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Hybrid Neutrosophic Multi-Criteria Decision Model for Guest Selection in Collaborative Tourism Platforms

Vladimir Vega Falcón [1], Yoarnelys Vasallo Villalonga [2] and Lorenzo Cevallos-Torres[3,4]

[1] International Center for Entrepreneurs in Barcelona (ICEB), España. vega.vladimir@gmail.com
[2] Universidad Técnica del Norte, Ibarra, Ecuador. yoarnelys@yahoo.es
[3] UBE Universidad Bolivariana del Ecuador, Km 5 ½, vía Durán, Durán-Ecuador. ljcevallost@ube.edu.ec
[4] Grupo de Investigación en Inteligencia Artificial, Facultad de ciencias Matemáticas y Físicas, Universidad de Guayaquil; Guayaquil-Ecuador. lorenzo.cevallost@iug.edu.ec

Abstract: This study presents a hybrid multi-criteria decision-making (MCDM) model applied to the guest selection process in Airbnb-style vacation rentals. The model integrates the PAPRIKA method, Analytic Hierarchy Process (AHP), and Neutrosophic TOPSIS to evaluate and rank potential guests based on multiple criteria prioritized by experienced property owners. Through the 1000minds software, pairwise comparisons were conducted to elicit preferences and derive normalized weights for six key criteria, with "review history" emerging as the most influential. These weights were then incorporated into classical and neutrosophic TOPSIS evaluations to account for uncertainty, indeterminacy, and subjectivity in guest profiles. Results highlight consistent rankings across both approaches, with the neutrosophic model providing deeper insight into decision-maker hesitation and risk perception. The proposed model demonstrates robustness, transparency, and adaptability for complex service environments and can be extended to broader collaborative economy contexts.

Keywords: Neutrosophic TOPSIS, PAPRIKA method, multi-criteria decision-making, Airbnb, guest selection, AHP, sharing economy, uncertainty modeling, decision support system

1. Introduction

The PAPRIKA method (an acronym for Potentially All Pairwise Rankings of all possible Alternatives), developed by Hansen and Ombler, is currently one of the most recognized techniques for supporting multi-criteria decision-making in a structured, transparent, and efficient manner [1]. This approach is patented and has received multiple awards, highlighting its relevance and reliability.

Specifically, PAPRIKA simplifies the evaluation process by presenting only two criteria at a time, allowing individuals to accurately establish their preferences without the cognitive complexity of evaluating multiple factors simultaneously. Furthermore, major research organizations, government administrations, and commercial users rely on PAPRIKA to solve prioritization problems in areas ranging from health and education to staff selection and investment project evaluation.

In this study, the application of PAPRIKA to the selection of tenants on a vacation rental platform such as Airbnb is particularly valuable. Given the growing demand for objective and transparent solutions in the sharing economy, the use of a multi-criteria decision-making model supported by PAPRIKA's methodological robustness facilitates the identification of fundamental criteria for hosts while promoting fairness and consistency in the allocation of slots or reservations. The relevance of this study lies in its ability to provide clear methodological guidelines tailored to a real market scenario, contributing to the body of knowledge on the adoption of analytical methods in collaborative tourism platforms.

Given the small sample size, PAPRIKA [1] is used, as it can determine partial utilities even for a single respondent. Both the selected target group and the method employed represent significant contributions to the field and reinforce the credibility of the results presented in this study, which is innovative in the Airbnb context. While the method has been successfully applied in other areas such as health technologies [1-7], it has not been used in the context of tenant selection on a rental platform.

The objective of this study is to establish a ranking of potential clients for Airbnb accommodation in the city of Valencia, Spain, using the PAPRIKA technique (Potentially All Pairwise Rankings of all possible Alternatives), from the perspective of property owners, to optimize selection and generate transparent criteria for guest acceptance.

2. Materials and Methods

This study falls within the applied level, aiming to optimize the guest selection process in Airbnb-style accommodations by constructing a ranking based on criteria valued by property owners. Following Supo's [8] methodological proposal, the adopted design is observational, analytical, and applied, as it does not intervene in the variables but allows for the establishment of hierarchical relationships for decision-making.

The study population consisted of owners of tourist accommodations in the city of Valencia, Spain, during the third quarter of 2024, with an intentional sample selected based on their experience and voluntary participation. A rigorous methodological control was applied through the verification of the transitive consistency of comparisons, ensuring the internal validity of the model and minimizing study variability, as suggested by Supo's [8] scientific approach.

