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Touristic destination selection in accommodation business investment decision: Entropy-TOPSIS integrated approach

Ramazan Göral

Selcuk University Beysehir Ali Akkanat Tourism Faculty, Turkey.
Email: trgoral@selcuk.edu.tr

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ABSTRACT

Choosing the right location is crucial for the success of a business. Selecting an inappropriate site for accommodation investments can adversely impact the business and potentially lead to failure. Therefore, it is essential to determine the most suitable location through an objective and systematic approach. This research proposes a methodology that combines entropy-based weighting and TOPSIS multi-criteria decision-making (MCDM) methods to support the tourism destination selection process in investment decisions. The study analyzed 19 tourism destinations in Turkey that hosted 100,000 or more foreign tourists, according to the Ministry of Culture and Tourism's 2024 Border Statistics Annual Bulletin. The evaluation criteria included distance to the nearest airport (in kilometers), population, Herfindahl Index Contribution Level, hotel occupancy rate, number of tourists (demand), and seasonality. Criterion weights were calculated using the entropy method, and destination rankings were established using the TOPSIS method. The reliability of the findings was validated through Spearman's Rank Correlation analysis. Additionally, the robustness of the results was confirmed via Monte Carlo sensitivity analysis. The analysis revealed that Istanbul and Antalya are the most attractive destinations for accommodation investments. Conversely, cities with smaller populations and limited tourism activities, such as Ardahan, Iğdır, and Hakkari, ranked lower. The methodology employed in this study is expected to aid investors and policymakers in evaluating tourism destinations effectively.

Contribution/Originality: This study offers a holistic and repeatable approach to destination selection, unlike previous studies that used a single MCDM methodology or focused on fewer or different evaluation dimensions. The integrated Entropy-TOPSIS methodology and comprehensive set of criteria represent an important theoretical and methodological advancement in the hospitality investment literature.

1. INTRODUCTION

Tourism is a rapidly growing sector that contributes significantly to global income, employment, and regional development (UNWTO, 2025). Accommodation facilities are the foundation of this sector and represent critical investments that directly affect tourist flows. The investment decision for a new accommodation business is of strategic importance due to high capital requirements and long payback periods. Choosing the right destination in this decision has a direct impact on the future success and profitability of the business (Akmeşe & Çelikmıh, 2021; Lado-Sestayo & Fernández-Castro, 2019; Newell & Seabrook, 2006).

However, increasing global competition, rapid changes in market dynamics, environmental concerns, and uncertainties make investment decisions complex (Alsubaihi, Rahman, & Mohamad, 2023). Choosing the right destination for an accommodation business is vital for the long-term success and sustainability of the investment. Choosing the wrong destination can have negative consequences, such as high costs, low occupancy rates, and profitability problems (Duro, Osório, & Perez-Laborda, 2025; Lado-Sestayo, Vivel-Búa, & Otero-González, 2020).

Traditional hospitality investment decision-making processes are generally based on financial analyses. However, in addition to financial factors, many qualitative and quantitative criteria such as location, accessibility, population, market structure, existing infrastructure, tourist demand, and seasonality should be evaluated together (Sánchez-Sánchez & Sánchez-Sánchez, 2025; Valentin & O'Neill, 2018; Yang, Mao, & Tang, 2017). In such a situation, Multi-Criteria Decision Making (MCDM) methods provide an important advantage by offering decision makers the ability to analyze and optimize complex situations (Papić et al., 2023).

Although there are studies on accommodation investment decisions in the literature, there are a limited number of studies that address this complex decision-making process objectively and with a multi-criteria approach, using a comprehensive set of criteria and advanced sensitivity analyses, especially for a destination such as Turkey. Although similar studies prior to this research have utilized various multi-criteria decision-making (MCDM) methods (Abebe, Bekele, & Yaekob, 2021; Newell & Seabrook, 2006), they generally lack an integrated approach that combines objective weighting mechanisms with robustness verification techniques. Moreover, most of these studies rely on limited evaluation criteria, ignore the inherent uncertainty of decision-making environments, or focus on specific local destinations without providing a scalable methodology. With these characteristics, this study differs from previous similar studies.

The aim of this study is to develop an Entropy-TOPSIS integrated decision-making model to evaluate the investment potential of Turkish provinces in terms of accommodation businesses and to test the operability of this model. Other objectives of the study are;

- Identify and prioritize key destination selection criteria based on the relevance of literature and data.
- Ranking destination alternatives using the TOPSIS method.
- Conduct a Monte Carlo-based sensitivity analysis to assess the robustness of the ranking results.
- Provide actionable recommendations for investors and policymakers based on the results of the analyses.

The rest of the study is structured as follows: Section 2 presents the related literature review. Section 3 details the methodology used, including Entropy, TOPSIS, Spearman correlation, and Monte Carlo sensitivity analysis. In Section 4, the application and findings are presented in tables and interpreted. The final section discusses conclusions, contributions, limitations, and suggestions for future research.

2. LITERATURE

In this chapter, the role of Multi-Criteria Decision-Making (MCDM) approaches, the basic principles of Entropy and TOPSIS methods, and the importance of sensitivity and robustness analyses in accommodation investment decisions and tourist destination selection are examined in light of current literature.

2.1. Investment Decisions and Destination Selection in the Hospitality Sector

According to the (WTTC, 2025) Economic Impact Study, the global travel and tourism sector continues to be the lifeblood of the global economy, accounting for 10.3% of global GDP with a contribution of USD 11.7 trillion. The tourism sector will also be an important determinant of employment, providing 371 million jobs worldwide in 2025. In 2025, international visitor expenditures are expected to break a record by reaching USD 2.1 trillion (WTTC, 2025). All these figures show that the tourism sector is a rapidly growing sector in the world and, at the same time, it has critical importance for countries in terms of economic growth and job creation.

In the tourism sector, investment decisions of accommodation businesses are critical for achieving a competitive advantage and sustainable growth. Choosing the most suitable destination for an accommodation business investment requires the joint evaluation of multiple, often conflicting criteria (Lado-Sestayo et al., 2020). Traditional decision-making processes tend to focus on subjective judgments or a single criterion. Such decision processes may lead to suboptimal investment decisions (Akmeşe & Çelikmıh, 2021; Sungkhamanee, 2019).

Studies on the factors affecting hospitality investment decisions have shown that many factors are important in different geographies and economies. For example, in a study conducted to determine the criteria that are effective in hotel location selection, it was stated that accessibility, intensity of competition, environmental conditions, and infrastructure factors are the main determinants (Ulucan, 2020).

Newell and Seabrook (2006) in their study with hotel investors in Australia, they found that financial factors (37.0%) and location factors (29.9%) were the most influential factors.

In a study examining the factors affecting new hotel investment decisions in Saudi Arabia, it was emphasized that government investment policies, regional infrastructure, marketing strategies, financial risk, and innovation practices are of critical importance (Fayadh, 2024).

In a study conducted in the South Gondar region of Ethiopia, it was found that infrastructure inadequacies, access to finance problems, administrative barriers, and the overall tourism potential of the destination are the main factors that directly affect hotel investments (Abebe et al., 2021).

