Annals of Tourism Research 89 (2021) 103210

Contents lists available at ScienceDirect

Annals of Tourism Research

journal homepage: https://www.journals.elsevier.com/annals-of-tourism-research

Rural tourism preferences in Spain: Best-worst choices

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A R T I C L E I N F O

Article history:
Received 20 June 2020
Received in revised form 5 April 2021
Accepted 7 April 2021
Available online xxxx

Associate editor: Kemperman Astrid

Keywords:
Rural tourism
Best-worst discrete choice experiments
Multinomial logit
Mixed logit
Rank ordered logit
Sequential best-worst multinomial logit

A B S T R A C T

Understanding the effects of choice attributes on rural tourism has been important in order to find the way to offer services and products that can appeal to customers. The goal of this investigation in rural tourism is the exploration of tourist preferences and the examination of the individual determinants of these preferences. To achieve this goal, the survey was conducted on 452 tourists who live in either Madrid or Barcelona and best-worst discrete choice experiments were also applied. The results revealed that tourists choose the rural tourism that is expected to have the highest utility after comprehensive consideration of various attributes. Relatively important attributes for preferences were staff hospitality, outdoor activities, additional facilities, and location.

Introduction

Rural tourism in Spain has been heavily invested and developed in recognizing its own importance, in terms of generating rural development and additional economic benefits for farmers (Besteiro, 2006). In recent years, however, competition has intensified due to excess supply, and compared to other leisure travels, the market share of rural tourism is also declining as its competitive advantages are not appealing (Correia & Oliveira, 2016). Overall, the profitability of rural tourism is declining, and many small self-employed business owners' survival is threatened (INE, 2018). Rural tourism in Spain is faced with the problem situation of looking for survival strategies for small business owning families, and they need clear directions on how to offer a range of products. In this context, in order to overcome this situation and provide rural tourism products that can earn the hearts of customers, it is very important to identify and respond to customers' rural tourism needs. In particular, assessing customer preferences for rural tourism is a top priority among verified activities used for satisfying their needs.

Understanding customers' choice behavior in rural tourism is very important for building marketing strategies (Albaladejo-Pina & Díaz-Delfa, 2009). For this reason, various studies in the field of rural tourism have tried to understand it through the discrete choice experiments, which are one of the traditional research methods used to derive consumers' preferences based on customers' perspectives (Albaladejo-Pina & Díaz-Delfa, 2009; Crouch & Louviere, 2004; Hyde, 2008). This method obtains one choice per set by requiring respondents to select the best option among the various options offered in each choice set (Kim & Park, 2017). Discrete choice experiments in rural tourism require participants to choose only the best option among the various options in each choice set in order to be able to extract information for the development of new services and products (Flynn et al., 2010).

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https://doi.org/10.1016/j.annals.2021.103210
0160-7383/

Customers normally make their choices based on context when selecting the tourism destination (Kim & Park, 2017). In other words, they make their tourism choices by comprehensively considering the circumstances they dislike as well as those that they like (Flynn et al., 2010). However, discrete choice experiments studies in the field of rural tourism have analyzed only the most preferred one among alternatives suggested through the combination of attributes that they prefer (Scarpa et al., 2011). Thus, existing discrete choice experiments studies in rural tourism have the disadvantage of not being able to conduct a more in-depth analysis that considers situations with low preference as well as high preference. To address these gaps, this study uses a method called best-worst discrete choice experiments, which are designed to make respondents choose the worst option as well as the best option in each choice set (Scarpa et al., 2011).

They provide a wealth of information on alternatives and relative preferences among a considerable amount of choice data, which can improve statistical efficiency (Marley & Louviere, 2005). Since this method gains more choice data by asking additional questions to the same respondent, there is no need for an effort to secure more sample sizes for the statistical usefulness (Potoglou et al., 2011). Therefore, it is very cost efficient (Aizaki et al., 2014). Also, since this method asks additional questions within the same choice set, there is no need to apply more choice sets to obtain more data (Potoglou et al., 2011). Thus, it minimizes the burden on the respondent by adding a few simple additional questions per choice set instead of employing larger choice sets (Louviere et al., 2008).

