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TOURISM COMPETITIVENESS AND MOBILE DATA: A GREY RELATIONAL ANALYSIS FOR EUROPEAN ENTREPRENEURSHIP PRE & DURING PANDEMIC

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ABSTRACT

The tourism country's competitiveness is important especially when countries strive for bigger market shares as European countries are. The COVID-19 pandemic has had devastating effects on tourism and the entire tourism industry must be rethinking and reshaping given some opportunities and challenges to the entrepreneurs, local communities, local administrations, governments of competitiveness destinations. In this paper we measured if the Google and Apple mobility indices cand predict (or not) the movement of TTCI during pandemic compared with pre-pandemic TTCI ranks by using grey system theory and statistical methods. The aim of the paper is to validate the Grey Relational Analysis (GRA) as identifier of the good predictor (statistically significant for p-value< 0.05) for European tourism competitiveness (measured by TTCI) in particular conditions, especially before and during COVID-19 pandemic time by take into consideration the Google Mobility and Apple Mobility data and their relationship with overnight stays for 11 European countries. To validate the GRA as method for good and accurate predictor for tourism competitiveness for TTCI 2021 (during COVID-19 pandemic time) a GLM – General Linear Model ANOVA with interaction effects and Tukey HSD Post Hoc Multiple Comparisons was applied. Our results validated the powerful of GRA for tourism competitiveness, statistically significant according to GLM with interaction effects, and emphasis (especially for entrepreneurs) that the overnight stays will give the right rank on top of tourism competitiveness, prior to other ITC support as Google and Apple Mobility indices proved by reflection of overnights on TTCI 2021 – during pandemic.

Keywords: *competitiveness, tourism, GRA – Grey Relational Analysis, Google mobility data, Apple Mobility Data, General Linear Model, ANOVA with interaction effects*

1. INTRODUCTION

The tourism country's competitiveness is important especially when countries strive for bigger market shares (Lin & Huang, 2009; Huang & Lin, 2009: Popović, 2017; Bacoş & Gabor, 2021) as European countries are (Moraliyska, 2023). The COVID-19 pandemic has had devastating effects on tourism (Nagy et al., 2023) and the entire tourism industry (Gabor et al., 2023) must be rethinking and reshaping given some opportunities and challenges to the entrepreneurs, local communities, local administrations, governments of competitiveness destinations (Mastilo et

al., 2023; Mijajlović et al., 2020). The importance of sustainability related to competitiveness of a destination is even more visible during COVID-19 pandemic (Skrinjaric, 2021; Vladymyr, 2023). The management of tourism destination is very important in developing tourism, investments, and exports and finally in developing a country or a city (Gabor et al., 2021), the tourism competitiveness has become an important issue in marketing research in tourism (Lin & Huang, 2009). The basic elements of tourism competitiveness could be different according to country, region, etc. and could change on time. A recent study (Gabor et. al, 2021) emphasized that after ten years, the elements (pillars) of Travel & Tourism Competitiveness Index (published by World Economic Forum, 2022) that discriminate between the most competitive destinations (European countries) are: ICT readiness, price competitiveness and air transport infrastructure pillars (Gabor et. al, 2021). Two of three elements were considerable affected by COVID-19 pandemic but the ITC gain, after pandemic time, in importance (Rahman, 2023). During the COVID pandemic and ever since, we have a large-scale open database about the movement and real motion of people in different types of urban and nonurban areas around the world (Nagy et al., 2022; Nagy et al., 2023) as Google Mobility data and Apple Mobility data, no study of shown how many movements may affect a country's overall competitiveness (Lin & Huang, 2009) and this aspect justified to take into consideration the mobility data reported during a particular time, respectively the COVID-19 pandemic. So, we intend to measure if the Google and Apple mobility indices cand predict (or not) the movement of TTCI during pandemic compared with pre-pandemic TTCI ranks.

The grey systems are an effective method for modelling and forecasting short-term time series that can be applied in all areas based on models with limited, incomplete, or uncertain data ranging from social sciences, through economy and economics, to technical sciences (Gerus – Gosciewska & Gosciewski, 2022). The Grey Relational Analysis (GRA), developed by Sunt & Dang (Xu et al., 2014), part of the grey system theory (Pakkar, 2016) can be applied to solve practical problems related to social participation (Gerus – Gosciewska & Gosciewski, 2022; Lin & Huang, 2009) as tourism enterprises development (Gerus – Gosciewska & Gosciewski, 2022) and for data that can be ranked as competitiveness indices and other indicators which can define the competitiveness. More, for data and/or studied with specified ranks, the GRA enables the determination of a significance sequence which indicates those characteristics/particularities that have the greatest influence on the phenomenon under study (Gerus – Gosciewska & Gosciewski, 2022).

GRA has many applications in different field, from medicine to technology, economics, and tourism. For economic field, the GRA method was applied for different studies such as: analysis of the macroeconomic performance of European countries (Altin, 2020), for ranking of Latin America and Caribbean economies using macroeconomic indicators (Yildirim et al., 2015), classification of consumers' textual evaluation in e-commerce (Fidan, 2020), evaluation human resources to implement sustainable consumption and production for automotive industry (Uniyal et al., 2020),as method in comprehensive evaluation on the customer satisfaction of automobile 4S enterprises (Cenglin, 2012), evaluation financial performance of manufacturing companies listed on Borsa Istanbul (Ozdagoglu et al., 2017). We also found some studies from technical field such as: analyzing the characteristic of inscribed core (IC-GRA) and its application on seven-pilot carbon trading markets in China (Wang et al., 2019), to choose high reliability of the network node (Wang, 2019), Taguchi GRA for parametric optimization of severe plastic deformation process (Girish et al., 2019), for multi-attribute decision making in turning machine (S. Bangphan & P. Bangphan, 2022), for optimizing multi-response simulation problems (Kuo et al., 2008), material selection of natural fibre (Maidin et al., 2022), evaluation of road traffic safety measures (Lu & Wevers, 2007).

For *tourism* industry in general and *tourism competitiveness* in special, as field of research, the GRA was applied standalone or complementary with other methods such as: sensitivity analysis (Lin & Huang, 2009) by using the TTCI 2007 data for Asian countries, hierarchy evaluation criteria for European tourism competitiveness (Huang & Lin, 2009), listed tourism companies growth based on grey relational degree model in China (Su & Liu, 2016), fiscal expenditure and tourism development for urban tourism (Wu & Zhan, 2017), influence factors of tourism industry with GRA applied to time series (Yu & Wu, 2016), structure of inbound tourism industry in China using time series data (Han & Yu, 2016), ranking environmental aspects of sustainable tourism for selected European countries (Skrinjaric, 2021) combing GRA with Multiple Criteria Decision Making (MCDM), selection a development strategy of mining tourism (Maksimivic et al., 2016).

