The Disruptive Effect of Technological Innovation in the Tourist Accommodation Industry

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This work focuses on the disruptive effect generated by online tourist accommodation platforms. This technological innovation has brought about changes not only in the tourism industry, but also in the lives of the citizens of host communities. This research analyzes the perception that citizens economically dependent on tourism have of the socio-economic impacts linked to the activity of these online platforms. The field work was carried out in Spain in April 2020 by means of a survey in which citizens residing in one of the main tourist cities in the country took part. This analysis has allowed for the construction of four categories of positive impacts and four categories of negative impacts, all linked to disruptive technological innovation in the tourism sector. The most salient impact is related to how citizens economically dependent on tourism assess the changes taking place in the existing business network. This group's assessment might possibly be the consequence of a shift in the focus of local businesses, which have gone from resident-oriented businesses to tourist-oriented businesses.

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Keywords: peer-to-peer accommodation, tourism innovation, urban tourism, sharing economy, online sharing platform, Airbnb, home-sharing, overtourism, social sustainability.

1. Introduction

In recent years, the tourism industry has undergone major changes which can potentially alter the competitive balances in the sector [Sigalat-Signes *et al.*, 2020], as well as generate multiple unintended consequences for the collectives involved in this activity [(Puczkó and Rátz , 2000)]. Specifically, the key changes in the tourism context have derived from the spread of low-cost tourism and the expansion of online tourist accommodation platforms [(Martin *et al. 2018a*; Abril-Sellarés *et al.*, 2015)]. Both innovations have contributed to increasing tourist flows as well as pressure on the historic centers of certain cities [(Martin *et al.*, *2019a*; Gravari-Barbas and Guinand, 2017)]. The impact of these effects has been exacerbated by the unprecedented escalation in the offer of accommodation places in residential buildings [(Guaita *et al.*, 2020a; Guaita *et al*., 2020b)], which has generated multiple unintended consequences for residents, as well as numerous business opportunities.

This work focuses on the impacts to stakeholder groups that result from the expansion of the use of tourist accommodation intermediation platforms. The 2008 creation of Airbnb in Los Angeles was the start of an intermediation system which has been acclaimed as one of the greatest technological innovations of all times in the tourism sector. Ever since its creation, this firm has enjoyed a spectacular growth with current estimations of over five million accommodations in more than 190 countries. This company offers on their website accommodation options based on the supply of private homes [(Guttentag and Smith, 2017; Hajibaba and Dolnicar, 2017)] a concept that allows them to house more than one million travelers [(Dogru *et al.*, 2019)] on any given night. This intermediation system is part of the so-called "sharing economy" which groups together activities for the exchange of goods and services supported by online technological means [(Botsman and Rogers, 2010; Geron, 2013; Sacks, 2011; Agarwal and Steinmetz, 2019)].

Given that this type of intermediation system is of recent creation, the existing academic literature generated around its effects is also novel and scarce. However, some of the existing works have focused on the positive and negative impacts generated from the new interactions derived from these platforms. Within, these, a few have focused on the analysis of the perceptions of the stakeholders involved with regard to the impacts generated. Even though some research has been published in this sub-area, its authors coincide in emphasizing that this work needs to be expanded [(Mody *et al.*, 2020; Yeager *et al.*, 2020)]. One key reason, is that the success of a tourist destination requires the support of the groups involved in it [(Gursoy *et al.*, 2010)]. And this support is conditioned by the perception of the positive and negative impacts derived from the tourist activity [(Guaita *et al.*, 2019)].

One cannot forget that, with this technology, an economic activity is being introduced in residential settings forging a constant interaction between residents and tourists, and the interferences generated in the daily lives of the locals can compromise the social sustainability of the economic activity [(Prayag *et al.*, 2013)]. The potential of this model of accommodation intermediation, and in general of the collaborative economy, to generate wealth and entrepreneurship is very high. Therefore, rather than rejecting this type of activity, it is necessary to move towards a balanced model that respects the rights and needs of the different groups involved [(Nunkoo and So, 2016; Mody *et al.*, 2019; Suess *et al.*, 2020)].

