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# Pairwise Voting to Rank Touristic Destinations Based on Preference Valuation

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Received: 24 September 2019; Accepted: 20 October 2019; Published: 23 October 2019

**Abstract:** This paper presents a novel approach for ranking tourist destinations based on the eigenvector method for pairwise voting (EMPV). The proposed approach relies solely on pairwise comparisons instead of direct-vote polling. The EMPV method was tested over a real-world case application to rank various tourist destinations in the Costa del Sol region, Spain, and its outcome was compared against a polling approach using a Likert-type scale. Results show that the EMPV and the Likert-based approach provided different rankings of preferred tourist destinations. Furthermore, both the EMPV and the Likert-based approaches shared the same preference patterns per ranking position, thus confirming that the reported predilection of the tourist is independent of the measurement approach. Finally, results show that the ranking produced by the EMPV methodology was highly related to the real number of visitors of the Costa del Sol tourist destinations, surpassing the Likert-based approach in both ordering and value similarities.

**Keywords:** tourism ranking; preference valuation; multiple criteria decision analysis; pairwise voting

## 1. Introduction

Tourism is a sector where people are constantly making choices, driven by a wide range of interconnected experiences and motivations, and determined by emotional, physical, or spiritual needs [1]. The choices of tourists are expressed as the preferences between destinations, service providers, transportation, and accommodation, among other comparable alternatives along the journey [2]. The analysis of these preferences is a powerful tool for tourism management [3–5]. Local governments and tourism administrations often rely on polling data to rank preferred destinations [6,7], where the resultant ranks can be translated to alternative courses of actions in resource allocation and spending prioritization; specially when not all the tourism-related projects can be funded due to budgetary constraints [5,8].

On the other hand, the process of modelling the several attributes that influence the experience of tourists is also a highly demanding task that has been addressed numerous times in decision science, mainly by the implementation of multiple-criteria decision making analysis (MCDA) methods [9–11]. Previous studies have successfully employed MCDA methods to measure tourists preferences [12–14]; however, these kinds of methods are best suited for assessing decisions of a reduced group of experts, such as business shareholders or political administration officers where negotiation and consensus is possible and enough time is available to complete the often lengthy procedures [15].

The aggregation of the priorities of large populations (e.g., tourists arriving to a hub) requires faster and lighter methods, such as polls using Likert-based or Condorcet-based scales [16,17]. Nevertheless, one of the main disadvantages of these kind of approaches is that they may not reflect the overall actual preference of tourists, mainly because of the conflicts created when various alternatives obtain similarly high scores [8,18,19]. In this regard, the analysis of preferences has been widely studied in social choice theory; which is a research field centred in finding the most desirable outcome for a group of heterogeneous individuals given a set of options. The final choice is the product of a complex thought-process that combines a synergy of inner preferences and criteria valuation [20].

The social choice field studies multiple aspects closely related to decision-making such as voting and how to achieve the fairest outcome given multiple interests, detecting common points within different perspectives and ranking different alternatives in the most desirable order for people as a group while taking into account the opinions of every member [21]. One of the most widespread methods for reaching the most desired outcome for group decision-making is preference aggregation, this is, the process of building a collective preference ranking for a given set of alternatives from multiple rankings obtained from different individuals [22–27]. In this sense, Arrow [28] defines five conditions that any methodology leading to a group decision must met to fairly and truly reflect the opinions of each member, as given below.

- Pareto Postulate: If any given option is preferred by everyone, this preference shall be preserved in the final ordering.
- No-Dictatorship: No individual enjoys a position in which his preference over any two alternatives is directly preserved in the final ranking without considering the preferences expressed by other voters.
- Transitivity: The order of the final ranking is consistent. That means that if A is preferred to B and B is preferred to C, it is not possible for C to be preferred over A.
- Unrestricted Domain: For any set of individual voter preferences the aggregated ranking should be unique and deterministic. It must also allow and consider any possible ranking from the voters.
- Independence of Irrelevant Alternatives: The social choice between any two alternatives shall not be affected by the removal or addition of other alternatives to the field of feasible alternatives under consideration.

According to Arrow it is impossible to build a social welfare function that satisfies simultaneously all the above postulates [28,29]. This means that any preference aggregation process must at least weaken one of the axioms, which in turn affects the fairness of the aggregated ranking. On the other hand, in the words of Saaty and Sagir, ranking or ordering things according to preference is a purely human activity, while ranking in accordance to importance or likelihood is a more scientific and objective process; furthermore, there is no naturally predefined rank for the preference of alternatives, but it is people who stablish the criteria [30]. Moreover, previous studies suggest that people are not bothered about the consistency of their own judgements as much as they are worried about the non-dictatorial nature of the final decision [8,31,32]; even the transitivity axiom can be weakened in some cases without compromising the acceptability of the final aggregated ranking [8,23,27].

