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How Can Risk-Averse and Risk-Taking Approaches be Considered in a Group Multi-Criteria Decision-Making Problem?

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Abstract

We propose an alternative decision-making methodology based on adopting a mixed risk-averse and risk-taking behavior, improving the objectivity of decision-making. We demonstrate the methodology by prioritizing Iranian tourism centers' activity under pandemic conditions, providing insights to policymakers on those to keep active or reduce the activity of – hence, those worth developing ahead of future disease outbreaks. This research follows a three-step methodology. First, criteria for evaluation are identified and categorized into *tourist attractions*, *infrastructure*, and *healthcare* dimensions. Second, criterion weights are calculated based on expert opinions, collected using a best-worst method-based questionnaire. Third, tourism centers are evaluated by employing risk-averse and risk-taking best-worst methods. We identify *popular attractions*, *general services*, and *drugstore accessibility* as the primary indicators of *tourist attractions*, *infrastructure*, and *healthcare*, respectively. By clustering tourism centers using K-means algorithm, we find that, in order, the cities of Semnan, Kerman and Zahedan are the tourism centers most suited to staying active during disease outbreaks. For multi-criteria decision-making problems that rely on experts' evaluations, the proposed methodology can improve the reliability of decision-making. The methodology and framework presented can be used to support various types of decision-making, including evaluation, ranking, selection or sorting.

Keywords Risk-averse and risk-taking best-worst method · Disease Outbreaks · COVID-19 · Clustering Tourist Centers

Extended author information available on the last page of the article

1 Introduction

Traditionally, pairwise comparison-based multi-criteria decision-making methods follow the assumption that decision-makers possess the ability to consider the value of options across decision-making criteria. For decision-making problems with multiple dimensions (criteria and options), existing methods may lead to decisions lacking necessary long-term efficacy. This is due to the trade-off that occurs between the criteria of each option in the decision-making process (Hwang and Yoon 2012).

Researchers have sought to solve this challenge by developing models incorporating risk-averse, risk-taking, and balanced approaches considering decision matrix information as parameters (Kheybari and Ishizaka 2022; Yoon and Kim 2017). This has been achieved by leveraging trade-off adjustments to increase the effectiveness of the decision. In previous studies, the effectiveness of these models has been proven independently (Xu et al. 2024). But how might a combination of such models be employed to help solve decision-making problems? To answer this question, we aim to demonstrate how to combine both risk-averse and risk-taking approaches to prioritize which tourism centers (geographic locations) should remain active (continue to operate) during disease outbreaks.

Evaluating tourism centers (any location which includes touristic attractions) requires consideration of *tourist attractions*(Chen and Hsu 2021), *infrastructure* (Juan and Lin 2011a), and *healthcare* dimensions (Önüt et al. 2010), as well as adopting a 'hybrid' risk-taking and risk-averse decision-making attitude (Ural 2016). That is, deliberately choosing evaluation criterion weights on the higher or lower end of the range which they may be assigned based on the primary aim of the dimension. In other words, emphasizing high performing criteria in dimensions in which we wish to maximize potential performance (adopting a risk-taking attitude), alternatively, emphasizing low performing criteria in dimensions in which we wish to minimize potential risk (adopting a risk-averse attitude) (Kheybari 2021). By taking into consideration the aims of decision-makers across each dimension, a hybrid approach can therefore improve the objectivity of decision-making processes. In the context of reducing tourist center restrictions under pandemic conditions, this suggests prioritizing alternatives which score the highest with respect to criteria within the *tourist attraction* dimension whilst possessing the least weak points among criteria of the *healthcare* and *infrastructure* dimensions. Thus, we consider a maximum trade-off for criteria belonging to the *tourist attraction* dimension and a minimum trade-off for criteria falling into the *healthcare* and *infrastructure* dimensions. This is necessary as weak points of an alternative in terms of the *tourist attraction* dimension may be ignored at the expense of its high performance in the other dimensions. This is because a singular criterion of the *tourist attraction* dimension can draw tourists to any alternative location (Lee 2016); however, *healthcare* and *infrastructure* dimensions should have a minimum number of weak points (criterion), as they are directly associated with tourists' lives. For instance, in a pandemic situation as COVID-19, there should be a minimum level of trade-off between wearing masks, complying with social distance, and washing hands for effective healthcare, with no compromise among these three measures.

Keeping in mind the significance of aforementioned arguments and prior art, the goals of this study are to:

- Identify criteria of importance in literature, which influences tourist center evaluation in the context tourism development.
- Propose a framework of criteria categorized into *tourism attraction*, *infrastructure*, and *healthcare* dimensions.
- Develop a 'hybrid' multi-criteria decision-making (MCDM) method that simultaneously considers risk-averse and risk-taking attitudes to prioritize tourist centers' activity under pandemic circumstances.
- Validate the proposed framework and method with a real case study.

The remaining sections of this paper are organized as follows. In Sect. 2, we review the literature on location selection in the tourism industry and identify research gaps. In Sect. 3, we present the methodology used in this investigation. We introduce and describe the case study in Sect. 4. In Sect. 5, we discuss the results obtained from implementing the proposed methodology in the case study context. Finally, conclusions and suggestions for future work are presented in Sect. 6.

2 Literature Review

Multi-Criteria Decision Making (MCDM) is among the methods that offer a structured approach to managing risk in decision-making problems by systematically evaluating multiple criteria and considering various alternatives. In MCDM, scenario analysis and sensitivity analysis can help decision-makers to explore different outcomes, to understand the impact of uncertainties, and finally to identify robust strategies. MCDM integrates both qualitative and quantitative criteria for risk management in decision-making. Qualitative scales, like "excellent, good, medium, bad, very bad," require conversion to quantitative scales through methods like pairwise comparison. It is important to be able to consider both type of criteria because some are clearly quantifiable (e.g., speed, high, cost, etc.) and some are easier to evaluate in a qualitative way (e.g., comfort, security, quality, etc.).

MCDM helps manage risks effectively by analyzing decisions thoroughly. It identifies key factors, including risks factors. It weights and aggregates them to derive well-informed and transparent decisions with a balance between different factors (Montibeller and Franco 2007). MCDM also considers uncertainties, allowing subjective assessments of risks (Keeney and Raiffa 1993). By combining MCDM with traditional risk analysis methods, decisions can consider both the probability and severity of negative outcomes, giving a complete view (Mendoza and Martins 2006). Moreover, MCDM facilitates stakeholder engagement, ensuring diverse perspectives are considered in risk management decisions. Overall, MCDM equips decision-makers with tools to make informed choices that balance trade-offs and maximize outcomes in uncertain environments. Most recently, Abed and Rashid (2024) developed a novel risk assessment model for construction projects that integrates organizational maturity as a new dimension. By combining the BWM and a Fuzzy Rule-Based

System (FRBS) with a 3D risk matrix, their model enhances the precision and effectiveness of risk evaluation and prioritization. This hybrid approach offers a comprehensive method for managing risks in complex projects, demonstrating the utility of advanced MCDM techniques in practical applications.

The literature section of this paper will focus on reviewing prior art on multiple criteria decision-making (MCDM) problems, paying particular attention to studies taking decision-makers' risk attitudes into consideration. Our intention is to show how our study fills a gap in the existing literature by considering both the theoretical and practical aspects of incorporating risk attitudes into MCDM models. Therefore, Sect. 2.1 will address this issue in terms of theory, exploring the ways in which risk attitudes have been incorporated into MCDM models, while Sect. 2.2 will examine the existing literature in terms of how previous studies.