This new model for the provision of tourism services represents an example in which technology has created an entire economic activity with a growth that advances faster than the regulation that would affect it [(Martin *et al.*, 2019)]. The lack of regulation is precisely a problem highlighted in several studies as a driver of conflicts between groups involved [(Martin *et al.*, 2020)]. In order to improve this regulation, it is necessary first of all to know the fact itself to a greater extent, this being what this work aims to contribute. The contribution of this work derives from acknowledging that online tourist accommodation platforms entail a disruptive innovation in the sector. Specifically, our intention is to answer two research questions (RQ). RQ1: in which categories can the impacts perceived by citizens economically dependent on tourism be grouped? RQ2: what is the attitude of citizens economically dependent on tourism regarding the effects of this technological innovation? The results presented are based on a field work carried out in 2020 in the city of Granada (Spain). This is one of the main tourist destinations in the country, attracting more than 2 million annual visitors [(National Statistics Institute, 2020a)]. In addition, being a medium-sized city with 250,000 inhabitants [(National Statistics Institute, 2020b)], it is the Spanish city with the highest tourist pressure. This makes it an ideal environment to carry out the aforementioned analysis.

2. Theoretical Framework

Platforms for the intermediation of tourist accommodations have increased and simplified the interactions that take place between the local population and tourists [(Russo and Quaglieri, 2014)], which has brought about changes in the host community. The effects resulting from the development of tourist activity are known as tourist impacts, which can be positive or negative [(Youell, 1998; Pérez *et al.,* 2020)]. Positive impacts contribute to fostering local support for this activity and economic growth and can even result in the social regeneration of some destinations [(Andereck and Nyaupane, 2011; Andereck *et al.,* 2005)]. For their part, negative impacts may worsen the lifestyle of residents, reducing their support for tourism activity, and, in extreme cases, lead to the loss of local population [(Martín *et al.,* 2017; Jiménez *et al.,* 2014; Salinas *et al.,* 2020)]. As the activity of companies such as Airbnb has expanded, new impacts have been generated, both positive and negative. As noted by several authors, research on the impacts associated with this activity is growing but incomplete (Guttentag, 2015; Cheng, 2016)].

The academic literature has reported and analyzed numerous impacts that could be classified as negative, partly derived from the lack of planning of this disruptive business model, as well as from a poor regulation that fails to address the reality of this activity [(Martin *et al.,* 2019a; Nieuwlanda and van Melik, 2020)]. Although this new business model can increase the income of certain groups, there has been a deterioration in working conditions when the only source of income is associated with this type of activity [(Lyons and Wearing, 2015; Schor and Fitzmaurice, 2015)]. Effects on the traditional accommodation industry have also been described, such as a drop in employee wages [(Suciu, 2016)] and a lower occupancy rate [(Fang *et al.,* 2016). Also, impacts on the residential market have been reported, e.g. evictions of long-term tenants, increasing rental prices, and housing shortages in tourist areas [(Edelman and Geradin, 2016; Jefferson-Jones, 2014; Lines, 2015)]. Studies have also shown a loss of cohesion in traditional neighborhoods [(Cócola, 2016; Gallagher, 2017)], and other nuisances for neighbors, such as increased traffic, greater feeling of insecurity, noise in residential buildings, appropriation of public space, and crowding of public spaces in general [(Gallagher, 2017; Gurran and Phibbs, 2017; Martin *et al.,* 2017; Suess *et al.,* 2020)]. As regards society as a whole, there are concerns related to tax evasion and unfair competition associated with this type of activity [(Lyons and Wearing, 2015; Oskam and Boswijk, 2016)]. The traditional consumer and supplier roles have been transformed, which calls for new instruments capable of ensuring the safety of travelers and economic transactions [(Sigala, 2017)].

Obviously, not all impacts are negative. Many interactions or positive impacts have been described in association with the activity of these platforms. The implementation of activities related to collaborative economy can promote values such as honesty, empathy, equality, reciprocity, and openness [(John, 2013)]. A counter-intuitive finding is that there could emerge a greater feeling of belonging to the community in response to the increased presence of strangers [(Martin *et al.,* 2015)]. Travelers will also find benefits. It is possible to enjoy a more authentic experience [(Forno and Garibaldi, 2015; Sigala, 2017; OECD, 2016; Tussyadiah and Pesonen, 2018; Russo and Quaglieri, 2016], and greater interaction with the locals [(Belarmino *et al.,* 2017)]. In addition, these platforms provide a wider range of accommodation options at an affordable price [(Shaheen et al., 2012; Juul, 2015; Ioannides *et al.,* 2018)] and, in general, increase the carrying capacity of tourist destinations at peak times [(Juul, 2015)] The decrease in the cost of accommodations can lead to an increase in the number of trips, as well as a greater expenditure on other services [(Zervas *et al.,* 2014)]. A balanced distribution of tourist accommodation across the city may enable tourist spending to fall on areas that were traditionally not reached [(Porges, 2013)]. Furthermore, it is easier to undertake businesses linked to this type of activity within the framework of collaborative economy [(Nadler, 2014; Guaita and Martín, 2020)]. The social and economic context is of great importance to promote innovation and entrepreneurship [(Stahl *et al.,* 2017; Agarwal et al., 2017; Brem and Ivens, 2013; Brem *et al.,* 2016)].