The study made use of the 1000minds program [15], which applies the PAPRIKA approach and was verified in a pilot study conducted within the research setting. According to the scientific methodology described by Supo (2024) [8], the entire methodological process was in line with the goal of the study, which was to create a priority ranking of possible clients to enable a more effective selection process based on objective criteria.

The PAPRIKA method presents decision-makers with pairwise comparisons of hypothetical alternatives, each defined by only two criteria, while other judgments remain constant. This approach minimizes cognitive load by focusing on simple "trade-offs" that reflect the relative importance of the criteria [1]. After each explicit comparison (whether indicating preference or indifference), PAPRIKA leverages transitive consistency to automatically infer additional implicit comparisons, reducing the total number of required questions.

The process continues sequentially and adaptively. Once the phase of two-criteria questions is complete, it is possible—if the model's precision requires it—to formulate questions involving three or more criteria at once. However, most applications, including cases such as tenant selection in tourist accommodations, typically require only the initial level of comparisons to reveal preferences closely aligned with reality. Upon completion, a system of equations is solved in which partial scores for each criterion category are adjusted to reproduce the declared preferences. The result is an additive model that enables quick prioritization of alternatives over time, a crucial factor when managing a continuous flow of tenants or reservations for a rental space. [13].

2.1. General description of the PAPRIKA Method in this study.

The PAPRIKA method enabled the derivation of values or scores for each category within the criteria comprising the multi-criteria decision model, to rank a set of alternatives. This was achieved by focusing on:

1. The identification and pairwise comparison of alternatives.
2. Leveraging dominance and transitive consistency to reduce the number of explicit comparisons required by decision-makers.

In general, the preferences of the decision-maker were represented through systematic pairwise comparisons of alternatives that differed in at least two criteria (referred to as "non-dominated pairs"). Comparisons that could be logically and transitively inferred were considered "implicit," meaning the decision-maker did not need to respond to them directly. Since there were no cases involving a very large number of criteria or categories, the method did not require the incorporation of efficient algorithms to identify and discard redundant comparisons, minimizing the effort demanded of the decision-maker [1].

Table 1. PAPRIKA Methodology (Tabular Summary).

Stage	Key Description	Example/Note
1. Model Definition	- Selection of criteria and categories (e.g., a1, a2)	a2 = category "better" than a1
	- Additive model: sum of partial scores	
2. Non-Dominated Pairs	- Generate all possible combinations	Only compare pairs with trade-offs
	- Discard dominated pairs (one better in all aspects)	
3. Explicit Comparisons	- Start with pairs differing in 2 criteria	Reduces cognitive load
	- Decision-maker indicates preference/indifference	
4. Implicit Inference	- Use transitivity to deduce preferences	E.g., If X > Y and Y > Z → X > Z (without asking)
	- Discard already resolved pairs	
5. Final Model	- Assign scores via linear programming	Solution may not be unique, but ranking is
	- Respect explicit/implicit preferences	
6. Verification	- Check consistency with new comparisons	Avoids cyclic preferences (e.g., X > Y > Z > X)
	- Correct inconsistencies	
Tool	**1000minds Software**	Optimizes time and precision
	- Automates comparisons	
	- Visualizes rankings and weights	

2.2. Application of the Hybrid Model PAPRIKA + AHP + TOPSIS Neutrosophic.

The current study successfully used a multi-criteria hybrid decision model that included the PAPRIKA, AHP, and TOPSIS Neutrosophic methodologies for selecting interviewee profiles in the context of vacation assignments. First and foremost, the PAPRIKA component allowed for the establishment of strong correlations between the evaluation criteria through peer comparisons, expressed in clearly different percentages (for example, Review History at 43.8% and Length of Stay at 6.2%). This procedure implicitly incorporates the AHP methodology's foundations since it ensures consistency in the criteria's hierarchical organization and validates its relative importance structure.

Subsequently, the quantitative categories of each criterion were converted into numerical values and neutrosophic triplets (T, I, and F), allowing the TOPSIS Neutrosophic approach to be applied. This paradigm integrated truth, uncertainty, and falsity into the evaluation of each alternative, capturing not just the objective value but also the degree of uncertainty inherent in the evaluators' perceptions. Combining these three approaches strengthened the final ranking's accuracy and transparency and provided a strong tool for making complex decisions with many criteria and subjective weight. [14].