2.1 Incorporating Risk Attitudes into MCDM Models

Behavioral decision-making is a critical area of study in the context of MCDM, as it seeks to understand how psychological factors impact decision-making processes (Yoon and Kim 2017). Cognitive biases, heuristics, emotions, and other psychological factors can all lead to deviating from rational decision-making, which can have significant consequences in complex decision-making situations. In the context of MCDM, decision-makers' risk preferences can also be viewed as a cognitive bias, as their tendency towards risk-seeking or risk-aversion can impact their decision-making process.

Several studies in literature incorporate the risk attitude of decision-makers in their analysis. For example, Yoon and Kim (2017) present a pioneering study that merges insights from behavioral economics with the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). Their study represents a significant stride toward understanding the nuanced effects of psychological factors, such as cognitive biases and risk preferences, on decision-making processes. They argue that traditional MCDM methods, including the conventional TOPSIS approach, often do not account for the decision-maker's inherent behavioral tendencies, such as loss aversion and the endowment effect. These behavioral tendencies can significantly influence decision-makers' choices, leading to outcomes that deviate from what would be expected under purely rational decision-making models.

To bridge this gap, Yoon and Kim propose an innovative modification to the TOPSIS methodology, incorporating the concept of loss aversion directly into the decision-making process. The cornerstone of their approach lies in the introduction of a loss aversion ratio into the TOPSIS calculation. This ratio allows for the explicit consideration of the decision-maker's subjective experience of losses and gains, reflecting the well-documented behavioral economics finding that losses loom larger than gains in the human psyche. By adjusting the loss aversion ratio, decision-makers can modulate the TOPSIS model to align more closely with their personal risk preferences, thereby producing a ranking of alternatives that more accurately reflects their behavioral inclinations.

They demonstrate the practical application of their behavioral TOPSIS method through illustrative examples, highlighting how different settings of the loss aversion ratio can lead to diverse decision outcomes. This empirical evidence underscores the versatility and adaptability of the behavioral TOPSIS model in accommodating varying degrees of loss aversion among decision-makers. Roghani et al. (2024) introduced a fuzzy multidimensional risk assessment framework for sewer asset management that incorporates both qualitative and quantitative criteria to evaluate the risk of structural failure. Their study emphasizes the integration of fuzzy logic and MCDM to manage uncertainty and enhance decision-making robustness, showcasing its application in Tehran's sewer network. This approach aligns with the current discussion on the necessity of integrating psychological and subjective risk assessments into MCDM models.

Several studies explore the outcomes of decision-making processes when Decision-Makers (DMs) adopt multiple risk behaviors in literature. For example, Kheybari and Ishizaka (2022) demonstrated how the risk-averse (concave value function) and risk-seeking (convex value function) attitude of DMs might result in different outcomes for alternatives in the BWM. For his purpose, three mathematical models considering the logic presented in Data Envelopment Analysis (DEA) and Ahanoon's entropy model were developed, and the performance of the models was verified through statistical analysis. Similarly, Rezaei (2018) showed how different DMs' preference functions reflect their attitude toward a specific problem. They proposed a family of piecewise value functions which can be used for different decision criteria and problems. The functions can mitigate risk in a MCDM problem by considering the decision-maker's behavior regarding intervals of criteria performance. Additionally, they compared monotonic linear value functions, piecewise linear value functions, and exponential value functions and their effects on outcomes for ranking a set of alternatives.

Moreover, in the study by Miccoli and Ishizaka (2017), risk is intricately incorporated into the decision-making framework through the development of Analytic Hierarchy Process (AHP)Sort II, a refined multi-criteria sorting method applied to assess the risk of wolf attacks in Umbria's municipalities. This innovative approach leverages a clustering-based method to efficiently handle a large number of alternatives, significantly reducing the complexity and number of comparisons required in traditional AHP applications, thereby streamlining the process for detailed risk categorization. Their framework provides decision-makers with a nuanced, quantifiable system for prioritizing areas that require mitigation strategies. Younsi et al. (2020) improved an existing decision support system in monitoring and influenza risk assessment by employing a dominance-based rough set approach whilst considering risk in the decision-making process. Their framework innovatively merges a compartmental model (SEIR) with a social network (SW) using a simulation-based approach, enhancing its analytical capabilities. This is further augmented by integrating multicriteria analysis into the subsystem, relying on spatial online analytical processing (S-OLAP) technology.

While the majority of literature covering behavioral decision-making models have focused on whether decision-makers are risk-seeking or risk-averse (Gómez-Limón et al. 2003) or whether clustering risk based on experts opinions and what the corresponding outcomes would be in their analyses, it is important to recognize individuals' conflicting risk preferences depending on the context and the criteria being evaluated (Tuncel and

Doucet 2023). Take for instance a high-level manager in a healthcare system. While they may be risk-seeking toward improving patient outcomes, they may be risk-averse toward potential legal liabilities. Nonetheless, mentioned studies do not consider the conflicting risk-attitude of DMs toward different criteria for the same set of alternatives (e.g., in Kheybari et al. (2021a, b), DMs only have a risk-averse attitude). Another example of conflicting risk preference could be a business owner who wants to expand their company by investing in a new product line or market. They may be risk-seeking in terms of potential profits and growth opportunities, but risk-averse when it comes to capital risks or reputational impact in case of failure. Therefore, a nuanced approach is required to understand decision-making behaviors in the context of MCDM problems, one that accounts for decision-makers' risk-averse and risk-seeking preferences.

Consequently, top-level decision-makers may make better informed by recognizing and incorporating these mixed preferences into the decision-making process, in alignment with their values and priorities. This could lead to positive outcomes whilst minimizing potentially negative consequences. Accordingly, our approach aims to combine DMs' risk-averse and risk-taking attitudes concurrently.

2.2 Tourist Centers Location Selection Related Works

Location-selection problems in the tourism industry context may be interpreted and solved differently based on the decision-making attitude and the type of data dealt with. Thus, we divide relevant studies into three types: (1) statistical methods, (2) mathematical programming, and (3) multi-attribute decision-making (MADM) methods. Given the multi-dimensional nature of the problem involving numerous stakeholders and infrastructure considerations, and the fact that our location-selection problem presents a finite set of alternatives with implicit rather than explicit objectives (such as minimizing or maximizing a specific function), an MADM approach may be more appropriate. In reviewing literature, we found that it is possible to broadly categorize tourism-related location-selection problems based on context across hotels, restaurants, casinos, and resort parks. In each sub-section, we outline how our work can benefit from exploring various domains of study.