Based on the above, it is necessary to ascertain how the impacts associated with disruptive innovation, in this case technology, are perceived by the tourism industry, as the preservation of a destination's social sustainability is crucial to its continuity. This must and can be compatible with promoting legitimate economic interests and providing a quality experience for the visitor [(Bramwell and Lane, 1993; Park *et al.,* 2008; Martin *et al.,* 2019b)]. Indeed, tourist activity must be economically viable, but also socially sustainable [(Puczkó and Rátz, 2000)]. To further progress in this regard, it is necessary to improve the knowledge of how tourism impacts are perceived by the stakeholders [(Gursoy *et al.,* 2010; Martin, 2019)]. In order to promote entrepreneurship and innovation, it is necessary to generate an adequate framework, capable of promoting the implementation of new technologies and the development of technology-based companies [(Furue *et al.,* 2020, Reith *et al.*, 2020, Aldhaban *et al.,* 2020)]. In this sense, it is undeniable that technological innovations of this kind can become great generators of employment and wealth [(Csuka *et al.*, 2019; Guderian, 2019, Philipson, 2020)].

3. Methodology

A fifteen-question survey was used to assess the extent to which economic self-interest affects the opinion of the residents of Granada with respect to the impacts that online accommodation platform services for the rental of tourist homes such as Airbnb has on their city. This city has a population of 230,000 inhabitants [(National Statistics Institute, 2020b)]. The city receives more than 2 million tourists annually (National Statistics Institute, 2020a). This figure does not include those housed in establishments mediated on online platforms, as there are no statistics on the flows of visitors associated with this type of accommodation. However, it is possible to generate an idea of the aforementioned flows by comparing the hotel offer (15,000 beds) [(National Statistics Institute, 2020a)] with that associated with online platforms (3,7,500 beds) [(Datahippo, 2020)]. These figures offer an image of the high tourist pressure that this city suffers. Although it is the sixth most visited city in Spain, it is the one with the highest tourist pressure per inhabitant, 11.7% compared to the national average of 7.4% [(Exceltur 2018)]. Based on these data, the selection of this city is justified, since it is an environment in which in addition to suffering high tourist pressure, this activity represents one of the main sources of income.

This survey was designed by the Public Economy and Globalization Research Group of the University of Granada to be answered by exclusively by residents. A first group of these questions aimed to identify the background of the participant (i.e., age group, educational level, residency within the tourist high impact area, etc). A second group tried to disclose if the participant benefited from this sector's activities in the city (i.e., do you own real estate property rented to tourists, do you work in a tourist shop, etc.). And a third group asked the participants' opinion on the positive and negative impacts derived from this sector's activities in the city (i.e.: it generates employment, it Increases congestion in public spaces). The surveys were disseminated simultaneously by providing a link to it through various means including: Facebook, Linkedin, the local press, distribution lists of associations and other groups. The final sample resulted from information sent by 600 spontaneous participants who volunteered their answers. Thus, the recipients of the questionnaire were not pre-selected in anyway. The only prerequisite was a minimum one-year resident status in the city. The field work used in this study was developed during the month of April 2020.

In this paper we look at two aspects of the survey summarized in 10 potentially positive and 10 potentially negative impacts of the Airbnb-type of tourism. Specifically, for the first set of potentially positive impacts, we asked participants use a scale of 1 to 10 to grade the effects that online platforms for the rental of tourist homes generates in their environment. This was done by giving 10 to the one impact perceived as the most positive and 1 to the least positive. For the second set, they were required to order a list of impacts according to those perceived as the most negative, granting a 10 to the most negative one and a 1 to the least negative. To quantify the qualitative variables, we used the optimal scaling. We then perform a Exploratory Regression Analysis to assess whether the number of correlated observed variables could be reduced to a smaller set of important independent composite variables. Finally we interpreted our results.

3.1. *Optimal scaling*

The variables used in our survey can be best classified as ordinal. The reason is that they reflect order but not the precise degree to which individuals differ. That is, the intervals in these scales are not equal and this fact creates a problem: If we are trying to determine the relationship between income from the tourism activity and the opinion of the participants on the impact that tourist housing rental platforms has on their environment and the latter is measured on a 5 point ordinal scale, a scatterplot of these variables would not conform to a straight line. Hence, linear regression would not reveal the true relationship between these variables. It is necessary then, to convert the ordinal variables obtained into interval variables that allow measurement so that once the transformation is done and the distance between consecutive levels of opinion are deemed to be equal, the data will conform more closely to a straight line. This conversion on the observed data can be done using "optimal scaling". This technology achieves two things simultaneously: (a) it uses a transformation appropriate for the scale level to transform the data, and (b) it fits a model to the transformed data to account for the data.