2.2.1. General definitions

Let be a set of alternatives (tenant profiles):

$$A = \{a1, a2, \ldots, am\}$$

Let a set of criteria be:

$$C = \{c1, c2, \ldots, cn\}$$

For each alternative a_i and criteria c_j, is assigned:

- In classic ***TOPSIS***: a numerical value $\boldsymbol{x_{ij}} \in \boldsymbol{R}$
- In neutrosophic ***TOPSIS***: a neutrosophic triplet $\boldsymbol{N_{ij}} = (\boldsymbol{T_{ij}}, \boldsymbol{I_{ij}}, \boldsymbol{F_{ij}})$, with: $\boldsymbol{T_{ij}}, \boldsymbol{I_{ij}}, \boldsymbol{F_{ij}} \in [0,1]$ y $\boldsymbol{T_{ij}} + \boldsymbol{I_{ij}} + \boldsymbol{F_{ij}} \leq 3$

2.2.2. Structure of the Classical Weighted Model (classic TOPSIS).

A popular multi-criteria decision-making technique is the traditional TOPSIS (Technique for Order Preference by Similarity to Ideal answer), which ranks options according to how close they are to an ideal answer geometrically. According to this assumption, the optimal option should be the one that is closest to the ideal solution and the furthest from the worst.

TOPSIS offers a transparent and impartial assessment of options by using weighted distances and normalizing data. It is appropriate for complicated decision issues in a variety of domains because to its simplicity and efficacy.

a. **Normalization of the decision matrix**:

Normalization of the decision matrix in TOPSIS transforms various criteria into a comparable scale, typically using vector normalization. This ensures that all criteria, regardless of their original units, contribute proportionally to the final decision.

$$r_{ij} = {x_{ij}} \Big/ {\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{1}$$

b. **Weighting (if applicable)**:

Weighting in TOPSIS involves assigning relative importance to each criterion based on expert judgment or decision-maker preferences. These weights adjust the normalized values to reflect the significance of each criterion in the overall evaluation.

$$v_{ij} = w_j \cdot r_{ij} \tag{2}$$

c. **Determine the positive and negative ideal**:

In TOPSIS, the positive ideal solution represents the best achievable values for each criterion, while the negative ideal solution represents the worst. These ideal points are used as reference anchors to measure the distance of each alternative in the decision space.

- Positive ideal: $A^+ = \{\max_i v_{ij}\}$
- Negative ideal: $\boldsymbol{A^-} = \{\boldsymbol{min_i\ v_{ij}}\}$

d. **Calculate distances**:

In this step, the Euclidean distance of each alternative is calculated from both the positive and negative ideal solutions. These distances reflect how close or far each alternative is from the optimal and worst scenarios, forming the basis for the final ranking.

$$D_i^+ = \sqrt{\sum_{j=1}^{n}(v_{ij} - A_j^+)^2} \tag{3}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n}(v_{ij} - A_j^-)^2} \tag{4}$$

e. **Calculate the proximity index**.

The proximity index in TOPSIS is calculated as the ratio of the distance to the negative ideal over the sum of distances to both the positive and negative ideals. This index, ranging from 0 to 1, indicates how close each alternative is to the ideal solution—the higher the value, the better the alternative.

$$NCi = \frac{Di^-}{Di^+ + Di^-} \tag{5}$$

2.2.3. Structure of the Weighted Neutrosophic Model (TOPSIS Neutrosófico).

a. **Construction of the neutrosophic matrix**:

The construction of the neutrosophic matrix involves representing each alternative and criterion using a triplet (T, I, F), where T is the degree of truth, I is indeterminacy, and F is falsity. This allows the model to incorporate uncertainty and imprecision directly into the decision-making process.

$$\boldsymbol{N_{ij}} = (\boldsymbol{T_{ij}}, \boldsymbol{I_{ij}}, \boldsymbol{F_{ij}}) \text{ for each profile and criterion}$$

b. **Determination of the positive and negative neutrosophic ideal**:

The positive neutrosophic ideal is formed by selecting the maximum truth (T), and minimum indeterminacy (I) and falsity (F) values across all alternatives for each criterion. Conversely, the negative neutrosophic ideal uses the minimum T and the maximum I and F, serving as benchmarks for evaluation.