Although there are broadly accepted methods for assessing and aggregating the preferences of people such as the analytical hierarchy process [32], the analytical network process [20], COPRAS-G [33], and TOPSIS [34], they are not suited for large populations with heterogeneous viewpoints. In this regard, Vargas proposed a novel voting method based on the idea of pairwise voting to rank alternatives: the eigenvector method for pairwise voting (EMPV) [8]. Previous results suggest that the EMPV approach provides comparable results to letting the decision-makers vote with intensity of preferences while relying solely on pairwise comparisons; most importantly, it does not violate democracy. Therefore, in this study we explore the possibility of valuating the preferences of tourists for preferred tourist destinations using the EMPV approach.

The aim of this study is to assess the validity of the eigenvector method for pairwise voting as a mean for ranking tourist destinations. The hypotheses tested in this study were that:

1. The EMPV ranking of tourist destinations differs from the direct-vote polling rating positions.
2. There are no significant differences in the proportions of preferred destinations between the EMPV ranking approach and direct-vote polling.
3. The EMPV ranking aggregation outcome performs better that direct-vote polling at explaining the real number of visits in tourist destinations.

## 2. Materials and Methods

### *2.1. The Eigenvector Method for Pairwise Voting*

The EMPV is based on pairwise voting and AHP but considers the order of preferences obtained from multiple decision-makers over a set of alternatives; a brief graphical representation of the EMPV methodology is shown in Figure 1.

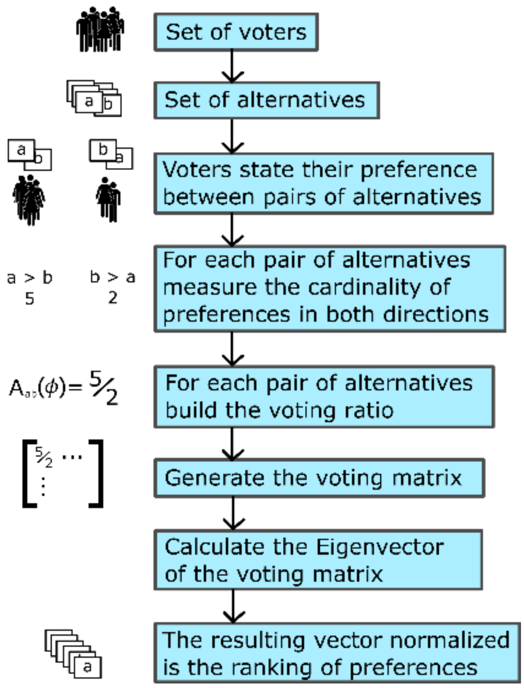


**Figure 1.** The eigenvector method for pairwise voting (EMPV) methodology.

The EMPV methodology works by defining a set of alternatives to rank, $A = \{a_1, a_2, \ldots, a_n\}$; and a set of voters, $N = \{1, 2, \ldots\}$ which cast their vote between pairs of alternatives according to their preferences. A profile on a group of voters $\phi$ is the mapping of preference orders given the set of users. Then, the number of voters who preferred alternative $i$ to alternative $j$ is defined as $v_{ij}(\phi)$; the voting ratio between criteria is defined as:

$$a_{ij}(\phi) \equiv \frac{v_{ij}(\phi)}{v_{ji}(\phi)} \text{ with } v_{ij}(\phi) > 0, \tag{1}$$

which gives the resulting voting matrix $A(\phi)$:

$$A(\phi) = \left\{a_{ij}(\phi) \equiv \frac{v_{ij}(\phi)}{v_{ji}(\phi)}\right\}. \tag{2}$$

Note that in situations in which no voter expresses preference for $j$ over $i$ this would cause a zero denominator. In order to avert this situation, a fictitious voter can be introduced which prefers $j$ over $i$ and has no other preferences. Considering a large enough number of voters, the addition of this voter would make no difference in the overall result. Applying the previous equation for $m$ alternatives on every combination pairs the matrix of voting ratios is:

$$A(\phi) = \begin{bmatrix} 1 & \frac{v_{12}(\phi)}{v_{21}(\phi)} & \cdots & \frac{v_{1n}(\phi)}{v_{n1}(\phi)} \\ \frac{v_{21}(\phi)}{v_{12}(\phi)} & 1 & \cdots & \frac{v_{2n}(\phi)}{v_{n2}(\phi)} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{v_{n1}(\phi)}{v_{1n}(\phi)} & \frac{v_{n2}(\phi)}{v_{2n}(\phi)} & \cdots & 1 \end{bmatrix}. \tag{3}$$

The principal eigenvector of $A(\phi)$ is the most accurate representation of the voters' preferences, resulting in a ranking of alternatives ordered by their desirability expressed by the set of voters.