2.2.1 Hotel Location Selection

Successful investment in the hotel industry, as one of the most important pillars of tourism and hospitality (Antara and Sumarniasih 2017), heavily depends on location factors (Kim and Okamoto 2006). Since hotel location selection is a long-term fixed investment, a flawed location strategy can be very difficult to rectify (Yang et al. 2014). Appropriately, scholars have addressed hotel location-selection problems. For example, Chou et al. (2008) used the fuzzy AHP method for hotel selection for international tourists in Taiwan. They considered four dimensions: geographic conditions, traffic conditions, hotel characteristics, and operations management, with their respective criteria (including both qualitative and quantitative). Hotel characteristics and operation management are found to be the most and second most important dimensions among those considered. Regarding six dimensions (factor endowments, demand conditions, firm strategy structure & rivalry, related and supported industries, government, and chanceJuan and Lin (2011b) presented a novel decision framework for optimizing hotel location selection in Taiwan with modified Delphi modeling. Juan and Lin (2011a) considered all the dimensions mentioned in Juan and Lin (2011b), with exception of the chance dimension, to optimize hotel location selection using the AHP method. Among 34 factors (including both qualitative and quantitative), results show that labor resources, natural resources, zoning limitations and political environment are the most important criteria for hotel location selection problem. Considering three dimensions (geography, traffic, and management) and with respective criteria different from Chou et al. (2008), Chang et al. (2015) integrated the fuzzy Delphi method, ANP, and TOPSIS to help effectively select optimal locations for Taiwanese service apartments. Surveys based on a 9-point Likert scale were distributed to 31 high-level executives to assess the significance of various criteria. The foremost 12 criteria (primarily quantitative) were identified and categorized under the three dimensions: geography (2nd priority), traffic (3rd priority), and management (1st priority). These were then used to organize the framework for choosing the best location. Two years later, using the Preference Selection Index (PSI), Aksoy and Ozbuk (2017) identify criteria that influence tourists' hotel location choices in Turkey. They grouped criteria into three quantitative dimensions: accessibility, urban development, and tourist attractions. They found the most important criterion in tourists' hotel location choice is the closeness of tourist attractions measured by walking distance to the hotel. Popovic et al. (2019) presented an efficient model for the selection of an optimal location for the construction of a tourist hotel. They used stepwise weight assessment ratio analysis (SWARA) for the determination of the weights of qualitative and quantitative criteria (infrastructure, access, surrounding environment, investment, rest resources, and human resources) and weighted sum technique for the final prioritization and ranking of alternative locations in Serbian mountain areas. Among the criteria, investment and rest resources were ranked most important.

2.2.2 Culinary and Entertainment Tourism Development Location Selection

Food has become an emerging theme for the tourism and hospitality industry (De Albuquerque Meneguel et al. 2019). De Albuquerque Meneguel et al. (2019) employs a qualitative and descriptive approach, utilizing indirect observation and detailed interviews as its primary data gathering tools. The findings indicate that the restaurant under examination plays a pivotal role in promoting the development and innovation of culinary tourism offerings. Moreover, gastronomy has emerged as an integral part of regional brand and image diversification and definition. Perhaps scholars have focused on location-selection due to the criticality of location with regards to the success of restaurants. For example, Chang (Chang 2010) utilized fuzzy preference relations to select restaurant locations. Pairwise comparisons were conducted to obtain the importance weights of five evaluation criteria, each with 11 respective sub-criteria, and the performance rating of alternative locations served as an illustrative case. Based on the importance weights assigned to evaluation criteria, incorporating both qualitative and quantitative aspects, it was determined that rent cost and transportation cost held greater significance compared to other criteria.

Casino gaming industries in many countries have experienced substantial growth and expansion as one of the entertainment sub-categories (Eadington 2003). Much of this has been a direct result of explicit strategies adopted by state, provincial, or national governments that believe that casinos can be an important catalyst in creating or otherwise stimulating growth and tourism within their borders (Eadington 2003). For instance, Ishizaka et al. (2013) presented a location selection analysis for choosing a suitable borough in the region of Greater London to construct a large casino. By taking two viewpoints into consideration (one focused on profitability and the other on social benefits manifested by quantitative criteria), they evaluated the alternatives using the weighted sum, TOPSIS, and PROMETHEE methods. They found that PROMETHEE and Weighted Sum (WS) methods are more suitable than TOPSIS to address this problem. The top criterion is number of customers which has a weight of 0.6, Regional or social benefits weighs 0.4 and all sub-criteria have an equal weight.

2.2.3 Resort Park Location Selection

Following the growth of nature-based tourism, national parks have turned into important tourist attractions and important locations to consider in regional development. Accordingly, scholars have tried to address the role of resort areas in tourism development (Prideaux 2000). Zucca et al. (2008) provided a site selection process to establish a local park in Italy. Their study focused on four quantitative criteria (suitability, environmental and ecological effects, social effects, and economic effects) with their respective sub-criteria. It was supported by a value-focused approach and spatial multi-criteria evaluation (SMCE) techniques. A first set of spatial criteria was used to design a number of potential sites. Then, a new set of spatial and non-spatial criteria was employed, including the social functions and financial costs, together with the degree of suitability for the park, to evaluate the potential sites and recommend the most acceptable one. Lin and Juan (2009) examined international resort park type selection using ANP in Taiwan. They considered five qualitative criteria: factor conditions, demand conditions, firm strategy structure and rivalry, government, and chance together with their respective elements as sub criteria. Factor conditions, demand conditions were ranked as the most important factors.

2.3 Research Gaps

Bearing in mind what was mentioned in the literature review, we identified the following research gaps and compare them to our present study:

- Literature employing MADM methods as primary methodology are most often AHP-based. Yet, the BWM (Rezaei 2015) has been shown to outperform AHP in three ways. First, since BWM leads to fewer pairwise comparisons than AHP (Gupta and Barua 2016), it provides more consistent results than AHP (Kheybari et al. 2020). Second, as BWM is easy to understand, rectifying mistakes is easier in BWM than in similar methods (Kheybari et al. 2021a, b). Third, the BWM weighting process produces less anchoring bias than other weighting methods (Rezaei 2020).
- The absence of a MADM methodology that adequately incorporates both risk-averse and risk-taking approaches in tourism-related location selection problems is notable. While existing studies have focused on various decision-making methods, they often lack a comprehensive integration of risk assessment and management strategies. MADM, with its ability to accommodate multiple criteria and preferences, presents

a promising avenue for addressing this gap. By developing an MADM framework tailored to the tourism industry, researchers can effectively capture the complexities of risk perception and decision-making attitudes among stakeholders. This methodology would enable a more nuanced evaluation of potential locations, considering both the potential rewards and the associated risks, thus enhancing decision-making processes in the tourism sector.

- Conceptually speaking, we should consider the advent of undesirable phenomena, such as that of a pandemic, at the location-selection and other decision-making process stage, as they constitute part of a long-term strategy. However, none of the studies found in literature (Table 1) have considered criteria related to disease outbreaks, particularly in location-selection and in the tourism industry (Streimikiene et al. 2021).
- Table 1 reveals that there are no studies in the literature considering either the three aforementioned dimensions simultaneously or the risk factor in decision-making process.

3 Methodology

3.1 Research Framework

We followed a sixth-step approach, visually represented in Fig. 1. After conducting a comprehensive literature review, we categorized the relevant criteria into dimensions of healthcare, tourist attractions, and infrastructure. These dimensions were selected for their operationalization, indicating their capacity to be translated into measurable indicators. Tourist attractions were included because of their pivotal role in attracting visitors and generating revenue(Chen and Hsu 2021), while infrastructure quality directly influences accessibility and convenience for tourists (Juan and Lin 2011a). Furthermore, healthcare facilities are crucial for ensuring tourists' well-being and safety (Önüt et al. 2010). These dimensions can be comprehended from both risk-averse and risk-taking perspectives, providing clarity for readers.