Positive ideal:

$$A_J^+ = (max\ T_{ij}, min\ I_{ij}, min\ F_{ij}) \tag{6}$$

Negative ideal:

$$A_J^- = (min\ T_{ij}, max\ I_{ij}, max\ F_{ij}) \tag{7}$$

c. **Calculation of the neutrosophic Euclidean distance**:

The neutrosophic Euclidean distance is calculated by measuring the squared differences between each alternative's (T, I, F) values and those of the ideal solutions. This distance quantifies how far an alternative is from the ideal or anti-ideal, incorporating uncertainty into the evaluation

$$\boldsymbol{D_i^+} = \sqrt{\sum_{j=1}^{n}(\boldsymbol{T_{ij}} - \boldsymbol{T_j^+})^2 + (\boldsymbol{I_{ij}} - \boldsymbol{I_j^+})^2} + (\boldsymbol{F_{ij}} - \boldsymbol{F_j^+})^2 \tag{8}$$

$$\boldsymbol{D_i^-} = \sqrt{\sum_{j=1}^{n}(\boldsymbol{T_{ij}} - \boldsymbol{T_j^-})^2 + (\boldsymbol{I_{ij}} - \boldsymbol{I_j^-})^2} + (\boldsymbol{F_{ij}} - \boldsymbol{F_j^-})^2 \quad (9)$$

d. **Neutrosophic closeness index**:

$$NC_{(N)}^{i} = \frac{D_i^-}{D_i^- + D_i^+} \quad (10)$$

2.2.4. Using the PAPRIKA Matrix

Pairwise comparisons based on the decision-maker's assessments can be used to prioritize criteria through the usage of the PAPRIKA matrix (Potentially All Pairwise Rankings of all possible Alternatives). This matrix creates a consistent and rational weighting system by clearly indicating the relative importance of each criterion. It is not necessary to evaluate every potential pair of alternatives in order to arrive at an accurate ranking thanks to these iterative comparisons.

For sound multi-criteria decisions, the model guarantees logical coherence among the conclusions reached. The PAPRIKA matrix is also adaptable in situations when criteria are not entirely quantifiable because it may be used with both qualitative and ordinal data. Building a strong foundation of weights for evaluating options is made possible by its interaction with models like AHP or TOPSIS.

The PAPRIKA matrix serves as a validation step before quantitative analysis in this regard. By documenting every comparison that is done, it also encourages openness in the decision-making process. In conclusion, this matrix uses a methodical and repeatable methodology to reinforce the model's subjective base.

2.2.5. Interpretation of the final ranking

Tenant profiles were compared and prioritized based on several factors important to owners of vacation rentals, thanks to the combined use of the traditional TOPSIS model and its neutrosophic version. The neutrosophic model added the degrees of uncertainty (I) and discontent (F) connected to each criterion, giving the decision-making process a more comprehensive and realistic dimension than the classic model, which assessed profiles using direct normalized values.

It was found that while both methods agreed that tenant 2 was the most similar to the ideal profile, the other profiles' proximity ratings differed when taking into account the uncertainty included in subjective categories like "communication" and "flexibility." This shows that the neutrosophic approach considers skepticism or inconsistencies in the evaluators' perceptions in addition to quantifying performance. Thus, the neutrosophic index offers a more contextualized and flexible metric for choosing the ideal tenant.

This method works particularly well in tourism settings when host preferences and experiences might differ greatly. As a result, using both models together improves the selection process's validity and enables better decision-making. By clearly stating the level of certainty and imprecision in each assessment, it also promotes transparency.

3. Results

This section presents the evaluation criteria used to rate possible renters, the relative weights given to each criterion, and the ranking of the alternatives that were examined. The ultimate preference order is also explained, along with a description of each tenant's results. The PAPRIKA methodology, which required pairwise assessments of alternatives depending on the specified criteria, was used to create all of the data using an additive model.

3.1. Adaptation of the hybrid model to the PAPRIKA table

1. *Criteria and Weights (W_j)*

Important parameters that represent hosts' interests when choosing visitors were developed to accurately assess tenant profiles. The PAPRIKA approach, which is based on pairwise comparisons, was used to weight each criterion. This allowed proportional weights to be assigned according to their importance. The list of criteria and their corresponding normalized weights is provided below:

Table 2. Adaptation of the hybrid model to the paprika table.

Criterion	Abbrev.	Weight (%)	Normalized Weight (Wj)
1. Review History	RH	43.8	0.438
2. Communication	COM	20.5	0.205
3. Flexibility	FLEX	12.5	0.125
4. Number of Guests	GUEST	9.7	0.097
5. Purpose	PURP	7.4	0.074
6. Length of Stay	LOS	6.2	0.062

The findings show a distinct hierarchy in the significance of the evaluation factors for visitors. With an impressive weight of 43.8%, the Review History (RH) criterion shows that hosts give careful consideration to previous visitors' experiences when making judgments. Communication (20.5%) and Flexibility (12.5%) come next, both of which have a big impact but not as much.

