ISSN: 2029-4913 / eISSN: 2029-4921

TECHNOLOGICAL and ECONOMIC DEVELOPMENT of ECONOMY

2024
Volume 30
Issue 4
Pages 1064–1086
https://doi.org/10.3846/tede.2024.20821

INVESTIGATING THE EFFECTS OF COVID-19 ON TOURISM IN THE G7 COUNTRIES

Hossein KOMASI[1], Alireza NEMATI[2], Sarfaraz HASHEMKHANI ZOLFANI[1,3]✉,
Nigel L WILLIAMS[3], Ramin BAZRAFSHAN[2]

[1] *School of Engineering, Universidad Catolica del Norte, Larrondo 1281, Coquimbo, Chile*
[2] *Department of Industrial Engineering and Management Systems, Amirkabir University of Technology (Tehran Polytechnic), Tehran 15875-4413, Iran*
[3] *Faculty of Business and Law, University of Portsmouth, Portsmouth, UK*

Article History:
- received 20 September 2023
- accepted 19 December 2023

Abstract. Natural and human-made crises can significantly impact the development of countries' tourism industries. The susceptibility of countries to these crises depends on their policies, planning, and management in facing diverse challenges. This article aims to investigate the effects of the COVID-19 pandemic on the tourism industry in G7 countries by comparing rankings and positions on indices in 2016 and 2020. Data collected from the RANking COMparison (RANCOM), Proximity Indexed Value (PIV), and Double Normalization Compromise Ranking of Alternatives from Distance to Ideal Solution (DNCRADIS) models have been utilized for data analysis. The research findings indicate noticeable differences in using different models, as the rankings and positions of G7 countries for the years 2016 and 2020, except for two countries, the United States and France, have been different. The research results demonstrate that the COVID-19 crisis had significant impacts on the tourism industries of G7 countries. Countries like the United States, France, and the United Kingdom appear as leading nations in the tourism industry, while Japan and Canada faced challenges, and Germany and Italy experienced changes in their positions. Based on these results, officials and planners in the tourism industry of G7 countries can make appropriate decisions for the development and improvement of tourism under similar crisis conditions. Moreover, these findings can serve as a valuable guide for other countries in managing similar crises in the tourism industry.

Keywords: tourism, COVID-19, G7 countries, RANking COMparison (RANCOM), Proximity Indexed Value (PIV), Double Normalization Compromise Ranking of Alternatives from Distance to Ideal Solution (DNCRADIS).

JEL Classification: Z3, C6, F6.

✉Corresponding author. E-mail: ***sa.hashemkhani@gmail.com***

1. Introduction

Tourism development is affected by a variety of economic (Sahoo et al., 2022; Febryano et al., 2022), socio-cultural (Ji et al., 2023), and environmental (Yuedi et al., 2023) variables. On the other hand, it also influences these elements (Macdonald et al., 2023; Rahmawati et al., 2023). In addition to natural events like floods and earthquakes, human activities have also had a significant effect on the development of tourism. The spread of COVID-19 has been one of the most significant recent influences on almost all spheres of the economy, including social, cultural, and political spheres, have been affected by COVID-19 (Alves et al., 2023; Liu et al., 2023; Akhter Shareef et al., 2023) and as a result of the introduction of regulations like remaining at home, time limits, and border closures; lifestyles suffered significant adjustments (Georgeades & Flynn-Obrien, 2023; Goh, 2021). The tourist industry was one of the major sectors that COVID-19 most negatively impacted (Komasi et al., 2022). Governments attempted to get back to their economies as soon as possible when the intensity of the COVID-19 outbreak lessened (Takyi et al., 2023; Sharma et al., 2021). In order to speed up the process of reviving the tourist industry, governments attempted to promote both local and overseas travel (Wickramasinghe & Naranpanawa, 2023). The G7 nations-Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States, are categorized as developed nations by the International Monetary Fund (IMF) and the World Bank (Fernández-Rodriguez et al., 2023; Rungmaitree et al., 2022; Ghosh et al., 2022). The COVID-19 pandemic may have changed their rankings on tourism indicators.

The economic impacts of COVID-19 on G7 countries have been substantial. For instance, the (Total outbound tourism expenditure, disaggregated by Travel (US$ Millions)) indicator for Canada in 2016 was approximately 32,712 million dollars. However, this indicator decreased to 12,078 million dollars in 2020. Similarly, the (Total inbound tourism expenditure, disaggregated by Travel (US$ Millions)) indicator for Japan in 2016 was around 30,752 million dollars, but it decreased to 10,598 million dollars in 2020. Using the Multiple Criteria Decision Making (MCDM) approach, it is possible to determine which of the G7 countries has experienced the greatest economic impacts in the tourism sector due to COVID-19. Through this analysis and by benchmarking successful countries – those that have experienced the least impact – planners and policymakers can effectively manage similar crises in the future.

The key contribution of this paper is to demonstrate how Multi Criteria Decision Making (MCDM) can be used to generate insights into Tourism phenomena from secondary data. MCDM is gaining increasing prominence in Tourism and Hospitality research (Vatankhah et al., 2023). Using UNWTO data, this paper extends applications of MCDM by introducing a novel integrated multi-criteria decision-making model. The model evaluates the effects of Covid-19 on tourism in the G7 by comparing indicators in 2016 and 2020.

Almost with the occurrence of COVID-19, numerous research studies were conducted within academic forums regarding the effects of COVID-19 on various economic sectors, particularly in the tourism industry. Many studies have been carried out on G7 countries in this regard. However, in terms of comparing the susceptibility of G7 countries to the effects of COVID-19, especially in the tourism sector, comprehensive studies comparing their susceptibility to impacts with other countries have not been conducted. This study is dedicated to the comparative assessment of G7 countries regarding their susceptibility to the effects of COVID-19 in the tourism sector.

The rest of the paper is organized as follows. In section 2, The literature on how the MCDM method has been applied to tourism is reviewed. In section 3, materials and data for use for this research are presented. In section 4, a methodology that is used in this research is discussed. In section 5, the results will be provided. In section 6, sensitivity analysis is performed. Section 7 evaluates tourism rankings among the G7 countries based on the PIV and DNCRADIS models. In section 8, the results and decisions will be concluded.

2. Literature review

Since late 2019, Covid-19 has caused disruptions in the global tourism business, particularly in urban regions (Liu, 2023). The World Travel and Tourism Council (2021) estimates that the loss of 62 million tourism jobs- or 18.5% of all employment in the tourism and hospitality industries- was led by COVID-19 (Seyitoglu et al., 2022). The scientific and academic community has been trying to evaluate the impact of COVID-19 on economic, social, and environmental issues in addition to providing methods to lessen these effects almost since the start of COVID-19 (Sharifi & Khavarian-Garmsir, 2020). The conceptual model of the present study is shown in Figure 1 in accordance with the context of the research while considering the available data.

MCDM approaches have been applied to examine tourism phenomena and outcomes. Satpathy and Mahalik (2010) used AHP for selecting spiritual tourism destinations in India. Huang and Peng (2012) combined TOPSIS with the Fuzzy Rasch model to evaluate destination competitiveness in: China, Hong Kong, Japan, Korea, Malaysia, Singapore, Taiwan, Thailand and the Philippines using six criteria and 15 indexes. Liu et al. (2012) modelled the improvement strategy that should be pursued as part of tourism policy implementation in Taiwan using DEMATEL-based analytic network process (DANP) to obtain the weight of each