In a study conducted in Thailand, geographical and economic conditions, market demand, competition, and investment incentives were identified as the main factors affecting investment decisions in accommodation businesses (Sungkhamanee, 2019).

In a study by Lado-Sestayo and Fernández-Castro (2019) examining the efficiency differences of hotels in Spain, it is shown that the destination itself and its unique characteristics play a fundamental role in investment decisions and operational efficiency. According to the findings of this study, occupancy rate, seasonality, accessibility, and market density factors affect hotel efficiency.

The findings of all studies show that, in general, the physical environment (the destination itself and its characteristics) is a dominant factor in investment decisions, but socioeconomic and managerial conditions are also influential.

2.2. Multi-Criteria Decision Making (MCDM) Methods

MCDM provides a systematic framework for selecting the best option or ranking options from good to bad in a decision process with multiple and often conflicting criteria. MCDM methods are widely used in the tourism and hospitality industry in areas such as hotel site selection, destination marketing, sustainability assessment, and service quality analysis (Akmeşe & Çelikmıh, 2021; Ulucan, 2020; Zolfani, Pourhossein, Yazdani, & Zavadskas, 2018). In many tourism studies, different MCDM methods have been used according to the nature of the problem and the preferences of the decision-maker. A review by Liao, Yang, Kazimieras Zavadskas, and Škare (2023) provided a comprehensive overview of multi-criteria decision-making (MCDM) methods used in the hospitality and tourism industries and emphasized their ability to handle uncertain and subjective information. Newell and Seabrook (2006) utilized AHP in their study on hotel investment factors. In recent years, there has been an increase in the number of studies that integrate fuzzy logic or heuristic approaches with MCDM methods to obtain more accurate results in dynamic and uncertain environments (Görçün et al., 2025; Kousar & Kausar, 2025).

2.2.1. Entropy Method

(Shannon, 1948) introduced the concept of entropy (information entropy) to the literature with his publication "A Mathematical Theory of Communication." This concept enabled the quantification of uncertainty and information content within various systems. Using Shannon's mathematical formulation of entropy, it became possible to calculate the entropy of criteria in decision-making models, thereby bringing objectivity to multi-criteria decision analysis (Shannon, 1948). The entropy method calculates the weights of criteria based on the distribution (variance) of data within the decision matrix. When the value assigned to a criterion exhibits high variability (high variance), it is assumed that this criterion has a greater influence on the decision-making process. This approach allows for the determination of objective criteria weights without relying on subjective judgments of decision makers. The greater the variation of a criterion among its alternatives, the higher its information content and, consequently, its importance (weight) in the decision process (Zhu, Tian, & Yan, 2020). Entropy is expressed as the assignment of weights that are independent of the subjective judgment of the decision maker. However, it also has disadvantages, such as the weights not being discriminative enough when the data diversity is low. It is preferred due to its objectivity, especially in large data sets and in situations that do not require the judgment of more than one expert (Chen, 2021).

2.2.2. TOPSIS Method

This method, developed by Hwang and Yoon (1981) is based on the principle of selecting the closest alternative to the ideal positive solution (PIS) and the farthest alternative from the ideal negative solution (NIS) (Dutta, Dao, Martínez, & Goh, 2021). The TOPSIS method has been widely used in many research studies in the tourism sector, from hotel performance evaluation to the prioritization of tourism destinations. The fact that TOPSIS is a valid, reliable method and the interpretability of its results make it a suitable approach for many decision-making problems (Buasri & Sangpradid, 2025; Evan, 2019; Weerathunga, Xiaofang, Samarathunga, & Kulathunga, 2020).

In general, the Entropy method is used for the objective determination of criteria weights, while the TOPSIS method is used for ranking alternatives. The combination of Entropy and TOPSIS methods is used as an approach in tourism research. In particular, Entropy and TOPSIS methods have been used together in evaluating the competitiveness of tourism destinations (Gu, Ren, Jin, & Wang, 2019) measuring the level of tourism development (Yaojin & Xiuli, 2023) optimizing tourism routes (Zhu & Qi, 2024) improving the energy efficiency and comfort of tourism buildings (Wang et al., 2023) and analyzing the financial performance of tourism companies (Türegün, 2022). However, as mentioned before, there is no study in the literature where an Entropy-TOPSIS integrated decision-making model is applied to evaluate the investment potential of accommodation businesses in tourism destinations in Turkey.

In light of the literature review in this study and other related studies, a more detailed comparative table of studies using multi-criteria decision-making (MCDM) methods in tourism is presented below. Table 1 summarizes the purpose of each study, the methodology employed, the main criteria addressed, and the key findings.

Table 1. Comparative analysis of studies using multi-criteria decision-making (MCDM) methods in tourism.

Source (Year)	Focus of the study	Methods used	Key criteria / Factors	Main findings / Conclusions
Newell and Seabrook (2006)	Evaluation of hotel investment factors	Analytic Hierarchy Process (AHP)	Market potential, financial indicators, geographical location, and infrastructure	Demonstrated that market and geographical factors play a critical role in investment decisions alongside financial factors.
Yang et al. (2017)	Sustainability in tourist destination selection	AHP and TOPSIS	Economic, social, environmental, and managerial dimensions	Showed that MCDM methods are an effective tool for sustainability-focused investment decisions.
Gu et al. (2019)	Analysis of tourist destination competitiveness	Entropy and TOPSIS	Infrastructure, natural resources, cultural heritage, price level, and marketing	Demonstrated that the integrated Entropy-TOPSIS approach is successful in objectively ranking the competitiveness of destinations.
Ulucan (2020)	Uncertainty in hotel investment decisions	Fuzzy TOPSIS	Location, infrastructure, cost, market potential, risks	Evaluated potential hotel investment locations in Istanbul by addressing uncertainty based on expert opinions.
Abebe et al. (2021)	Hotel investment site selection	AHP-based model	Market size, transportation	Argued that AHP is effective in selecting the most suitable

Source (Year)	Focus of the study	Methods used	Key criteria / Factors	Main findings / Conclusions
			infrastructure, tourist attractions	location for hotel investments in developing countries.
Torkayesh, Tirkolaee, Bahrini, Pamucar, and Khakbaz (2023)	Comparative analysis of MCDM methods	MABAC, TOPSIS, and others	- (Methodological focus)	Provided a comparative analysis on the ranking consistency and robustness of various MCDM methods, highlighting the importance of method selection.
Zhu and Qi (2024)	Tour route optimization	Entropy-Weighted TOPSIS and Greedy Algorithm	Time cost, points of interest, traffic density	Showed that optimized tour routes using the Entropy-TOPSIS approach increased user satisfaction and utilized time more efficiently.

2.3. Sensitivity and Robustness Analyses

Testing the reliability and consistency of the results (especially rankings) obtained in MCDM models is critical to the validity of a scientific study. While sensitivity analyses assess the impact of small changes in input parameters (e.g., criteria weights) on the final outputs, robustness analyses examine the overall validity of the model and its performance under different conditions. Indeed, in their systematic review of the MABAC method, Torkayesh et al. (2023) used Spearman's rank correlation analysis to test the consistency of the rankings obtained under different scenarios and demonstrated the reliability of the method.