Optimal scaling derives interval measures from nominal and ordinal measures to attempt to overcome the drawbacks of ordinal variables. Thus, after implementing this transformation, the scatterplot will conform to a straight line and the new scale will reflect the distances between consecutive levels that optimize the relationship between the variables under observation. This scale is then deemed to be interval.

Earlier authors of multidimensional scaling works [(Shepard, 1962; Kruskal, 1964, Carroll and Chang, 1970)] highlighted problems faced by dealing with data using different measurement levels. Steven's [1951] measurement theory, considers these terms correspond to three of four measurement levels: ordinal (nonmetric) and interval or ratio (metric). However, one can also recognize other measurement processes such as discrete and continuous and different types of conditionality such as unconditional, matrix conditional, and row conditional. Fisher's discussion of optimal scaling [(Fisher, 1946)] analyzes the problems confronted when facing data with such variety of measurement characteristics while using an analysis technology. Fisher's optimal scaling proposal attempted to scale the observations so that a) they would fit the model as well as possible in a least square sense, and b) they would strictly maintain the measurement characteristics of the observations.

In this paper, we use a scale reliability coefficient, Cronbach alpha values, to indicate whether there is an acceptable level of internal consistency. An acceptable level of internal consistency refers to the degree of correlation between all the items belonging to a scale, provided they measure the construct they claim to measure. Cronbach's alpha speaks as to the degree to which all the items really measure the same concept. If so, the validity of the assessment instrument has been determined. This method is one of the most popular methods for this purpose when non-quantitative variables are present. The formula used for this estimate is:

$$\alpha_{est} = \frac{kp}{1+p(k-1)} \tag{1}$$

where:

k = is the number of items

p = is the average of the lineal correlations between each of the items (there will be [k(k-1)]/2 pairs of correlations).

Gardner [1995, 285], stated that Cronbach's alpha is the most used statistic for estimating internal consistency. He explained that "alpha is maximized when every item in a scale shares common variance with at least some other items in the scale" (p.286); and he further pointed out that "a scale may be composed of several clusters of items each measuring a distinct factor; as long as every item correlates well with some other items, the scales is likely to give a high overall alpha as long as the scales themselves have high internal consistency". In his discussion, Gardner declared that a high value of alpha indicated that every item in the instrument was measuring something similar to some of the other items. This conclusion can be thought of as corresponding to the existence of a degree of interrelatedness among the variables.

Cronbach's alpha coefficient turns a value between 0 and 1. The closer it is to one, the greater the internal consistency of the instrument. The result indicates the magnitude in which the variables measure the same constructor and its homogeneity. To determine if the level of internal consistency, we use George and Mallery [2003] classification which provides the following rules of thumb: "_> .9 - Excellent, _> .8 - Good, _>. 7 - Acceptable, _> .6 - Questionable, _> .5 - Poor, and _ <.5 - Unacceptable " (p. 231).

The minimum acceptable value is set at 0.70 while the maximum is 0.90. Alpha values between 0.80 and 0.90 are often preferred because values above are subject to perceived redundancy while those lower are considered to add no information. Nonetheless, with respect to the desirable alpha level, Cronbach [1951] had suggested that regardless of its value, the main point is that the obtained scores remain interpretable. Also, Schmitt [1996] suggested that a threshold such as that of 0.70 where the alpha becomes acceptable could result arbitrary depending on the situation as even instruments with low values could prove useful in some instances.

Exploratory Regression (factor) Analysis with Principal Components

When gathering a moderate to large number of predictors to estimate a dependent variable, the number of simple correlations among the variables can scale up fast [(de Castro *et al.*, 2019; de Castro *et al.*, 2020)]. For 10 variables we have 90 simple correlations and with 30 variables the number of correlations goes up to 435. Therefore, even recognizing if there is an existing pattern among them is difficult if attempting to do it just by inspection. In this situation it is helpful to determine if there exists a small number of underlying constructs that account for the main sources of variation in the correlation set. In our case, it makes sense to think that 10 variables are not measuring 10 different constructs. Hence a variable reduction scheme that sheds light on how these variables cluster around each other would help understand what underlying situations constraint the participants opinions given these are not evident.