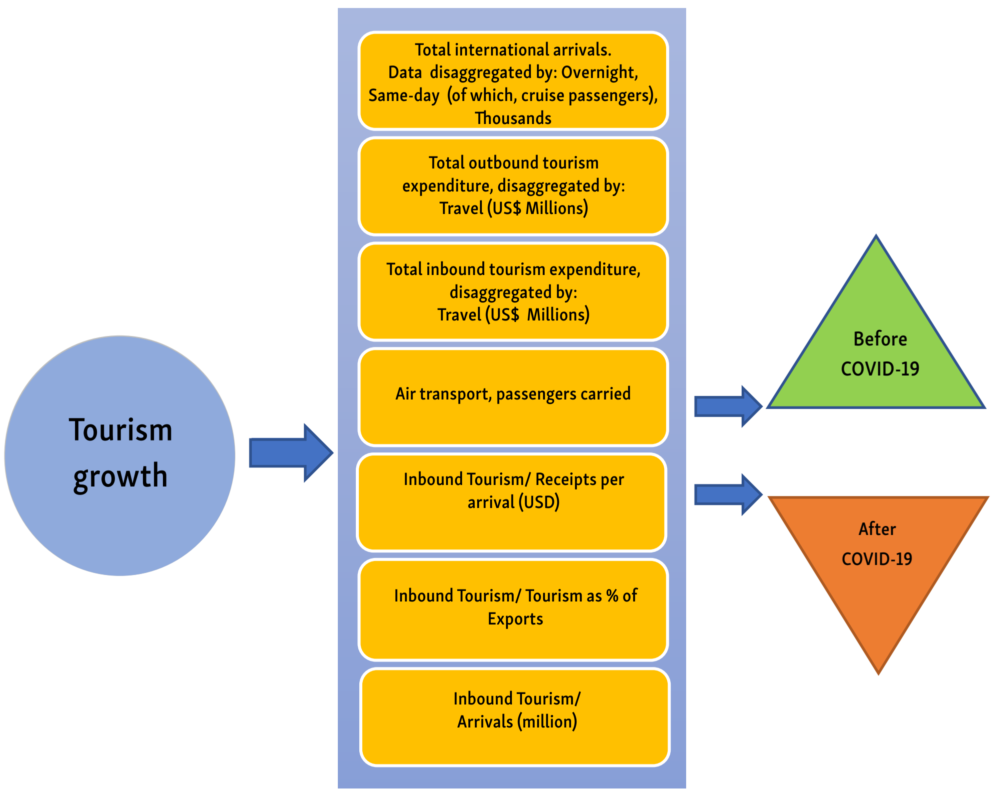

Figure 1. Conceptual model of research

criterion and achieve the desired level of tourism policy implementation by VIKOR, based on network relation map (NRM) from decision-making trial and evaluation laboratory (DEMATEL) technique. Among many criteria, Göksu and Kaya (2014) extract the main criteria that affect tourists visiting Bosnia and Herzegovina and rank the most popular destination for tourists. Due to the ambiguity of data, they used Fuzzy AHP for weighting criteria and TOPSIS for ranking. Jafari-Moghadam et al. (2017) proposed a model for entrepreneurship tourism policy and used DEMATEL-based ANP to calculate the weights of policy criteria. Niavis and Tsiotas (2019) assessed the comparative tourism performance of Mediterranean coastal destinations. The results of the analysis provide some useful implications in the field of destinations' benchmarking theory as well as practical insights for decision-makers. In theoretical terms, this paper used a multi-dimensional DEA approach describing a combined efficiency and effectiveness consideration. The efficiency component was expressed by two DEA models (CRS and VRS), consisting of capacity and demand configuration, whereas the effectiveness component was expressed by a DEA (VRS) model incorporating five tourism dimensions. An aggregated indicator (2effI) was introduced for the joint efficiency and effectiveness consideration, and all the available variables were included in a further parametric and non-parametric analysis. The proposed framework of the present paper is capable of assessing more dimensions of the competitiveness concept than the previous frontier methods applications, which mostly concentrated only on the efficiency of destinations. Therefore, the major achievement of the paper is to pave the way for the wider incorporation of frontier methods towards the holistic evaluation of destinations' performance. Yang et al. (2020) studied the mutual relationship between sport and tourism. They implemented two-stage MCDM models by Bayesian BWM and rough DEMATEL and evaluated the related criteria. Abellana et al. (2021) used a hybrid support vector regression-seasonal autoregressive integrated moving averages model (PROMETHEE II) to forecast tourism demand due to its capability to handle the data's linear, nonlinear and seasonal components. Liu et al. (2021) MCDM of four dimensions and 21 criteria by experts used to create a network-relationship map of the night marketing tourism brand equity development model. Jena and Dwivedi (2021) used DEMATEL to analyse the interrelationship between different barriers that affect rural tourism growth in India. Škrinjarić (2021) evaluated sustainable tourism in European countries and, for showing the robustness of these evaluations, used the MCDM approach MOORA and Multi-MOORA. Dina and Juniarta (2022) employed VIKOR to identify criteria and rank the hotel based on users' reviews. Nuriyev (2022), to select development sites for tourists in Azerbaijan, implemented Fuzzy Z-information-based TOPSIS and PROMETHEE methods. Mohammed et al. (2023) used a decision modeling approach for smart E-Tourism data management applications based on a Spherical fuzzy rough sets environment (SFR-WZIC and SFR-DOSM). Zorlu and Dede (2023), by CRITIC and PROMETHEE-GAIA approaches, determined the NBT potentials and NBT competitiveness difference between the three lakes. Vatankhah et al. (2023) systematically assessed the MCDM method to solve hospitality and tourist problems. Following this, these studies that have used the Multiple Criteria Decision Making (MCDM) model methodology are introduced in Table 1.

Table 1. Some of the studies that have used the Multiple Criteria Decision Making (MCDM) model

Author	Year	MCDM methods	Cause of Implementation
Satpathy and Mahalik	2010	AHP	Selecting spiritual tourism destinations in India
Huang and Peng	2012	TOPSIS with the Fuzzy Rasch model	Evaluation of destination competitiveness in China, Hong Kong, Japan, Korea, Malaysia, Singapore, Taiwan, Thailand and the Philippines
Liu et al.	2012	DEMATEL-based analytic network process (DANP)	Defining improvement strategies that should be pursued as part of tourism policy implementation in Taiwan
Göksu and Kaya	2014	Fuzzy AHP and TOPSIS	Ranking the most popular destination for tourists in Bosnia and Herzegovina
Jafari-Moghadam et al.	2017	DEMATEL-based ANP	Proposing a model for entrepreneurship tourism policy
Niavis and Tsiotas	2019	multi-dimensional DEA approach	Assessing the comparative tourism performance of the Mediterranean coastal destinations
Abellana et al.	2021	PROMETHEE II	Forecast tourism demand
Yang et al.	2020	Bayesian BWM and rough DEMATEL	Determining the mutual relationship between sport and tourism
Škrinjari	2021	MOORA and Multi-MOORA	Evaluation of sustainable tourism in European countries
Liu et al.	2021	DEMATEL-based ANP	To create a network-relationship map of the night marketing tourism brand equity development model
Jena and Dwivedi	2021	The integration of ISM and DEMATEL	Analyse the interrelationship between different barriers that affect rural tourism growth in India
Dina and Juniarta	2022	VIKOR	Rank the hotel based on users' reviews
Nuriyev	2022	TOPSIS and PROMETHEE	Selection development sites for tourists in Azerbaijan
Ocampo	2022	Fuzzy FUCOM & Fuzzy WSM	Evaluating the sustainability of farm tourism sites
Mohammed et al.	2023	Spherical fuzzy rough sets environment (SFR-WZIC and SFR-DOSM)	Decision modeling approach for smart E-Tourism data management applications
Zorlu and Dede	2023	CRITIC and PROMETHEE-GAIA approaches	Determining the NBT potentials and NBT competitiveness difference between three lakes
Vatankhah et al.	2023	Systematically assess the use of Multi-criteria decision-making techniques	Solve hospitality and tourism (H&T) problems while minimizing the risk of failure
Wang and Fu	2023	F-AHP & radial basis function neural network	Regional tourism performance evaluation

3. Materials and data

The evaluation of tourism might use a variety of indicators. Seven indicators have been used to examine the situation of tourists in these nations for the years 2016 and 2020 due to the lack of data for all G7 nations Table 2. The reason for selecting these two years was also due to the fact that for the year 2016, the highest indices were available for G7 countries compared to 2017, 2018, and 2015. By comparing this period with the year 2020 – when COVID-19 had virtually involved almost all countries worldwide – the possibility of comparing the impacts of COVID-19 on the tourism of G7 countries has been feasible.