Table 1 A comparison between the present study and the most relevant ones in literature

Studies	Tourist attractions	Infrastructure	Healthcare	Technique(s) used	Risk of DM's attitude
(Popovic et al. 2019)	✓	✓	×	SWARA, WS	Not considered
(Tzeng et al. 2002)	✓	✓	×	AHP	Not considered
(Chang 2010)	✓	✓	×	Fuzzy Preference Relations	Not considered
(Cheng et al. 2005)	✓	✓	×	ANP, AHP	Not considered
(Önüt et al. 2010)	✓	✓	×	FAHP, FTOPSIS	Not considered
(Lin and Juan 2009)	×	✓	×	ANP	Not considered
This study	✓	✓	✓	Risk-averse and risk-taking BWM, K-Means	Considered

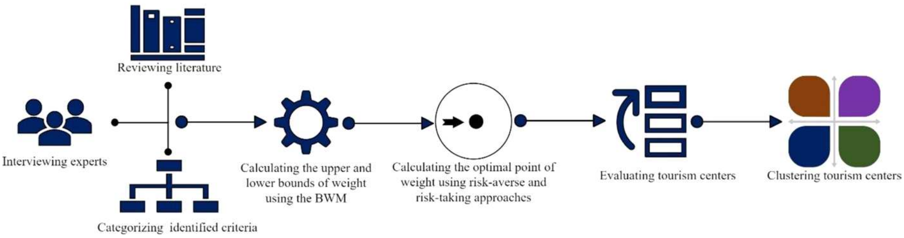

Fig. 1 Research steps

Table 2 Expert demographics

Role	Qty	Average work experience (years)
Managers of touristic activities and hotels	7	6.7
Academics with a hospitality management focus	7	7.2
Travel and tourism service centers directors	8	10.3
International tour guides	8	13.4

In the next step, a representative subset of expert respondents (2 from each role presented in Tables 2 and 3 in total) were interviewed to validate the dimension-criteria hierarchy: both confirming the relevance of criteria found in literature, and to suggest additional pertinent criteria for consideration. While there were no suggested additions in the *tourist attractions* and *infrastructure* dimensions, two criteria were suggested by respondents for the *healthcare* dimension: citizen's education level and hospital bed accessibility (the hierarchy and criteria definitions can be found in Table 4). These additions could be attributed to the comparably lower attention given to the *healthcare* dimension in previous research and practice.

Third, we gathered 30 experts' opinions using an online survey created based on the BWM, and calculated the upper and lower bounds of criteria weights. Experts were identified via social media profile search (LinkedIn) and a summary of their demographics can be found in Table 2. Next, we applied risk-averse and risk-taking approaches on BWM results to calculate optimal criteria weights. As discussed previously, the risk-averse approach is employed for criteria categorized under *infrastructure* and *healthcare* dimensions while the risk-taking approach is used for the criteria under the *tourist attraction* dimension. Tourism centers are then evaluated by determining the global weights of the criteria, and using a simple additive value function to calculate tourism centers' overall score across decision-making criteria. Finally, tourism centers are clustered using a K-Means algorithm, as a means to identify which centers might be best suited to keep active in disease outbreaks. The following sub-sections provide additional details on these steps.

Table 3 A hierarchical structure of criteria and their definitions for tourism centers evaluation found in the literature

Dimension	Criteria	Definition	Source
Tourist attraction	Popular attractions	The number of historic sites, natural parks, book fairs, museums, zoos, amusement parks	(Chen and Hsu 2021; Molinillo and Japutra 2017)
	Musical attractions	The number of music festivals, concerts	(Molinillo and Japutra 2017)
	Classical attractions	The number of ballet events, opera events, theater events	(Lin and Juan 2009; Önüt et al. 2010; Prideaux 2000) (Molinillo and Japutra 2017)
Infrastructure	General services	Number of rooms in hotels or any accommodation providers (lodging), restaurants, parking	(Juan and Lin 2011a; Wilson et al. 2001)
	Hospitality	The percentage of citizens that speak English at least at a basic level, Local resident attitudes, citizens' satisfaction	(Wilson et al. 2001)
	Public transportation	The percentage of road coverage, railroad coverage, the number of airports, trains, subway lines, seaports and buses, how convenient it is to make a U-turn at crossroads, parking capacity, proximity to metro, bus, highway, and railway	(Chang 2010; Chen and Tsai 2016; Juan and Lin 2011b; Tzeng et al. 2002)
	Supply services	Cost of electricity, gas, and water supplies	(Juan and Lin 2011b; Wilson et al. 2001)
Healthcare	Drugstore accessibility	Number of existing drugstores	(Kheybari et al. 2021)
	Emergency equipment accessibility	The average number of emergency equipment, such as ambulances, ventilators, etc., in local hospitals	(Kheybari et al. 2021a; Littrell et al. 2004; Önüt et al. 2010)
	Education level of citizens*	Percentage of citizens holding at least a bachelor's degree	Recommended by experts
	Reception accessibility*	Number of hospital beds per capita	Recommended by experts
	Demographics	Population density, population growth rate, age, income	(Chen and Tsai 2016; Kheybari et al. 2021a)

*Identified in interviews (see Sect. 3.1)

Table 4 Primary dimension weights

Dimension	Weight	Rank
Tourist attractions	0.545	1
Infrastructure	0.321	2
Healthcare	0.133	3

3.2 BWM

BWM is a vector-based pairwise comparison technique which has been used for weighting criteria in numerous contexts, including risk management (Kheybari and Ishizaka 2022; Yazdani et al. 2019), performance management (Mahdiraji et al. 2020), and location selection (Kheybari et al. 2020, 2021a, b, 2024). The main advantages of BWM over other weighting methods (e.g., SMART family methods) are reduced anchoring bias, fewer and better consistency of pairwise comparisons. BWM consists of five steps:

Step (1) Identify relevant evaluation criteria through reviewing literature / interviewing experts $\{C_1, C_2, ..., C_n\}$.
Step (2) Specify the best *(B)* and the worst *(W)* indicator (criterion) from the set of criteria.
Step (3) On a scale from 1-to-9, determine the superiority of *B* over *other* criteria. The number scale relates to a qualitative measure of importance ranging from "*B* is equally important to *other*" (1) to "*B* is extremely more important than *other*" (9). The result of these best-to-other pairwise comparisons can be expressed as:
$A_B = (a_{B1,}\ a_{B2,...,}\ a_{Bj,...,}\ a_{Bn})$, where a_{Bj} is the preference of *B* over criterion *j*.
Step (4) On the same 1-to-9 scale, determine the superiority of *other* criteria over *W*. The result of these other-to-worst pairwise comparisons can be expressed as:
$A_W = (a_{1W},\ a_{2W,...,}\ a_{jW...,}\ a_{nW})$ where a_{jW} is the preference of criterion *j* over *W*.
Step (5) Using Model 1, calculate the weight of the criteria $\left(w_{1,}^{*} w_2^{*}, \ldots, w_n^{*}\right)$.

Model 1:

$$\begin{aligned}
&\min \max_{j} \{|w_B - a_{Bj}w_j|, |w_j - a_{jW}w_W|\} \\
&\text{such that} \\
&\sum_{j=1}^{n} w_j = 1 \\
&w_j \geq 0, \text{ for all } j
\end{aligned}$$

To reach the optimal solution $\left(w_{1,}^{*} w_2^{*}, \ldots, w_n^{*}\right)$, Model 1 is converted to Model 2, as follows:

Model 2:

$$\begin{aligned}
&\min \xi \\
&\text{such that} \\
&|w_B - w_j a_{Bj}| \leq \xi, \text{ for all j} \\
&|w_j - w_W a_j| \leq \xi, \text{ for all j} \\
&\sum_{j=1}^{n} w_j = 1 \\
&w_j \geq 0, \text{ for all j}
\end{aligned}$$

Model 2 establishes the local weights of each criterion at each level of the problem's hierarchical structure. As our decision-making problem deals with more than 9 criteria, these were clustered across 3 dimensions based on literature, each comprising 3, 4, and 5 criteria respectively. Hence, the BWM linear model excel solver had to be used once to obtain dimension weights and thrice to obtain the weight of criteria belonging to each dimension (Rezaei, 2016). The objective function of Model 2 (ξ^*) indicates the inconsistency rate of pairwise comparisons. Surveys with an inconsistency rate over the threshold level indicated by Liang et al. (2020) should be revised or removed. None of the responses collected in this study surpassed the threshold level, suggesting acceptable consistency.

