ranking with Ideal Evaluation (ARIE). *European Journal of Pure and Applied Mathematics*, *18*(4), 6578. https://doi.org/10.29020/nybg.ejpam.v18i4.6578

Alshamrani, A., Majumder, P., Das, A., Hezam, I. M., & Božanić, D. (2023). An integrated BWM-TOPSIS-I approach to determine the ranking of alternatives and application of sustainability analysis of renewable energy. *Axioms*, *12*(2), 159. https://doi.org/10.3390/axioms12020159

Alturkustani, S., Durfee, A., O'Leary, O. F., O'Mahony, S. M., O'Mahony, C., Lone, M., & Factor, A. (2025). Measuring students' perceptions of virtual reality for learning anatomy using the general extended technology acceptance model for E-learning. *Anatomical Sciences Education*, *18*(6), 579–595. https://doi.org/10.1002/ase.70045

Benabbes, K., Housni, K., Mezouary, A. El, & Zellou, A. (2022). Recommendation System Issues, Approaches and Challenges Based on User Reviews. *Journal of Web Engineering*, *21*(4), 1017–1054. https://doi.org/10.13052/jwe1540-9589.2143

Bhagat, M., & Kumar, D. (2023). Performance evaluation of PCA based reduced features of leaf images extracted by DWT using random Forest and XGBoost classifier. *Multimedia Tools and Applications*, *82*(17), 26225–26254. https://doi.org/10.1007/s11042-023-14370-9

Chakraborty, S. (2022). TOPSIS and Modified TOPSIS: A comparative analysis. *Decision Analytics Journal*, *2*, 100021. https://doi.org/10.1016/j.dajour.2021.100021

Champati, S., Moahanty, B., & Barisal, S. K. (2025). MLDSS: Customer-Centric Retail Recommendation via Multi-Layered Decision Support System. *IEEE Access*, *13*, 140644–140666. https://doi.org/10.1109/ACCESS.2025.3596795

Ciardiello, F., & Genovese, A. (2023). A comparison between TOPSIS and SAW methods. *Annals of Operations Research*, *325*(2), 967–994. https://doi.org/10.1007/s10479-023-05339-w

Das, K., & Kumar, R. (2023). Assessment of Electric Two-Wheeler Ecosystem Using Novel Pareto Optimality and TOPSIS Methods for an Ideal Design Solution. In *World Electric Vehicle Journal* (Vol. 14, Issue 8, p. 215). https://doi.org/10.3390/wevj14080215

Deepika, S., Anandakumar, S., Bhuvanesh Kumar, M., & Baskar, C. (2023). Performance appraisement of supplier selection in construction company with Fuzzy AHP, Fuzzy TOPSIS, and DEA: A case study based approach. *Journal of Intelligent & Fuzzy Systems*, *45*(6), 10515–10528. https://doi.org/10.3233/JIFS-231790

Deta, B., & Bedanaen, S. M. I. (2025). Comparison of SAW, AHP, and TOPSIS methods in a decision support system for teacher performance evaluation. *Research Horizon*, *5*(5), 1995–2008. https://doi.org/10.54518/rh.5.5.2025.798

Du, Q., & Zhai, J. (2024). Application of artificial intelligence Sensors based on random forest algorithm in financial recognition models. *Measurement: Sensors*, *33*, 101245. https://doi.org/10.1016/j.measen.2024.101245

Gao, Y., Zheng, H., & Cui, H. (2025). User preference modeling for movie recommendations based on deep learning. *Scientific Reports*, *15*(1), 16592. https://doi.org/10.1038/s41598-025-00030-5

Garapati, R., & Chakraborty, M. (2025). Recommender systems in the digital age: a comprehensive review of methods, challenges, and applications. *Knowledge and Information Systems*, *67*(8), 6367–6411. https://doi.org/10.1007/s10115-025-02453-y

He, X., Liu, Q., & Jung, S. (2024). The Impact of Recommendation System on User Satisfaction: A Moderated Mediation Approach. In *Journal of Theoretical and Applied Electronic Commerce Research* (Vol. 19, Issue 1, pp. 448–466). https://doi.org/10.3390/jtaer19010024