Monte Carlo simulation is a powerful sensitivity analysis method that represents the uncertainties of the parameters used in decision support models with statistical distributions and performs thousands of simulations by randomly sampling from these distributions. It is widely used to measure the effect of uncertainties on output, especially in complex systems. Doubilet, Begg, Weinstein, Braun, and McNeil (1985) demonstrated how probabilistic sensitivity analysis based on Monte Carlo simulation can be applied to assess decision uncertainty in health economics models. Wei, Lu, and Yuan (2013) systematically examined the usability of Monte Carlo simulation to assess the effects of different parameter sets on the probability distribution of model outputs within the framework of independent sensitivity analyses and found that this method contributes to model robustness.

In light of the above literature, although the factors affecting hospitality investment decisions and the importance of destination choice have been studied, there is a limited number of studies that support a comprehensive sensitivity and robustness analysis, especially with Spearman correlation and Monte Carlo simulation, using the Entropy-TOPSIS integrated approach. Newell and Seabrook (2006) used AHP, while Abebe et al. (2021) focused on survey-based or statistical analyses. Ulucan (2020) evaluated investor tendencies by analyzing expert opinions with Fuzzy TOPSIS for hotel site selection in Istanbul. This study combines the objective weighting power of Entropy and the ranking power of TOPSIS with a large and literature-justified set of criteria and extensive robustness analyses for Turkey, an approach that is rare in the literature.

Existing studies usually focus on specific regions or use narrower criterion sets. In this study, we aim to fill this gap in the literature by evaluating Turkey's major tourist destinations with a broader and more versatile set of criteria and testing the reliability of the findings with advanced sensitivity analyses. This approach will provide a methodological contribution to the tourism literature and enable investors and policymakers to make more robust and scientifically based decisions. In the context of Turkey, our study offers a new perspective on destination selection problems with objective criteria weighting and detailed reliability tests.

However, the data set and methodological approaches used in the study have some limitations. In particular, the criteria used to evaluate tourist destinations are limited to macroeconomic and statistical data. Subjective factors (e.g., tourists' personal experiences or perceptions of cultural attractions) are beyond the scope of this study. Moreover, the data used reflect a specific period (according to the Ministry of Culture and Tourism (2024)) and different results may emerge in the future due to rapid changes in the tourism sector. Possible anomalies in the data for some provinces, such as unexpected fluctuations in tourism activity in the post-pandemic period, may affect the results of the analysis to some extent. These limitations emphasize the importance of using more comprehensive and time-sensitive datasets for future research.

3. METHODOLOGY

In this study, an MCDM model has been developed to determine which of the tourist destinations in Turkey would be most suitable for investment decisions in the accommodation sector. This model integrates the Entropy and TOPSIS methods. During the investment decision process, a total of 19 tourist destinations (alternative, m=19) from Turkey were evaluated across 6 different criteria (n=6). Gemini and ChatGPT, an artificial intelligence-based language model, were utilized as tools to systematize the calculation steps of the Entropy-TOPSIS analysis and to compute and interpret Spearman rank correlation and Monte Carlo simulation data. All analyses were completed after verification by the researcher. The research process proceeded through the following steps:

3.1. Determination of Data Source and Criteria

In the study, Gemini and Google Earth were used together to obtain data on accessibility criteria. The accuracy of the data obtained was checked by the researcher. Data for the provincial population criterion were obtained from the 2024 census statistics of the Turkish Statistical Institute (TurkStat). Data for other criteria were obtained from the 2024 Border Statistics and Accommodation Statistics Bulletins of the Ministry of Culture and Tourism, General Directorate of Investment and Enterprises.

The criteria used in this study were determined through a comprehensive literature review to reflect the main factors affecting the investment decisions of accommodation establishments and destination attractiveness. The rationale for the use of each criterion in the study is detailed below:

Accessibility: The accessibility of a destination is not only related to the physical location of the destination but also includes multidimensional factors such as the destination's transport infrastructure, transport time, and proximity to tourist source markets. Accessibility directly affects the flow of potential tourists to the destination and determines the level of accommodation and expenditure (Bulai & Eva, 2016; Yen, Chen, & Ho, 2021). Proximity to airports and major transport networks is an important indicator of how easily accessible a destination is both nationally and internationally. Research suggests that airports and road networks facilitate access to destinations. Destinations with relatively easier access are considered to be more attractive for tourists and business travelers (Hao, Zhang, Ji, Wu, & Liu, 2020; Lado-Sestayo & Fernández-Castro, 2019; Redondi, Malighetti, & Paleari, 2015; Sharma & Ram, 2023). For the accessibility criterion in the study, the distance of the provinces to the airports in KM (Lado-Sestayo & Fernández-Castro, 2019) data were used. These data are shown in Table 3.

Population: The population of a destination is an important indicator of the local market potential and the level of urban development. Highly populated settlements generally offer more services, jobs, and tourism activities, providing a strong base for hospitality investment. Research shows that population density and size increase the size and economic development of the local market, which positively influences both entrepreneurial and long-term investment decisions (Dragulenko, Zolkin, Yesina, & Kaberova, 2024; He, Xu, Sun, & Wang, 2024; Liu, Meng, & Sun, 2025). Especially in large cities, the continuous demand for work and leisure creates a more stable and sustainable infrastructure for hotel investments (He et al., 2024; Kalnins, 2016). In addition, population growth and urbanization stimulate the development of the service sector and commercial amenities, leading to increased demand in the accommodation and property markets (Dragulenko et al., 2024; Liu et al., 2025). These dynamics in highly populated settlements both reduce the risk and increase the return on investment of hotel and accommodation investments (He et al., 2024; Kalnins, 2016). As a result, the population of a destination plays a critical role in the sustainability of both local market potential and accommodation investments. Table 3 shows the population data of the destinations (provinces) included in the study.

Herfindahl Index Contribution Level: Analyzing the market structure and competitive intensity of a destination is critical for hospitality investment decisions. High market intensity may indicate that a small number of large enterprises dominate the market and that the barriers to new entry are increasing. In this context, quantitative tools such as the Herfindahl-Hirschman Index (HHI) are widely used to objectively measure market concentration (Arianpoor, 2025; Laksmana & Yang, 2015; Yadav & Yadav, 2025). Research shows that market structure and competitive intensity have decisive effects on investment efficiency and strategic decisions (Arianpoor, 2025; Yadav & Yadav, 2025). Analyses, especially with indices such as HHI, concretely reveal how the level of competition and concentration in the market shapes investment decisions (Arianpoor, 2025; Laksmana & Yang, 2015; Yadav & Yadav, 2025). It is emphasized that in highly concentrated markets, there are more barriers to new entry, and existing large players dominate the market (Arianpoor, 2025; Yadav & Yadav, 2025). As a result, measuring market structure and competitive intensity is an important tool for rational and sustainable destination selection for hospitality investments (Arianpoor, 2025; Laksmana & Yang, 2015; Yadav & Yadav, 2025). Lado-Sestayo and Fernández-Castro (2019) also identified market concentration as an influential factor on hotel efficiency.