Next, we determine the upper (w_j^u) and lower (w_j^l) bounds criteria weights by taking the sample standard deviation of the criteria weights across expert opinions. Using the range of weights and the score of alternatives across the decision-making criteria, we can further analyze the decision-making problem from both risk-averse and risk-taking perspectives.

3.3 Risk-Averse BWM

In a risk-averse approach, emphasis is placed on criteria which alternatives poorly perform in, to minimize potential risk. As such, the objective of the optimization model is to weigh criteria in a manner which best highlights alternatives' shortcomings. To achieve this, we adopt the optimization model developed by Kheybari and Ishizaka (2022) (Mehrpour et. 2024) (Model 3):

Model 3:

$$\begin{aligned}
&\min_i \sum_j w_{ij} u_{ij} \\
&\text{such that :} \\
&\sum_j w_{ij} = 1 \text{ for all } i \\
&w_j^l \leq w_{ij} \leq w_j^u \text{ for all } j
\end{aligned}$$

This model ensures any criterion whose weight is set to the maximum amount is considered when determining how well the selected alternative performs. The upper and lower bounds of criterion *j* (c_j) are denoted by w_j^u and w_j^l, respectively, and the weight of criteria *j* for the alternative *i* is denoted by w_{ij}. As aforementioned and in our case study context, we apply this model for the *healthcare* and *infrastructure* dimensions, where our aim is to achieve minimum tradeoff across criteria. Results of Eqs. 1 and 2 are used to determine u_{ij}, which stands for alternative *i*'s normalized value for criterion *j*.

$$u_{ij} = \frac{x_{ij}}{\max_i(x_{ij})} \quad \text{for all } i \text{ and positive criterion } j \tag{1}$$

$$u_{ij} = \frac{\min_i(x_{ij})}{x_{ij}} \quad \text{for all } i \text{ and negative criterion } j \tag{2}$$

Where x_{ij} denotes the score of alternative *i* with respect to criterion *j*.

3.4 Risk-Taking BWM

A risk-taking approach aims to maximize alternatives' performance, while placing emphasis on alternatives which perform particularly strongly in individual criterion. That is, strongly performing criteria have increased importance. Again, we adopt the optimization model proposed by Kheybari and Ishizaka (2022)(Model 4):

Model 4:

$$\max_i \sum_j w_{ij}u_{ij}$$
$$\text{such that :}$$
$$\sum_j w_{ij} = 1 \text{ for all } i$$
$$w_j^l \leq w_{ij} \leq w_j^u \quad \text{for all } j$$

The objective function of Model 4 is to enable the maximum amount of trade-off between the criteria of potential choices. Hence, in our case study context, we apply this model for criteria in the *tourist attractions* dimension.

3.5 Global Weight

After determining the optimal weight of dimensions and criteria (result of Model 3 and 4), the global weight of the criteria is derived by multiplying the weights of primary dimensions by the weight of criteria in the corresponding dimensions. Finally, to rank candidate alternatives, we obtained the alternatives' overall scores using the simple weighted sum function shown in Eq. 3.

$$V_i = \sum {}_j u_{ij}w_{ji} \quad \text{for all } i \tag{3}$$

3.6 K-Means

K-Means clustering is a simple and widely used unsupervised machine learning algorithm. Unsupervised algorithms, including K-Means, tend to make inferences from datasets using only input vectors and without reference to known, or labelled, outcomes. The K-means algorithm places K centroids at random locations within a dataset, assigns each data point to the closest centroid and iteratively repositions centroids until no datapoint switches centroid or cluster 'membership', while keeping the centroids as small as possible. "Means" in K-Means refers to the averaging of distance vectors used to relocate the centroid each iteration. Here, we employ K-means to cluster tourism centers for policymaking on tourism center activity under pandemic conditions. In our case, the K-means clustering can be used also with a relative low number of alternatives, because it is a one-dimensional problem, i.e., we need to separate the score of the alternatives obtained by the hybrid-BWM approach.

4 Case Study

In this section, we introduce the dimensions used in the process of evaluating alternatives, explain their necessity, and then investigate why we want to implement the proposed method in Iran.

4.1 Tourist Attraction

Tourist attraction is synonymous with cultural attraction (Muštra et al. 2023; Panzera et al. 2021). Molinillo and Japutra (2017) refer to cultural attractions as facilities, sites, or events that motivate tourists to visit a location, be it for the attraction's historical, artistic or scientific value, its heritage, or other individual tourist preferences. On the later, Rojek states that "the urge to travel to witness the 'extraordinary' or the 'wonderful' object seems to be deep in all human cultures" (Richards 2002). Hence, the creation and production of attractions have received a great deal of scholars' attention (Cohen 1979; Leiper 1990; Lew 1987). Cohen's semiotic analysis (Cohen 1979) shows that attractions are firmly anchored in the (post) modern economy of signs (information behind pictures and symbols) and that their significance as markers of meaning and social consumption exceeds their role as activity sites. For example, based on the results of the study done by Richards (2002), places with stronger cultural motivations are more likely to be visited before embarking on a journey. In fact, tourist attractions or cultural attractions are staples that drive tourists' decision to embark on a journey. The cultural attractions are broadly grouped into three clusters: popular attractions, musical attractions, and classical attractions (Molinillo and Japutra 2017). Criteria of *tourist attraction*, along with their definitions, are summarized in Table 4.

4.2 Infrastructure

Infrastructure refers to general facilities or services that assist tourists in moving from one location to another or staying in one location. *Infrastructure* is an integral part of a country's tourism package and has a statistically significant relationship with tourism development (Adeola and Evans 2020). Multiple studies provide empirical evidence of the importance of infrastructure to the tourism industry and demonstrate why infrastructure is a key determining factor of the industry's development. For example, through case studies in Africa (Adeola and Evans 2020), Turkey (Adeola and Evans 2020), Thailand (Tang and Rochananond 1990), and South Africa (Kim et al. 2000). Additionally, there are studies suggesting that Europe/America and Asia are sensitive to the transport infrastructure, and Europe/America are sensitive to its non-transport infrastructure (groups 2, 3, and 4 as listed) (Khadaroo and Seetanah 2007). To evaluate our alternatives, we categorize *infrastructure* into four groups of services: (1) public transportation, (2) general services, (3) supply services, and (4) hospitality (Wilson et al. 2001)(Table 4).

4.3 Healthcare

In this study, the *healthcare* dimension refers to criteria which must be considered when dealing with pandemics or epidemics. Addressing such outbreaks is crucial as they can adversely affect tourism. For example, the COVID-19 outbreak posed new challenges to sustainable tourism development (Streimikiene et al. 2021). As suggested in our Introduction section, the tourism industry has been shown to be, at least in light of the recent pandemic, among the most vulnerable. As such, healthcare-related criteria need to be addressed in future research on tourism development (Streimikiene et al. 2021). This is especially important as health experts predict that pandemics are increasingly likely to occur, and businesses' survival will rely on the development of more resilient services, able to adapt to consumer demands (Rodríguez-Rodríguez and Hernández-Martín 2020). In order to evaluate the performance of alternatives in the *healthcare* dimension, it is important to have easily quantifiable criteria. We define five criteria in relation to *healthcare*, three of which were found in literature, including (1) drugstore accessibility, (2) emergency equipment accessibility, and 5) population demographics, and two of which were recommended by experts, including citizens' (3) education level and (4) reception accessibility (Table 4).