Table 2. The G4 countries' tourist status according to the indicators examined (source: United Nations World Tourism Organization [UNWTO], 2023)

G7 Countries	Indicators							
	Total international arrivals. Data disaggregated by: Overnight, Same-day (of which, cruise passengers), Thousands		Total outbound tourism expenditure, disaggregated by: Travel, (US$ Millions)		Total inbound tourism expenditure, disaggregated by: Travel (US$ Millions)		Air transport, passengers carried	
	2016	2020	2016	2020	2016	2020	2016	2020
Canada	30142	5068	32712	12078	22676	13535	8540642400	2762000000
France	203042	117109	40436	27758	55338	32646	6536274400	2495634400
Germany	35555	12449	79923	38752	37476	22068	11671358400	2575845000
Italy	84925	38419	24987	10871	40381	19895	2912004000	780149000
Japan	24039	4116	18562	5448	30752	10598	11770800000	5113112000
United Kingdom	39129	11101	67124	21743	49257	18944	14378171200	3096752000
United States	175261	44792	109156	34159	192866	72483	82403897600	36950099200
G7 Countries	Inbound Tourism/ Receipts per arrival (USD)		Inbound Tourism/ Tourism as % of Exports		Inbound Tourism/ Arrivals (million)			
Canada	1132	4589	4.7	2.8%	19.97	2.96		
France	667	781	8.3	4.8%	82.70	41.70		
Germany	1179	2031	3.2	1.3%	31.76	10.89		
Italy	768	786	7.5	3.5%	52.37	25.19		
Japan	1276	2600	4.1	1.4%	24.04	4.12		
United Kingdom	1421	2398	6.8	3.4%	37.36	11.10		
United States	2524	3773	10.2	3.9%	76.41	19.21		

4. Methodology

This module introduces a novel integrated multi-criteria decision-making model to evaluate the effects of Covid-19 on tourism in the G7 countries from 2016 to 2020. First, according to experts' statements, RANCOM has been utilized to obtain the criteria weights. In the second step, a modified version of DNCRADIS is introduced and used along with PIV to prioritize the alternatives according to research criteria. Figure 2 shows the methodology procedure.

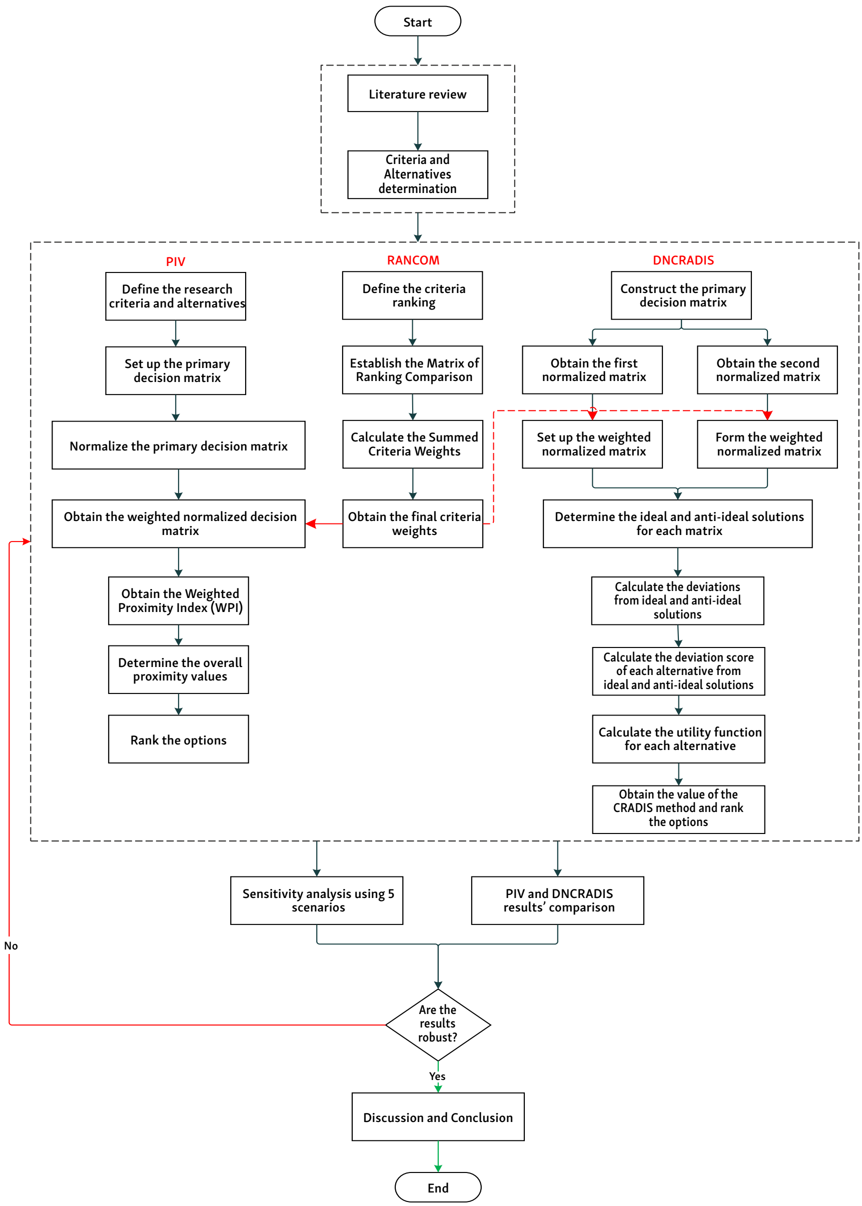

Figure 2. Research methodology process

4.1. RANCOM

Experts based on deep knowledge and skills in their specific fields always attempt to make precise decisions. However, in complex problems such as Multi-criteria decision making, it may cause hesitance for experts to determine the relevance of criteria to each other (especially in pair-wise methods). In this regard, some researchers proposed an approach to handle experts' hesitance effectively. Więckowski et al. (2023) introduced RANCOM and showed that even for a small hesitance, this method is reliable. Its operation is based on defining the criteria ranking order to obtain the weights vector. Therefore, it provides accurate results based on experts' opinions. Considering this, this project implements this approach, and in continuing these steps are presented.

Step 1. Define the criteria ranking

In this step, the following procedures are implemented:

- Establish the ranking of criteria
- Score the criteria
- Order criteria using sorting algorithm
- Use the tournament method.

Step 2. Construct the Matrix of Ranking Comparision (MAC)

The MAC is determined by pair-wise comparison, and then the result is demonstrated by A_{ij} as follows:

$$a_{ij} = \begin{Bmatrix} \text{If} & f(C_i) < f(C_j) & \text{then } 1 \\ \text{If} & f(C_i) = f(C_j) & \text{then } 0.5 \\ \text{If} & f(C_i) > f(C_j) & \text{then } 0 \end{Bmatrix}. \tag{1}$$

Step 3. Calculate the Summed Criteria Weight (SCW)

The SCW is obtained by

$$SCW_i = \sum_{j=1}^{n} a_{ij}. \tag{2}$$

Step 4. Calculate the Final Criteria Weight

The value of preference for each criterion is calculated as follows:

$$w_i = \frac{SCW_i}{\sum_{i=1}^{n} SCW_i}. \tag{3}$$

4.2. PIV

Adding or deleting an alternative to existing alternatives changes the rank of alternatives. This phenomenon occurs because of the normalization process, which is used in all decision-making problems. In literature, researchers say the Rank Reversal phenomenon to mentioned problem. To minimize the rank reversal, this research implements Mufazzal and Muzakkir (2018) method in which they proposed a model based on proximity index value (PIV) for minimizing rank reversal. The steps of this method are as follows:

Step 1. Formulation of the Decision Problem

Defining criteria and alternatives.

Step 2. Construction of the Decision Matrix (DM)

Making a matrix in which each row represents alternatives, and each column shows attributes. The value of the matrix is shown by x_{ij}.

Step 3. Normalization of Data

To bring each value to the same scale, the following formulation (4) is used.

$$r_i = \frac{x_i}{\sqrt{\sum_{i=1}^{m} x_i^2}}. \tag{4}$$

Step 4. Determine the Weight of DM

The weighted normalized value is achieved by (5):

$$v_j = w_j * r_j. \tag{5}$$

Step 5. Evaluation of Weighted Proximity Index (WPI)

In this step, the deviation between each alternative from the best value (benefit attribute) and the worst value (cost attribute). If u_i be weighted proximity index, the WPI (u_i) is calculated by the differences between v_i and best or worst value.

Step 6. Determining of Overall Proximity Value

The overall proximity value (d_i) is equal to the summation of the weighted proximity value corresponding to each criterion.

$$d_i = \sum_{j=1}^{n} u_j. \tag{6}$$

Step 7. Ranking

Considering the least d_i as the best alternative.