The *aim* of the paper is to validate the Grey Relational Analysis (GRA) as identifier of the good predictor (statistically significant for p-value< 0.05) for European tourism competitiveness (measured by TTCI) in particular conditions, especially before and during COVID-19 pandemic time by take into consideration the Google Mobility data and Apple Mobility Data and their relationship with overnight stays. Starting from this research purpose, the main *objectives* of our study are:

(1) to apply the *GRA* to data set formed by the following indicators for 2019 – 2020 (before COVID-19 pandemic): *Tourism & Travel Competitiveness Index* (TTCI), *overnight stays* (thousand) in 2019, *overnight stays as fixed base for February 2020*, the *six Google Mobility indicators*, the *three Apple Mobility indicators* to analysis the relationship between these variables and how affect the hierarchy of TTCI 2019 ranking *for 11 European countries* (only the countries with complete statistical data for these indicators and time) as follows: Spain, Germany, Italy, Netherlands, Norway, Luxembourg, Belgium, Finland, Czech republic, Estonia and Slovakia;

(2) to visualize these relationships through *relationship maps*;

(3) to validate the GRA as method for good and accurate predictor for tourism competitiveness for TTCI 2021 (during OCVID-19 pandemic time) by using *GLM – General Linear Model ANOVA with interaction effects and Tukey HSD Post Hoc Multiple Comparisons*.

2. METHODS

According to main purpose of the research and its objectives, the variable used in this research are:

- *rank of Tourism & Travel Competitiveness Index* (TTCI) for 2019 (before COVID-19 pandemic time, pre-pandemic) and 2021 (for during COVID-19 pandemic time as last available data) for pre-pandemic and during competitiveness for 11 European countries;
- *11 European countries* with completed statistical data for all the indicators from the study (Belgium, Italy, Spain, Germany, Czech Republic, Slovakia, Finland, Estonia, Luxembourg, Netherlands, and Norway) being also ensure the representativeness of the data (Nagy et al., 2023) having also a relatively good spatial representativeness of the research sample, and therefore, the present results can be inferred in the general population at the European level (Nagy et al., 2023)
- *Overnight stays* (thousands) as absolute frequencies for 2019 from Eurostat database (2023) and for better and more comparable data, *as a fixed base for February 2020* because the mobility indicators are being presented in Google and Apple reports starting with this time;
- *the Google Mobility (GM) indices* as follows: *GM Retail & Recreation, GM Grocery & Pharmacy, GM Parks, GM Transit Stations, GM Workplace, GM Residential*;

- *the Apple Mobility indices* as follows: *Apple Driving, Apple Transit, Apple Walking*

The initial data included in the study are presented in Table 1 with red color being marked the bigger value for each indicator for choosing the reference values for applying the GRA. These data are the starting step for applying GRA.

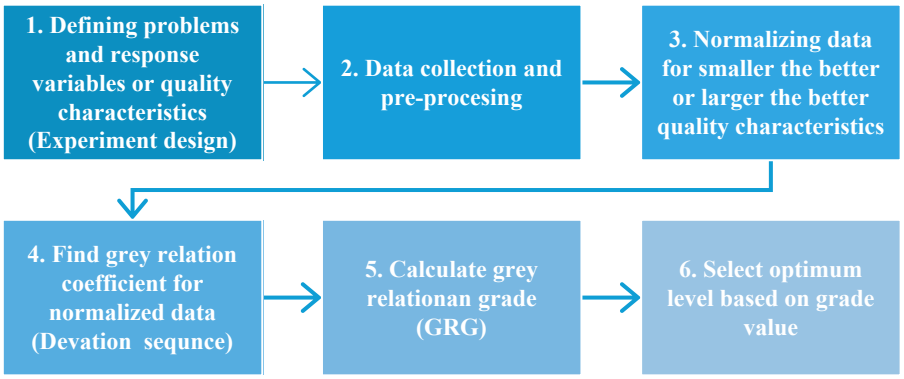
Table 1. Initial indicators used in the study

Rank TTCI 2019	Country	Overnights_stays (thousand)	Overnights_BF_ February 2020	GM_Retail & Recreation	GM_Grocery & Pharmacy	GM_Parks	GM_Transit stations	GM_Workplace	GM_Residential	Apple_Driving	Apple_Transit	Apple_Walking
24	Belgium	984.17	92.62	-35.02	-6.28	29.26	-35.30	-30.52	12.01	85.77	64.20	68.22
28	Finland	934.74	75.23	-19.80	-1.99	**78.76**	-38.67	-25.47	6.57	89.55	67.56	95.28
20	Norway	1478.34	97.31	**-13.46**	**2.01**	59.27	-34.25	-26.77	6.59	68.22	57.58	**100.71**
38	Czech Rep.	1544.17	77.92	-31.24	1.35	23.49	-24.69	**-21.93**	7.46	90.22	49.19	48.49
3	Germany	**15594.74**	77.92	-30.00	-3.21	48.18	-30.99	-22.98	8.15	105.19	**82.31**	87.93
46	Estonia	166.87	99.15	-16.39	0.59	48.96	**-21.01**	-24.80	5.84	**110.30**	80.40	77.45
1	Spain	5656.86	68.54	-36.13	-10.42	-5.25	-37.68	-29.93	10.14	92.10	78.43	47.28
8	Italy	9166.71	120.77	-34.02	-13.37	6.66	-38.94	-30.61	10.64	82.07	51.97	58.27
23	Luxembourg	22.08	112.62	-35.47	-11.28	26.78	-29.87	-33.00	**12.33**	84.91	66.51	83.62
15	Netherlands	4482.19	**129.54**	-27.51	-4.42	60.04	-45.21	-26.94	9.59	86.69	42.14	73.74
60	Slovakia	452.68	50.08	-33.71	-8.23	36.99	-33.55	-25.94	8.24	110.15	69.50	80.93

Source: made by the authors based on statistical data collected from WEF, Google and Apple reports

To apply the GRA method we respect the methodological steps and algorithm according to the international literature (Lusi et al., 2020; Nayakappa et al., 2019; Xu et al., 2014; Gerus – Gosciewska & Gosciewski, 2022; Lin & Huang, 2009; Huang & Lin, 2009; Wu & Zhan, 2017; Skrinjaric, 2021; Lusi et al., 2020; Ertugrul et al., 2018; Badi and Elghoul, 2023; Sarpkaya & Sabir, 2016; Fidan, 2020; Girish et al., 2019; Krstić et al., 2023) as follows (Figure 1) and mentioned in Appendix A.

Figure 1. Grey Relational Analysis steps



Source: (made by the authors based on Nayakappa et al., 2019, p. 409; JAER, 2020 and Maidin et al., 2022)

For the first step of GRA, in order to compare correctly the data with different measure units a pre-processing raw data was applied by concerting an original sequence into a decimal sequence between 0.00 and 1.00 for a better comparison, this step being considered one of the important one for entire process (Gerus – Gosciewska & Gosciewski, 2022). Therefore, for

correctly choose of reference sequence and comparable sequence (Step 2 from Appendix A) for normalization, "*the larger-the-better*" characteristics the original sequence can be *normalized* with formula (1):

$$x_i^*(k) = \frac{x_i^{(O)}(k) - \min x_i^{(O)}(k)}{\max x_i^{(O)}(k) - \min x_i^{(O)}(k)} \quad (1)$$

where $x_i^{(o)}(k)$ is the original sequence, $x_i^*(k)$ the sequence after the data preprocessing, max $x_i^{(o)}(k)$ the largest value of $x_i^{(o)}(k)$, and min $x_i^{(o)}$. Finaly, as the simplest method normalization can be made dividing sequence values by the first value of sequence by using formula (2):

$$x_i^*(k) = \frac{x_i^{(O)}(k)}{x_i^{(O)}(1)} \quad (2)$$

After data processing, *Grey Relational Coefficient* is calculated based on normalized sequences (step 3 from appendix A) (Ertugrul et al., 2018) based on equation (3):

$$\gamma\left[(x_0^*(k), x_i^*(k)\right] = \frac{\Delta_{\min} + \xi\Delta_{\max}}{\Delta_{0i}(k) + \xi\Delta_{\max}}, \qquad 0 < \gamma\left[(x_0^*(k), x_i^*(k)\right] \le 1 \quad (3)$$