### 2.2. Example

Let us suppose that 30 students are choosing an end-of-school trip destination and there are three available options: City A, City B, and City C. Since it is highly unlikely that all the students have the same interests and preferences, they must use a decision-making method to reach an agreement which satisfies the majority of the group.

For this purpose, the students decide to rank each of the alternatives in their order of preference and then use EMPV to aggregate the rankings. The results of the individual ranking process are shown in Table 1.

**Table 1.** Example: Cardinality of individual rankings.

| Ranking | Order | Number of Students |
|---|---|---|
| $r_{abc}$ | City A > City B > City C | 5 |
| $r_{acb}$ | City A > City C > City B | 16 |
| $r_{bac}$ | City B > City A > City C | 2 |
| $r_{bca}$ | City B > City C > City A | 4 |
| $r_{cab}$ | City C > City A > City B | 3 |
| $r_{cba}$ | City C > City B > City A | 0 |

From these results the preferences of pairs of options is obtained. Although this process of pairwise comparison could be performed directly by the students, opting to ask for a ranking reduces the number of comparisons performed by the students and the cardinalities of preferences could be extracted as shown in Table 2.

**Table 2.** Example: Cardinality of preferences.

| Pair of Options | Pair of Options | Calculation | Preferred |
|---|---|---|---|
| $p_{ab}$ | City A > City B | $r_{abc} + r_{acb} + r_{cab}$ | 24 |
| $p_{ac}$ | City A > City C | $r_{abc} + r_{acb} + r_{bac}$ | 23 |
| $p_{ba}$ | City B > City A | $r_{bac} + r_{bca} + r_{cba}$ | 6 |
| $p_{bc}$ | City B > City C | $r_{abc} + r_{bac} + r_{bca}$ | 11 |
| $p_{ca}$ | City C > City A | $r_{bca} + r_{cab} + r_{cba}$ | 7 |
| $p_{cb}$ | City C > City B | $r_{acb} + r_{cab} + r_{cba}$ | 19 |

With the preferences for each pair of options, the voting matrix $A$ is calculated using the following equation:

$$A = \left\{ \begin{array}{ccc} 1 & \frac{p_{ab}}{p_{ba}} & \frac{p_{ac}}{p_{ca}} \\ \frac{p_{ba}}{p_{ab}} & 1 & \frac{p_{bc}}{p_{cb}} \\ \frac{p_{ca}}{p_{ac}} & \frac{p_{cb}}{p_{bc}} & 1 \end{array} \right\} = \left\{ \begin{array}{ccc} 1 & \frac{24}{6} & \frac{23}{7} \\ \frac{6}{24} & 1 & \frac{11}{19} \\ \frac{7}{23} & \frac{19}{11} & 1 \end{array} \right\}. \tag{4}$$

From this matrix, the eigenvector associated with the largest eigenvalue in modulus is given by $v = [0.92590\ 0.20600\ 0.31665]$. After this vector is normalized to unity with the $l_1$-norm the following rank is obtained $r = [0.63919\ 0.14221\ 0.21860]$. Table 3 shows that the most preferred alternative is City A, which was expected considering that over two-thirds of the students opted for this destination as the top of their rankings. The second option would be City C which is globally preferred over City B.

**Table 3.** Example: Ranking with EMPV.

| Order | Alternative | Weight |
|---|---|---|
| 1 | City A | 0.63919 |
| 2 | City C | 0.21860 |
| 3 | City B | 0.14221 |

Note that if instead of requesting each student to arrange every alternative in their preferred order, they were asked to just state their most desired option this would result in a global ranking such as the one shown in Table 4.

**Table 4.** Example: Ranking with cardinality of votes.

| Order | Alternative | # of Votes |
|---|---|---|
| 1 | City A | 21 |
| 2 | City B | 6 |
| 3 | City C | 3 |

#: Number of votes.

Although the first option remains the same, this approach can cause rank reversal if, for any reason such as bad weather or unavailability of lodging, the first option becomes unavailable. Since City B is not the second option of the majority, but the first option among the minorities, choosing City B solely based on the ranking shown in Table 4 would be unfair, so the students who chose City A should be asked to take a new survey on their preference between the remaining options. This would result in the ranking shown in Table 5.

**Table 5.** Example: Ranking with cardinality of votes, City A unavailable.

| Order | Alternative | # of Votes |
|---|---|---|
| 1 | City C | 19 |
| 2 | City B | 11 |

#: Number of votes.

This alters the order previously obtained in Table 4, hence causing rank reversal. The EMPV ranking, however would not alter its ordering, as it considers every position in the individual orderings obtained from the students. Calculating the EMPV without City A would result in Table 6.

The results shown in Table 6 maintain the previous order from Table 3.