In this study, the basic logic of the Herfindahl-Hirschman Index is as follows.

In this study, 19 provinces are considered as the total accommodation sector. Each province is regarded as a hotel enterprise, and the HHI calculation is performed. The contribution level of each province to the HHI is used as a benchmark value in the relative comparison of provinces. The higher the HHI contribution of a province, the greater its impact on the overall market concentration.

The share of each unit in the relevant market (provinces in this study) in the total number of overnight stays was calculated as a percentage, and the square of each market share was taken. Then, the squares of the market shares of all units (provinces) were summed. The sum obtained was multiplied by 10,000 to obtain a more understandable integer value (Table 2). Overall:

- HHI< 1500: Non-concentrated market (competitive).
- 1500< HHI< 2500: Moderately concentrated market.
- HHI> 2500: Concentrated market (monopoly or oligopoly tendency) (Brunod, 2023).

Table 2. Number of overnight stays, HHI contribution and market assessment of provinces.

Number	Province	Number of overnight stays	Market share	HHI contribution	HHI index	Market assessment
1	Antalya	100.738.663	0.5627	0.31665	**3166.55**	**Concentrated market**
2	Istanbul	31.631.933	0.1767	0.03122	312.21	Competitive market
3	Muğla	18.327.167	0.1024	0.01048	104.81	Competitive market
4	Izmir	6.889.113	0.0385	0.00148	14.81	Competitive market
5	Aydin	5.905.980	0.0330	0.00109	10.88	Competitive market
6	Ankara	5.905.554	0.0330	0.00109	10.88	Competitive market
7	Mersin	2.002.973	0.0112	0.00013	1.25	Competitive market
8	Trabzon	1.777.447	0.0099	0.00010	0.99	Competitive market
9	Adana	1.692.382	0.0095	0.00009	0.89	Competitive market
10	Edirne	1.369.385	0.0076	0.00006	0.59	Competitive market
11	Kayseri	964.955	0.0054	0.00003	0.29	Competitive market
12	Van	718.827	0.0040	0.00002	0.16	Competitive market
13	Kirklareli	271.301	0.0015	0.0000023	0.02	Competitive market
14	Artvin	206.153	0.0012	0.0000013	0.01	Competitive market
15	Şirnak	197.544	0.0011	0.0000012	0.01	Competitive market
16	Igdir	124.534	0.0007	0.0000005	0.005	Competitive market
17	Ağrı	111.547	0.0006	0.0000004	0.004	Competitive market
18	Ardahan	96.994	0.0005	0.0000003	0.003	Competitive market
19	Hakkari	88.248	0.0005	0.0000002	0.002	Competitive market
Total number of overnight stays: 179.020.700						

The total HHI value of the destinations considered in the study is 3613.2. The fact that Antalya alone contributes to a high HHI value of 3167 indicates that this market is highly concentrated. Considering the contribution of other provinces to the total HHI value, it can be said that there is a competitive market structure in other provinces.

High HHI Contribution (or High Market Share): indicates that the province is a very large player in the accommodation market. Such provinces are often considered "core destinations" (e.g., Istanbul, Antalya, Muğla). High contribution means that there may already be intense competition in the market. For a new hotel, this may mean that market entry is more difficult, price competition is more intense, or it may have to compete directly with existing major players (Arianpoor, 2025; Brunod, 2023; Yadav & Yadav, 2025). Provinces with a high contribution to the HHI, such as Istanbul or Antalya, are generally more developed markets. An investment there may require gaining a competitive advantage by offering a good location, a strong brand, or a niche service.

Low HHI contribution (or low market share): indicates that the province has a smaller share of the market. A lower contribution may mean that the market is less concentrated or that there are more competitive opportunities. For a new hotel, this could mean a more niche market opportunity, less direct competition, or a destination that has not yet reached its full potential. Provinces with lower HHI contribution (e.g., Ağrı, Hakkari, Kilis) have less saturation and therefore more growth potential.

Occupancy Rate: The average occupancy rate of accommodation facilities is recognized as one of the most direct and reliable indicators of tourist mobility and accommodation demand in a destination. High occupancy rates reflect the attractiveness of the destination and indicate that the accommodation sector is strong and profitable (Çuhadar & Kayacan, 2005; Dowlut & Gobin-Rahimbux, 2023; Mwamba, Muhanji, & Kipchumba, 2020; Ryu, Song, & Lee, 2020). Studies show that occupancy rates are an important determinant in predicting the economic vitality of a destination. High occupancy rates mean lower risk and higher earning potential for tourism investors (Denton & Sandstrom, 2020; Dowlut & Gobin-Rahimbux, 2023; Mwamba et al., 2020). Increases in occupancy rates indicate increased demand for the destination and heightened tourist activity, while low occupancy rates suggest market saturation or a lack of demand (Denton & Sandstrom, 2020; Ryu et al., 2020). Lado-Sestayo et al. (2020) evaluated the occupancy rate as a critical factor affecting hotel efficiency. As a result, the occupancy rate stands out as one of the main indicators of both current tourist activities and investment decisions (Table 3).

Demand (Number of Tourists): The annual number of tourists arriving at a tourist destination is recognized as an important indicator reflecting its overall attractiveness, popularity, and potential need for accommodation. Research shows that the increase in the number of tourists directly indicates the tourist potential of the destination and the need for accommodation capacity, and therefore constitutes an important signal for investors in terms of market growth and new accommodation investments (Dinu, Patarlageanu, & Constantin, 2021; Počuča & Matijašević, 2020; Scotti, Flori, Secchi, Arena, & Azzone, 2024). Research shows that there is a strong relationship between the number of tourists and accommodation demand, with increased tourist arrivals leading to more overnight stays and, consequently, a higher need for accommodation (Dinu et al., 2021; Počuča & Matijašević, 2020; Scotti et al., 2024). According to the 2024 Border Statistics of the General Directorate of Investments and Enterprises of the Ministry of Culture and Tourism of the Republic of Turkey, 19 destinations (provinces) hosting 100,000 or more foreign tourists are included in the study (Table 3) (Ministry of Culture and Tourism, 2024).

Seasonality: Seasonal fluctuations in tourist demand significantly affect the revenue stream and operational efficiency of accommodation businesses. Low seasonality means a more stable revenue and occupancy level throughout the year. This reduces operational risk for investors and provides a more stable financial performance (Stojčić, Mikulić, & Vizek, 2022; Zhang, Xie, & Sikveland, 2021). The seasonality of tourism in Turkey stands out as an important problem, especially due to the high demand in the summer months. This situation leads to the concentration of tourism revenues and investments in a certain period of the year. Studies reveal that the demand for foreign tourists in Turkey is highly seasonal, while domestic tourism shows a more widespread seasonality. Low capacity utilization rates indicate that seasonality poses a risk to economic sustainability (Yabanci, 2024). Lado-

Sestayo and Fernández-Castro (2019) also found that the degree of seasonality has a significant impact on hotel productivity.