However, variables like the number of guests, the purpose, and most importantly, the length of stay, have a far lower weight, indicating that they are viewed as secondary. A strong decision-making model that is in line with the actual priorities of people who oversee holiday rentals can be created thanks to this weight distribution.

Case 1: One of the best options is a renter with a stellar record (RH = 5), strong communication skills (COM = 2), and a high degree of flexibility (FLEX = 5). The dominant weight of review history (43.8%) makes up for any slight shortcomings in communication, notwithstanding its imperfections. This profile has a high score, maybe first or second, due to its exceptional performance on the most crucial criterion and strong adaptability.

Case 2: This profile depicts a visitor who has no past experiences or unfavorable reviews (RH = 1), but who is highly adaptable (FLEX = 5) and has outstanding communication skills (COM = 3). Their rating is the lowest, which drastically lowers their overall score even though they perform exceptionally well in soft criteria. As a result, they should receive a medium-low score because hosts place a high value on review history.

Case 3: The visitor goes in a big group (GUEST = 1) and has a passable record (RH = 3), but struggles in important areas like communication (COM = 1). Even though they have a good record, their poor performance on other factors, particularly communication, breeds mistrust. Because of their substantial shortcomings and moderate strengths, they are probably ranked in the middle or lower.

Table 3. Comparison matrix.

	COM	FLEX	GUEST	PURP	LOS
RH	2.1	3.5	4.5	5.9	7

The row that corresponds to Review History (RH) in the table indicates that this criterion is thought to be substantially more significant than the others. For instance, it is worth 5.9 times more than the Purpose of Visit (PURP) and 7 times more than the Length of Stay (LOS). This suggests that when assessing tenants, decision-makers give the most weight to review history. The matrix illustrates a distinct hierarchy of priorities that serves as the foundation for the multi-criteria model's weight assignment.

The result obtained in the pairwise comparison matrix reflects that the Review History (RH) criterion was systematically rated as more important than the others during the decision-making process. For example, RH was determined to be 2.1 times more important than Communication, 3.5 times more than Flexibility, and up to 7 times more relevant than Length of Stay. These values emerge from the PAPRIKA method, which interprets the evaluator's decisions by comparing combinations of criteria and assigns relative weights consistent with those preferences. Thus, the matrix justifies Review History receiving the greatest weight (43.8%) in the decision model, as it was perceived as the most determining factor when selecting a tenant. This process ensures that the weights faithfully reflect the subjective priorities of the decision-maker in a systematic and replicable manner. [9].

In conclusion, the hybrid PAPRIKA-TOPSIS classic-TOPSIS neutrosophic model made it possible to combine quantitative analysis, expert opinion, and uncertainty management into a single decision-making procedure. Through pairwise comparisons, PAPRIKA was able to establish consistent weights, strengthening the model's foundation.

3.2. Preferential Valuation by Category.

Category Preference Rating makes it easier to utilize in multi-criteria decision models by enabling the assignment of numeric scores to qualitative levels inside a criterion. Terms like "Good" and "Excellent" are converted into numerical values in this table that represent their respective contributions to the decision goal. This makes the comparison of options more precise and reliable.

Table 4. Assignment of preferential values and normalized scores.

Category	Weight	Score (0–100)	Preference Value
Poor	0.438	0	0.00%
Fair	—	38.3	16.80%
Good	—	76.6	33.50%
Very good	—	88.3	38.60%
Excellent	—	100	43.80%

This table summarizes how the qualitative evaluation of a criterion is translated into quantitative values within a multi-criteria decision model. Specifically, it allows for assigning an objective score to each category within the Review History criterion, facilitating its integration with other numerical criteria. In this way, subjective data is transformed into comparable and measurable data..

Categories are the various qualitative labels that describe a tenant's performance levels based on the Review History criteria. They include terms such as "Poor," "Good," or "Excellent," which represent different perceived qualities of previous behavior. These labels form the basis of human judgment, which will then be quantified in the model Categories are the various qualitative labels that describe a tenant's performance levels based on the Review History criteria. They include terms such as "Poor," "Good," or "Excellent," which represent different perceived qualities of previous behavior. These labels form the basis of human judgment, which will then be quantified in the model. [16].