**Table 6.** Example: Ranking with EMPV, City A unavailable.

| Order | Alternative | Weight |
|---|---|---|
| 1 | City C | 0.6333 |
| 2 | City B | 0.3666 |

### 2.3. Case Application

The proposed EMPV approach was used to rank the preferred destinations of tourists visiting the Costa del Sol region in the province of Málaga in Spain. According to the information provided by the Tourism Observatory of the Costa del Sol in 2017 the number of international passengers arriving to the airport of Malaga increased from 7,171,820 in the year 2016 to 8,067,811 in the year 2017; there are 20,657 accommodation facilities accounting for 277,185 vacancies and these received a total of 5,345,736 registered clients seeking accommodation, accounting for 52,442,732 night-stays during that period [35]. Furthermore, the impact of tourism in the Costa del Sol region ascended to 7462 million of euros in the year 2017.

The Tourism and Planning Society for the Costa del Sol region (TPCS) constantly gathers data about the tourist facilities, accommodation, passengers, visitors, tourist attractions and social-media opinions. Within this context, the TPCS performs a yearly-based survey on tourists arriving to and leaving from the airport of Málaga, cruise ports, and train stations all over the region, intended to evaluate the expectations and experiences of tourists visiting the Costa del Sol.

#### 2.3.1. Sample and Procedure

This study benefited from the logistics of a larger survey performed by the TPCS, carried out on a daily basis from 15 July to 28 August 2017 in order to cover the summer holiday period. It comprised English, Spanish, German, and Dutch speaking tourists returning from the Airport of Málaga–Costa del Sol in the year 2017 (exit survey). The survey included most of the flights scheduled for international European Union destinations. The inclusion criteria were:

- Being 18 years old or older.
- Leisure traveller.
- Have stayed overnight in at least one of the destinations of the Costa del Sol region.

One of the goals of this stage of the TPCS survey was to rate the experiences of travellers in their destination of choice of the Costa del Sol. In this regard, this study explored the possibility of using the EMPV procedure to create a ranking of the destinations that tourists visited during their stay. To do so, a subsets of tourist was randomly sampled to answer an additional question designed to rate the overall experience in the cities of Marbella, Nerja, Torremolinos, Benalmádena, Fuengirola, or Málaga, as these destinations account for more than the 60% of the tourist-related income of the Costa del Sol region [35]. Tourists that visited less than two of the selected destinations were excluded from the study.

#### 2.3.2. Questionnaire Design

The main survey instrument was not designed for this study but was conceived for one of the stages of the TPCS annual survey and was available in Spanish, English, German, and Dutch. The key variables monitored in the main survey were gender, age, education level, country of residence, type of accommodation, and stay duration. This questionnaire has been in use since 2007 with successful results and it is revised annually by a board of experts.

Subjects that were randomly selected for this study were asked to answer one of two additional questions following the decision pattern shown in Figure 2. Using a simple pseudo-random number generation algorithm, the survey system determined if the current subject would be included in the study or not; if included, the system decided whether the subject would be asked to compare and rank the studied destinations (EMPV approach) or to rate each destination using a 7-point Likert-type scale. The Likert-type scale ranged from completely dissatisfied to completely satisfied (Table 7) [36–38]. The subjects were only asked to evaluate the cities that they already visited, leaving the other alternatives in blank.

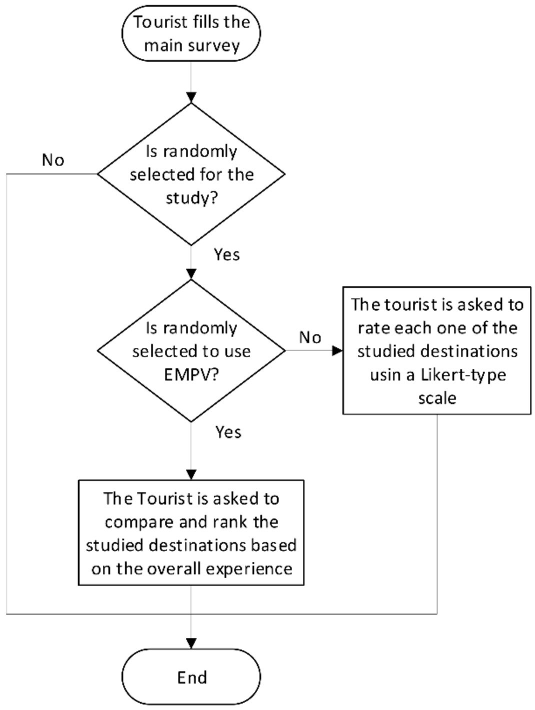


**Figure 2.** Logic decision pattern to randomly select the subjects for the study.

**Table 7.** Likert-type scale used to rate the overall experience satisfaction for each of the studied destinations.

| Value | Tag |
|---|---|
| 1 | Completely dissatisfied |
| 2 | Mostly dissatisfied |
| 3 | Somewhat dissatisfied |
| 4 | Neither satisfied nor dissatisfied |
| 5 | Somewhat satisfied |
| 6 | Mostly satisfied |
| 7 | Completely satisfied |

#### 2.3.3. Statistical Analysis

The data were analysed using IBM SPSS Statistics 25. First, we computed the descriptive statistics for age, origin, education level, income level, and accommodation type. Second, we tested the normality of the distribution of the age per type of survey using the Kolmogorov–Smirnov and Shapiro–Wilk tests; and the possible differences between the distribution of the age between the types of surveys was assessed with the Student's $t$-test for independent samples with a significance level of 0.05.