Since understanding the effects of choice attributes on rural tourism has been one of the most important themes, the purpose of this investigation is to explore overall tourist preferences for rural tourism in Spain and examine the individual determinants of these preferences in terms of the heterogeneity of preferences. In terms of the new application of best-worst discrete choice experiments in rural tourism, the goal is to verify whether the method is well-conducted in rural tourism, and to provide guidance on implementing and analyzing best-worst discrete choice experiments.

The first contribution of this study is to understand behaviors of tourists who choose rural tourism, by comprehensively evaluating their various preferences for rural tourism. The findings may help rural tourism providers and policymakers improve their products and services. The second contribution of this study to the existing literature is that it is the first in the field to apply best-worst discrete choice experiments in assessing the importance of choice attributes and analyzing heterogeneity in tourist preferences. By using more choice information on not only the best choice, but also the attributes to be considered when choosing the worst choice, it was confirmed that the best-worst discrete choice experiments model greatly improved the statistical efficiency over discrete choice experiments that provide just the best option (Aizaki et al., 2014). The third contribution is to propose the adoption of the model with the best model fit among best-worst discrete choice experiments. This study found that models with sequential best-worst data were better than models with rank-based data.

Literature review

Rural tourism refers to multidimensional activities through a combination of natural tourism, adventure and sports, food tourism, wine tourism, ecotourism, and cultural tourism (Figueiredo & Raschi, 2012). Various rural tourism-related studies have shown that landscape is one of the most essential factors influencing customer experiences (Figueiredo & Raschi, 2012). The various landscapes found in nature allow tourists to cleanse their minds by providing rich visual experiences (Frochot, 2005). Tourists seek out their experiences in pursuit of an opposition to the negative emotions generated from urban life (Figueiredo & Raschi, 2012). In other words, the main reason for urban people to choose rural tourism is to relieve themselves of the stress from civic life (Kastenholz et al., 2018). Sims (2009) suggested that authenticity, which is related to the tourists' experience of a rural lifestyle, is another crucial factor of rural tourism. Authenticity is a feature pursued by urban-dwelling populations because they want to escape from their incomplete daily life and find an ideal image of the past (Sims, 2009). Tranquility related to the spiritual dimension of emotional fulfillment can be a critical rural tourism experience for tourists (Sharpley & Jepson, 2011).

Human interaction with rural people can be a significant experience pursued by tourists who choose rural tourism (Frochot, 2005). First of all, experiences created by meetings between tourists and the hosts of rural tourism destinations are essential factors in rural tourism (Albaladejo-Pina & Díaz-Delfa, 2005). The interaction between tourists and hosts in rural environments can influence the quality of the experiences (Albaladejo-Pina & Díaz-Delfa, 2005). In addition, rural communities are considered important in helping tourists have intense experiences through rural visits because locals can show tourists their traditional way of life, provide experiences with locally-produced products and share knowledge about local culture and history (Kastenholz et al., 2012). Interaction with local people provide essential experiences and guide tourists to a broader range of experiences (Albaladejo-Pina & Díaz-Delfa, 2005).

Regarding rural tourism in Spain, various studies have been conducted. Campón-Cerro et al. (2017) devised a way to secure tourist loyalty in order to ensure that the Spanish rural tourism market, where competition is intensifying, can have sustainable competitiveness. Millán-Vazquez de la Torre et al. (2017) focused on Spanish olive oil tourism, suggesting a strategic direction for rural tourism to promote synergy with gastronomic routes. Sánchez-Rivero et al. (2016) proposed an assessment method for various attibutes affecting rural tourism in Caceres, Spain. Frías-Jamilena et al. (2013) analyzed the determinants that influence the tourist satisfaction in rural tourism, mainly in Andalusia, Spain. Fernández-Hernández et al. (2016) used environmental attitudes to segment rural tourists, finding that those groups with greater awareness of the environment provided greater economic impact. Polo Peña et al. (2014) studied different online marketing strategies implemented by rural tourism firms and their effects on various types of tourists segmented by motivation.