Jadiga, S. (2025). Understanding the Role of AI in Personalized Recommendation Systems, Applications, Concepts, and Algorithms. *International Journal of Computer Trends and Technology (IJCTT)*, *73*(1), 106–118. https://doi.org/10.14445/22312803/IJCTT-V73I1P113

JingFang Liu, Nelson R. Garcia, & Wang Zhi. (2025). Predicting Housing Prices in China Towards Real Estate Recommendation System Framework. *Journal of Business and Management Studies*, *7*(4 SE-Research Article), 326–339. https://doi.org/10.32996/jbms.2025.7.4.20.22

Lakshmi Yerrabolu, V., Kasireddy, I., Jasmine, K. M., Murali Krishna Vamsi, T. B., Joshua, N., Shyam Kumar, V., &

Rao, D. (2024). Performance Comparison of Random Forest Regressor and Support Vector Regression for Solar Energy Prediction. *IOP Conference Series: Earth and Environmental Science*, *1375*(1), 12013. https://doi.org/10.1088/1755-1315/1375/1/012013

Lamrini, L., Abounaima, M. C., & Talibi Alaoui, M. (2023). New distributed-topsis approach for multi-criteria decision-making problems in a big data context. *Journal of Big Data*, *10*(1), 97. https://doi.org/10.1186/s40537-023-00788-3

Legramante, D., Azevedo, A., & Azevedo, J. M. (2023). Integration of the technology acceptance model and the information systems success model in the analysis of Moodle's satisfaction and continuity of use. *International Journal of Information and Learning Technology*, *40*(5), 467–484. https://doi.org/10.1108/IJILT-12-2022-0231

Li, C., Ishak, I., Ibrahim, H., Zolkepli, M., Sidi, F., & Li, C. (2023). Deep Learning-Based Recommendation System: Systematic Review and Classification. *IEEE Access*, *11*, 113790–113835. https://doi.org/10.1109/ACCESS.2023.3323353

Marcuzzo, M., Zangari, A., Albarelli, A., & Gasparetto, A. (2022). Recommendation Systems: An Insight Into Current Development and Future Research Challenges. *IEEE Access*, *10*, 86578–86623. https://doi.org/10.1109/ACCESS.2022.3194536

Masudin, I., Habibah, I. Z., Wardana, R. W., Restuputri, D. P., & Shariff, S. S. R. (2024). Enhancing supplier selection for sustainable Raw materials: A comprehensive analysis using analytical network process (ANP) and TOPSIS methods. *Logistics*, *8*(3), 74. https://doi.org/10.3390/logistics8030074

Matias, S. M. M., & Latip, M. C. (2025). A Comparative Study of Classification Algorithms for a Recommendation System. *2025 7th International Conference on Control and Robotics (ICCR)*, 225–229. https://doi.org/10.1109/ICCR67607.2025.11372079

Modibbo, U. M., Hassan, M., Ahmed, A., & Ali, I. (2022). Multi-criteria decision analysis for pharmaceutical supplier selection problem using fuzzy TOPSIS. *Management Decision*, *60*(3), 806–836. https://doi.org/10.1108/MD-10-2020-1335

Mubarak, M., Tahir, A., Waqar, F., Haneef, I., McArdle, G., Bertolotto, M., & Saeed, M. T. (2022). A Map-Based Recommendation System and House Price Prediction Model for Real Estate. In *ISPRS International Journal of Geo-Information* (Vol. 11, Issue 3, p. 178). https://doi.org/10.3390/ijgi11030178

Natasia, S. R., Wiranti, Y. T., & Parastika, A. (2022). Acceptance analysis of NUADU as e-learning platform using the Technology Acceptance Model (TAM) approach. *Procedia Computer Science*, *197*, 512–520. https://doi.org/10.1016/j.procs.2021.12.168

Outay, F., Adnan, M., Gazder, U., Baqueri, S. F. A., & Awan, H. H. (2023). Random forest models for motorcycle accident prediction using naturalistic driving based big data. *International Journal of Injury Control and Safety Promotion*, *30*(2), 282–293. https://doi.org/10.1080/17457300.2022.2164310