4.3. DNCRADIS

There are many methods in the literature for ranking alternatives. As you know, all of these methods need normalization to put data in the same order. However, there are some methods that use double normalization. Puska et al. (2023) declare that the ranking of alternatives is more stable when implementing methods with double normalization than methods with one more time normalization. By this fact, researchers of this article make a decision to use a method for ranking with this property. Among some methods, DNCRADIS is selected because of calculating the deviation from ideal and anti-ideal solutions and calculating the value of alternatives in relation to optimal alternatives. By these properties, the robustness of ranking can be evaluated easily. The steps of this method are as follows:

Step 1. Formation of a decision matrix

In this step, the primary decision matrix based on designated criteria and alternatives is constructed.

Step 2. Normalization of decision matrix

In this approach, a double normalization is used as follows:

$$n_{ij} = \frac{x_{ij}}{x_{j\max}}, \text{ and } n'_{ij} = \frac{x_{j\min}}{x_{ij}}, \text{ for benefit criteria;} \tag{7}$$

$$n_{ij} = \frac{x_{j\min}}{x_{ij}}, \text{ and } n'_{ij} = \frac{x_{ij}}{x_{j\max}}, \text{ for benefit criteria.} \tag{8}$$

Step 3. Weighting the normalized decision matrix

The value of the normalized decision matrix is calculated as follows:

$$v_{ij} = n_{ij} * w_j, \text{ and } v'_{ij} = n'_{ij} * w_j. \tag{9}$$

Step 4. Determination of ideal and anti-ideal solutions

The highest and the lowest value of the weighted decision matrix are ideal and anti-ideal solutions.

$$t_i = \max v_{ij}, \text{ and } t'_i = \max v'_{ij}; \tag{10}$$

$$t_{ai} = \min v_{ij}, \text{ and } t'_{ai} = \min v'_{ij}. \tag{11}$$

Step 5. Calculation of deviation from ideal and anti-ideal solution

The weighted data values are subtracted from max or min values.

$$d^+ = t_i - v_{ij} \text{ and } d'^+ = t'_i - v'_{ij}; \tag{12}$$

$$d^- = v_{ij} - t_{ai} \text{ and } d'^- = v'_{ij} - t'_{ai}. \tag{13}$$

Step 6. Calculation of the deviation score

Deviation values are summed up, and optimal alternatives.

$$S_i^+ = \sum_{j=1}^{n} d^+, \text{ and } S_i'^+ = \sum_{j=1}^{n} d'^+; \tag{14}$$

$$S_i^- = \sum_{j=1}^{n} d^-, \text{ and } S_i'^- = \sum_{j=1}^{n} d'^-. \tag{15}$$

Step 7. Calculate the utility function

Each alternative is compared with optimal alternatives.

$$K_i^+ = \frac{S_0^+}{S_i^+}, \text{ and } K_i'^+ = \frac{S_0'^+}{S_i'^+}; \tag{16}$$

$$K_i^- = \frac{S_0^-}{S_i^-}, \text{ and } K_i'^- = \frac{S_0'^-}{S_i'^-}. \tag{17}$$

S_0^+, and S_0^- is an optimal alternative for ideal and anti-ideal solutions.

Step 8. Calculate the value of CARDIS in relation to utility function

$$Q_i = \frac{K_i^+ + K_i^+}{2}, \text{ and } Q_i = \frac{K_i'^+ + K_i'^+}{2}. \tag{18}$$

Step 9. Final Ranking

It is obtained by dividing Q_i and Q'_i, and the highest value is the best alternative.

5. Results

This section presents the results of our novel integrated MCDM model. First, the criteria weights are calculated using RANCOM, and then research options are evaluated using DN-CRADIS and PIV.

5.1. RANCOM results

Firstly, four experts provided their opinions based on the criteria in Table 1, and then the matrix of comparison was constructed. In the next step, the criteria weights are evaluated. Table 3 shows the comparison matrix and Summed Criteria Weights (SCW) to obtain the final weights of the research criteria.

Table 3. RANCOM results

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	SCW	Weights
C_1	0.5	0.5	1	1	1	1	1	6	0.203389831
C_2	0.5	0.5	1	1	1	1	1	6	0.203389831
C_3	0.5	0	0.5	1	1	1	0	4	0.13559322
C_4	0.5	0	0	0.5	1	0	0	2	0.06779661
C_5	0.5	0	0	1	0.5	0	1	3	0.101694915
C_6	0.5	0	0	1	1	0.5	0.5	3.5	0.118644068
C_7	0.5	0	1	1	1	1	0.5	5	0.169491525

5.2. PIV results

In this sub-section, PIV method results are presented. The PIV procedure is utilized twice to assess alternatives according to available data from 2016 and 2020. In the first step, Table 1 is taken as the primary decision matrix, and then G7 countries are assessed according to research criteria. Table 4 shows the primary decision matrix for 2016.

Table 4. Primary decision matrix for 2016

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
Canada	8540642400	22676	30142	32712	4.7	19.97	1132
France	6536274400	55338	203042	40436	8.3	82.7	667
Germany	11671358400	37476	35555	79923	3.2	31.76	1179
Italy	2912004000	40381	84925	24987	7.5	52.37	768
Japan	11770800000	30752	24039	18562	4.1	24.04	1276
United Kingdom	14378171200	49257	39129	67124	6.8	37.36	1421
United States	82403897600	192866	175261	109156	10.2	76.41	2524

Furthermore, Table 5 presents the weighted normalized decision matrix.

Table 5. Weighted normalized decision matrix for 2016

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
Canada	0.020	0.021	0.014	0.014	0.027	0.017	0.052
France	0.015	0.052	0.095	0.017	0.047	0.072	0.031
Germany	0.028	0.035	0.017	0.033	0.018	0.027	0.054
Italy	0.007	0.038	0.040	0.010	0.042	0.045	0.035
Japan	0.028	0.029	0.011	0.008	0.023	0.021	0.058
United Kingdom	0.034	0.046	0.018	0.028	0.038	0.032	0.065
United States	0.195	0.181	0.082	0.045	0.058	0.066	0.115
Max	0.195	0.181	0.095	0.045	0.058	0.072	0.115

Finally, the G7 countries are ranked according to Table 6 by obtaining weighted proximity indexes and overall proximity values.

Table 6. PIV results for 2016

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	Overall Proximity Value	Rank
Canada	0.175	0.159	0.081	0.032	0.031	0.054	0.064	0.596	7
France	0.179	0.129	0.000	0.029	0.011	0.000	0.085	0.433	2
Germany	0.167	0.146	0.079	0.012	0.040	0.044	0.062	0.549	5
Italy	0.188	0.143	0.055	0.035	0.015	0.026	0.080	0.543	4
Japan	0.167	0.152	0.084	0.038	0.034	0.051	0.057	0.583	6
United Kingdom	0.161	0.134	0.077	0.018	0.019	0.039	0.050	0.499	3
United States	0.000	0.000	0.013	0.000	0.000	0.005	0.000	0.018	1

Moreover, Table 7, Table 8, and Table 9 show the mentioned process for available 2020 data.

Table 7. Primary decision matrix for 2020

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
Canada	2762000000	13535	5068	12078	2.8	2.96	4589
France	2495634400	32646	117109	27758	4.8	41.7	781
Germany	2575845000	22068	12449	38752	1.3	10.89	2031
Italy	780149000	19895	38419	10871	3.5	25.19	786
Japan	5113112000	10598	4116	5448	1.4	4.12	2600
United Kingdom	3096752000	18944	11101	21743	3.4	11.1	2398
United States	36950099200	72483	44792	34159	3.9	19.21	3773

Table 8. Weighted normalized decision matrix for 2020

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
Canada	0.013	0.033	0.006	0.107	0.013	0.033	0.006
France	0.029	0.057	0.090	0.018	0.029	0.057	0.090
Germany	0.041	0.015	0.024	0.047	0.041	0.015	0.024
Italy	0.011	0.042	0.054	0.018	0.011	0.042	0.054
Japan	0.006	0.017	0.009	0.060	0.006	0.017	0.009
United Kingdom	0.023	0.040	0.024	0.056	0.023	0.040	0.024
United States	0.036	0.046	0.042	0.088	0.036	0.046	0.042
Max	0.041	0.057	0.090	0.107	0.041	0.057	0.090

The final results of PIV method for 2020 are shown in Table 9.