Factor analysis is a technology that derives the linear combinations of a group of original variables (the factors) given that just a few of these will account for most of the variation [(Rodríguez *et al.*, 2018a; Rodríguez *et al.*, 2018b)] . This technique will produce, from a large number of variables, a small number of factors X_1, X_2, X_3,…, X_p that explain the variance observed in the original larger set. To achieve this objective, it tries to find common dimensions to these variables: the factors. Thus, factor analysis finds a set of $k<p$ factors not directly observable (F_1, F_2, F_3,…, F_k) that sufficiently explain the observed variables whilst losing the minimum amount of information. The principles of interpretability and parsimony give this selection. These factors must be independent of each other to ensure there is no multicollinearity between them. For this reason, factor analysis is a data reduction technique that examines the interdependence of the variables and provides knowledge of the underlying structure of the data. Factor analysis is a multi-step process: (1) A correlation matrix is generated for all the variables. This matrix shows the correlation coefficients of the variables with each other. (2) Factors are extracted from the correlation matrix generated. This extraction is based on the estimated coefficients. (3) The factors are rotated in order to maximize the relationship between the variables and some of the factors. The objective is to establish factors with a with a level of variance 60% higher than the common variance. Before initiating the factor analysis multi step process, some key requirements must be met. For instance, a) there should be a linear relationship between the observed variables, 2) the

measurement scale has to be either interval or ratio, 3) the random sample has to be of at least five observations per observed variable, and 4) there have to be at least 100 observations. Large sample sizes are recommended for more stable estimates.

4. Results

We use (3) datasets: A, B, and C. A and B each contain 10 items as responses to the A and B questions respectively. The items are numbered under the "Variable" column in Table 1, and they are described under the "Data Question A: Positive Perception" and " Data Question B: Negative Perception " columns respectively.

Table 1. Data

Variable	Positive Perception Data Question A[a]	Negative Perception Data Question B[b]
1	Promotes the conservation of buildings	Diminished tranquility in buildings & neighborhoods
2	Enhances urban or historical areas	Loss of social cohesion in neighborhoods
3	Increases the value of property	Harm of traditional lodging services
4	Improves city image	Increase of traffic & congestion in public spaces.
5	Boosts cultural interactions	Boost of alcohol & drug consumption & insecurity
6	Betters the leisure offer in the area	Foster the abandonment of the resident population in the city center.
7	Generates opportunities for local entrepreneurs	Loss of traditional neighborhood shops
8	Creates employment associated with tourism	Rent and for sale significant housing prices increases
9	Spurs wealth and economic activity	Potentially spark contagion of diseases from tourists
10	Enlarges the collection of taxes	General price increases (shops, bars etc.)

We use SPSS v25 to run this test. See Table 2 for results for optimal scaling. We used the Formula 1 to obtain this estimate for each dataset. The obtained coefficients are 0.858 and 0.863 for Dataset A and Dataset B respectively. To assess the value of these we use George and Mallery [2003, p. 231] classification. Given that in both cases these exceed 0.8 (threshold of 0.7) the implication is a good internal consistency. Hence, the results of this reliability analysis provide a degree of trust in the instrument that will allow the reduction of dimensions using PCA.

Table 2. Model Summary

	Question A[a]		Question B[b]	
Dimension	Cronbach Alpha	Variance for the Total eigenvalue	Cronbach Alpha	Variance for the Total eigenvalue
1	0.656	2.439	0.624	2.279
2	0.542	1.953	0.605	2.198
Total	0.858[a]	4.392	0.863[b]	4.476

a. The total Cronbach's alpha is used in the total eigenvalue.
b. The total Cronbach's alpha is used in the total eigenvalue.

We use SPSS v25 to run the Factor Analysis. This technology extracts from a set of p variables a reduced group of m components that carry the largest portion of the variance in the p variables. Thus, the set of p variables is reduced to a set of m underlying dimensions. The objective is to establish the factors with a variance level 60% greater than the common factor. We can see the results in Table 3.

Table 3. Total Variance Explained Positive Perception Question A[a]

	Initial Eigenvalues			Extraction Sums Of Square Loadings			Rotation Sums Of Square Loadings		
Component	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	2.664	26.643	26.643	2.664	26.643	26.643	2.237	22.369	22.369
2	1.905	19.052	45.695	1.905	19.052	45.695	1.688	16.877	39.246
3	1.193	11.935	57.630	1.193	11.935	57.630	1.641	16.412	55.658
4	1.110	11.100	68.729	1.110	11.100	68.729	1.307	13.071	68.729

Extraction Method: Principal Component Analysis. Variance 68.729 > than 60%.
a. Only the cases for which Income depend on the tourism sector = 1 are used in the analysis phase.