Pandey, V., Komal, & Dincer, H. (2023). A review on TOPSIS method and its extensions for different applications with recent development: V. Pandey et al. *Soft Computing*, *27*(23), 18011–18039. https://doi.org/10.1007/s00500-023-09011-0

Papakostas, C., Troussas, C., Krouska, A., & Sgouropoulou, C. (2023). Exploring users' behavioral intention to adopt mobile augmented reality in education through an extended technology acceptance model. *International Journal of Human–Computer Interaction*, *39*(6), 1294–1302. https://doi.org/10.1080/10447318.2022.2062551

Park, J. H., Lee, C. W., & Do, C. (2025). Examining users' acceptance intention of health applications based on the technology acceptance model. *Healthcare*, *13*(6), 596. https://doi.org/10.3390/healthcare13060596

Pathak, S., Quraishi, S. J., Singh, A., Singh, M., Arora, K., & Ather, D. (2023). A comparative analysis of machine learning models: Svm, naive bayes, random forest, and lstm in predictive analytics. *2023 3rd International Conference on Technological Advancements in Computational Sciences (ICTACS)*, 790–795. https://doi.org/10.1109/ICTACS59847.2023.10390255

Rachman, A. P., Ichwania, C., Mangkuto, R. A., Pradipta, J., Koerniawan, M. D., & Sarwono, J. (2024). Comparison of multi-criteria decision-making methods for selection of optimum passive design strategy. *Energy and Buildings*, *314*, 114285. https://doi.org/10.1016/j.enbuild.2024.114285

Ravi, M., Negi, A., Bommi, N. S., & Rouf, N. (2025). Evolution of AI-driven decision making with decision support systems, expert systems, recommender systems, and XAI. *IETE Technical Review*, *42*(4), 428–465. https://doi.org/10.1080/02564602.2025.2512086

Rimal, Y., Sharma, N., Paudel, S., Alsadoon, A., Koirala, M. P., & Gill, S. (2025). Comparative analysis of heart disease prediction using logistic regression, SVM, KNN, and random forest with cross-validation for improved accuracy. *Scientific Reports*, *15*(1), 13444. https://doi.org/10.1038/s41598-025-93675-1

Roy, D., & Dutta, M. (2022). A systematic review and research perspective on recommender systems. *Journal of Big Data*, *9*(1), 59. https://doi.org/10.1186/s40537-022-00592-5

Rustam, F., Imtiaz, Z., Mehmood, A., Rupapara, V., Choi, G. S., Din, S., & Ashraf, I. (2022). Automated disease diagnosis and precaution recommender system using supervised machine learning. *Multimedia Tools and Applications*, *81*(22), 31929–31952. https://doi.org/10.1007/s11042-022-12897-x

Sahoo, S. K., & Goswami, S. S. (2023). A comprehensive review of multiple criteria decision-making (MCDM) methods: advancements, applications, and future directions. *Decision Making Advances*, *1*(1), 25–48. https://doi.org/10.31181/dma1120237

Şenyüzlüler, F., & Baykasoglu, A. (2026). Development of web based data-driven recommendation system for house rental via hierarchical fuzzy axiomatic design. *Kybernetes*, *55*(2), 1156–1182. https://doi.org/10.1108/K-08-2024-2211

Shafik, W. (2024). Artificial intelligence and machine learning with cyber ethics for the future world. In *Future communication systems using artificial intelligence, internet of things and data science* (pp. 110–130). CRC Press. https://doi.org/10.1201/9781032648309-9

Shrivastava, R., Sisodia, D. S., & Nagwani, N. K. (2024). Deep ensembled multi-criteria recommendation system for enhancing and personalizing the user experience on e-commerce platforms. *Knowledge and Information Systems*, *66*(12), 7799–7836. https://doi.org/10.1007/s10115-024-02187-3

Singun, A. J. (2025). Unveiling the barriers to digital transformation in higher education institutions: a systematic literature review. *Discover Education*, *4*(1), 37. https://doi.org/10.1007/s44217-025-00430-9

Stemn, E., Koomson, E., & Fosu, S. (2024). Determinants of university students' choice of accommodation: an analysis of risk perception and safety awareness. *Journal of Housing and the Built Environment*, *39*(4), 2171–2193. https://doi.org/10.1007/s10901-024-10162-1