Where $\Delta_{0i}(k)$ is the *deviation sequence* (step 4 from Appendix A) between $x_0^*(k)$ reference sequence and $x_i^*(k)$ comparable sequence and calculated with equation (4):

$$\Delta_{0i}(k) = \left|x_0^*(k) - x_i^*(k)\right| \quad (4)$$

The biggest *deviation* (for our research data) is calculated with equation (5):

$$\Delta_{\max} = \max_{\forall j \in i} \max_{\forall k} \left|x_0^*(k) - x_j^*(k)\right| \quad (5)$$

The term γ from equation (3) is distinguishing or identification coefficient: ζ ϵ [0, 1] and its values usually is ζ = 0.5 in literature (Lu, 2015). Grey relational coefficient is calculated to express the relationship between the ideal and actual normalized experimental results. Thus, the *Grey Relational Coefficient* can be expressed as show in equation (3) where $\Delta_{oi}(k)$ is the deviation sequence of the reference sequence (step 5 from Appendix A). After obtaining the grey relational coefficient, normally the average of the grey relational coefficient is taken as the *Grey Relational Grade* (GRG) defined as (equation (6)):

$$\gamma(x_0^*, x_i^*) = \sum_{k=1}^{n} \beta_k \gamma\left[x_0^*(k), x_i^*(k)\right] \quad (6)$$

with

$$\sum_{k=1}^{n} \beta_k = 1 \quad (7)$$

In the equation (6) $\gamma(x_0^*, x_i^*)$ Grey Relational Grade represents the level of correlation between the reference sequence and comparable sequences and is equal with 1 if two series are identical to each other. Grey Relational Grade shows that level of influence applied to reference sequence by comparable sequence (Ertugrul et al., 2018).

By splitting the group of countries into quartiles based on ranking of *GRG overnight stays*, top *rank of TTCI 2019 pre-pandemic* and *top rank of TTCI 2021 during pandemic*, *GRG of Google Mobility indices* and *GRG of Apple Mobility indices* and, for a better visualization of the

relationships according to these quartiles of each 11 European countries, the *relationship maps* were built with SPSS 29.0 (licensed).

To validate the results of GRA as a method for good and accurate predictor for tourism competitiveness for TTCI 2021 (during OCVID-19 pandemic time) we applied a *GLM – General Linear Model ANOVA* with *interaction effects* and *Tukey HSD Post Hoc Multiple Comparisons* (for observed means) take into consideration that according to the scientific literature regarding the GRA method, in different scientific fields, a combination of GRA and ANOVA are usually applied known as *Taguchi – GRA* (Sarpkaya & Sabir, 2016; JAER, 2020). Therefore, starting with the new ranks resulted from GRA and considering as *dependent variable* of the GLM model the *rank of TTCI 2021- during pandemic,* the *independent variables* of the model were considered*: quartile GRA rank of TTCI 2019*, *quartile of GRA rank for overnight stays*, *interaction effects* of *quartile GRA rank of TTCI 2019 * quartile of GRA rank for overnight stays.* For all the quantitative analysis the Microsoft Excel (for GRA) and SPSS 29.0 (licensed) was used.

3. RESULTS AND DISCUSSIONS

For the first objective of the research, we apply the GRA by using variables from Table 1, all the intermediate calculus of GRA (from step 2 to step 5) being presented in detail in Appendix A, in Table 2 are presented only the results of GRA, respectively the *grey relational grade* (GRG) for our research data.

Table 2 .Grey Relational Grade (GRG)

Ranking pre-pandemic by TTCI 2019 (used in GRA)	Ranking during-pandemic by TTCI 2021	Country	Pre-pandemic Ranking based on TTCI	GRG according to Overnight in pandemic	Ranking based on GRG for Overnight in pandemic	GRG according to Google Mobility	Ranking based on GRG for Google mobility	GRG according to Apple mobility	Ranking based on GRG for Apple mobility
1	3 ↓	Spain	1	0.4169	8 ↓	0.4124	**11**	0.5692	6 ↓
3	5 ↓	Germany	2	0.7175	1 ↑	0.5676	5	0.8269	**1** ↑
8	10 ↓	Italy	**3**	0.6835	**3** =	0.4176	10	0.4038	**11** ↓
15	14 ↑	Netherlands	4	0.7060	2 ↑	0.5138	6	0.4340	9 ↓
20	ND	Norway	**5**	0.4538	**5** =	0.6756	2	0.5938	**5** =
23	21 ↑	Luxembourg	6	0.5173	4 ↑	0.5105	7	0.5409	7 ↓
24	22 ↑	Belgium	**7**	0.4330	**7** =	0.5074	8	0.4795	8 ↓
28	18 ↑	Finland	8	0.3847	10 ↓	0.6124	4	0.6370	4 ↑
38	26 ↑	Czech Rep.	**9**	0.3958	9 =	0.6512	3	0.4092	10 ↓
46	29 ↑	Estonia	10	0.4510	6 ↑	0.7024	**1**	0.8158	2 ↑
60	56 ↑	Slovakia	**11**	0.3365	**11** =	0.4669	9	0.7261	3 ↑