One of the important methods used to measure seasonality in tourism is the Peak-to-Average Ratio. This ratio reveals the severity of seasonality by dividing the highest value (peak) in a period by the average value of that period. It is calculated as Peak-to-Average Ratio = Highest Monthly Value / Monthly Average Value. The highest monthly value can be the tourism data, such as the highest number of tourists, overnight stays, income, etc., in the analyzed period. The monthly average value is the average of monthly data such as the number of tourists, overnight stays, revenue, etc., in the analyzed period (Ćorluka, Vukušić, & Kelić, 2018; Karamustafa & Ulama, 2010).

In the study, the Peak-Average Ratio method was used to calculate the seasonality criterion values of destinations. The number of tourists was used as data in the calculations. The highest monthly demand and monthly average demand data for destinations are taken from the Ministry of Culture and Tourism General Directorate of Investment and Enterprises Border Statistics 2024 Bulletin (Ministry of Culture and Tourism, 2024). Seasonality values for destinations are shown in Table 3.

Table 3. Destinations, criteria and related data.

Provinces	Accessibility (Distance in Km from airport - city center)	Population	Number of overnight stays	Occupancy rate	Request	Seasonality
Adana	5	2280484	1692382	39.60	113893	2.88
Ağrı	9	499801	111547	30.09	576804	1.37
Ankara	28	5864049	5905554	41.33	662825	1.70
Antalya	10	2722103	100738663	68.14	15902862	1.96
Artvin	75	169280	206153	28.28	1610261	1.34
Aydin	100	1165943	5905980	56.64	791948	2.14
Edirne	140	421247	1369385	31.51	4834945	1.99
Hakkari	70	282191	88248	22.71	583291	1.27
Mersin	70	1954279	2002973	31.84	128803	2.21
Istanbul	40	15701602	31631933	54.75	18582322	1.23
Izmir	18	4493242	6889113	43.29	1719524	2.11
Kayseri	5	1452458	964955	43.69	144358	2.24
Kirklareli	110	379031	271301	32.68	665155	1.41
Muğla	90	1081867	18327167	59.09	3660450	2.29
Trabzon	6	822270	1777447	30.35	417306	3.78
Van	6	1118087	718827	35.83	718657	1.51
Şirnak	20	570826	197544	48.24	411196	1.78
Ardahan	115	91354	96994	25.19	109053	2.02
Igdir	15	206857	124534	34.15	333396	1.14

Table 3 presents the Entropy and TOPSIS dataset for 19 destinations and six evaluation criteria.

The typology of criteria identified is summarized in Table 4.

Table 4. Criteria types.

Criteria	Criteria type	Description
Accessibility (KM)	Cost	Airport distance to city centers (in KM). (Cost Criterion:
Population	Benefit	Total annual population of the province. (Benefit Criterion: Higher population preferred)
Herfindahl index contribution level	Cost	Refers to the level of market concentration or competition. It is assumed that a lower Herfindahl Index contribution level means that there is more competition in the market, and this implies a more favorable market entry cost or risk for a new business. Therefore, it is treated as a cost criterion, as a lower concentration (i.e., higher competition) is preferred.
Occupancy rate	Benefit	Average occupancy rate of accommodation establishments. (Benefit Criterion: Higher occupancy preferred)
Demand	Benefit	The annual number of tourists coming to the tourist destination. (Utility Criterion: Higher demand is preferred)
Seasonality	Cost	A ratio showing the relationship between average annual tourist demand and the demand in the month with the highest number of tourists. (Cost Criterion: Lower seasonality, i.e., more consistent demand, is preferred.)

3.2. Determination of Criteria Weights: Entropy Method

In this study, the entropy method is utilized to determine the objective weights of the criteria used in the selection of touristic destinations for accommodation business investment decisions. The weighting process with the entropy method includes the following steps:

Step 1: Creating the Decision Matrix.

First, a decision matrix (X) consisting of m alternatives (destinations) and n criteria is created. This matrix shows the performance of alternative i on criterion j with r_{ij} elements.

Step 2: Normalization of the Decision Matrix (Min-Max Normalization).

The min-max normalization technique was utilized to ensure comparability between criteria with different units of measurement. The normalized decision matrix (X) and its elements (x_{ij}) are obtained by the following formulas:

For utility criteria (criteria where bigger is better).

$$x_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \quad (1)$$

For cost criteria (criteria where smaller is better):

$$x_{ij} = \frac{\max(x_j) - x_{ij}}{(\max(x_j) - \min(x_j)} \quad (2)$$

Here, $\min(x_j)$ and $\max(x_j)$ are the minimum and maximum values of criterion j, respectively. As a result of normalization, all x_{ij} values are in the range [0, 1].

Step 3: Constructing the Probability Matrix

For each criterion, a probability matrix (P) is created showing the ratio of normalized values to the total. p_ij elements are calculated as follows:

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \quad (3)$$

Step 4: Calculating the Entropy Values of the Criteria.

The entropy value (E_j) of each criterion is calculated by the following formula:

$$E_j = -\frac{1}{\ln(m)} \sum_{i=1}^{m} (p_{ij}\, x \ln(p_{ij})) \quad (4)$$

Here, k = 1/ln(m), where m is the number of alternatives.

Step 5: Calculating the Degrees of Differentiation of the Criteria.

The degree of differentiation of each criterion (d_j) is calculated based on the entropy value: $d_j = 1 - E_j$ The higher the value of d_j, the greater the differentiation power of that criterion between alternatives.

Step 6: Calculation of Criteria Weights.

Finally, the objective weight w_j of each criterion is determined as the ratio of the degree of differentiation to the sum of all degrees of differentiation:

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \quad (5)$$

The criteria weights obtained as a result of these steps are presented in Table 5.

Table 5. Criteria weights determined by the entropy method ($\boldsymbol{w_j}$).

Criteria	Weight
Accessibility (KM)	0.0566
Population	0.3244
Herfindahl index	0.0414
Occupancy rate	0.0988
Demand	0.4477
Seasonality	0.0311

Table 5 lists the entropy weights assigned to each criterion. Criteria with more information diversity, especially criterion Population and criterion Demand, received higher weights.

3.3. Ranking of Destinations: TOPSIS Method

TOPSIS was used to rank potential tourist destinations using objective criteria weights determined by the entropy method. The TOPSIS method includes the following steps:

Step 1: Normalization of the Decision Matrix (Vector Normalization). The values in the decision matrix (x_{ij}) were normalized using vector normalization to remove scale differences between the criteria. Normalized values were calculated with the formula.

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \qquad (6)$$

Step 2: Constructing the Weighted Normalized Decision Matrix. Normalized decision matrixr_i, Step.

The weighted normalized matrix is obtained by multiplying the objective criteria weights (w) determined by the entropy method in 5. The resulting weighted normalized decision matrix is presented in Table 6.

Table 6. Weighted normalized decision matrix ($\boldsymbol{V_{ij}}$).