Table 3, shows the results of the PCA in 10 columns and 10 rows for the dataset A. The "Component" column assigns a number to each of the variables that were put into the Factor Analysis. Given that we used 10 variables for each question A and B, we have 10 components in each of these two cases. The following three columns under the overall heading of Initial Eigenvalues (Total, % of Variance, and Cumulative %) refer to the variances of the principal components. Eigenvalues are a ratio of the shared variance to the unique variance accounted for in a given construct by each "factor" obtained from the extraction of principal components. The rule of thumb is to interpret those factors that obtain an eigenvalue of 1.0 or greater. The reason is that the amount of shared variance explained by a "factor" should be at least the same as the unique variance the "factor" shows in the overall construct. The column Total contains the eigenvalues ordered from highest, the one with the most variance, to lowest because each successive component shows as much of the remaining variance as it can. Next, the column % of Variance shows the percent of variance in each principal component. The column Cumulative % contains the cumulative percentage of variance of all prior components in addition to the current one. For instance, in the 4th raw we see 68.729. The interpretation is that the first four components together account for 68.729% of the total variance. Since 68.729 is greater than 60%, we have achieved our explanatory objective. The next three columns stand below the general heading of Extraction Sums of Squared Loadings. Squared Loadings represents only the total common variance excluding unique variance. These columns reproduce the values in the prior three columns for all the principal components whose eigenvalues are 1 or greater. We only keep the principal components with eigenvalues greater than 1 as those smaller account for less variance than the original variables which was 1. Here, with four factors we explain 68.7% of the common variance. Since 68.729 is greater than 60%, we have achieved our explanatory objective. Last, we rotate the extracted "factors." This "rotation" helps eliminate the multiple inter-correlatedness with items on several different "factors" by forcing items onto the "factor" with which it has the strongest association. The PCA technology has readjusted the variance in the correlation matrix to redistribute the variance to the first components extracted. This rotation helps interpret the extracted factors, but impedes the estimation of the shared variance associated with the factor. We then focus on the important results: the total number of factors, the amount of variance each factor accounts for, and the final amount of variance accounted for by all factors with eigenvalues above 1.0. We see that the Total and the % of variance come to 1.307 and 13.071 up from 1.110 and 11.100.

Table 4 summarizes the Rotated Component Matrix of Question A. Here the matrix is rotated to simplify its structure and help with its interpretability. A key benefit of using orthogonal rotation in this step is that its underlying assumption is that the factors are not correlated. Loadings are correlations of items with factors, and standardized solutions estimate the contribution of each factor. The most common type of orthogonal rotation procedure is Varimax. To ensure the factor solution will be orthogonal and solutions will be stable, we use it in conjunction to Kaiser Normalization. Kaiser normalization is used to obtain stability of solutions. When effecting the rotation equal weight is given to all items. So the loadings are rescaled to the correct size thereafter. Table 4. Rotated Component

Matrix Positive Perception Question A shows the factor loadings after the rotation. If we recall, the items are possible answers to be graded by the participant from 10 (max) to 1 (min) in response to the following question: "With regard to online platforms for the rental of tourist homes such as Airbnb and the effects that their activity generates in their environment: order the following impacts according to which you perceive the most positive. Give a 10 to the most positive and a 1 to the least positive."

The table lists the responses to be quantified in the first column, and components 1 to 4 in the ensuing ones. In bold we mark the largest loadings. Interestingly some are positively correlated and some negatively correlated. With a rule of thumb of 0.4 none are contributing to two components. However, if this changes and we use a rule of thumb of .3. and in some instances it would contribute positively and negatively as well. As a cut off rule of thumb we use an effect size approach of 0.4. This helps us determine which variables are contributing to the component in a meaningful way. As a summary Table 4 collects the items under each factor.

Table 4. Rotated Component Matrix Positive Perception Question A[a,b]

	Component			
Responses to be quantified	1	2	3	4
x_1 =Promotes the conservation of buildings.	-.711	-.114	-.310	-.012
x_2 =Enhances urban or historical areas.	-.735	-.222	-.263	.004
x_3 =Boosts cultural interactions.	.636	-.371	.212	-.031
x_4 =Betters the leisure offer in the area.	.786	-.143	-.306	-.173
x_5 =Improves city image.	-.032	-.775	.162	-.023
x_6 =Spurs wealth and economic activity.	-.030	.784	.279	.069
x_7 =Increases the value of property.	-.209	.288	-.697	.074
x_8 =Creates employment associated with tourism.	.117	.277	.835	.031
x_9 =Generates opportunities for local entrepreneurs.	.134	.252	.129	.829
x_{10} =Enlarges the collection of taxes.	.304	.169	.186	-.760

Extraction Method: Principal Components Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 5 iterations.
b. Only the cases for which Income depend on the tourism sector = 1, are used in the analysis phase.