Discrete choice experiments have been broadly used in verified fields of study such as hospitality, leisure, and tourism. The tourists´ process of choosing a destination is made up of a lot of elements such as when to go, where to go, with whom to go, how long to stay, how much to pay, what to do, and which experience to seek (Hyde, 2008). Discrete choice experiments have generally been used to explore the relationships between products and services offered by providers and the tourist's choice (Crouch & Louviere, 2000).

There are several discrete choice experiments studies that analyzed tourist preferences in rural tourism. Hearne and Salinas (2002) applied them to examine tourist preferences for ecotourism and revealed that domestic as well as foreign tourists prefer low price, more information and improved infrastructure. Chaminuka et al. (2012) estimated the possibility of developing rural ecotourism through analyzing the determined value of each attribute that tourists preferred by using discrete choice modeling. The results revealed that tourists were positive towards the experience related to crafts and village tours but had a negative outlook on accommodation. Hearne and Santos (2005) examined the preferences of stakeholders, who consist of locals and foreign tourists, for various scenarios related to ecotourism in a nature reserve in Guatemala and revealed that all stakeholders have similar preferences for hiring expert tour guides and strengthening nature reserve management.

Several studies have also applied choice experiments to analyze tourists' experience preferences in rural tourism in Spain. Albaladejo-Pina and Díaz-Delfa (2009) evaluated customers' preferences for attributes existing in rural tourism in Murcia, Spain by applying discrete choice modeling, which is a stated preference experiment. The results showed that tourists valued the attributes such as quality certification, no. of rooms, location, and traditional building as important. Albaladejo-Pina and Díaz-Delfa (2020) analyzed the choices of rural tourists visiting Murcia, Spain by applying new variables such as motivation as well as cognitive attributes. The results show that the importance of motivation-related factors is increasing when choosing rural accommodations. Sayadi et al. (2009) analyzed the choices of tourists visiting Mediterranean areas in Spain to confirm their preference for rural landscapes. The result of this study is that attributes such as density of rural accommodations and the presence of layers of vegetation have a great influence on landscape attractiveness. Albaladejo-Pina and Díaz-Delfa (2005) revealed the characteristics of tourists who were more likely to choose specific items from a variety of accommodation products by the application of multinomial logit. Findings showed that the variety in the size and type of accommodations plays an important role in attracting different profiles of tourists.

Materials and methods

Best-worst discrete choice experiments

Generally, discrete choice experiments are applied with the stated preference data obtained by individuals required to choose an option in research environments designed by researchers (Aizaki et al., 2014). Through requiring respondents to select the best option among the various options offered in each choice set, discrete choice experiments enable researchers to extract the implications for developing a new product and service (Albaladejo-Pina & Díaz-Delfa, 2009). In order to have enough data to judge the participants' choice behavior, they are asked to repeat choosing the best option within the choice set several times (Kim & Park, 2017). If the number of choice sets required is excessive, respondents respond with simplified judgment when making decisions, resulting in poor data quality (Aizaki et al., 2014). This causes the validity of the results derived through discrete choice experiments to be compromised (Potoglou et al., 2011).

In order to solve this problem, the use of best-worst discrete choice experiments has been extended to enhance the ability of discrete choice experiments (Marley & Louviere, 2005). Best-worst discrete choice experiments are similar to discrete choice experiments in that it is possible to derive information about preferences through respondents repeatedly selecting one of the options contained in the choice sets (Aizaki et al., 2014). However, unlike the latter, the former select the next option sequentially rather than ending with respondents choosing the first best option (Marley & Louviere, 2005). For instance, if there is a choice set with several options, the respondents are requested to not only select the first best option but also the first worst option, the next best option from the remaining alternatives and finally the next worst option. In best-worst discrete choice experiments more data about preferences can be derived, since respondents make more choices than one for each choice set (Louviere et al., 2008). In addition, the burden on respondents is not high because researchers let them make additional judgments within the same choice sets, as can also be done in discrete choice experiments (Marley & Louviere, 2005).