Third, we performed the chi-squared test of homogeneity to test the null hypotheses that, for each ranking position (e.g., 1st, 2nd, 3rd) the proportions of preferred destinations between the EMPV and direct-vote polling with a Likert-style scale approaches are identical. Thus, the alternative hypothesis is that at least one of the ranking positions exhibits a different proportion of preferred destinations. For this analysis, the significance level is 0.05.

Fourth, we compared the resulting Likert-based and EMPV destination rankings with real-world data about the number of tourists visiting these destinations during the summer vacations of 2017. To do so, the Likert-based ranking and the number-of-visitors ranking were normalised to the 0 to 1 scale; then, we computed the goodness of fit of a linear regression model considering the number-of-visitors scale as the independent variable and the normalised survey rankings as separate dependent variables.

## 3. Results

### 3.1. Descriptive Statistics of the Survey Outcome

A total of 800 tourists were randomly selected for this study (N = 800); where 402 subjects answered a direct-vote survey, and 398 answered an EMPV-style survey. The mean age was 45.81 years old, with a standard deviation of 14.319. The normality of the age distribution was confirmed using the Kolmogorov–Smirnov and Shapiro–Wilk tests with $p > 0.05$ for both survey types. Furthermore, there were no significant differences in the distributions of ages between the survey types, verified with the Student's *t*-test for independent samples with $p > 0.05$.

The sex of the participants was evenly distributed across the types of surveys, with 52.1% females and 47.9% males. The most reported education level was high school (63%), followed by higher education (35.4%) and none (1.6%); moreover, the education level was evenly distributed across the types of surveys.

The origin of most of the subjects was Spain (44.1%), followed by the United Kingdom (19.5%), France (7.4%), Germany (7.0%), Scandinavia (5.5%), Ireland (4.9%), the Netherlands (4.1%), Belgium (2.8%), Italy (2.1%), Portugal (1.9%), Switzerland (0.5%), and the United States of America (0.3%).

### 3.2. Differences Between Survey Types

The chi-squared test of homogeneity did not reject the null hypothesis that the proportions of preferred destinations are identical for each rank; with $p > 0.26$ in all ranks as detailed in Table 8. Therefore, the analysis confirms that the distribution of preferences is the same in both the EMPV and Likert-style approaches. A graphical representation of the preference count per survey type and rank is shown in Figure 3.

**Table 8.** Chi-Squared Tests of Homogeneity.

| Rank | | Value | Df | Asymptotic Significance (2-Sided) |
|---|---|---|---|---|
| 1 | Pearson Chi-Squared | 1.622 | 5 | 0.899 |
| | Likelihood Ratio | 1.625 | 5 | 0.898 |
| | Linear-by-Linear Association | 0.166 | 1 | 0.684 |
| | N of Valid Cases | 872 | - | - |
| 2 | Pearson Chi-Squared | 1.999 | 5 | 0.849 |
| | Likelihood Ratio | 2.001 | 5 | 0.849 |
| | Linear-by-Linear Association | 0.041 | 1 | 0.840 |
| | N of Valid Cases | 534 | - | - |
| 3 | Pearson Chi-Squared | 6.458 | 5 | 0.264 |
| | Likelihood Ratio | 6.409 | 5 | 0.268 |
| | Linear-by-Linear Association | 0.705 | 1 | 0.401 |
| | N of Valid Cases | 193 | - | - |
| 4 | Pearson Chi-Squared | 2.662 | 5 | 0.752 |
| | Likelihood Ratio | 2.588 | 5 | 0.763 |
| | Linear-by-Linear Association | 0.243 | 1 | 0.622 |
| | N of Valid Cases | 45 | - | - |
| 5 | Pearson Chi-Squared | 1.905 | 2 | 0.386 |
| | Likelihood Ratio | 2.209 | 2 | 0.331 |
| | Linear-by-Linear Association | 1.090 | 1 | 0.296 |
| | N of Valid Cases | 8 | - | - |
| 6 | Pearson Chi-Squared | - | - | - |
| | N of Valid Cases | 2 | - | - |
| Total | Pearson Chi-Squared | 1.131 | 5 | 0.951 |
| | Likelihood Ratio | 1.132 | 5 | 0.951 |
| | Linear-by-Linear Association | 0.846 | 1 | 0.358 |
| | N of Valid Cases | 1654 | - | - |