Table 9. PIV results for 2020

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	Overall Proximity Value	Rank
Canada	0.028	0.024	0.084	0.000	0.028	0.024	0.084	0.000	5
France	0.011	0.000	0.000	0.089	0.011	0.000	0.000	0.089	2
Germany	0.000	0.042	0.067	0.059	0.000	0.042	0.067	0.059	6
Italy	0.029	0.015	0.036	0.088	0.029	0.015	0.036	0.088	3
Japan	0.035	0.040	0.081	0.046	0.035	0.040	0.081	0.046	7
United Kingdom	0.018	0.017	0.066	0.051	0.018	0.017	0.066	0.051	4
United States	0.005	0.011	0.049	0.019	0.005	0.011	0.049	0.019	1

5.3. DNCRADIS results

In order to assess the G7 countries' tourism industry more accurately, the double normalized CRADIS method is also utilized in this research. Tables 10 and 11 show the DNCRADIS results for G7 countries in 2016 and 2020, respectively.

Table 10. DNCRADIS results for 2016

	S_i^+	K_i^+	S_i^-	K_i^-	$S_i'^+$	$K_i'^+$	$S_i'^-$	$K_i'^-$	Q_i	Q_i'	R_i	Rank
Canada	1.187	1.061	0.187	0.197	0.717	1.758	0.657	0.692	0.629	1.225	0.514	7
France	0.942	1.337	0.431	0.454	0.965	1.305	0.408	0.430	0.895	0.867	1.032	2
Germany	1.125	1.119	0.248	0.261	0.870	1.447	0.503	0.530	0.690	0.989	0.698	4
Italy	1.100	1.145	0.273	0.288	0.782	1.612	0.592	0.623	0.716	1.118	0.641	5
Japan	1.174	1.073	0.200	0.210	0.754	1.672	0.620	0.653	0.642	1.162	0.552	6
United Kingdom	1.052	1.198	0.322	0.339	0.996	1.265	0.377	0.397	0.768	0.831	0.924	3
United States	0.451	2.791	0.922	0.971	1.255	1.004	0.119	0.125	1.881	0.564	3.333	1

Table 11. DNCRADIS results for 2020

	S_i^+	K_i^+	S_i^-	K_i^-	$S_i'^+$	$K_i'^+$	$S_i'^-$	$K_i'^-$	Q_i	Q_i'	R_i	Rank
Canada	1.106	1.185	0.287	0.296	0.872	1.504	0.522	0.538	0.740	1.021	0.725	5
France	0.885	1.481	0.509	0.524	1.071	1.224	0.323	0.333	1.003	0.779	1.288	2
Germany	1.132	1.158	0.262	0.270	1.011	1.296	0.383	0.395	0.714	0.845	0.844	4
Italy	1.125	1.165	0.268	0.277	0.843	1.554	0.550	0.567	0.721	1.061	0.679	6
Japan	1.214	1.079	0.180	0.185	0.755	1.735	0.638	0.658	0.632	1.197	0.528	7
United Kingdom	1.110	1.180	0.283	0.292	1.066	1.230	0.328	0.338	0.736	0.784	0.939	3
United States	0.629	2.085	0.765	0.789	1.279	1.025	0.115	0.118	1.437	0.571	2.515	1

6. Sensitivity analysis

The robustness of the research methodology will be evaluated through two experiments. For PIV and DNCRADIS results, the Pearson correlation coefficient test is utilized first. Then, we applied a sensitivity analysis using five strict scenarios to observe the ranking discrepancies.

6.1. Results comparison

Our research methodology is constructed based on two newly developed MCDM methods, which are PIV and DNCRADIS. Therefore, comparing their results can show the accuracy of G7 countries' tourism evaluation. Figures 3 and 4 show the comparison of the results.

Furthermore, the Pearson correlation coefficient test is implemented to analyze the performance of PIV and DNCRADIS. The results are shown in Tables 12 and 13.

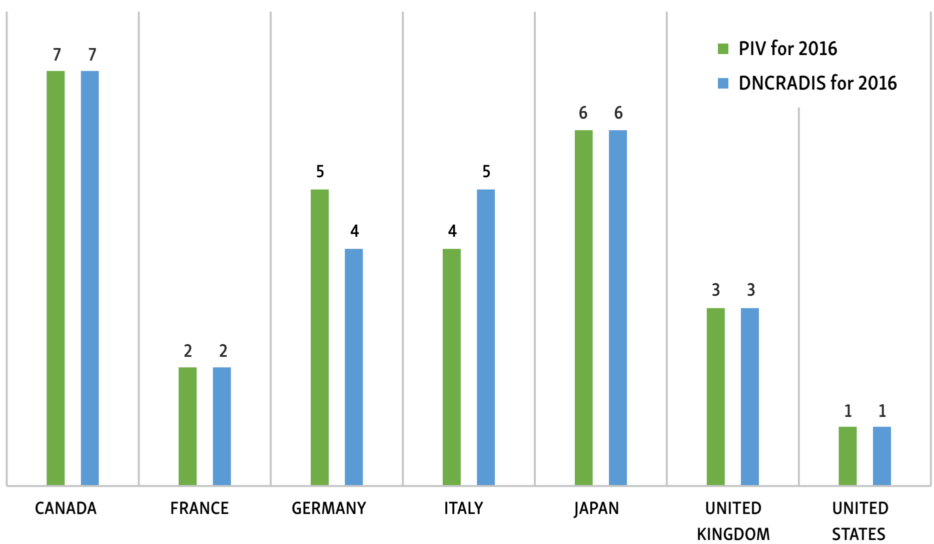

Figure 3. PIV and DNCRADIS results for 2016 data

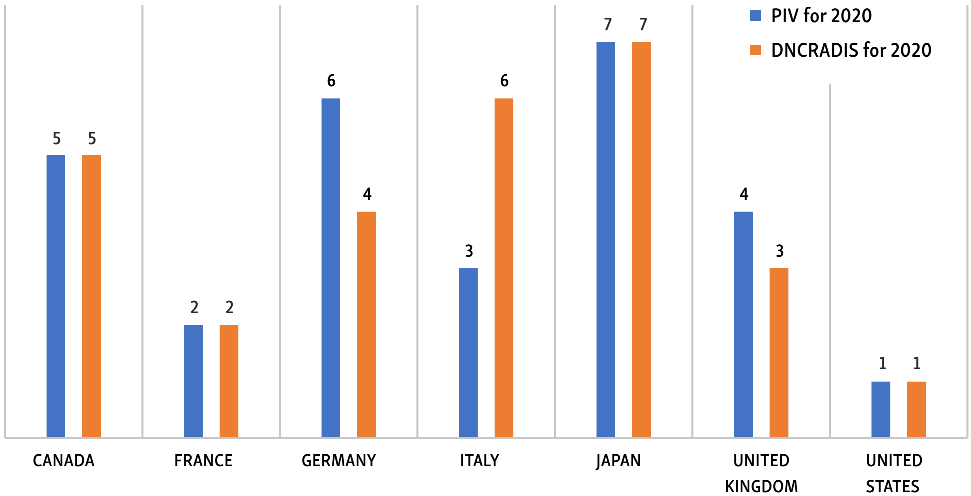

Figure 4. PIV and DNCRADIS results for 2020 data

Table 12. Pearson correlation coefficient test for 2016 data

	DNCRADIS	PIV
DNCRADIS	1	0.964285714
PIV	0.964285714	1

Table 13. Pearson correlation coefficient test for 2020 data

	DNCRADIS	PIV
DNCRADIS	1	0.75
PIV	0.75	1

Pearson correlation coefficient test results indicate that the experimental design is robust and that modified DNCRADIS and PIV produce highly correlated results.

6.2. Scenario implementation

It is unlikely that a model will experience severe fluctuations under changing criteria weights if it is robust enough. Thus, an experiment based on five scenarios is implemented to assess the research methodology's validity. Table 14 shows the implemented scenarios.

Table 14. Sensitivity analysis scenarios

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
Base	0.203	0.203	0.136	0.068	0.102	0.119	0.169
Scenario 1	0.143	0.143	0.143	0.143	0.143	0.143	0.143
Scenario 2	0.2	0.2	0.25	0.2	0.05	0.05	0.05
Scenario 3	0.25	0.2	0.2	0.2	0.05	0.05	0.05
Scenario 4	0.2	0.25	0.2	0.2	0.05	0.05	0.05
Scenario 5	0.05	0.1	0.05	0.05	0.3	0.25	0.2

Moreover, Figures 5 to 8 show the results of scenario implementation.

Scenario implementation shows that our research methodology is valid, and discrepancies in rankings are neglectable. Moreover, the results indicate that PIV is more sensitive than DNCRADIS to changing criteria weights.