With a weight of 0.438, Review History accounts for 43.8% of the assessment model's overall value. The PAPRIKA approach, which uses pairwise comparisons to assess the relative significance of criteria, produced this number. Its size supports the notion that this factor is the most important one when choosing tenants.

On a scale of 0 to 100, the score given to each category represents its relative importance within the criterion. For instance, "Excellent" earns 100 points for being the finest assessment conceivable, while "Poor" receives 0 points for being the least desirable choice. The proportional scores for intermediate categories, like "Good" or "Very Good," reflect quality gradations.

This figure indicates the relative contribution of each category to the overall weight of the Review History criterion. If a renter receives a rating of "Good," for instance, their contribution to the model is 33.5% of the 43.8% that the criterion reflects overall. This enables us to precisely determine the impact of each qualitative level on the evaluation's outcome.

This table refines the decision model by detailing the subcriteria or internal categories of the *Review History* criterion, assigning each a quantifiable value. It directly supports the construction of the decision matrix used in both classical and neutrosophic TOPSIS, providing essential inputs for analysis. By translating qualitative labels such as "Good" or "Excellent" into numerical scores, the model bridges subjective judgment and objective evaluation. Furthermore, these scores can be transformed into neutrosophic triplets—for instance, a "Good" rating with 76.6 points could correspond to T = 0.76, I = 0.18, F = 0.06—allowing the incorporation of uncertainty and imprecision into the decision process.

3.3. Result of the decision model.

The final ranking of the tenant profiles assessed using a multi-criteria decision model that combines weights obtained from the PAPRIKA approach with scores allocated to each qualitative category is shown in the following table. The relative importance of each criterion and the degree attained in each were taken into consideration while evaluating each tenant based on factors including communication, flexibility, review history, and others.

On a normalized scale of 0 to 100, the Total Score shows the cumulative percentage that each profile achieved about the highest value that could be achieved. This method made it possible to transform subjective data into equivalent and objective findings. Tenants are ranked from most similar to the ideal profile to least favorable. The following describes the order of preference that was determined following the analysis.

Table 5. Ranking Table of Alternatives by Total Score.

Ranking	Tenant	Score Total
1	2	99.10%
2	1	81.50%
3	5	73.00%
4	4	72.40%
5	3	52.00%

The tenant ranking table is directly linked to the previous tables by showing the consolidated results of the multi-criteria decision model. Each tenant was evaluated on various criteria, such as Review History, Communication, Flexibility, among others, assigning specific scores based on their performance in each category. These scores were multiplied by the corresponding weights for each criterion, previously determined using the **PAPRIKA** method, reflecting the relative importance of each in the decision-making process. The sum of these results gave each tenant's Total Score, expressed as a percentage of the maximum possible value. For example, a tenant with a "Good" review history (76.6 points) and "Excellent" communication (100 points) would have a weighted score calculated as:

$$Total\ Score\ = (76.6 \times 0.438 + 100 \times 0.205 + \cdots) \div 100 \tag{11}$$

To determine the Total Score, this computation is done for every criterion and totaled. As a result, the ranking table shows each tenant's relative position based on a thorough and weighted evaluation of their attributes, enabling an unbiased comparison of them.

3.3.1. Relationship with qualitative categories.

Scores per category (e.g., “Excellent” = 100.0, “Good” = 76.6, etc.) come from tables like this:

Table 6. Preferential Valuation Table by Category.

Category	Score	Preference (%)
Excellent	100	43.8% (max criterion)
Good	76.6	33.50%
Fair	38.3	16.80%
Poor	0	0.00%

These tables allow the qualitative profiles of tenants to be transformed into quantifiable values, which are then weighted and added together.

3.3.2. Relationship with the neutrosophic model.

Despite being based on a classical model, the tenet ranking table can be used as a benchmark for the neutrosophic model. In the latter, each alternative's proximity to the ideal profile is represented by a closeness index $NCi \in [0,1]$which is computed similarly to the Total Score. A more thorough assessment of each option is made possible by the neutrosophic model, which adds more dimensions of falsity (F) and uncertainty (I). Comparing the two rankings allows one to examine how the ranking of alternatives is impacted by the consideration of indeterminacy and falsity, offering a more realistic and nuanced perspective in situations where information is lacking or unclear. [17].

Below is a comparative graph between the Total Score of the classic model and the Closeness Index (NCi) of the neutrosophic model, also expressed as a percentage. You can see that:

Tenant 2 remains the highest-rated tenant in both models.

The relative positions of the other tenants differ slightly, reflecting how uncertainty and ambiguity affect the evaluation in the neutrosophic model.