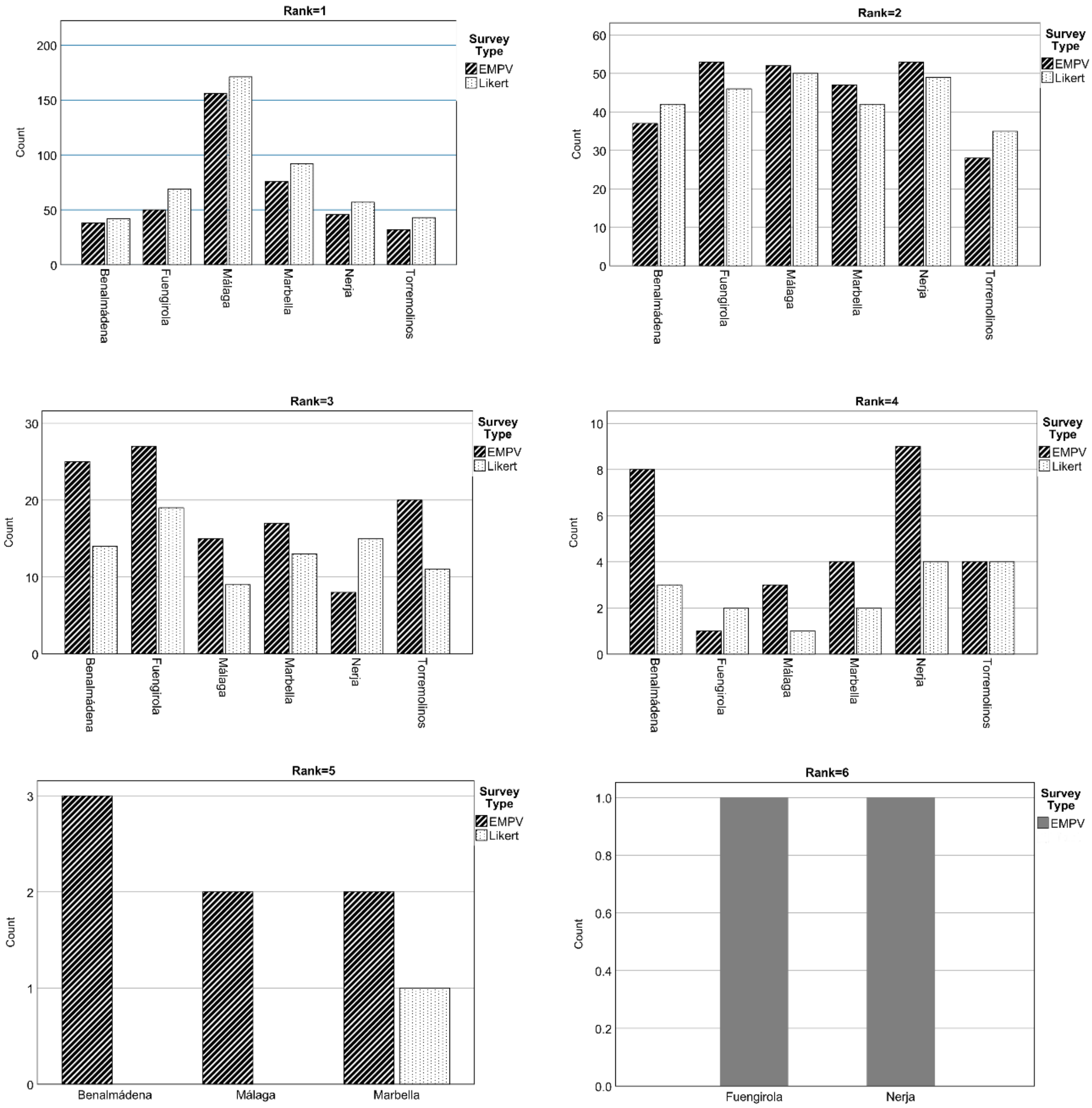


**Figure 3.** Preference counts per survey type.

### 3.3. Preference Aggregation Results

Direct aggregation of the Likert-style survey using the arithmetic mean as the aggregation operator provided the following scores: Málaga = 5.77, Marbella = 5.30, Fuengirola = 5.43, Nerja = 5.15, Torremolinos = 4.68, Benalmádena = 4.97. Thus, the Likert-based ranking of destinations is:

$$\text{Málaga} > \text{Fuengirola} > \text{Marbella} > \text{Nerja} > \text{Benalmádena} > \text{Torremolinos}. \tag{5}$$

On the other hand, the EMPV approach resulted in the following scores: Málaga = 0.3206, Marbella = 0.2236, Fuengirola = 0.1265, Nerja = 0.1249, Torremolinos = 0.1136, Benalmádena = 0.0908. Therefore, the EMPV ranking of destinations is:

$$\text{Málaga} > \text{Marbella} > \text{Fuengirola} > \text{Nerja} > \text{Torremolinos} > \text{Benalmádena}. \tag{6}$$

Consequently, there are two reversal differences between the Likert-based and EMPV rankings, specifically in the 2nd ↔ 3rd and in the 5th ↔ 6th places. These differences between rankings can be visualised in Figure 4.