Sun, Z., Wang, G., Li, P., Wang, H., Zhang, M., & Liang, X. (2024). An improved random forest based on the classification accuracy and correlation measurement of decision trees. *Expert Systems with Applications*, *237*, 121549. https://doi.org/10.1016/j.eswa.2023.121549

Taye, M. M. (2023). Understanding of machine learning with deep learning: architectures, workflow, applications and future directions. *Computers*, *12*(5), 91. https://doi.org/10.3390/computers12050091

Trivedi, P., Shah, J., Čep, R., Abualigah, L., & Kalita, K. (2024). A hybrid best-worst method (BWM)—technique for order of preference by similarity to ideal solution (TOPSIS) approach for prioritizing road safety improvements. *IEEe Access*, *12*, 30054–30065. https://doi.org/10.1109/ACCESS.2024.3368395

Vafaei, N., Ribeiro, R. A., & Camarinha-Matos, L. M. (2022). Assessing normalization techniques for simple additive weighting method. *Procedia Computer Science*, *199*, 1229–1236. https://doi.org/10.1016/j.procs.2022.01.156

Vahidnia, M. H., Vahidi, H., Hassanabad, M. G., & Shafiei, M. (2022). A Spatial Decision Support System Based on a Hybrid AHP and TOPSIS Method for Fire Station Site Selection. *Journal of Geovisualization and Spatial Analysis*, *6*(2), 30. https://doi.org/10.1007/s41651-022-00125-x

Vössing, M., Kühl, N., Lind, M., & Satzger, G. (2022). Designing transparency for effective human-AI collaboration. *Information Systems Frontiers*, *24*(3), 877–895. https://doi.org/10.1007/s10796-022-10284-3

Wachowicz, T., & Roszkowska, E. (2025). Enhancing TOPSIS to Evaluate Negotiation Offers with Subjectively Defined Reference Points. *Group Decision and Negotiation*, *34*(4), 715–749. https://doi.org/10.1007/s10726-025-09929-w

Wang, Y.-M., & Luo, Y. (2009). Area ranking of fuzzy numbers based on positive and negative ideal points. *Computers & Mathematics with Applications*, *58*(9), 1769–1779. https://doi.org/10.1016/j.camwa.2009.07.064

Winarno, H., & Riezky, A. (2023). Designing a Human Resources Performance System in a Company using the Analytical Hierarchy Process (AHP) Method. *International Journal of Engineering Technology and Natural Sciences*, *5*(1), 26–36. https://doi.org/10.46923/ijets.v5i1.197

Wu, R., & Yu, Z. (2024). Investigating users' acceptance of the metaverse with an extended technology acceptance model. *International Journal of Human–Computer Interaction*, *40*(19), 5810–5826. https://doi.org/10.1080/10447318.2023.2241295

Yang, H., Goh, T. S., & Sormin, P. (2022). Computer Anxiety and Computer Attitude in Increasing Staffs' Interest in Using the System through Perceived Usefulness and Perceived Ease of Use. *Quantitative Economics and*

Management Studies, *3*(3 SE-Articles), 298–309. https://doi.org/10.35877/454RI.qems923

Yaqoob, A., Verma, N. K., Mir, M. A., Tejani, G. G., Eisa, N. H. B., Mamoun Hussien Osman, H., & Shah, M. A. (2025). SGA-Driven feature selection and random forest classification for enhanced breast cancer diagnosis: A comparative study. *Scientific Reports*, *15*(1), 10944. https://doi.org/10.1038/s41598-025-95786-1

Zeng, N., Han, L., Liu, Y., Yuan, J., & Li, Q. (2025). Design science research (DSR) in construction: Theoretical conceptualization of practice and practical realization of theory. *Automation in Construction*, *176*, 106298. https://doi.org/10.1016/j.autcon.2025.106298

Zhu, H., Tong, G., Duan, N., Ma, H., Song, Q., Wang, J., Luo, Y., Zhang, Q., Yu, X., & Jin, S. (2025). Analysis of the complex correlations between land use and water quality using the PLS-SEM method combined with fluorescence fingerprinting data. *Journal of Environmental Management*, *373*, 123688. https://doi.org/10.1016/j.jenvman.2024.123688