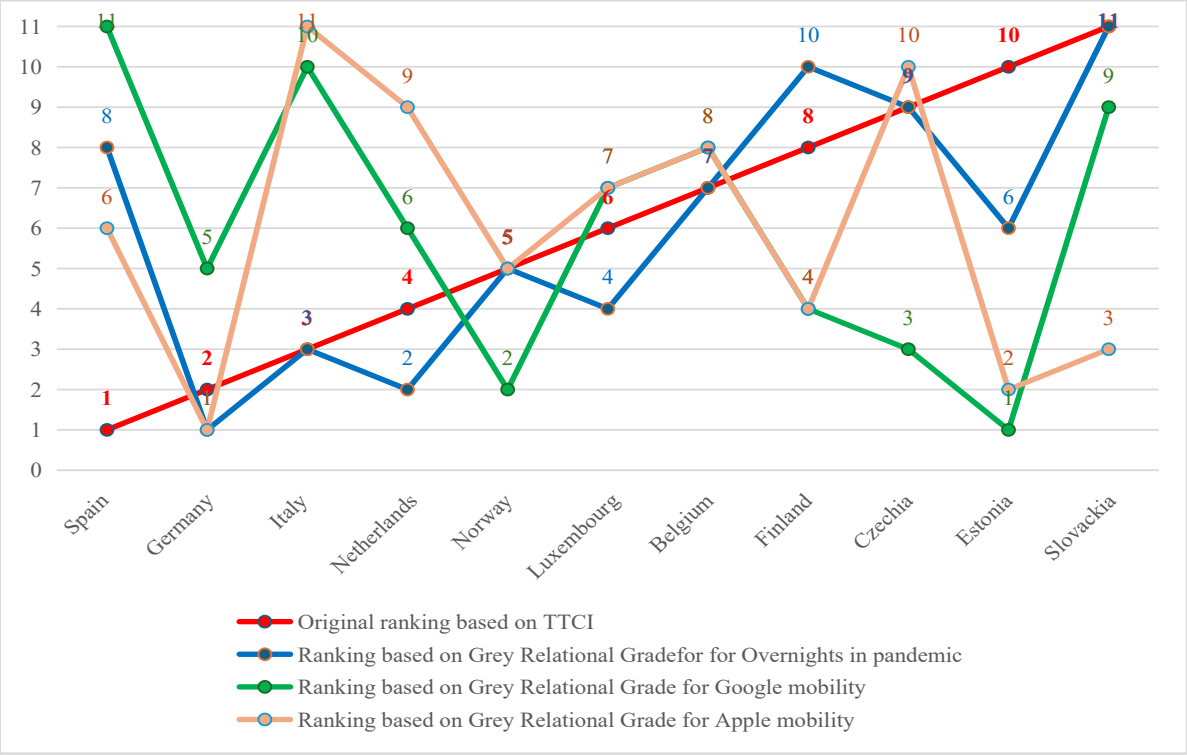
Source: authors' calculations

To choose the reference sequences and comparable sequences the "*the-larger – the-better*" criteria was applied so that the reference sequence values are equal to the maximum of the column values. GRA measure the correlation between the reference sequence and comparable sequence, all these details being presented in step 2 from Appendix A. Due of the facts that the variables have different measure units for the variable from the research, the data was normalized (step 3 from Appendix A) the values being transformed into [0, 1] interval by normalization operation. After normalized sequence obtains, firstly the deviation sequence is calculated between

reference sequence and comparable sequence (step 4 from Appendix A) to calculate Grey Relational Coefficient (step 5 from Appendix A). grey Relational Coefficients are calculated using equation (3), (4) and (5) after deviation sequence obtained and the results being presented in the step 5 from Appendix A and by take into consideration a value of 0.5 for the coefficient ξ in the equation (3). Grey Relational Grade is calculated using equation (6) and are shown in Table 2. These grades represent correlation between reference sequence and comparable sequence and for this reason, the alternative with highest correlation is selected the best choice/decision. After GRA method, all the 11 European countries are ranked from the biggest (best place being consider number one) to smallest (last) ranks for ranking based on TTCI 2019 (before COVID-19 pandemic). The comparison of the 11 European countries is shown in Table 2 by marking the increasing/decreasing of ranking compared with the original rank based on TTCI 2019.

So according to the results from Table 2 the TTCI hierarchy before COVID-19 pandemic (based on TTCI 2019) was, for the 11 European countries from the study (from the top ranked number 1 to the last rank, 60): Spain, Germany, Italy, Netherlands, Norway, Luxembourg, Belgium, Finland, Czech Republic, Estonia and Slovakia. During COVID-19 pandemic, according to the TTCI 2021 (the last data available from WEF), there are some changes in the ranks position with some particularities: from the countries from the superior half of the top, the rank position decrease for all top three European countries (Spain, Germany and Italy) with two position down and for all the other countries (except Norway with no data for TTCI 2021) increase the rank position, the most spectacular being Estonia with 17 position follow by Czech Republic with 12 position, Finland with 10 position. All these movement in TTCI hierarchy being marked with colored narrows, red for decreases and blue for increases. In the Figure 2 is the graphical representation of Grey Relational Grade (GRG) for rankings *before – original tank based on TTCI 2019 (with red line)* and *after Grey Relational Analysis* for overnight stays (blue line), Google Mobility data (green line) and Apple Mobility data (orange line).

Figure 2. Grey relational Grade for rankings before (red) and after GRA



Source: made by the authors

It can be observed, based on the results from Table 2 and Figure 2 that the hierarchy changed after we applied GRA method, as follows:

- for *overnight stays*, GRG indicate the new hierarchy: Germany, Netherlands, Italy, Luxembourg, Norway, Estonia, Belgium, Spain, Czech republic, Finland and Slovakia with some particularities: Italy, Norway, Belgium, Czech Republic and Slovakia keep their rank compared with the original rank based on TTCI 2019, Spain decrease 7 ranks, Finland decrease also but only 2 ranks and Germany increase 1 rank (occupying the first place), Netherlands and Luxembourg increase 2 ranks, Estonia increase 4 ranks;
- for *Google Mobility indices*, GRG indicate the following hierarchy: on the first place Estonia increase 9 ranks, Norway up to 2nd position by increase 3 ranks, Czech Republic up 3nd position by increasing 6 positions, Finland is on 4th position by increase 4 ranks, Germany is on 5th place by decreasing 3 ranks, Netherland on 6th by decrease 2 positions, Luxembourg and Belgium decrease only 1 rank, Slovakia increase 2 position from 11 to 9, Italy decrease 7 rank occupying the 10th position and Spain simply went from the bottom of top to the last position. This new hierarchy based on GRG, in our opinion reflect the mobility (together with all restrictions for travel during COVID-19 pandemic) of persons and/or tourists in these country, Spain and Italy being one of the countries with the most visited destinations worldwide and with the most affected population in pandemic time.
- For Apple Mobility indices, the GRG indicate, in most countries the same evolution as Google Mobility data but with 2 particularities: for Germany which increase on the 1st place and for Czech Republic by decrease one position. According to value of GRG for Apple Mobility data, Italy is on the last place, Netherland decrease from 4 to 9, Estonia increases from 10 to 2nd position, Slovakia increase also spectaculars from 11th to 3th position and Norway keep the 5th position.

For the second objective of the research, we used the relationship maps from SPSS by splitting the countries on quartiles based on *GRG ranking* for: overnights, top ranks for TTCI 2019 – before COVID-19 pandemic, top ranks for TTCI 2021 – during COVID-19 pandemic, Google Mobility data and Apple Mobility data, all these relationships being presented in the Figures 3 – 7. Stronger relations are marked with thick lines and the less with thin lines.