7. Discussion

Findings from the comparison of tourism rankings among the G7 countries based on the PIV and DNCRADIS models, as depicted in Figure 3, indicate that in 2016, the rankings of five countries (United States, United Kingdom, Japan, France, and Canada) remained stable out of the total seven G7 nations, while the rankings of two countries (Italy and Germany) varied between the two models. Notably, the United States consistently secured the top position in both models, underscoring its robustness and appeal in attracting tourists. Furthermore,

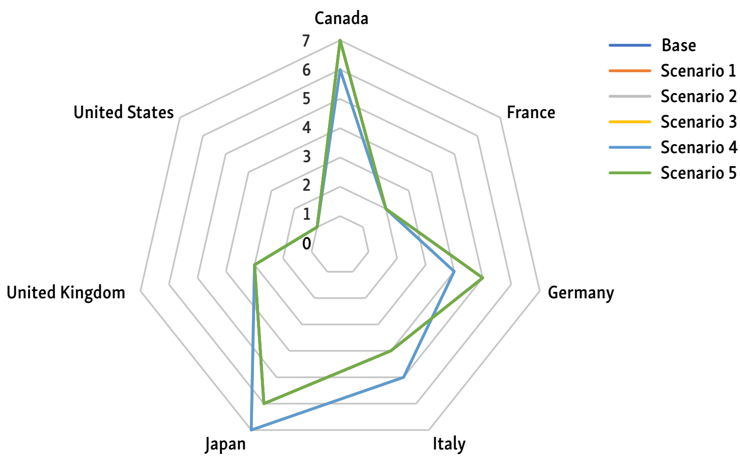

Figure 5. PIV results for implementing scenarios on 2016 data

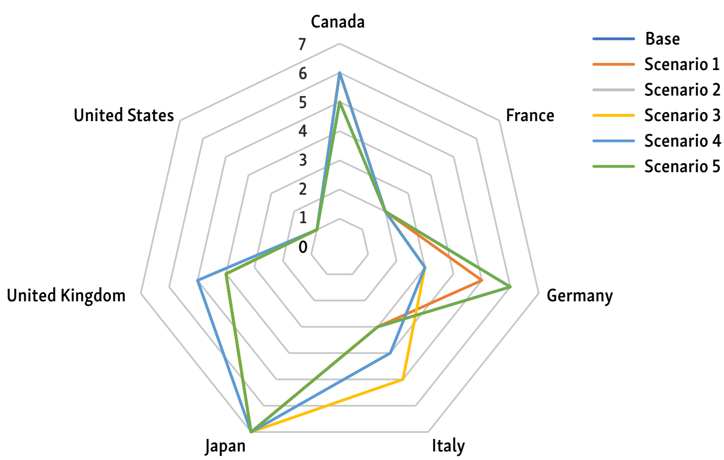

Figure 6. PIV results for implementing scenarios on 2020 data

France and the United Kingdom played significant roles in the tourism industry, holding the second and third positions, respectively, in both models during the studied period, highlighting the significance and allure of their tourist destinations.

Conversely, Japan and Canada faced the lowest tourism rankings among the G7 countries, occupying the sixth and seventh positions in both PIV and DNCRADIS models, respectively. These results underscore the influence of diverse factors on the tourism trends in these countries.

The examination of Germany and Italy's rankings in 2016 reveals divergent positions in both PIV and DNCRADIS models. Germany secured the fourth position in the DNCRADIS model and the fifth position in the PIV model, whereas Italy occupied the fifth position in the DNCRADIS model and the fourth position in the PIV model.

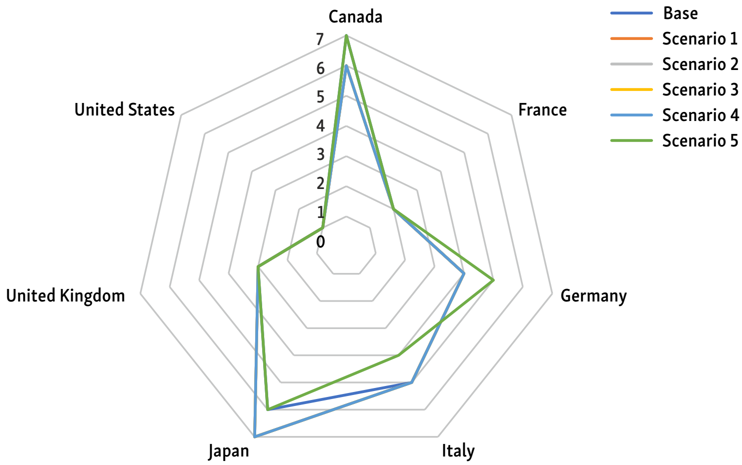

Figure 7. DNCRADIS results for implementing scenarios on 2016 data

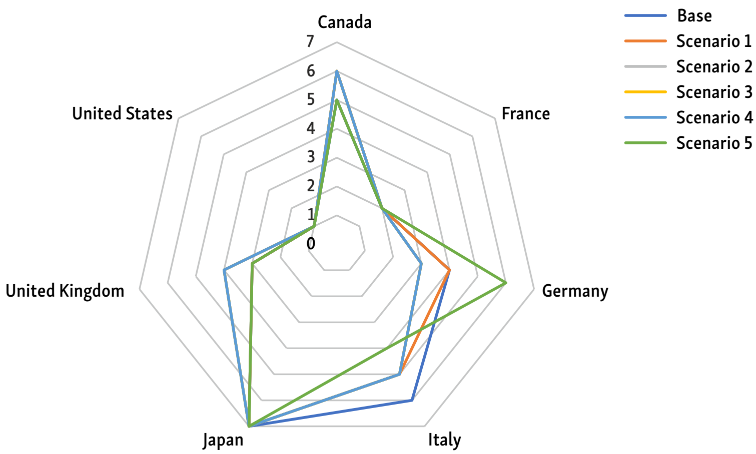

Figure 8. DNCRADIS results for implementing scenarios on 2020 data

The findings from the investigation of the G7 countries' tourism rankings for the year 2020 based on the PIV and DNCRADIS models, as shown in Figure 4, indicate that except for the United States and France, which maintained stable positions in both rankings and results compared to 2016, with the United States in the first position and France in the second position, the other countries (United Kingdom, Japan, Italy, Germany, and Canada) experienced changes either in their rankings or in the results from both models.

In 2020, the United Kingdom, similar to 2016, ranked third based on the DNCRADIS model and fourth based on the PIV model. Canada, on the other hand, secured the fifth position in both models, whereas it was in the seventh position in 2016, based on both models.

Japan also experienced a shift, ranking seventh in 2020 according to both models, while it held the sixth position in 2016 according to both models. The most significant changes were observed in Italy in 2020. Italy ranked third based on the PIV model and sixth based on the DNCRADIS model, in contrast to 2016 when it held the fourth position based on the PIV model and the fifth position based on the DNCRADIS model. The examination of Germany's rankings in 2020 also revealed notable differences, with the country securing the fourth position in the DNCRADIS model and the sixth position in the PIV model. It is worth noting that Germany's ranking remained consistent in both 2016 and 2020, holding the fourth position in both years based on the DNCRADIS model. However, based on the PIV model, Germany ranked fifth in 2016 and sixth in 2020.

Therefore, the study presents valuable insights into the effects of the Covid-19 pandemic on tourism in the G7 countries between 2016 and 2020. The findings highlight the resilience of the United States' tourism industry and the significant roles played by France and the United Kingdom in attracting tourists. Additionally, the research identifies Japan and Canada as facing challenges in their tourism sectors. Moreover, Italy and Germany displayed fluctuations in their rankings, indicating the dynamic nature of tourism trends. The results of this study can guide future researchers and policymakers in developing effective strategies to navigate and mitigate the impacts of crises on the tourism industry.

7.1. Future implications

The COVID-19 pandemic has brought about profound social, economic, and environmental impacts that have reverberated across all sectors of the economy. The tourism industry, too, has not remained exempt from these effects, experiencing a multitude of repercussions. Beyond the direct ramifications on the tourism sector, there have been cascading and indirect impacts on related industries, including transportation, restaurants, retail, and other businesses.

Given the sudden and unanticipated onset of the COVID-19 pandemic, numerous countries faced severe damage and struggled to adapt to the new circumstances. The experience of this crisis and understanding the extent of economic damages suffered by countries, particularly when compared to peer nations, can serve as a pivotal lesson for preparedness in facing future crises within the tourism industry. Furthermore, this experience can facilitate the enhancement of policies and programs pertaining to health and travel security.