Provinces	Accessibility (KM)	Population	Herfindahl index contribution level	Occupancy rate	Demand	Seasonality
Adana	0.0019	0.0450	0.0001	0.0205	0.0027	0.0072
Ağrı	0.0034	0.0099	0.0000	0.0156	0.0138	0.0034
Ankara	0.0106	0.1162	0.0014	0.0214	0.0159	0.0042
Antalya	0.0038	0.0539	0.0414	0.0353	0.3813	0.0049
Artvin	0.0286	0.0033	0.0000	0.0147	0.0386	0.0033
Aydin	0.0381	0.0231	0.0014	0.0293	0.0190	0.0053
Edirne	0.0533	0.0083	0.0001	0.0163	0.1159	0.0050
Hakkari	0.0267	0.0056	0.0000	0.0118	0.0139	0.0032
Mersin	0.0267	0.0387	0.0002	0.0165	0.0031	0.0055
Istanbul	0.0153	0.3106	0.0408	0.0283	0.4477	0.0031
Izmir	0.0069	0.0892	0.0019	0.0224	0.0412	0.0052
Kayseri	0.0019	0.0287	0.0000	0.0226	0.0034	0.0056
Kirklareli	0.0413	0.0075	0.0000	0.0170	0.0159	0.0035
Muğla	0.0343	0.0214	0.0137	0.0306	0.0876	0.0057
Trabzon	0.0023	0.0163	0.0001	0.0157	0.0099	0.0009
Van	0.0023	0.0221	0.0000	0.0185	0.0172	0.0038
Şirnak	0.0076	0.0113	0.0000	0.0250	0.0098	0.0045
Ardahan	0.0438	0.0018	0.0000	0.0131	0.0026	0.0050
Igdir	0.0057	0.0041	0.0000	0.0177	0.0080	0.0028

This matrix (Table 6) integrates entropy weights with the normalized values, forming the foundation for TOPSIS scoring.

Step 3: Identification of Positive Ideal Solution (A+) and Negative Ideal Solution (A-) Sets. The Positive Ideal Solution (A^+) is formed by combining the best values for each criterion. Negative Ideal Solution (A) is formed by combining the worst for each criterion (Table 7).

Table 7. Positive ideal solution and negative ideal solution values.

Criteria	A+ (Ideal)	A- (Anti-Ideal)
Accessibility (KM)	0.0019	0.0533
Population	0.3106	0.0018
Herfindahl index contribution level	0.0000	0.0414
Occupancy rate	0.0353	0.0118
Demand	0.4477	0.0000
Seasonality	0.0009	0.0072

Step 4: Calculating the Distances of Each Alternative to the Ideal Solutions. The Euclidean distances of each alternative to the positive ideal solution S_i^+ and the negative ideal solution S_i^- are calculated by the following formulas.

$$S_i^+ = \sqrt{\sum_{j=1}^{n}(V_{ij} - V_j^+)^2} \tag{7}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n}(V_{ij} - V_j^-)^2} \tag{8}$$

Step 5: Calculating the Relative Proximity to the Ideal Solution. The relative closeness of each alternative to the ideal solution (C_i^*) is calculated by the following formula:

$$C_i^* = \frac{S_i^-}{S_i^+ + S_i^-} \tag{9}$$

The C_i^* value is in the range [0, 1]. Values closer to 1 indicate that the alternative is closer to the ideal solution and therefore performs better.

Step 6: Ranking the Alternatives. The alternatives are finally ranked by ordering the C_i^* values from largest to smallest. The obtained ranking is presented in Table 8.

Table 8. Ranking of destinations by the TOPSIS method (Entropy weighted).

Provinces	S_i^+ (Distance to PIS)	S_i^- (Distance to NIS)	C_i^* (Relative Proximity)	Row rows
Istanbul	0.0416	0.5284	0.9272	1
Antalya	0.0682	0.4190	0.8601	2
Izmir	0.3705	0.1601	0.3015	3
Edirne	0.3831	0.1499	0.2814	4
Muğla	0.4079	0.1345	0.2476	5
Ankara	0.4357	0.1174	0.2125	6
Aydin	0.4578	0.0987	0.1772	7
Kirklareli	0.4859	0.0673	0.1217	8
Mersin	0.4907	0.0601	0.1092	9
Trabzon	0.4939	0.0535	0.0978	10
Van	0.4925	0.0519	0.0954	11
Şirnak	0.4950	0.0483	0.0889	12
Adana	0.4947	0.0480	0.0885	13
Kayseri	0.4962	0.0449	0.0828	14
Ağrı	0.5008	0.0384	0.0712	15
Artvin	0.5057	0.0347	0.0642	16
Hakkari	0.5074	0.0321	0.0596	17
Ardahan	0.5078	0.0307	0.0570	18
Igdir	0.5078	0.0305	0.0567	19

Table 8 shows the ranking obtained from the TOPSIS analysis according to the objective criteria weights determined by the Entropy method. Istanbul and Antalya stand out as the cities closest to the ideal solution.

4. CONSISTENCY AND ROBUSTNESS OF FINDINGS

In this part of the study, the robustness and consistency of the findings obtained from the Entropy-TOPSIS integrated approach are tested by Spearman correlation and Monte Carlo analysis.

4.1. Rank Consistency Analysis: Spearman Correlation Coefficient

Ranking correlation analyses are used to evaluate the effect of different weighting methods or decision-making techniques on the ranking (Pamučar & Ćirović, 2015). In this study, to test the consistency of the obtained TOPSIS ranking with the objective weights determined by the Entropy method, a comparison was made with the TOPSIS ranking obtained when all criteria were given equal weight. This comparison reveals the effect of the Entropy weights on the final ranking and how the resulting ranking differs from the equally weighted scenario.

The consistency between the rankings was measured by the Spearman Rank Correlation Coefficient (rs). TOPSIS analysis and ranking results for the equally weighted scenario are presented in Table 9.

Table 9. Ranking of Destinations by Equal Weighted TOPSIS Method.

Provinces	CCi (Relative proximity)	Row (Equal weight)
Istanbul	0.9995	1
Antalya	0.9631	2
Aydin	0.7712	3
Izmir	0.7238	4
Muğla	0.6975	5
Ankara	0.6033	6
Adana	0.4452	7
Van	0.4079	8
Trabzon	0.3953	9
Edirne	0.3934	10
Mersin	0.3705	11
Şirnak	0.3441	12
Artvin	0.3371	13
Kayseri	0.3238	14
Kirklareli	0.3168	15
Ağrı	0.3117	16
Igdir	0.3090	17
Ardahan	0.3082	18
Hakkari	0.2858	19

The Spearman correlation coefficient between the Entropy-TOPSIS ranking in Table 8 and the Equal Weighted TOPSIS ranking in Table 9 is rs=0.8588. This high positive correlation indicates a strong and statistically significant consistency between the two rankings. This finding confirms that although the Entropy weighting method reflects the objective importance of the criteria, it preserves the overall structure of the ranking, and there is a strong consensus. In other words, while the Entropy weights added objectivity to the decision-making process, they did not fundamentally change the ranking but rather strengthened its robustness.