Figure 3. Countries grouped by overnights, TTCI 2019 and TTCI 2021

Figure 3a

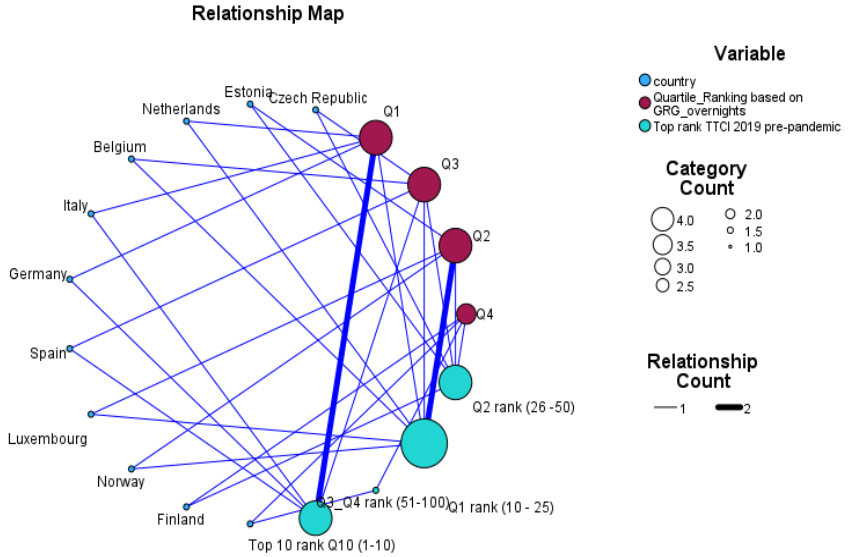


Figure 3b

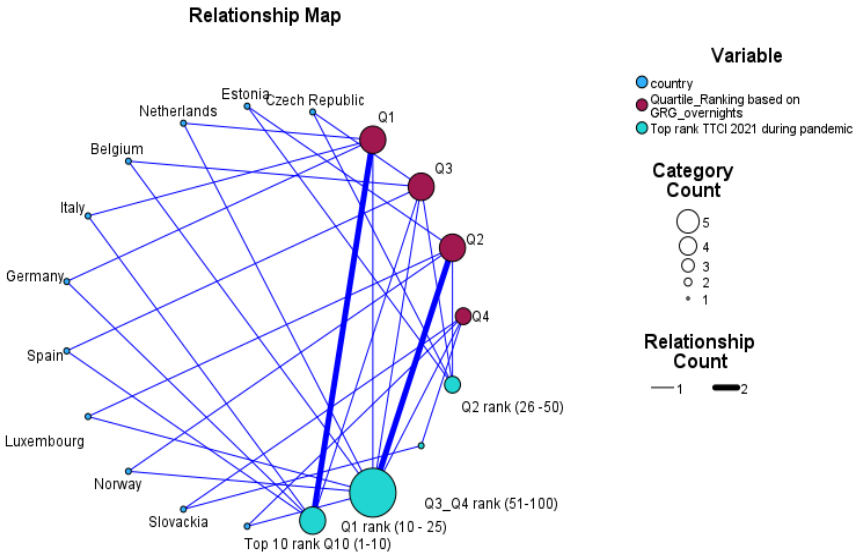
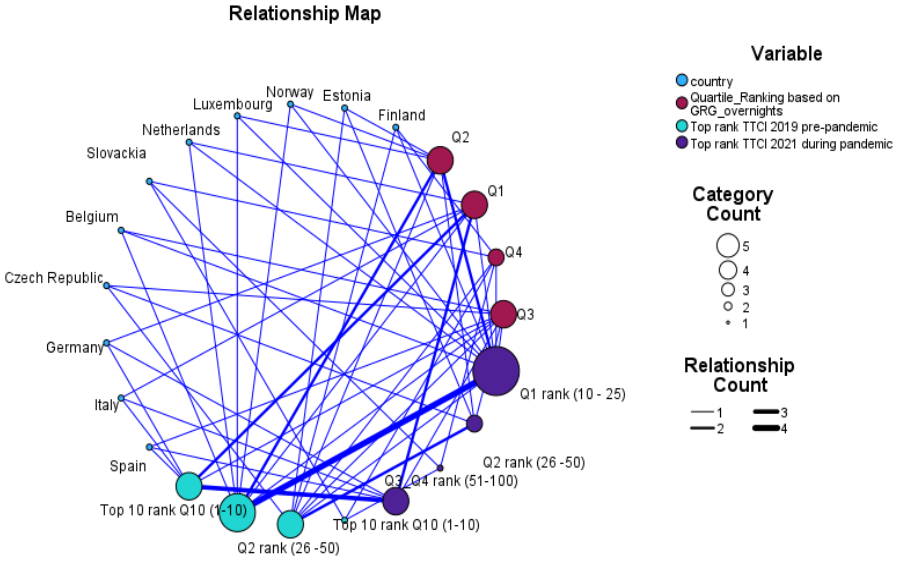
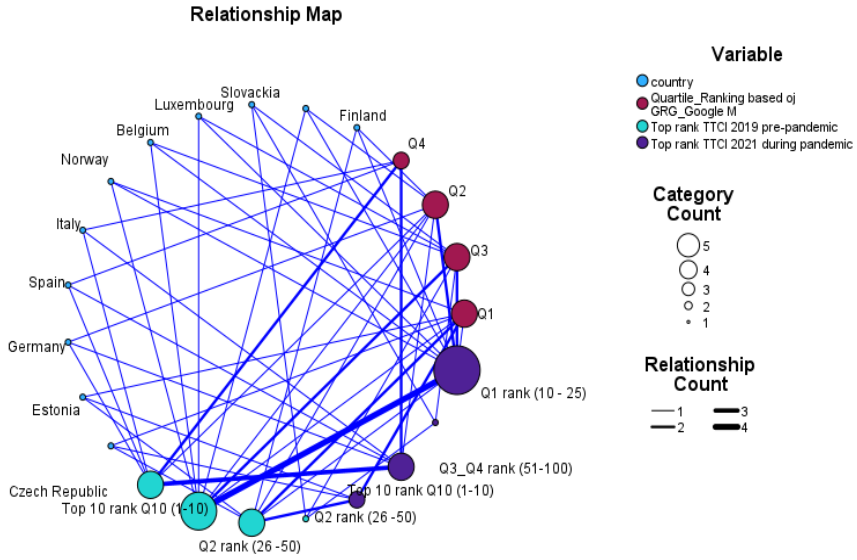