Similar to standard discrete choice experiments, an indirect utility function based on random utility theory can be estimated in the best-worst discrete choice experiments, that use data related to the individual's preference at large for alternatives of each choice set (McFadden & Train, 2000). The utility that an individual has for each alternative can be broken down into deterministically meaningful components from the viewpoint of his/her attitude towards that alternative and an unobserved random component (Viney et al., 2002). It is assumed that the utility for individual i who selects choice j in the presented choice set s consists of an explanatory component V_{isj} and a random component ε_{isj}.

$$U_{isj} = V_{isj} + \varepsilon_{isj} \tag{1}$$

Using first best data: multinomial logit

The first analysis of best-worst discrete choice experiments begins with multinomial logit, which rests on maximum likelihood estimation (McFadden & Train, 2000). Multinomial logit has the characteristic of the related independence of irrelevant alternatives (Gensch & Recker, 1979). Its assumption means that the ratio of choice probabilities between different destinations is always constant, even if a new alternative destination is introduced. The probability which alternative n from J in choice set s is selected by individual i can be expressed as follows:

$$Pisn = \frac{e^{\mu V_{isn}}}{\sum_{j=1}^{J} e^{\mu V_{isj}}} \tag{2}$$

The definition of μ is the scale parameter which is in inverse proportion to the variance of the error term. The first analysis of best-worst choice experiments can be performed with the multinomial logit using the first best choice without considering the added best choice nor the worst choice (Viney et al., 2002).

Using additional data in the preference rank: rank-ordered logit

Because best-worst discrete choice experiments can get repeated additional preference information for the best and worst choice beyond just the first best choice, the rank order logit can be applied by inferring rank order information for alternatives (Lancsar, 2009). For instance, a rank order logit model based on the ranking of four alternatives A > B > C > D can be used as follows; the probability that A is chosen as the best choice among the alternatives of a choice set (A, B, C, D) times the probability that B is chosen as the best choice among the remaining alternatives of a choice set (B, C, D) times the probability that C is chosen as the best choice among the remaining alternatives of a choice set (C, D).

$$P(ranking\ A, B, C, D) = \frac{e^{V_A}}{\sum\limits_{j=A,B,C,D} e^{V_j}} * \frac{e^{V_B}}{\sum\limits_{j=B,C,D} e^{V_j}} * \frac{e^{V_C}}{\sum\limits_{j=C,D} e^{V_j}} \tag{3}$$

It is also called exploded logit since it is analyzed by exploding the data from a particular choice set into sub choice sets that are statistically independent such as the best from four options, the best from the remaining three options, and the best from the remaining two options (Allison & Christakis, 1994).

When estimating the inherent preferences order through applying the rank order logit in best-worst discrete choice experiments, it is assumed that it selects the best from consecutively exploded sub choice sets, so it is not necessary to consider the best-worst structure applied to derive the order beforehand. The same process as the discrete choice experiments' data generation process of choosing the best from a choice set is just repeated for sub choice sets (StataCorp, 2007).

Using an additional data in the preference order it was collected: sequential best-worst multinomial logit

According to Lancsar (2009), the sequential best-worst multinomial logit is a model in which a succession of sequential best and worst choices is derived from a choice set as the output of multinomial logit. For example, the model based on the sequential choice of four alternatives A > B > C > D can be applied as follows; the probability that A is chosen as the best choice among the alternatives of a choice set (A, B, C, D) times the probability that D is chosen as the worst choice among the remaining alternatives of a choice set (B, C, D) times the probability that B is chosen as the best choice among the remaining alternatives of a choice set (B, C)

$$P(ranking\ A, B, C, D) = \frac{e^{V_A}}{\sum\limits_{j=A,B,C,D} e^{V_j}} * \frac{e^{-V_D}}{\sum\limits_{j=B,C,D} e^{V_j}} * \frac{e^{V_B}}{\sum\limits_{j=B,C} e^{V_j}} \tag{4}$$

This model increases data in a similar way to the rank-ordered logit such as expanding the data from a particular choice set with 4 options into additional sub choice sets containing 3 and 2 options in sequence. Nevertheless, the sequential best-worst multinomial logit applies the worst choice in the second place in Eq. (4) in contrast with the rank-ordered logit (Marley & Louviere, 2005).