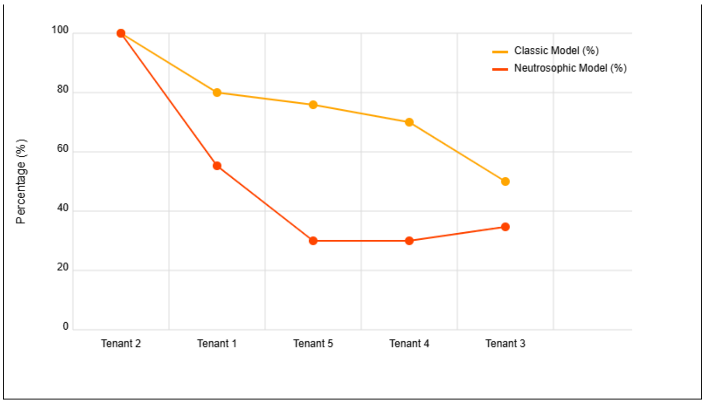

Figure 1: Comparative Analysis of Classic and Neutrosophic Models Performance Across Five Tenant Cases

Tenant 2 ranks closest to the ideal in both approaches, demonstrating the striking congruence between the classical and neutrosophic models in choosing the optimal tenant profile. However, notable variations in scores are shown when examining the remaining profiles. For instance, Tenant 5 is ranked third in the classical model but fifth in the neutrosophic model, indicating that there is more ambiguity or perceived risk in his score.

This happens because the neutrosophic model takes into account the associated uncertainty (U) and falsehood (F) in addition to the absolute value of each category. Therefore, when taking these diffuse elements into account, profiles like those of Tenants 3 and 4, who in the classical model receive average ratings, show more diversity. Thus, the neutrosophic model enables a more thorough and accurate assessment, which is particularly helpful when the criteria include subjective assessments. This method promotes increased decision-making transparency and lessens bias. As a result, integrating both models enhances the final selection's quality and the ranking's resilience.

4. Discussion

This study provides evidence regarding the utility and effectiveness of the PAPRIKA method as a tool to support complex decision-making in applied contexts, specifically in the selection of guests for Airbnb-style tourist accommodations. The results show that the criterion "review history" is significantly more valued by property owners compared to other factors, highlighting the importance of the guest's prior reputation as a reliable predictor of expected behavior. These findings align with previous studies emphasizing how trust generated by past reviews decisively influences multi-criteria decision-making [1,4].

The importance assigned to the communication criterion, identified as the second most significant, reinforces the notion presented in earlier research about the centrality of clarity and promptness in communication in contexts requiring high interaction between parties, such as tourist or healthcare services [3,5]. In particular, this significance could be explained by the owner's need to maintain an efficient and clear communication flow, ensuring proper accommodation management and reducing potential conflicts during the guest's stay.

The lower weighting given to flexibility, number of guests, purpose of the visit, and length of stay suggests that although these factors do influence the owner's perception, they are considered less critical compared to those directly related to risk perception (previous reviews) and immediate operational management (effective communication). This hierarchy is consistent with findings reported by [2,6], who conclude that in complex decision-making scenarios, attribute prioritization tends to favor criteria related to risk minimization and predictability maximization.

This research also confirms the relevance of PAPRIKA for applications beyond the healthcare or technological fields, as demonstrated by [1], extending its applicability to commercial and tourist service environments. Similar to studies conducted in clinical and health technology evaluation contexts [4,7], PAPRIKA has demonstrated its ability to simplify the decision-maker's cognitive task through straightforward comparisons and logical transitivity, producing robust and consistent results with reduced effort.

However, it is important to note that while the PAPRIKA method significantly facilitates subjective evaluation of multiple criteria, it still inherently depends on the quality of the decision-maker's judgment and the clarity of the criteria and categories initially defined. Consequently, future studies should assess the effect of different decision-making profiles, contrasting how various groups of property owners prioritize these criteria depending on specific contexts, such as the accommodation's location, market type, or the socio-economic profile of the target guest.

Additionally, it is acknowledged that in applications with numerous criteria or categories, the number of required comparisons may increase, potentially affecting the evaluator's interest or concentration. Nevertheless, the adaptive design of the PAPRIKA method, coupled with its ability to infer implicit comparisons, largely mitigates this limitation, enabling completion of the decision-making process with a reduced number of explicit trade-offs.