Conversely, it became evident for many countries that the tourism industry is not immune and is highly susceptible to both natural and anthropogenic crises. Hence, nations can strengthen other economic sectors alongside the tourism industry to fortify their economic structure against vulnerabilities. By diversifying their economic portfolios, countries can ensure a more resilient economic landscape less susceptible to disruption, particularly during crises such as COVID-19, thereby minimizing the damage incurred.

Another advantage of discerning the extent of COVID-19's impact on tourism lies in the capacity it offers to managers and planners. By understanding the tourism indicators influenced by COVID-19 and precisely identifying affected segments such as hotels, restaurants, and transportation, these stakeholders can amass the ability to manage and strategize for these sectors in the face of analogous crises. Therefore, the optimal course of action for them involves developing an array of diverse scenarios tailored to different situations and conditions. For instance, scenarios outlining alternative occupations to those associated with the tourism sector in the event of a human calamity such as war or disease must be tailored based on the duration of the said human calamity. These scenarios should be structured into short-term, medium-term, and long-term scenarios. This proposition necessitates a deeper study for each of the G7 countries.

7.2. Limitations of the study

Given the subject of the current article, the research limitations include:

- There are numerous indicators available to assess the state of tourism development, but there is insufficient data for all these indicators. The necessary data and information for some countries are comprehensive, but certain countries have not published sufficient data for specific indicators, leading to the exclusion of some important indices.
- In research conducted using MCDM (Multiple Criteria Decision Making), one of the most crucial aspects is assigning weight to the examined indicators. Considering the breadth of the study's constraints, the possibility of experts' weighing the indicators necessitates a significant amount of time and cost.
- Limited studies have been conducted on G7 countries, especially in various sectors of tourism.

8. Conclusions

The level of economic dependence of different countries on the tourism industry can determine their susceptibility to future natural and human-made crises. The higher a country's readiness to cope with such crises, the fewer negative impacts it may experience.

The COVID-19 crisis had significant effects on the tourism industries of G7 countries during the four-year period from 2016 to 2020. Countries like the United States, France, and the United Kingdom appeared as leading nations in the tourism industry, while Japan and Canada faced challenges, and Germany and Italy experienced changes in their positions. Based on these results, officials and planners in the tourism industry of G7 countries can make appropriate decisions for developing and improving tourism under similar crisis conditions. Moreover, these findings can serve as a valuable guide for other countries in managing similar crises in the tourism industry and fostering future research in this area.

The results of this study play a crucial role in advancing knowledge about the impacts of the COVID-19 crisis on the tourism industry in G7 countries. Hence, implementing the proposed suggestions can aid in enhancing the management and performance of the tourism industry in facing future challenges, as well as strengthening the required knowledge for future studies.

Investigating the factors influencing country rankings in the tourism industry can be an effective guide for tourism managers and policymakers. These analyses can contribute to a better understanding of how economic, social, and health factors affect the prosperity of the tourism industry.

To cope with sudden natural and human-made crises, such as the COVID-19 pandemic, the tourism industry of countries needs to be more flexible. Developing various scenarios tailored to different circumstances can enhance the industry's adaptability and resilience. Therefore, a novel MCDM approach (RANCOM-PIV-DNCRADIS) has been utilized to assess the effect of the COVID-19 pandemic on G7 tourism industries. The implemented hybrid model has shown to be robust enough to trust for future implications.

In conclusion, several recommendations are offered to future researchers:

1. Instead of the PIV and DNCRADIS models, more advanced data analysis methods and accurate predictive models can be utilized in future articles to achieve more precise analyses and results regarding the impact of COVID-19 on the tourism industry.
2. Future studies should employ up-to-date and more accurate data to attain more reliable results.
3. It is suggested to investigate the impacts of similar crises on the tourism industry in other countries, particularly advanced nations, to enhance and improve strategies for facing future crises.
4. Conducting more advanced research using accurate data analysis methods with a future-oriented approach can contribute to knowledge advancement in this field and make the tourism industry of these countries more resilient against future crises. Additionally, strategic planning and more precise forecasting for crisis management in the tourism industry should be implemented to minimize negative impacts on the sector.
5. Utilizing innovative technologies and tourism management innovations can aid in improving the performance of the tourism industry under critical natural and human-made crisis conditions. Hence, future researchers can focus on further research in areas such as artificial intelligence, tourism observation technologies, and tourist experience assessment.

References

Abellana, D. P. M., Rivero, D. M. C., Aparente, M. E., & Rivero, A. (2021). Hybrid SVR-SARIMA model for tourism forecasting using PROMETHEE II as a selection methodology: A Philippine scenario. *Journal of Tourism Futures*, *7*(1), 78–97. https://doi.org/10.1108/jtf-07-2019-0070

Akhter Shareef, M., Shakaib Akram, M., Tegwen Malik, F., Kumar, V., Dwivedi, Y. K., & Giannakis, M. (2023). An attitude-behavioural model for understanding people''s behaviour towards tourism during the COVID-19 pandemic. *Journal of Business Research*, *161*, Article 113839. https://doi.org/10.1016/j.jbusres.2023.113839

Alves, J. P., Eusébio, C., Carneiro, M. J., Teixeira, L., & Mesquita, S. (2023). Living in an untouchable world: Barriers to recreation and tourism for Portuguese blind people during the COVID-19 pandemic. *Journal of Outdoor Recreation and Tourism*, *42*, Article 100637. https://doi.org/10.1016/j.jort.2023.100637

Dina, N. Z., & Juniarta, J. N. (2022). Deriving customer's preferences for hotels from unstructured data. *GeoJournal of Tourism and Geosites*, *43*(3), 872–877. https://doi.org/10.30892/gtg.43305-899

Fernández-Rodríguez, E., García-Fernández, R., & Martínez-Arias, A. (2023). Institutional determinants of the effective tax rate in G7 and BRIC countries. *Economic Systems*, *47*(2), Article 101079. https://doi.org/10.1016/j.ecosys.2023.101079

Febryano, I. G., Wahyuni, P., Kaskoyo, H., Damai, A. A., & Mayaguezz, H. (2022). The potential of tourism in Pahawang Island, Lampung Province, Indonesia. *Journal of Green Economy and Low-Carbon Development*, *1*(1), 34–44. https://doi.org/10.56578/jgelcd010104

Georgeades, C., & Flynn-O'Brien, K. T. (2023). The effects of the COVID-19 pandemic on violent injuries in children: A literature review. *Advances in Pediatrics*, *70*(1), 17–44. https://doi.org/10.1016/j.yapd.2023.03.002

Ghosh, S., Balsalobre-Lorente, D., Doğan, B., Paiano, A., & Talbi, B. (2022). Modelling an empirical framework of the implications of tourism and economic complexity on environmental sustainability in G7 economies. *Journal of Cleaner Production*, *376*, Article 134281. https://doi.org/10.1016/j.jclepro.2022.134281

Goh, H. C. (2021). Strategies for post-Covid-19 prospects of Sabah's tourist market – Reactions to shocks caused by pandemic or reflection for sustainable tourism? *Research in Globalization*, *3*, Article 100056. https://doi.org/10.1016/j.resglo.2021.100056

Göksu, A., & Kaya, S. E. (2014). Ranking of tourist destinations with multi-criteria decision making methods in Bosnia and Herzegovina. *Economic Review: Journal of Economics and Business*, *12*(2), 91–103. http://hdl.handle.net/10419/193841

Huang, J.-H., & Peng, K.-H. (2012). Fuzzy Rasch model in TOPSIS: A new approach for generating fuzzy numbers to assess the competitiveness of the tourism industries in Asian countries. *Tourism Management*, *33*(2), 456–465. https://doi.org/10.1016/j.tourman.2011.05.006

Jafari-Moghadam, S., Zali, M. R., & Sanaeepour, H. (2017). Tourism entrepreneurship policy: A hybrid MCDM model combining DEMATEL and ANP (DANP). *Decision Science Letters*, *6*, 233–250. https://doi.org/10.5267/j.dsl.2016.12.006

Jena, R. K., & Dwivedi, Y. (2021). Prioritizing the barriers to tourism growth in rural India: An integrated multi-criteria decision making (MCDM) approach. *Journal of Tourism Futures*. https://doi.org/10.1108/jtf-10-2020-0171