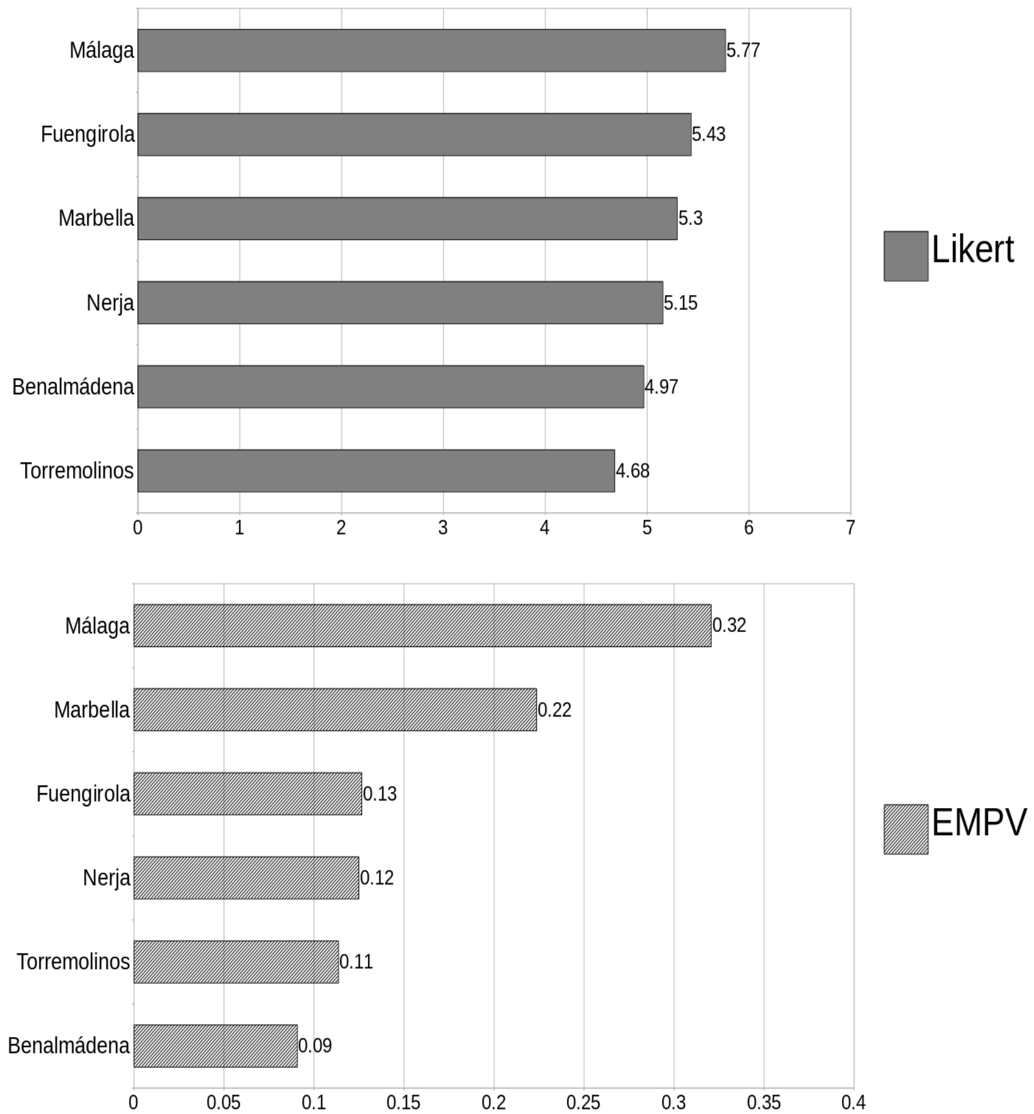


**Figure 4.** Preference aggregation results.

### *3.4. Relationship of the Aggregated Results with Real Number of Visitors*

The linear regression test confirmed that both the EMPV and the Likert-based rankings are related to the real number of visitors for the selected tourist destinations, with $R^2 = 0.87$ and $R^2 = 0.68$ respectively. However, the visitors ranking order differs in two positions with the Likert-based ranking order at the 2nd ↔ 3rd and the 5th ↔ 6th places. In this regard, Figure 5 shows a graphical comparison between the normalised values of the EMPV, Likert-based and visitors ranking.