Figure 3c



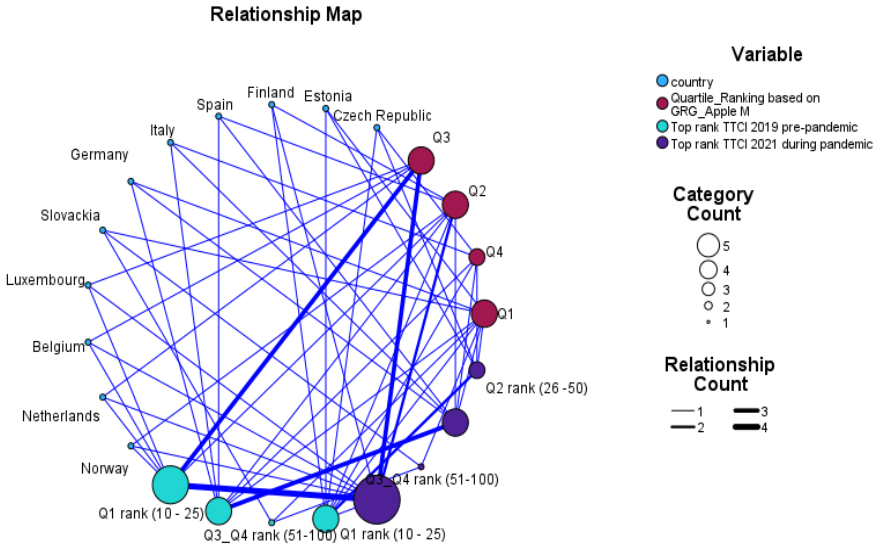
Source: made by the authors

Figure 4. Countries grouped by Google Mobility, TTCI 2019 and TTCI 2021



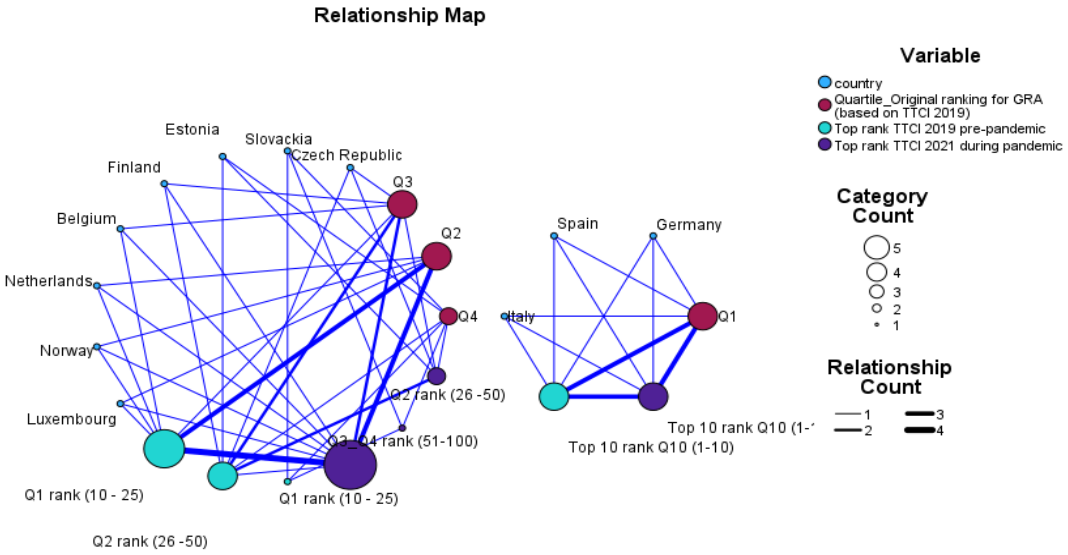
Source: made by the authors

Figure 5. Countries grouped by Apple Mobility TTCI 2019 and TTCI 2021



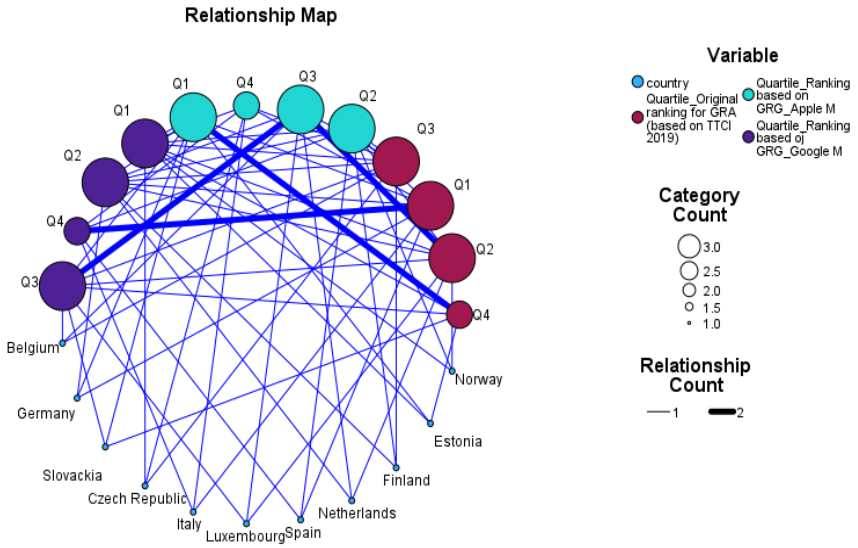
Source: made by the authors

Figure 6. Countries grouped by GRG rank, top rank TTC 2019 and TTCI 2021



Source: made by the authors

Figure 7 . Countries grouped by GRG rank, GRG for GM and GRG for Apple



Source: made by the authors

If we look back to the initial data from Table 1 and the Figures 3 -7 in a short conclusion, the GRA method emphasis that those indicators with their values, according to GRA algorithm, as references sequences predict the new hierarchy. For example, Germany has references for overnight stays and after GRA occupy the 1st place and for Apple Transit, Netherland (from 4 to 2nd position) with references for overnight stays as fixed base for February 2020, after GRA is on the second position, Italy maintain on the 3rd position, Norway maintain the 5th position due of the references for Google Mobility Retail & Recreation, Google Mobility Grocery & Pharmacy and Apple Walking, Finland up to 10 (from 8th position) due of reference sequence for Google Mobility Parks, Estonia increase from 10 to 6th position due of the reference sequences for Google Mobility Transit & Stations and Apple Driving. The relationship maps from figure

3-7 show better these migrations for each combination of variables/indicators from the study.

For the 3rd objective of this research, respectively *to validate the GRA as method for good and accurate predictor for tourism competitiveness for TTCI 2021 (during OCVID-19 pandemic time)* a *univariate GLM (General Linear Model) with Tukey HSD Post Hoc Multiple Comparisons /Two-way ANOVA (Univariate Analysis of Variance) with interaction effects and* was applied for observed means, the Levene's test of equality of error variances from Table 3 indicate that for mean, median, median with adjusted df (degree of freedom) and trimmed mean the population from quartiles have different variances but these can be explain by the number of the countries, respectively 11 European countries. As dependent variable the TTTCI 2021 rank (during COVID-19 pandemic) was considered.

Table 3. Levene's Test of Equality of Error Variances[a,b]

		Levene Statistic	df1	df2	Sig.
Rank during pandemic (TTCI 2021)	Based on Mean	23.321	3	7	<.001
	Based on Median	10.618	3	7	.005
	Based on Median and with adjusted df	10.618	3	5.521	.010
	Based on trimmed mean	22.372	3	7	<.001

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

a. Dependent variable: Rank during pandemic (TTCI 2021)

b. Design: Intercept + Quartile_GRA_orig_rank_TTCI_2019

Source: authors' calculations

The results from Table 4 for tests of between subjects effects indicate that the mean of ranks based on GRA) calculated based on TTCI rank 2019) are not equal for the countries from each quartiles (p-value = 0.010), some quartiles having lower mean than other. The different ranks calculated by GRA based on TTCI 2019 ranks account for some 78.2% of variance in the TTCI 2021 rank (during pandemic) and show the effect size as indicated by *partial eta squared* calculated as sum of squares for GRA rank based on TTCI 2019 divided by corrected total sums of squares (1619.379/2070.545 = 0.782*)* from Table 4. Eta-squared $\eta^2 > 0.14$ indicate a large effect of sample size (in our case only 11 countries with completed data for variables from the study) for 78.2% of population from sample.

Table 4 . Tests of Between-Subjects Effects

Dependent Variable: Rank during pandemic (TTCI 2021)

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	1619.379[a]	3	539.793	8.375	.010	.782
Intercept	5260.907	1	5260.907	81.625	<.001	.921
Quartile_GRA_orig_rank_ TTCI_2019	1619.379	3	539.793	8.375	***.010***	*.782*
Error	451.167	7	64.452			
Total	6632.000	11				
Corrected Total	2070.545	10				

a. R Squared = .782 (Adjusted R Squared = .689)

Source: authors' calculations

According to these results there are difference between rank mean for our European countries

but to identify the exactly between which quartile of original ranking of GRA (based on TTCI 2019) an ANOVA with *Post Hoc Tests Tukey's HSD* was applied, the results being presented in Table 5 with the same dependent variable, the TTCI 2021 rank (during pandemic). So, according to results from Table 5 only the differences are between the polarized quartiles (p-value = 0.007), respectively only between Q1 and Q4 (marked with * on mean difference column). For the rest of combination, the differences between means are not statistically significant with mention that for comparison Q2 and Q4 the p—value = 0.051 so closed to 0.05 but as a rule of thumb "*sig. < 0.05 indicates a statistically significant*" difference between two means.