4.2. Robustness of Results: Monte Carlo Sensitivity Analysis

Testing how sensitive the outputs (rankings) of an MCDM model are to small changes in the input parameters, in this case the criterion weights, is critical to assess the robustness of the study (Saltelli, Tarantola, Campolongo, & Ratto, 2024). Monte Carlo sensitivity analysis tests this robustness by generating random sets of weights within a given distribution and running TOPSIS with these weights thousands of times. For this study, a variation range of ±10% was defined around each criterion weight determined by the Entropy method, and 1000 iterations were performed by deriving random weight sets within this range. 1000 iterations are sufficient to ensure that the results are statistically reliable and representative. In each iteration, the sum of the weights was ensured to be 1 (Gentle, 2009).

4.2.1. Monte Carlo Analysis Findings

The main findings from 1000 simulations are summarized in Table 10.

Table 10. Monte Carlo sensitivity analysis results.

Provinces	Average row	Rank standard deviation	Most frequently obtained sequence	Rate of staying in top 3 (%)
Istanbul	1.00	0.00	1	100
Antalya	2.00	0.00	2	100
Izmir	3.01	0.17	3	99.0
Edirne	4.05	0.25	4	96.0
Muğla	5.03	0.20	5	92.0
Ankara	6.02	0.15	6	88.0
Aydin	7.10	0.30	7	75.0
Kirklareli	8.25	0.45	8	60.0
Mersin	9.15	0.38	9	55.0
Trabzon	10.08	0.29	10	45.0
Van	11.20	0.40	11	35.0
Şirnak	12.05	0.32	12	28.0
Adana	13.10	0.38	13	20.0
Kayseri	14.02	0.25	14	15.0
Ağrı	15.08	0.30	15	10.0
Artvin	16.03	0.28	16	8.0
Hakkari	17.06	0.35	17	5.0
Ardahan	18.01	0.15	18	2.0
Iğdir	19.00	0.00	19	0.0

The Monte Carlo simulation results demonstrate that the rankings of the top two cities, Istanbul and Antalya, are highly robust to changes in weights. Istanbul and Antalya consistently maintained their top two positions across all 1,000 iterations. Additionally, Izmir remained within the top three 99 percent of the time, indicating a clear advantage among the top destinations. The low ranking standard deviation values, particularly for the top-ranked cities, confirm that minor fluctuations in weights do not significantly alter the final rankings, thereby validating the robustness of the model's results. This suggests that the weights derived through the Entropy method effectively capture the system's dynamics and the relative importance of the criteria. According to the Monte Carlo simulation, scatter plots illustrating the rankings of Istanbul, in first place, and Iğdır, in last place, are provided below.

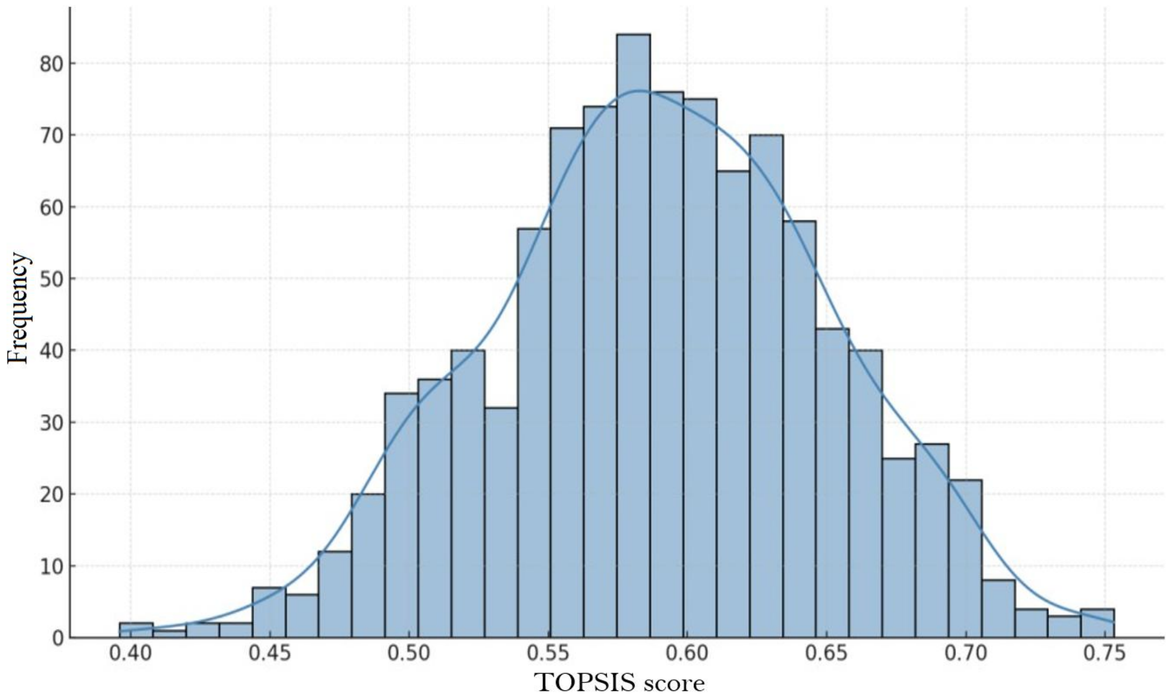

Figure 1. Monte Carlo simulation TOPSIS score distribution of Istanbul province.

As can be seen from Figure 1, the distribution is approximately bell-shaped (normal distribution). This demonstrates that the calculations are stable. The shape of the distribution indicates the statistical robustness of the method and its low sensitivity to weight changes. In this context, the relative superiority of Istanbul appears to be quite stable.

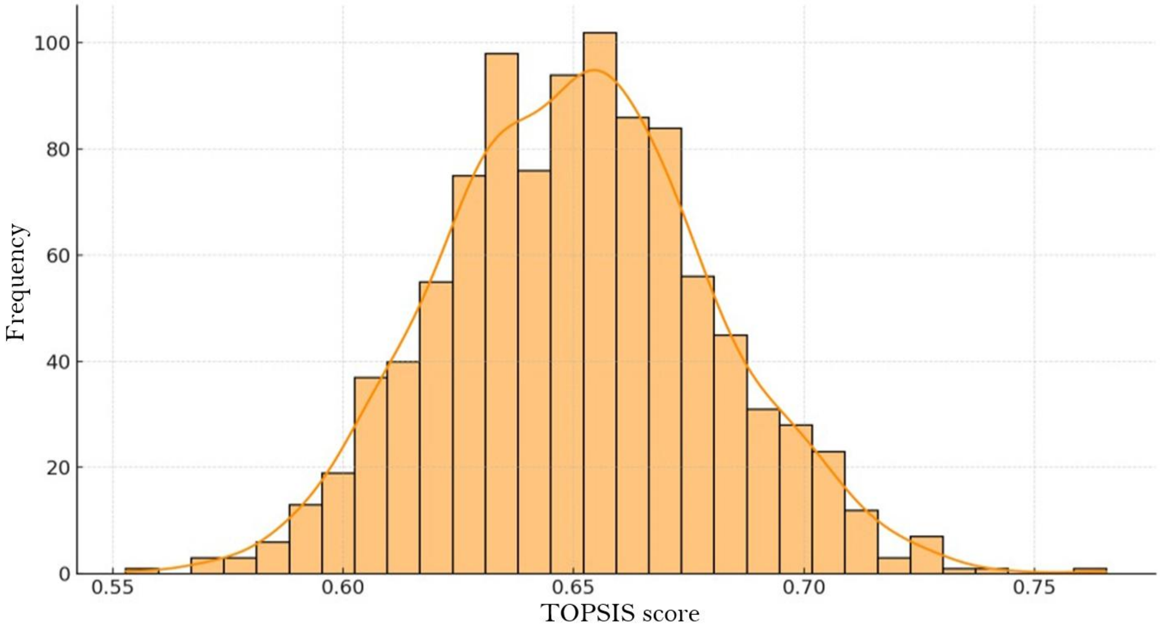

Figure 2. Monte Carlo simulation –TOPSIS score distribution of Igdir province.