We demonstrate the proposed methodology in the context of Iran. Iran's tourism industry, like others, has been greatly affected by the COVID-19 pandemic. In addition, according to the World Tourism Organization (WTO), while Iran is among the top 10 countries in terms of *tourist attraction*, it uses only 11% of its tourism potential and tourism makes up less than 5% of the country's foreign exchange income. Thus, there is potential to employ the proposed methodology for sustainable tourism development and to improve the industry's future disease outbreak response. We demonstrate the methodology by evaluating 26 Iranian cities by their suitability in keeping tourism activities running under pandemic conditions, for the Ministry of Cultural Heritage, Handicrafts, and Tourism of Iran. It is worth noting that we use publicly available databases including the Statistical Center of Iran, the Ministry of Science, the Ministry of Cultural Heritage of Iran, Handicrafts and Tourism of Iran, the Ministry of Housing and Urban Development of Iran, and the Ministry of Health and Medical Education of Iran to collect data regarding the criteria presented in Table 4.

5 Results and Discussion

In this section, we first calculate the optimal range of weights using Model 2. Using Model 3 and Model 4, we then obtain the optimal value of the weights within their respective ranges, for each of the criteria presented in Table 4. Next, we evaluate the performance of tourism centers using Eq. 3. Finally, we report the results of K-Means algorithm to cluster tourism centers under three scenarios.

Table 5 Tourist attractions dimension criteria weights

Criterion	Lower bound	Upper bound	Weight (middle)	Rank
Popular attractions (C_1)	0.419	0.707	0.563	1
Musical attractions (C_2)	0.137	0.417	0.277	2
Classical attractions (C_3)	0.074	0.246	0.160	3

Table 6 Infrastructure dimension criteria weights

Criterion	Lower bound	Upper bound	Weight (middle)	Rank
General services (C_4)	0.148	0.482	0.315	1
Hospitality (C_5)	0.105	0.390	0.248	2
Public transportation (C_6)	0.102	0.380	0.241	3
Supply Services (C_7)	0.057	0.337	0.197	4

5.1 Local Weight of Criteria

After applying Model 2 for each survey response, considering Table 4's hierarchy, we calculate the average weight of primary dimensions. Then, we consider these averages as local weights for criteria. Table 5 shows that *tourist attractions* is the most important dimension. This was expected, considering the mission of the industry is to leverage touristic locations. On the other hand, the lower importance of *healthcare* may be attributed to the similarity in alternatives' performance from experts' perspective, yielding approximately uniformly distributed results.

5.2 The Tourist Attractions Dimension

As seen in Table 6, *popular attractions*(C_1) is the *tourist attractions* dimension's criteria which captivated experts the most. This may be related to the importance of historical sites and natural parks in gaining competitive advantage (Zhu et al. 2017), or to the range of climates which can be observed across the evaluated tourist centers.

5.3 The Infrastructure Dimension

Experts determined *general services* (C_4) as the most notable criterion of the *infrastructure* dimension (Table 7). This is most likely a result of housing cost being of particular importance to tourists. Interestingly, experts give similar importance to *hospitality* (C_5) and *public transportation*(C_6). This may be explained by two factors. First, Iran's culture and differing regional customs, which may encourage tourists to travel. Second, hospitality is a deep-seated and highly-valued trait across Iranian cultures (Khodadadi 2016). A lack thereof would therefore inhibit tourism development.

5.4 The Healthcare Dimension

Drugstore *accessibility* (C_8) was found to be the most important factor in the *healthcare* dimension, followed closely by *emergency equipment accessibility*(C_9)

Table 7 Healthcare dimension criteria weights

Criterion	Lower bound	Upper bound	Weight (middle)	Rank
Drugstore accessibility (C_8)	0.140	0.390	0.265	1
Emergency equipment accessibility (C_9)	0.141	0.380	0.261	2
Education level of citizens (C_{10})	0.080	0.373	0.227	3
Reception accessibility (C_{11})	0.049	0.210	0.129	4
Demographics (C_{12})	0.026	0.211	0.118	5

(Table 8). One might have surmised this as they are closely related to healthcare-related crisis responsiveness, thus how effectively we might save people's lives if imperiled. It is also worth highlighting the significance of criteria suggested by experts ($C_{10}$and C_{11}).

5.5 Global Weight of Criteria and Evaluation of Alternatives

In this section, after implementing Models 3 and 4 for risk-averse and risk-taking dimensions, respectively, we multiplied the weight of each sub-criterion by the weight of its corresponding category (Table 3). Then, considering the output of Eq. 3, we calculated the overall score of 26 cities (Table 9). The overall scores for the hybrid approach are obtained by calculating element-wise products of the normalized decision matrix and the optimal weight matrix, then summing the resulting weights and experts' criterion scores for each tourism center (Eq. 3). The overall scores for the original BWM approach were calculated by averaging the scores provided by the 30 experts. In Table 9, we find A_{11}, A_{16}, and A_{12} as the top three and A_{18}, A_5, and A_4 as the bottom three of 26 alternatives based on the hybrid approach. These three alternatives also ranked top three in the *tourist attractions* dimension, which was previously shown as the most important dimension. Policymakers may use these rankings to decide whether to relax, continue to enforce activity restrictions, or prioritize the implementation of such restrictions under future pandemic scenarios in the regions of Iran.

5.6 Analyzing the Results of Hybrid Approach and Original BWM

The small differences in the results of both approaches (hybrid approach and original BWM) may prove impactful when taking decisions in sensitive contexts (here, in disease outbreaks), as highlighted by recent studies on weighting methods (Hatefi et al. 2023). This is seen in A_{21}'s rank increasing from 19th to 16th whilst A_{13}'s falls from 16th to 18th (original BWM and hybrid approach respectively), or by the two highest performing alternatives (A_{11} and A_{16}) swapping ranks (1st to 2nd and 2nd to 1st) (Table 9). Thus, in scenarios where decision-makers are likely to or must be risk-averse or risk-taking across primary dimensions, it may be beneficial to adopt a hybrid approach, rather than apply the original BWM. We provide additional detail in graphical representations of the difference in original BWM and hybrid approach

Table 8 Global weight of criteria considering both risk-averse and risk-taking approach