FACTOR 1. Urban improvement: physical and social

$y_{F1} = \mathbf{-.711x_1 + -.735x_2 + .636\ x_3 + .786x_4} + -.032x_5 + -.030x_6 + -.209\ x_7 + .117x_8 + .134\ x_9 + .304x_{10}$

FACTOR 2: General impulse to impact and wealth in the city

$y_{F2} = \mathbf{-.775x_5 + .784x_6} + -.114\ x_1 + -.222x_2 + -.371x_3 + -.143x_4 + .288x_7 + .277x_8 + .252x_9 + .169x_{10}$

FACTOR 3: Increase in wealth through job creation and asset revaluation.

$y_{F3} = \mathbf{-.697x_7 + .835x_8} + -.310x_1 + -.263x_2 + .212x_3 + -.306x_4 + .162x_5 + .279x_6 + .129\ x_9 + .186x_{10}$

FACTOR 4: Boost to business activity and tax collection.

$y_{F4} = \mathbf{.829x_9 + -.760x_{10}} + -.012x_1 + .004x_2 + -.031x_3 + -.173x_4 + -.023x_5 + .069x_6 + .074x_7 + .031x_8$

Note: significant results in bold

Table 5, shows the results of the PCA in 10 columns and 10 rows for the dataset Negative Perception Question B. This is describes the same content as Table 3. The one difference in the findings is that here the total percentage of variance explained is 63.937%. Given that the objective is to established factors with a variance level greater than 60%, of the common variance, this is significant.

Table 5. Total variance explained Negative Perception Question B[a]

	Initial Eigenvalues			Extraction Sums Of Square Loadings			Rotation Sums Of Square Loadings		
Component	**Total**	**% of variance**	**Cumulative %**	**Total**	**% of variance**	**Cumulative %**	**Total**		
1	2.374	23.742	23.742	2.374	23.742	23.742	1.978	19.782	19.782
2	1.757	17.567	41.309	1.757	17.567	41.309	1.621	16.212	35.994
3	1.159	11.590	52.899	1.159	11.590	52.899	1.530	15.303	51.297
4	1.104	11.038	63.937	1.104	11.038	63.937	1.264	12.640	63.937

Extraction Method: Principal Components Analysis.
a. We only use the cases for which Income depends on the tourism sector = 1 in the analysis phase.

Equivalently to the earlier described Table 4, Table 6. Rotated Component Matrix Negative Perception Question Ba shows the factor loadings after the rotation. Please see Table 1 for more information relative to the Data used. To summarize, the participants graded from 10 to 1 the most negative impacts, 10 being to the most negative and a 1 to the least negative.

The table lists the responses to be quantified in the first column, and components 1 to 4 in the ensuing ones. In bold we mark the largest loadings. Interestingly some are positively correlated and some negatively correlated. With a rule of thumb of 0.4 none are contributing to two components. However, if this changes and we use a rule of thumb of .3. and in some instances it would contribute positively and negatively as well. As a cut off rule of thumb we use an effect size approach of 0.4. This helps us determine which variables are contributing to the component in a meaningful way.

Table 6. Rotated Component Matrix Negative Perception Question B[a,b]

	Component			
Responses to be quantified	1	2	3	4
x_1 = Boost of alcohol&drug consumption & insecurity.	.587	-.238	.173	-.143
x_2 = Foster the abandonment of the resident population in the city center.	-.532	.381	.136	-.518
x_3 = Rent and for sale significant housing prices increases.	-.699	-.379	-.071	-.294
x_4 = Potentially spark contagion of diseases from tourists.	.850	-.002	.042	-.103
x_5 = Loss of social cohesion in neighborhoods.	-.090	.746	-.091	.089
x_6 = General price increases (shops, bars etc.)	-.039	-.794	.175	.009
x_7 = Harm of traditional lodging services.	.062	.155	-.804	-.081
x_8 = Loss of traditional neighborhood shops.	.237	-.079	.810	-.051
x_9 = Diminished tranquility in buildings & neighborhoods.	-.265	.239	-.328	.527
x_{10} = Increase of traffic & congestion in public spaces.	.016	.033	.162	.764

Extraction Method: Principal Components Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 5 iterations.
b. Only the cases for which Income depend on the tourism sector = 1, are used in the analysis phase.