According to a recent comparative analysis of pairwise comparison-based multi-criteria methodologies, the PAPRIKA method ranks among techniques—such as AHP, ANP, MACBETH, and DEMATEL—that stand out for allowing decision-makers to issue qualitative judgments rather than direct numerical evaluations, thereby facilitating the natural expression of preferences in everyday contexts [10]. This feature is particularly beneficial in the present study, as it reduces the cognitive burden during the evaluation of alternatives by property owners.

The application of the PAPRIKA method in diverse contexts has demonstrated its adaptability to complex problems requiring robust multi-criteria decisions sensitive to environmental conditions. For instance, [11], integrated PAPRIKA with neutrosophic logic and geographic information systems (GIS) to mitigate landslide risks in Egypt, prioritizing geospatial criteria under conditions of high uncertainty.

In contrast, the present study applies the same methodology to a completely different context: the selection of tenants for tourist accommodations. Nevertheless, in both cases, PAPRIKA facilitates a coherent hierarchical structuring of criteria, promotes transparency in decision-making, and allows adaptation of the model to the real preferences of decision-makers. This versatility, evidenced both in complex geospatial environments and in everyday real estate decision-making, reaffirms the value of PAPRIKA as a flexible and scientifically rigorous methodological tool.

Undoubtedly, the applicability of the PAPRIKA method has been validated in scenarios of high complexity and urgency, as evidenced by its use in prioritizing COVID-19 vaccination in contexts of scarcity, where it was integrated into a neutrosophic multi-criteria decision model to weigh multiple criteria under conditions of uncertainty [12]. In that study, PAPRIKA was rigorously employed to determine which population groups should be prioritized for vaccine administration, considering medical, social, and logistical factors.

Although the present study focuses on guest selection for tourist accommodations, both studies share the necessity of establishing decision hierarchies based on explicit and verifiable preferences. This demonstrates the method's capacity to adapt to different domains while maintaining logical coherence and efficiency in decision-making.

Lastly, it would be advisable to explore guest perceptions regarding these same criteria to complement the decision model and further enhance the efficiency of the selection process and mutual satisfaction in this type of tourist service. Such approaches could significantly enrich the understanding and practical application of the PAPRIKA method in increasingly diverse and dynamic contexts.

5. Conclusions

This study demonstrates the feasibility of the PAPRIKA method as a robust and effective tool for multi-criteria decision-making in unconventional contexts, such as the selection of tenants on tourist accommodation platforms. Its application allowed the translation of property owners' subjective preferences into a structured and quantifiable model, facilitating the objective and justified prioritization of candidates.

The model revealed that trust based on previous experiences, expressed through review history, constitutes the primary criterion for hosts when selecting guests. Communication also emerged as a key factor, reinforcing the need to establish clear and effective interactions between hosts and travelers. In contrast, other aspects such as flexibility, length of stay, or purpose of the trip, although considered, play a secondary role in the decision-making process.

The hybrid integration of PAPRIKA with neutrosophic TOPSIS represents a significant methodological advancement in decision-making under uncertainty. By incorporating neutrosophic triplets (T, I, F) into the evaluation process, the model successfully captures not only the objective values but also the degrees of indeterminacy and falsity associated with each criterion assessment. This neutrosophic dimension provides a more nuanced understanding of decision-maker hesitation and risk perception, particularly valuable when dealing with subjective evaluations in collaborative economy contexts.

The comparative analysis between classical and neutrosophic models revealed consistent rankings for the highest-rated alternatives while showing meaningful variations for others. These differences highlight how the consideration of uncertainty can impact final decisions, offering property owners a more comprehensive evaluation framework that acknowledges the inherent ambiguity in guest selection processes. The neutrosophic approach thus enhances the robustness of the decision model by accommodating the subjective nature of human judgment in service environments.

The use of the PAPRIKA method is particularly suitable due to its ability to reduce the cognitive load on the decision-maker through simple pairwise comparisons, as well as its adaptive nature, which optimizes the number of judgments required to construct a valid model. These methodological benefits, previously confirmed in other fields, find new validation here in the realm of personalized tourism services.

In summary, this research not only provides an innovative application of the PAPRIKA method but also demonstrates the value of neutrosophic logic in handling uncertainty within multi-criteria decision frameworks. The hybrid model opens new possibilities for decision-making processes where multiple criteria are involved, and transparency, consistency, and efficiency are sought in the evaluation of alternatives under conditions of imprecision and subjectivity. Its use is recommended in similar scenarios and for integration into technological platforms that manage user interactions, such as Airbnb and other collaborative economy services.

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