Tourism centres	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}
Urmia (A_1)	0.229	0.183	0.135	0.033	0.033	0.034	0.101	0.038	0.051	0.011	0.007	0.029
Ardabil (A_2)	0.229	0.228	0.090	0.033	0.033	0.034	0.101	0.052	0.019	0.011	0.024	0.029
Karaj (A_3)	0.229	0.183	0.135	0.033	0.033	0.034	0.101	0.052	0.019	0.011	0.024	0.029
Ilam (A_4)	0.386	0.075	0.086	0.115	0.115	0.034	0.019	0.019	0.051	0.011	0.028	0.026
Bushehr(A_5)	0.337	0.075	0.135	0.033	0.033	0.116	0.019	0.019	0.048	0.011	0.028	0.029
Shahrekord (A_6)	0.229	0.228	0.090	0.033	0.033	0.034	0.101	0.019	0.048	0.011	0.028	0.029
Birjand (A_7)	0.229	0.228	0.090	0.033	0.033	0.034	0.101	0.041	0.051	0.011	0.028	0.004
Bojnurd (A_8)	0.337	0.075	0.135	0.033	0.033	0.034	0.101	0.019	0.048	0.011	0.028	0.029
Ahvaz (A_9)	0.337	0.075	0.135	0.033	0.033	0.034	0.101	0.019	0.031	0.050	0.007	0.029
Zanjan (A_{10})	0.278	0.228	0.041	0.033	0.033	0.034	0.101	0.038	0.051	0.011	0.007	0.029
Semnan (A_{11})	0.386	0.120	0.041	0.033	0.033	0.034	0.101	0.041	0.051	0.011	0.028	0.004
Zahedn (A_{12})	0.278	0.228	0.041	0.033	0.033	0.034	0.101	0.019	0.070	0.011	0.007	0.029
Qazvin (A_{13})	0.229	0.228	0.090	0.033	0.033	0.034	0.101	0.038	0.051	0.011	0.007	0.029
Qom (A_{14})	0.229	0.183	0.135	0.033	0.033	0.034	0.101	0.052	0.015	0.011	0.028	0.029
Sanandaj (A_{15})	0.337	0.075	0.135	0.033	0.033	0.034	0.101	0.038	0.051	0.011	0.007	0.029
Kerman (A_{16})	0.386	0.075	0.086	0.033	0.033	0.034	0.101	0.019	0.019	0.040	0.028	0.029
Kermanshah (A_{17})	0.229	0.228	0.090	0.033	0.033	0.034	0.101	0.052	0.037	0.011	0.007	0.029
Yasuj (A_{18})	0.337	0.075	0.135	0.033	0.033	0.034	0.101	0.048	0.019	0.011	0.028	0.029
Gorgan (A_{19})	0.229	0.183	0.135	0.033	0.033	0.034	0.101	0.052	0.019	0.011	0.024	0.029
Rasht (A_{20})	0.229	0.183	0.135	0.041	0.041	0.126	0.109	0.052	0.019	0.011	0.024	0.029
Khorramabad (A_{21})	0.229	0.183	0.135	0.033	0.033	0.034	0.101	0.019	0.048	0.011	0.028	0.029
Sari (A_{22})	0.337	0.075	0.135	0.041	0.041	0.126	0.109	0.038	0.051	0.011	0.007	0.029
Arak (A_{23})	0.229	0.183	0.135	0.033	0.033	0.034	0.101	0.038	0.051	0.011	0.007	0.029
Bandar Abbas (A_{24})	0.386	0.120	0.041	0.033	0.033	0.034	0.101	0.019	0.048	0.011	0.028	0.029
Hamadan (A_{25})	0.229	0.228	0.090	0.033	0.033	0.116	0.019	0.038	0.051	0.011	0.007	0.029
Yazd (A_{26})	0.229	0.228	0.090	0.033	0.033	0.034	0.101	0.052	0.019	0.011	0.024	0.029

scores, captured as ranks across primary dimensions, in Figs. 2 and 3, and 4. Specifically, we consider the decision-maker's risk-taking behavior in the *tourist attraction* dimension (Fig. 2) and risk-averse behavior in the *infrastructure* and *healthcare* dimensions (Figs. 3 and 4). To illustrate, taking the A_{11} and A_{16} example, we can see that the swap in overall rank can be attributed to A_{11}'s lower performance in dimensions in which decision-makers adopt a risk-averse behavior (*infrastructure* and *healthcare*), despite A_{16}'s lower performance in the remaining *tourist attraction* dimension, which holds higher importance and in which decision-makers adopt a risk-taking behavior. Similarly, in the A_{13} and A_{21} example, A_{21}'s higher performance in the *healthcare* dimension drives the rank improvement, despite the dimension holding least importance and A_{21}'s comparatively larger drop in performance in the *tourist attraction* and *infrastructure* dimensions.

5.7 Clustering for Policymaking on Tourism-Related Businesses' Activity

During the pandemic, the Iranian government grouped businesses into three, four, or five clusters, by level of sensitivity or similarity, for policymaking action. Accordingly, we clustered tourism centers using the hybrid approach results presented in column 2, Table 9 as input of a K-Means algorithm, and clustered for $k = 3$, $k = 4$, and $k = 5$, where k denotes the number of clusters to be identified by the algorithm. To validate the meaningfulness of the clustering, we used an ANOVA test, confirming all three clustering states as statistically significant. Clustering results are presented in Table 10, with numbers 1 to 5 representing the cluster which a particular tourism center belongs to. These may be used for prioritizing the activity of tourist centers in future disease outbreak scenarios, following a chosen clustering state.

6 Conclusion and Suggestions

The recent pandemic and associated restrictions have driven the tourism industry down to a halt and generated significant economic losses. As such, finding a way to both keep the tourism industry alive during and reviving its activity post-pandemics appears to be an important challenge facing governments. For this purpose, we have tried to prioritize tourist centers' activity with regard to strict restriction policies using a decision tree of criteria categorized into *tourist attractions*, *infrastructure*, and *healthcare* dimensions.

The hybrid risk-averse and risk-taking best-worst method approach was applied to calculate the optimal weight of criteria, then utilized to rank cities with tourism development potential within the context of Iran. The results of this research suggest *tourist attractions* as the most important of the three dimensions, as well as the *popular attractions*, *general services* and *drugstore accessibility* criterion from *tourist attractions*, *infrastructure* and *healthcare* dimensions respectively, as the most important criteria in the evaluation process. Considering optimal weights of criteria and the score of candidate cities (tourist centers) across the criteria, Semnan (A_{11}), Kerman (A_{16}) and Zahedan (A_{12}) are ranked as top three cities to reduce strict activity restricting policies in under pandemic conditions.

Table 9 Ranking result of both risk-averse and risk-taking approach and original BWM

Alternatives	Hybrid approach (risk-averse and risk-taking)		Original BWM	
	Overall score	Rank	Overall score	Rank
A_1	0.375	6	0.385	7
A_2	0.186	20	0.229	18
A_3	0.288	9	0.336	9
A_4	0.121	26	0.150	26
A_5	0.150	25	0.164	25
A_6	0.193	17	0.266	15
A_7	0.184	21	0.202	20
A_8	0.231	14	0.312	11
A_9	0.350	8	0.354	8
A_{10}	0.251	11	0.312	12
A_{11}	0.522	1	0.510	2
A_{12}	0.481	3	0.465	3
A_{13}	0.193	18	0.256	16
A_{14}	0.172	22	0.184	23
A_{15}	0.164	23	0.180	24
A_{16}	0.499	2	0.512	1
A_{17}	0.240	13	0.280	14
A_{18}	0.154	24	0.185	22
A_{19}	0.189	19	0.193	21
A_{20}	0.269	10	0.329	10
A_{21}	0.195	16	0.228	19
A_{22}	0.373	7	0.425	5
A_{23}	0.205	15	0.244	17
A_{24}	0.407	5	0.405	6
A_{25}	0.240	12	0.282	13
A_{26}	0.410	4	0.436	4

The sensitivity analysis on the results of the hybrid approach when compared with the original best-worst method indicated that the hybrid approach leads to more reliable multi-criteria decision-making problem results. Following the output of the multicriteria analysis and the policies adopted in Iran at the time of COVID-19, we clustered the tourism centres into 3, 4, and 5 categories using the K-Means algorithm, to generate insights for future use by governments.