Table 5 . Multiple Comparisons

Dependent Variable: Rank during pandemic (TTCI 2021)

Tukey HSD

(I) Quartile_Original ranking for GRA (based on TTCI 2019)	(J) Quartile_Original ranking for GRA (based on TTCI 2019)	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Q1	Q2	-12.33	6.555	.316	-34.03	9.36
	Q3	-16.00	6.555	.156	-37.70	5.70
	Q4	-36.50*	7.329	***.007***	-60.76	-12.24
Q2	Q1	12.33	6.555	.316	-9.36	34.03
	Q3	-3.67	6.555	.941	-25.36	18.03
	Q4	-24.17	7.329	***.051***	-48.43	.09
Q3	Q1	16.00	6.555	.156	-5.70	37.70
	Q2	3.67	6.555	.941	-18.03	25.36
	Q4	-20.50	7.329	.098	-44.76	3.76
Q4	Q1	36.50*	7.329	***.007***	12.24	60.76
	Q2	24.17	7.329	***.051***	-.09	48.43
	Q3	20.50	7.329	.098	-3.76	44.76

Based on observed means.

The error term is Mean Square(Error) = 64.452.

*. The mean difference is significant at the 0.05 level

Source: authors' calculations

Finally, the *univariate GLM – ANOVA with interaction effects* was applied to *validate the GRA as method for good and accurate predictor for tourism competitiveness for TTCI 2021 (during OCVID-19 pandemic time),* the results are presented in Table 6.

Table 6. Tests of Between-Subjects Effects

Dependent Variable: Rank during pandemic (TTCI 2021)

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	2049.545[a]	7	292.792	41.827	.005	.990
Intercept	4551.385	1	4551.385	650.198	<.001	.995
Quartile_GRA_orig_rank_ TTCI_2019	880.733	3	293.578	41.940	***.006***	.977
Quartile_GRA_rank_overnights stay	183.489	3	61.163	8.738	***.054***	.897
Quartile_GRA_orig_rank_ TTCI_2019 * Quartile_GRA_ rank_overnights	297.846	1	297.846	42.549	***.007***	.934
Error	21.000	3	7.000			
Total	6632.000	11				
Corrected Total	2070.545	10				

a. R Squared = .990 (Adjusted R Squared = .966)

Source: authors' calculations

According to the results from Table 6 we identified the *main effect* of *GRA ranks for TTCI 2019 (before COVID-19 pandemic)* and *GRA rank for overnight stays* on TTCI 2021 ranks (during COVID-19 pandemic) but with a large effect of sample size (in our case only 11 countries with completed data for variables from the study) for 97.7% respectively 89.7% of population from sample. Also an interaction effect of both these GRA ranks, for TTCCI 2019 and for overnight stays is demonstrated (p-value = 0.007) with significance that during pandemic the overnight stays affect the TTCI rank and these could justified the movement in position of TTCI 2021 ranks.

The ANOVA analysis with interaction effect has been performed to predict the statistical significance of the process parameters, respectively the new ranks calculated with GRA method and finally to demonstrate the efficiency of Grey Relational Analysis as a good identifier of good predictor for TTCI 2021 ranks (during pandemic) by using both tourism indicators (overnight stays) and mobility data (Google and Apple) that indicate the travel of people during the COVID-19 pandemic.

4. CONCLUSIONS

Based on our results, this research pointed out the other *advantages* of applying the GRA method and grey systems method over ranking but for European tourism competitiveness linked to mobility pre and during COVID-19 pandemic, emphasizing, from the perspective of GRA methods, more particularities of the mobility of persons in a specific time. Therefore, in our opinion these novel contributions are linked to:

- the acceptance of small number of necessary data, incomplete data (Gerus – Gosciewska & Gosciewski, 2022; Han & Yu, 2016; Sallehuddin et al., 2008);
- the information is limited (Lin & Huang, 2009), poor information (Su & Liu, 2016; Sallehuddin et al., 2008) or insufficient (Fidan, 2020);
- compared with linear regression, univariate regression the GRA not require the typical distribution of small amount of calculation (Han & Yu, 2016);
- the results are straightforward and does not require any distribution assumption about

the observed data (Skrinjaric, 2021; Wu & Zhan, 2017; Sallehuddin et al., 2008).

- The results are based on original data (Ertugrul et al., 2018; Altin, 2020) and easy calculation (Ertugrul et al., 2018; Ozdagoglu et al., 2017).

These aspects justified our choice for GRA due of the missing data for most European studies regarding the Google and Apple Mobility data and due of the uncertain of these data (Skrinjaric, 2021), the location being marked only on smartphones and android systems. More, the tourism system has limited statistic data with greater fluctuation and less typical distribution law (Wu & Zhan, 2017), a true grey system, and therefore this is another pro-argument for GRA as valid method for tourism industry. Our results confirm the results from:

- Gerus – Gosciewska & Gosciewski (2022) that proved the effectiveness of GRA for data ranking and
- the results of Lin & Huang (2009) which show that tourism managers must identify and explore competitiveness advantage and analyze the destination's competitiveness position.
- the results of Skrinjaric (2021) that show that with smaller amount of data, reliable results can be obtained when comparing complex indicators from different world organizations.

In previous research made by the authors (Nagy, Gabor & Oltean, 2023) that natural resources are still an important part for European tourism (Huang & Lin, 2009) but also the role of entrepreneurship in tourism reveal the changes in the tourism demand and the need to adjust products and destinations to meet these changes. Therefore, we consider that the GRA approach for relation between competitiveness measured though TTCI and mobility data is a practical way to gather expert opinions to address a decision problem to use the mobility of persons/tourists as predictors for competitiveness or not or remain only the overnight stays as the best indicators for competitiveness in tourism, this being considered another contribution to the existing scientific literature.

The *limitations* of this research are linked to the fact that the TTCI rankings and data are published biannually, and the Google and Apple Mobility indices were published only during the COVID-19 pandemic time therefore this study can~~not~~ be replicate only for those worldwide countries with complete data for these indicators or to related to other statistical data.

The aim of this research was to determine the strength of the relationship between multiple independent variables such as overnights stays (as number and fixed base for February 2020 index), mobility data measured by Google and Apple in relationship with dependent variable competitiveness for tourism indicator, pre and during COVID-19 pandemic. Also, through this study we validated the powerful of GRA and grey system theory for tourism competitiveness, statistically significant according to GLM with interaction effects, and therefore emphasis (especially for entrepreneurs) that the overnight stays will give the right rank on top of tourism competitiveness, prior to other ITC support as Google and Apple Mobility indices proved by reflection of overnights on TTCI 2021 – during pandemic. With the GRA approach, analyses of scarce, incomplete, and uncertain data produce reliable results (Gerus – Gosciewska & Gosciewski, 2022).