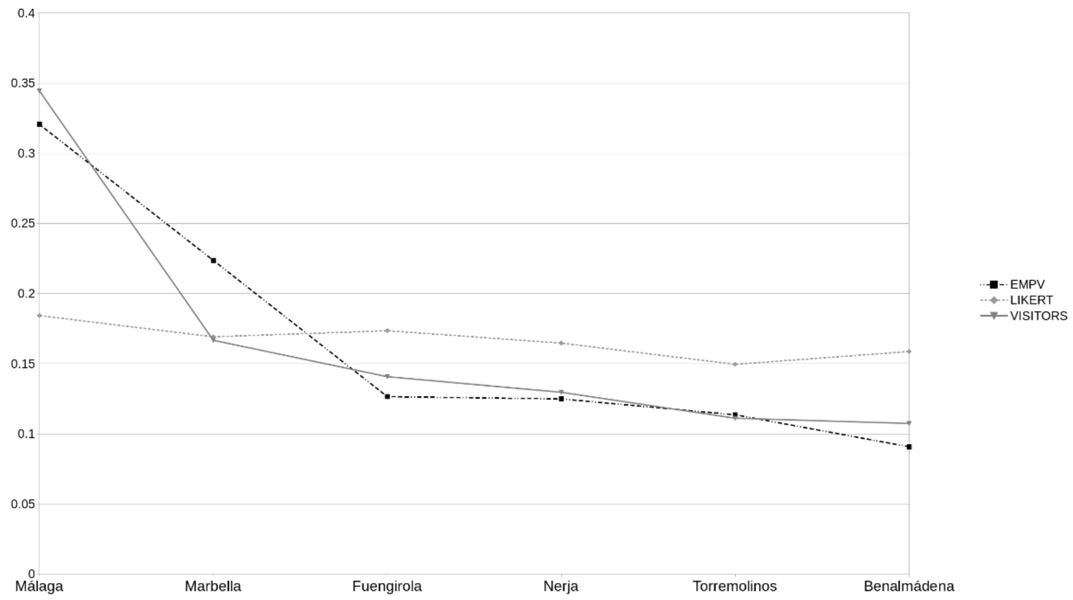


**Figure 5.** Comparison between the EMPV, Likert-based and visitors ranking.

## 4. Discussion and Conclusions

The findings of the research design were analysed to determine the aggregated preferred destinations between six cities of the Costa del Sol region. The city of Málaga was ranked first for both the EMPV and Likert-based approaches. The consensus in the first position indicates a dominant preference where most of the decision-makers chose Málaga before all the other alternatives. It is important to notice that the city of Málaga is the capital of the province of Málaga and is the largest city in the Costa del Sol region.

However, results show that the EMPV and the Likert-based approaches provided different rankings of preferred tourist destinations, thus confirming the first hypothesis of this work. The most significant rank reversal between the EMPV and Likert-based approaches was in the 2nd ↔ 3rd places, where the Likert-based approach placed Fuengirola before Marbella while the EMPV placed Marbella before Fuengirola. This discrepancy in the ranking indicates that Fuengirola is the first choice of the second-largest group of decision-makers, but it is not the second choice of the majority of decision-makers.

The differences in the outcomes of the tested preference aggregation approaches can affect the decision-making processes in tourism administration. Then again, results suggest that both the EMPV and Likert-based approaches are able to grasp the underlying preference patterns of the tourists visiting the Costa del Sol region in Andalucía; there are no significant differences in the proportions of preferred destinations per rank between the EMPV ranking and direct-vote Likert-based approaches, confirming the second hypothesis of this work. Moreover, the EMPV ranking was closer than the Likert-based approach to the real number of visitors to the selected tourist destinations during the same period, thus confirming the third hypothesis of this work.

In the words of Vargas (1987), why should any theory assume transitivity of preferences when it does not hold in real life? The transitivity of preferences relies in the concept of consistency [32]. In this regard, the consistency of preferences in the ordinal sense means that, given three alternatives A, B, and C, if A is preferred to B and B is preferred to C, then to be consistent A must be preferred to C [31]. However, the assumption of transitivity cannot be taken for granted, as people often express non-transitive preferences when tasked with rating alternatives using an ordinal scale such as the Likert-based approach. Rank reversals are a serious concern because they can happen naturally and affect outcomes in both desirable and undesirable ways [30]. Therefore, considering the overall preferences is important when dealing with the question of rank.

The findings of this study provide evidence that the first choice of the second-largest group of tourists is not necessarily the same as the second choice of the all the surveyed tourists. Therefore, the EMPV approach can be used to improve way that preference analysis results reflect the opinions of each tourist by considering the axioms proposed by Arrow [28] while keeping compatibility with traditional polling systems.

**Author Contributions:** Formal analysis: F.E.C.; Methodology: F.E.C.; Investigation: M.A.; Writing—original draft: G.F.V.W.; Writing—review and editing: M.A. and J.I.P.

**Funding:** This research received no external funding.

**Conflicts of Interest:** The authors declare no conflict of interest.

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