By integrating both risk-averse and risk-taking attitudes, the approach offers a nuanced understanding of decision-making processes in complex scenarios, aiding policymakers, public officials, and scholars alike. Through this methodology, decision-makers can make more informed choices that balance potential risks and rewards across multiple dimensions, enabling more effective resource allocation, resilience planning, and crisis mitigation strategies. For instance, in the context of urban development, city planners may need to decide on infrastructure investments where they

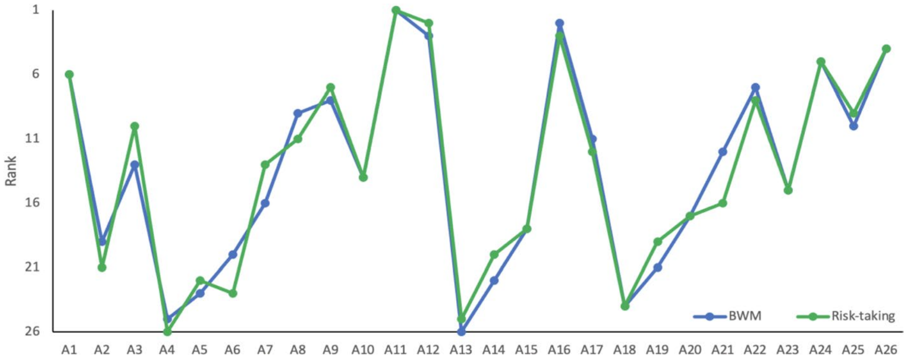

Fig. 2 City *tourist attractions* dimension ranks across original and and risk-taking BWM

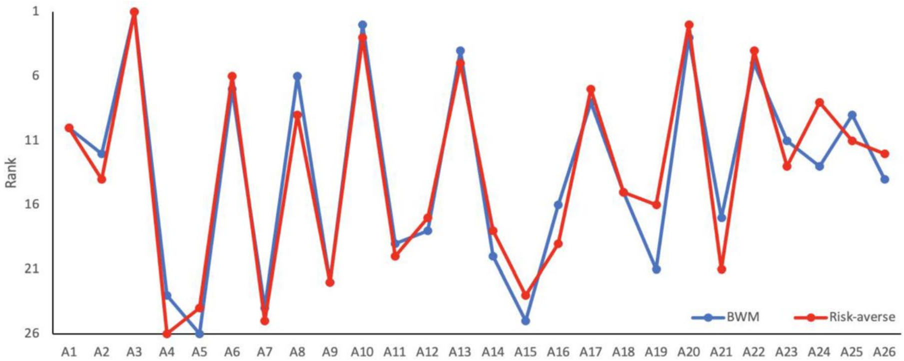

Fig. 3 City *infrastructure* dimension ranks across original and risk-averse BWM

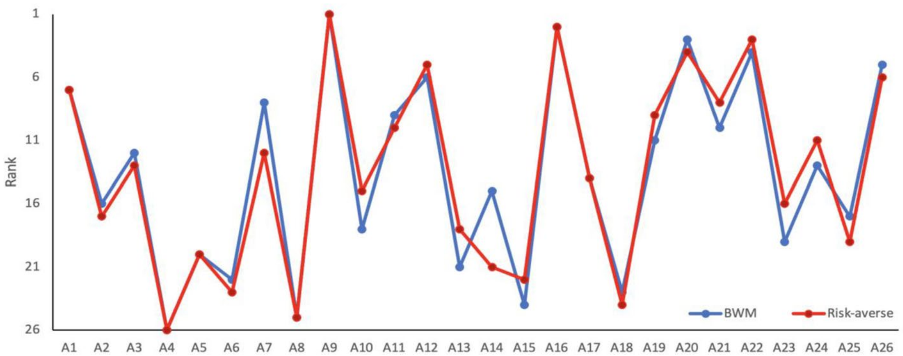

Fig. 4 City *healthcare* dimension ranks across original and risk-averse BWM

Table 10 The results of clustering tourist places based on the output of the hybrid approach

Tourism centers	Prioritizing tourism centers		
	$\boldsymbol{k}=3$	$\boldsymbol{k}=4$	$\boldsymbol{k}=5$
A_{11}	1	1	1
A_{16}	1	1	1
A_{12}	1	1	1
A_{26}	2	2	2
A_{24}	2	2	2
A_{1}	2	2	3
A_{22}	2	2	3
A_{9}	2	2	3
A_{3}	2	3	4
A_{20}	3	3	4
A_{10}	3	3	4
A_{25}	3	3	4
A_{17}	3	3	4
A_{8}	3	3	4
A_{23}	3	4	5
A_{21}	3	4	5
A_{6}	3	4	5
A_{13}	3	4	5
A_{19}	3	4	5
A_{2}	3	4	5
A_{7}	3	4	5
A_{14}	3	4	5
A_{15}	3	4	5
A_{18}	3	4	5
A_{5}	3	4	5
A_{4}	3	4	5

must consider both the potential for high returns on investment in certain areas (risk-taking) while also minimizing potential risks such as environmental hazards or social unrest (risk-averse). This model provides a structured framework to weigh these factors comprehensively. For policymakers, it provides actionable insights to formulate robust policies and allocate resources efficiently to mitigate socio-economic impacts during crises. Moreover, scholars benefit from addressing research gaps and advancing decision-making frameworks, fostering interdisciplinary collaboration and innovation. Ultimately, this methodology enhances decision-making efficacy, supporting public safety, economic stability, and long-term strategic planning.

By incorporating both risk-averse and risk-taking attitudes, the approach offers a nuanced comprehension of decision-making processes in intricate scenarios, benefiting policymakers, public officials, and academics. Through this method, decision-makers can make more informed decisions that balance potential risks and rewards across various dimensions, facilitating more effective resource allocation, resilience planning, and crisis mitigation strategies. For example, in urban development, city planners might need to decide on infrastructure investments where they must consider both the potential for high returns on investment in certain areas (risk-taking) while also minimizing potential risks such as environmental hazards or social unrest (risk-averse). This model provides a structured framework to comprehensively assess these factors. For policymakers, it offers actionable insights to craft robust policies and allocate resources efficiently to mitigate socio-economic impacts during crises. Furthermore, scholars benefit from addressing research gaps and advancing decision-making frameworks, fostering interdisciplinary collaboration and innovation. Ultimately, this methodology enhances decision-making efficacy, supporting public safety, economic stability, and long-term strategic planning.

Both the framework and methodology presented in this research have the following implications for practitioners and scholars: Public policymakers can use the framework to (i) increase the population's awareness of the importance of identified dimensions in disease outbreaks, (ii) support their decisions regarding tourism investment policies, and (iii) prioritize the strategies to deal with disease outbreaks. Moreover, using both risk-averse and risk-taking approaches in concomitance facilitates objectivity of decision-making for risk-sensitive problems, and may be used in other scenarios, including location selection for military centers or nuclear power plants. On the other hand, scholars can use the framework to (i) clarify, better capture and evaluate tourism industry requirements, and (ii) evaluate strategies of- tourist centers, both of which are potential topics for future research.

There are some limitations associated with this research. First, the framework proposed was limited to the city level. Evaluations beyond (e.g., regional, national) and below this level (e.g., city districts) would probably have to address concerns which have not been addressed. Second, this study did not clearly define the geographical boundary which constituted the tourism centers. We suggest that combining the proposed method with a geographical information system (GIS) would improve and clarify policymaking recommendations which may result from future, similar studies. Finally, designing a road map based on the dimensions and criteria presented, which can facilitate the process of relaxing pandemic restrictions, may be considered a potential topic for future research.

Declarations

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

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