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APPENDIX A

Results for the intermediate steps (2-5) of GRA

Rank TTCI 2019	Country	Overnights_stays (thousand)	Overnights_BF_February 2020	GM_Retail	GM_Grocery	GM_Parks	GM_Transit	GM_Workplace	GM_Residential	Apple_Driving	Apple_Transit	Apple_Walking
Step 2 of GRA: Reference sequence and comparable sequence												
0	Reference sequence (x_0)	**15594.74**	**129.54**	**-13.46**	**2.01**	**78.76**	**-21.01**	**-21.93**	**12.33**	**110.30**	**82.31**	**100.71**
1	Spain	5656.86	68.54	**-36.13**	-10.42	**-5.25**	-37.68	-29.93	10.14	92.10	78.43	**47.28**
3	Germany	15594.74	77.92	-30.00	-3.21	48.18	-30.99	-22.98	8.15	105.19	82.31	87.93
8	Italy	9166.71	120.77	-34.02	**-13.37**	6.66	-38.94	-30.61	10.64	82.07	51.97	58.27
15	Netherlands	4482.19	129.54	-27.51	-4.42	60.04	**-45.21**	-26.94	9.59	86.69	**42.14**	73.74
20	Norway	1478.34	97.31	-13.46	2.01	59.27	-34.25	-26.77	6.59	**68.22**	57.58	100.71
23	Luxembourg	**22.08**	112.62	-35.47	-11.28	26.78	-29.87	**-33.00**	12.33	84.91	66.51	83.62
24	Belgium	984.17	92.62	-35.02	-6.28	29.26	-35.30	-30.52	12.01	85.77	64.20	68.22
28	Finland	934.74	75.23	-19.80	-1.99	78.76	-38.67	-25.47	6.57	89.55	67.56	95.28
38	Czech Rep.	1544.17	77.92	-31.24	1.35	23.49	-24.69	-21.93	7.46	90.22	49.19	48.49
46	Estonia	166.87	99.15	-16.39	0.59	48.96	-21.01	-24.80	**5.84**	110.30	80.40	77.45
60	Slovakia	452.68	**50.08**	-33.71	-8.23	36.99	-33.55	-25.94	8.24	110.15	69.50	80.93
Step 3 of GRA: Normalized comparable sequences												
0	Reference sequence (x_0)	1.0000	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
1	Spain	0.3618	0.2323	0.0000	0.1917	0.0000	0.3111	0.2770	0.6629	0.5675	0.9034	0.0000
3	Germany	1.0000	0.3504	0.2707	0.6607	0.6361	0.5875	0.9051	0.3564	0.8785	1.0000	0.7609
8	Italy	0.5872	0.8896	0.0931	0.0000	0.1418	0.2593	0.2154	0.7396	0.3290	0.2446	0.2058
15	Netherlands	0.2864	1.0000	0.3805	0.5823	0.7773	0.0000	0.5474	0.5788	0.4388	0.0000	0.4954
20	Norway	0.0935	0.5944	1.0000	1.0000	0.7680	0.4528	0.5627	0.1159	0.0000	0.3845	1.0000
23	Luxembourg	0.0000	0.7870	0.0291	0.1358	0.3812	0.6338	0.0000	1.0000	0.3965	0.6067	0.6803
24	Belgium	0.0618	0.5353	0.0490	0.4612	0.4108	0.4096	0.2240	0.9506	0.4170	0.5491	0.3920
28	Finland	0.0586	0.3166	0.7204	0.7399	1.0000	0.2704	0.6800	0.1122	0.5069	0.6328	0.8985
38	Czech Rep.	0.0977	0.3504	0.2157	0.9572	0.3422	0.8479	1.0000	0.2499	0.5228	0.1754	0.0227
46	Estonia	0.0093	0.6176	0.8711	0.9078	0.6454	1.0000	0.7403	0.0000	1.0000	0.9523	0.5647
60	Slovakia	0.0277	0.0000	0.1068	0.3345	0.5028	0.4819	0.6371	0.3701	0.9966	0.6811	0.6299
Step 4 of GRA: Deviation sequence												
0	Reference sequence (x_0)	1.0000	1.0000	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
1	Spain	0.6382	0.7677	1.0000	0.8083	1.0000	0.6889	0.7230	0.3371	0.4325	0.0966	1.0000
3	Germany	0.0000	0.6496	0.7293	0.3393	0.3639	0.4125	0.0949	0.6436	0.1215	0.0000	0.2391
8	Italy	0.4128	0.1104	0.9069	1.0000	0.8582	0.7407	0.7846	0.2604	0.6710	0.7554	0.7942
15	Netherlands	0.7136	0.0000	0.6195	0.4177	0.2227	1.0000	0.4526	0.4212	0.5612	1.0000	0.5046
20	Norway	0.9065	0.4056	0.0000	0.0000	0.2320	0.5472	0.4373	0.8841	1.0000	0.6155	0.0000
23	Luxembourg	1.0000	0.2130	0.9709	0.8642	0.6188	0.3662	1.0000	0.0000	0.6035	0.3933	0.3197
24	Belgium	0.9382	0.4647	0.9510	0.5388	0.5892	0.5904	0.7760	0.0494	0.5830	0.4509	0.6080
28	Finland	0.9414	0.6834	0.2796	0.2601	0.0000	0.7296	0.3200	0.8878	0.4931	0.3672	0.1015
38	Czech Rep.	0.9023	0.6496	0.7843	0.0428	0.6578	0.1521	0.0000	0.7501	0.4772	0.8246	0.9773
46	Estonia	0.9907	0.3824	0.1289	0.0922	0.3546	0.0000	0.2597	1.0000	0.0000	0.0477	0.4353

Rank TTCI 2019	Country	Overnights_stays (thousand)	Overnights_BF_February 2020	GM_Retail	GM_Grocery	GM_Parks	GM_Transit	GM_Workplace	GM_Residential	Apple_Driving	Apple_Transit	Apple_Walking
60	Slovakia	0.9723	1.0000	0.8932	0.6655	0.4972	0.5181	0.3629	0.6299	0.0034	0.3189	0.3701
Step 5 of GRA: Grey Relational Coefficients												
0	Reference sequence (x_0)	1.0000	1.0000	1.0000	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
1	Spain	0.4393	0.3944	0.3333	0.3822	0.3333	0.4206	0.4088	0.5973	0.5362	0.8381	0.3333
3	Germany	1.0000	0.4349	0.4067	0.5957	0.5787	0.5480	0.8405	0.4372	0.8045	1.0000	0.6765
8	Italy	0.5478	0.8192	0.3554	0.3333	0.3681	0.4030	0.3892	0.6575	0.4270	0.3983	0.3863
15	Netherlands	0.4120	1.0000	0.4466	0.5448	0.6918	0.3333	0.5249	0.5428	0.4712	0.3333	0.4977
20	Norway	0.3555	0.5521	1.0000	1.0000	0.6831	0.4774	0.5334	0.3612	0.3333	0.4482	1.0000
23	Luxembourg	0.3333	0.7013	0.3399	0.3665	0.4469	0.5772	0.3333	1.0000	0.4531	0.5597	0.6100
24	Belgium	0.3477	0.5183	0.3446	0.4813	0.4591	0.4586	0.3919	0.9101	0.4617	0.5258	0.4512
28	Finland	0.3469	0.4225	0.6413	0.6578	1.0000	0.4066	0.6098	0.3603	0.5035	0.5766	0.8313
38	Czech Rep.	0.3566	0.4349	0.3893	0.9211	0.4318	0.7667	1.0000	0.4000	0.5117	0.3775	0.3385
46	Estonia	0.3354	0.5666	0.7950	0.8444	0.5850	1.0000	0.6581	0.3333	1.0000	0.9130	0.5346
60	Slovakia	0.3396	0.3333	0.3589	0.4290	0.5014	0.4911	0.5795	0.4425	0.9932	0.6106	0.5747