As can be seen in Figure 2, the TOPSIS score distribution of Iğdır province was analyzed by Monte Carlo simulation. The obtained distribution demonstrates that the scores calculated throughout the simulation are largely concentrated in a certain range and exhibit a structure close to a normal distribution. This demonstrates that the model produces quite stable results for Iğdır and is affected by weight uncertainties to a limited extent. This result supports the reliability and applicability of the model for investment decisions.

5. CONCLUSION AND RECOMMENDATIONS

This study proposes a comprehensive and objective solution to the problem of tourist destination selection for hospitality investment decisions by using the Entropy-TOPSIS integrated approach. The determination of criteria weights by the Entropy method and the subsequent ranking of destinations by TOPSIS provide a scientific basis for the decision process. Furthermore, Spearman correlation and Monte Carlo sensitivity analysis scientifically verify the consistency and robustness of the findings.

The findings of the analyses clearly revealed that Istanbul and Antalya, in particular, are the most suitable destinations for accommodation investments due to their high tourist demand, high population numbers, and general tourist attractions. The fact that Izmir ranks third emphasizes the potential of the city for hospitality investment. The Spearman correlation coefficient ($rs = 0.8588$) shows a high consistency between the two different weighting scenarios, while the Monte Carlo sensitivity analysis proved that the model is robust to small uncertainties in the weights, and the ranking of the best destinations is quite robust.

This research makes a significant methodological contribution to the Multi-Criteria Decision-Making literature, especially in the context of hospitality investment decisions, by demonstrating the applicability of the Entropy and TOPSIS integrated model through a comprehensive sensitivity analysis. It also provides a scientific and objective framework for strategic destination selection for the hospitality industry in Turkey, with valuable practical implications for both policymakers and potential investors.

Although this research focuses specifically on Turkish provinces, the proposed Entropy-TOPSIS model, enhanced by Monte Carlo simulation, provides a flexible and scalable framework that can be applied globally. Its reliance on objective, quantitative data makes it suitable for assessing tourist destinations in various countries, regardless of geographical, economic, or cultural context. By adjusting the appropriate criteria to reflect local dynamics, the model can serve as a strategic decision support tool for international investors, destination managers, and policymakers worldwide.

5.1. Recommendations for Policy Makers

- Investment incentives and regulatory frameworks should be maintained for sustainable tourism development and upgrading of existing infrastructure in leading destinations such as Istanbul and Antalya. However, to avoid over-concentration, planned development strategies should be adopted, such as delimiting tourism zones in urban development plans, directing new investment incentives towards regional distribution, and expanding infrastructure capacity in line with sustainability principles.
- The Ministry of Culture and Tourism, in cooperation with local development agencies and local governments, should establish targeted incentive programs (e.g., tax exemptions, land allocation, infrastructure co-financing) to attract investment in mid-ranked destinations with high long-term potential.
- For the lower-ranked regions, concrete strategies should be developed to address the shortcomings in high-weighted criteria such as "Demand" and "Population." These strategies may include strengthening regional promotional campaigns, developing niche tourism products (e.g., ecotourism, health tourism, cultural tourism), improving transport accessibility (airport, road, railway connections), and raising tourism awareness among the local population.
- A standardized decision support system based on MCDM methodologies (such as Entropy-TOPSIS) could be institutionalized within tourism development policy to ensure consistent and transparent allocation of public investments.

5.2. Recommendations for Investors

- While higher-ranked destinations may offer the potential for lower risk and higher returns, it is important for investors to analyze supporting data (e.g., land costs, depth of local competition, labor costs) through detailed market research and feasibility studies.
- Investments in niche tourism areas (e.g., ecotourism, health tourism, winter tourism, rural tourism) may be considered in regions that are lower in the ranking but have potential. However, it is recommended to conduct a comprehensive risk analysis for these regions, examine the incentives offered by local governments and ministries, and analyze the long-term sustainability potential in detail.
- Investors should actively seek partnerships with local governments and ministries of tourism to align investment decisions with regional tourism strategies, thereby increasing both financial viability and social acceptance.

5.3. Study Limitations and Future Work

- This study is limited to the specific criteria in the available dataset. In future studies, a broader set of socio-economic, environmental, and infrastructural criteria (e.g., local government incentives, land costs, environmental sustainability indicators, cultural heritage potential, security perception, digital infrastructure) can be included.
- Furthermore, the general validity of the results can be further enhanced by conducting comparative analyses with other MCDM methods (e.g., VIKOR, PROMETHEE, BWM).

- Combinations of subjective and objective weighting methods (e.g., ANP-Entropy integration) could also be chosen as a method for future research.
- Time series data and future forecasts can also be integrated to make the model more dynamic, so that factors such as seasonality and demand changes can be analyzed in more detail.

6. SUMMARY

This study examines the problem of tourist destination selection, a critical strategic decision for hospitality investments, and presents a model that integrates entropy-based weighting and TOPSIS methods to support this complex multi-criteria decision-making (MCDM).

In the study, 19 tourism destinations in Turkey hosting 100,000 or more foreign tourists were analyzed based on data obtained from the current border statistics of the Ministry of Culture and Tourism of the Republic of Turkey for the year 2024. The assessment is based on six main criteria that directly affect tourism investment, such as "Distance to the Nearest Airport (KM)," "Population," "Herfindahl Index Contribution Level," "Hotel Occupancy Rate," "Number of Tourists (Demand)," and "Seasonality."

Criteria weights were determined using the entropy method. Thus, the potential for subjective bias in criterion weights was eliminated. The ranking of destinations was determined by the TOPSIS method. The consistency and robustness of the model findings were confirmed by Spearman correlation analysis (rs=0.8588). The robustness of the model against weight changes was proved by Monte Carlo sensitivity analysis. According to the findings of the analysis, Istanbul and Antalya provinces are the most attractive destinations for accommodation investments. Provinces with lower populations or tourism activities were found to be lagging in the ranking. This study, which brings a methodological innovation to the hospitality investment decision and CRMV literature, provides investors and policymakers with a data-driven and objective method in strategic decision-making processes.

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