Ji, F., Wang, F., & Wu, B. (2023). How does virtual tourism involvement impact the social education effect of cultural heritage? *Journal of Destination Marketing & Management*, *28*, Article 100779. https://doi.org/10.1016/j.jdmm.2023.100779

Komasi, H., Hashemkhani Zolfani, S., & Cavallaro, F. (2022). The COVID-19 pandemic and nature-based tourism, scenario planning approach (Case study of nature-based tourism in Iran). *Sustainability*, *14*(7), Article 3954. https://doi.org/10.3390/su14073954

Liu, C.-H. S., Chou, S.-F., & Lin, J.-Y. (2021). Implementation and evaluation of tourism industry: Evidentiary case study of night market development in Taiwan. *Evaluation and Program Planning*, *89*, Article 101961. https://doi.org/10.1016/j.evalprogplan.2021.101961

Liu, C.-H., Tzeng, G.-H., & Lee, M.-H. (2012). Improving tourism policy implementation – The use of hybrid MCDM models. *Tourism Management*, *33*(2), 413–426. https://doi.org/10.1016/j.tourman.2011.05.002

Liu, S. T. (2023). Urban tourist profiles during the pandemic in Taiwan: A multigroup analysis. *Heliyon*, *9*(3), Article e14157. https://doi.org/10.1016/j.heliyon.2023.e14157

Liu, Y., Cheng, X., Liao, S. S., & Yang, F. (2023). The impact of COVID-19 on the tourism and hospitality Industry: Evidence from international stock markets. *North American Journal of Economics and Finance*, *64*, Article 101875. https://doi.org/10.1016/j.najef.2022.101875

Macdonald, C., Turffs, D., McEntee, K., Elliot, J., & Wester, J. (2023). The relationship between tourism and the environment in Florida, USA: A media content analysis. *Annals of Tourism Research Empirical Insights*, *4*(1), Article 100092. https://doi.org/10.1016/j.annale.2023.100092

Mohammed, R. T., Alamoodi, A. H., Albahri, O. S., Zaidan, A. A., AlSattar, H. A., Aickelin, U., Albahri, A. S., Zaidan, B. B., Ismail, A. R., & Malik, R. Q. (2023). A decision modelling approach for smart e-tourism data management applications based on spherical fuzzy rough environment. *Applied Soft Computing*, *143*, Article 110297. https://doi.org/10.1016/j.asoc.2023.110297

Mufazzal, S., & Muzakkir, S. M. (2018). A new multi-criterion decision-making (MCDM) method based on proximity indexed value for minimizing rank reversals. *Computers* & *Industrial Engineering*, *119*, 427–443. https://doi.org/10.1016/j.cie.2018.03.045

Niavis, S., & Tsiotas, D. (2019). Assessing the tourism performance of the mediterranean coastal destinations: A combined efficiency and effectiveness approach. *Journal of Destination Marketing* & *Management*, *14*, Article 100379. https://doi.org/10.1016/j.jdmm.2019.100379

Nuriyev, A. M. (2022). Fuzzy MCDM models for selection of the tourism development site: The case of Azerbaijan. *F1000Research*, *11*, Article 310. https://doi.org/10.12688/f1000research.109709.1

Ocampo, L. (2022). Full consistency method (FUCOM) and weighted sum under fuzzy information for evaluating the sustainability of farm tourism sites. *Soft Computing*, *26*, 12481–12508. https://doi.org/10.1007/s00500-022-07184-8

Puska, A., Bozanic, D., Mastilo, Z., & Pamucar, D. (2023). Extension of MEREC-CRADIS methods with double normalization-case study selection of electric cars. *Soft Computing*, *27*, 7097–7113. https://doi.org/10.1007/s00500-023-08054-7

Rahmawati, R., Prayitno, G., Firdausiyah, N., Dinanti, D., Hayat, A., Efendi, A., & Roskruge, M. (2023). Harnessing social capital for fostering non-tourism actor involvement in sustainable tourism: A case study of an Indonesian village. *Journal of Urban Development and Management*, *2*(2), 69–83. https://doi.org/10.56578/judm020202

Rungmaitree, P., Boateng, A., Ahiabor, F., & Lu, Q. (2022). Political risk, hedge fund strategies, and returns: Evidence from G7 countries. *Journal of International Financial Markets*, *Institutions and Money*, *81*, Article 101678. https://doi.org/10.1016/j.intfin.2022.101678

Sahoo, B. K., Nayak, R., & Mahalik, M. K. (2022). Factors affecting domestic tourism spending in India. *Annals of Tourism Research Empirical Insights*, *3*(2), Article 100050. https://doi.org/10.1016/j.annale.2022.100050

Satpathy, B., & Mahalik, D. K. (2010). A study on spiritual tourist site selection under multi-criteria. *South Asian Journal of Tourism and Heritage*, *3*(1), 107–117.

Seyitoğlu, F., Atsız, O., Kaya, F., & Taş, S. (2022). The two-way perspective of tourism undergraduates towards (post-)viral world: The future of tourism, and vocational development and career. *Journal of Hospitality*, *Leisure*, *Sport* & *Tourism Education*, *31*, Article 100400. https://doi.org/10.1016/j.jhlste.2022.100400

Sharifi, A., & Khavarian-Garmsir, A. R. (2020). The COVID-19 pandemic: Impacts on cities and major lessons for urban planning, design, and management. *Science of The Total Environment*, *749*, Article 142391. https://doi.org/10.1016/j.scitotenv.2020.142391

Sharma, G. D., Thomas, A., & Paul, J. (2021). Reviving tourism industry post-COVID-19: A resilience-based framework. *Tourism Management Perspectives*, *37*, Article 100786. https://doi.org/10.1016/j.tmp.2020.100786

Škrinjarić, T. (2021). Ranking environmental aspects of sustainable tourism: Case of selected European countries. *Sustainability*, *13*(10), Article 5701. https://doi.org/10.3390/su13105701

Takyi, P. O., Dramani, J. B., Akosah, N. K., & Aawaar, G. (2023). Economic activities' response to the COVID-19 pandemic in developing countries. *Scientific African*, *20*, Article 01642. https://doi.org/10.1016/j.sciaf.2023.e01642

United Nations World Tourism Organization. (2023). *UNWTO tourism data dashboard*. https://www.unwto.org/glossary-tourism-terms

Vatankhah, S., Darvishmotevali, M., Rahimi, R., Jamali, S. M., & Ebrahim, N. A. (2023). Assessing the application of multi-criteria decision making techniques in hospitality and tourism research: A bibliometric study. *International Journal of Contemporary Hospitality Management*, *35*(7), 2590–2623. https://doi.org/10.1108/ijchm-05-2022-0643

Wang, Y., & Fu, L. (2023). Study on regional tourism performance evaluation based on the fuzzy analytic hierarchy process and radial basis function neural network. *Annals of Operations Research*. https://doi.org/10.1007/s10479-023-05224-6

Wickramasinghe, K., & Naranpanawa, A. (2023). Tourism and COVID-19: An economy-wide assessment. *Journal of Hospitality and Tourism Management*, *55*, 131–138. https://doi.org/10.1016/j.jhtm.2023.03.013

Więckowski, J., Kizielewicz, B., Shekhovtsov, A., & Sałabun,W. (2023). RANCOM: A novel approach to identifying criteria relevance based on inaccuracy expert judgments. *Engineering Applications of Artificial Intelligence*, *122*, Article 106114. https://doi.org/10.1016/j.engappai.2023.106114

World Travel and Tourism Council. (2021). *Travel & tourism economic impact 2021*. Global Economic Impact & Trends.

Yang, J.-J., Chuang, Y.-C., Lo, H.-W., & Lee, T-I. (2020). A two-stage MCDM model for exploring the influential relationships of sustainable sports tourism criteria in Taichung City. *International Journal of Environmental Research and Public Health*, *17*(7), Article 2319. https://doi.org/10.3390/ijerph17072319

Yuedi, H., Sanagustín-Fons, V., Galiano Coronil, A., & Moseñe-Fierro, J. A. (2023). Analysis of tourism sustainability synthetic indicators. A case study of Aragon. *Heliyon*, *9*(4), Article 15206. https://doi.org/10.1016/j.heliyon.2023.e15206

Zorlu, K., & Dede, V. (2023). Evaluation of nature-based tourism potential in protected and sensitive areas by CRITIC and PROMETHEE-GAIA methods. *International Journal of Geoheritage and Parks*, *11*(3), 349–364. https://doi.org/10.1016/j.ijgeop.2023.05.004