FACTOR 1. Gentrification

$\mathbf{y_{F1} = .587x_1 + -.532x_2 + -.699x_3 + .850x_4} + -.090x_5 + -.039x_6 + .062x_7 + .237x_8 + -.265x_9 + .016x_{10}$

FACTOR 2: Alteration of the system of coexistence

$y_{F2} = \mathbf{.746x_5 + -.794x_6} + -.238x_1 + .381x_2 + -.379x_3 + -.002x_4 + .155x_7 + -.079x_8 + .239x_9 + .033x_{10}$

FACTOR 3: Negative changes in the existing business community.

$y_{F3} = \mathbf{-.804x_7 + .810x_8} + .173x_1 + .136x_2 + -.071x_3 + .042x_4 + -.091x_5 + .175x_6 +.-.328x_9 + . .162x_{10}$

FACTOR 4: Boost to business activity and tax collection.

$y_{F4} = .527x_9 + .764x_{10} + -.143x_1 + -.518x_2 + -.294x_3 + -.103x_4 + .089x_5 + .009x_6 + -.081x_7 + -.051x_8$

Note: significant results in bold

5. Conclusions, limitations, and avenues for further research

The objective of this work was to identify the latent dimensions of two subgroups of categorical items codified from 1 to 10. These data resulted from a survey which asked two questions related to the positive and negative impacts that online platforms for the rental of tourist homes such as Airbnb had on the subjects answering the survey. Our aim in performing this analysis was to learn how a group of participants who benefit financially from the tourism sector think with respect to the benefits and hindrance resulting from the widespread use of such booking technology. All the participants were residents in Granada and their income was affected by the tourism sector. The question used to segment the 600-participants original dataset was "Does your income depend to any extent on the tourism sector?" The final sample of positive answers added to 131.

To identify the unobserved variables underlying the answers to the two questions, we used Exploratory Factor Analysis with Extraction of Principal Components, using the correlations of the observed variables of each of the two subgroups. The objective of the factor analysis was to identify at least 60% of the common variance. The results found were positive and coherent with a study using qualitative variables. For the subgroup of "positive effects", we identified 4 components explaining 68.729% of the variance of the 10 items. These components are independent amongst themselves but the correlated to the unobservable variable. To simplify the interpretation of the obtained factors we used Varimax rotation. This technology allowed us to verify 4 factors from first to last: Urban improvement: physical and social; General impulse to impact and wealth in the city; Increase in wealth through job creation and asset revaluation, and Boost to business activity and tax collection. For the subgroup of "negative effects", we identified 4 components explaining 63.937% of the variance of the 10 items. After implementing the Varimax rotation, verified 4 factors from first to last: Gentrification, Alteration of the system of coexistence, Negative changes in the existing business community, and Alteration of coexistence. The creation of these categories' "summary" of the positive and negative impacts, allows to understand more precisely the attitude towards changes in the environment. That is, what type of impacts are valued the most by citizens. Specifically for citizens whose income depends on tourism.

The principal component analysis used in this paper is of the exploratory factor analysis family, a technology identified as a "theory-generating" rather than as a "theory-testing" procedure. It is a hands-on methodology, a heuristic method that will help determine the number of factors underlying a dataset and whether these are correlated or uncorrelated, while the variables are free to load on all factors. The findings for each of our two subgroups have explained 68.729% and 63.937% respectively of the common variance. The intuition behind these figures is comparable to that of an R2 in a multivariate regression context in that they speak as to the percentage of variance explained by the variables. The difference is that the former ones are considered extremely high values for an exploratory context. Also, here the correlations shown are between the factor and the given item. For instance, there is a very strong positive correlation (0.810) between loss of traditional neighborhood shops and Factor 3: Negative changes in the existing business community. Therefore, one of the main conclusions drawn from this study is that citizens have seen a shift in the orientation of businesses located in tourist areas. Specifically, citizens whose income depends on tourism are the ones highlighting such a change. This group's assessment might possibly be the consequence of a shift in the focus of local businesses, which have gone from resident-oriented businesses to tourist-oriented businesses. Our goals for the future are to repeat our test for the subgroup (1-N) not directly benefiting financially from the tourism industry, comparing those results to the ones in this work and potentially setting the findings in the context of Maslow (1943) theory of human motivation. In addition, future work will redesign the survey so that instead of working with categorical variables with optimal scaling, we can obtain conclusive results with quantitative variables.

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