Exploring heterogeneity: mixed logit

The multinomial logit is characterized by the independence of irrelevant alternatives assumption, which means that the ratio of choice probabilities between different destinations is always constant, even if a new alternative destination is introduced (Gensch & Recker, 1979). It can be said to be very unrealistic because of the overly strong constraint on substitutive relationships between choice attributes. In addition, because of starting from the assumption of independent and identically distributed, which means that the distribution of error terms of the utility function has mutual independence and equal variance among alternatives, the multinomial logit is basically views all customers as having similar preferences in choosing rural tourism attributes. This has the advantage of easy estimation and easy interpretation of the results, but it has the disadvantage that it does not reflect the fact that various heterogeneity exists. To solve this problem, the simple form of the logit model has evolved into a more generalized model such as the probit logit model, the nested logit model, and the mixed logit model (Borgers & Vosters, 2011).

Among these models, the mixed logit model, which was used in this study, has the benefit of being applicable to any type of random utility models, as it is a very flexible model (McFadden & Train, 2000). Moreover, it enables to analyze by incorporate diverse respondents with different preferences and explain the correlation of unobserved factors, which are generated when each respondent repeatedly makes choices (Greene & Hensher, 2003). The mixed logit models allow for individual random

Table 1
Attributes for discrete choice experiments derived from literature studies.

Authors	Attributes
Albaladejo-Pina and Díaz-Delfa (2009)	Booking, type of rent, mini farm, meal service, horse-riding, no. of bedrooms, building type, quality certification, bathroom, swimming pool, play area, price, location
Kim and Park (2017)	Overall atmosphere, entertaining, room quality, comfortable, brand, sports facilities, price
Lacher et al. (2013)	Trip cost, restaurant quality, types of restaurant ownership, emphasis on local character, availability of activities, destination
Chaminuka et al. (2012)	Price, experience related to craft, village tour, accommodation
Albaladejo-Pina and Díaz-Delfa (2005)	Quality certification, mini-farm, swimming pool, sports facilities, location, meal service, building type, no. of bedrooms, no. of toilets
Hearne and Santos (2005)	Price, village, approach roads, expert tour guide, accommodation available, nature reserve management
Hearne and Salinas (2002)	Price, location, access restrictions, information type, infrastructure

heterogeneity by assuming that individuals have different preferences. Therefore, the coefficient of the utility function is not the same for all respondents but constitutes a utility function with different coefficient for each individual. Most studies show that the mixed logit model is superior to the multinomial logit from the viewpoint of model fit (Albaladejo-Pina & Díaz-Delfa, 2009).

Design of the best-worst choice experiments

The process of this study followed four steps of choice modeling: (1) extraction of attributes and levels, (2) experimental design, (3) administration of survey, and (4) estimating the best-worst discrete choice experiments.

Extraction of attributes and levels

For the identification of the attributes and the levels to be applied to best-worst discrete choice experiments, this investigation conducted an online participatory observation technique, which extends traditional and cultural research methods into the technological development (Kozinets, 2015), and extensive literature research. First of all, important customer experiences in rural tourism, on which 1007 customers reported directly to online communities related to rural tourism such as clubrural.com, escapadarural.com, and toprural.com, were analyzed. In sequence, this study filtered them through literature studies in order to extract an initial pool of attributes (Table 1).

Later, 10 expert interviews were conducted to confirm the final attributes. This included three professors in related fields, four rural tourism owners, and three representatives of rural tourism associations. Each interviewee was asked what attributes are relatively important to tourists in the choice of rural tourism, which are relatively insignificant, and how the level of each attribute is constructed. In this way, seven attributes that match the characteristics of rural tourism in Spain were finally derived: location, price per room for one night, outdoor activities, cultural experiences, room quality, additional facilities, and staff hospitality (Table 2).

Table 2
Attributes and their levels.

Attributes	Specification	Definition	Code
1. Location	Town	Located in a town	Location $^{\text{Status quo}}$
	Farming area	Located in a fruit and vegetable growing area	Location $^{\text{Farming area}}$
	Nature	Located near nature like a mountain, river, or lake	Location $^{\text{Nature}}$
2. Outdoor activities	None	There is no activity	Activity $^{\text{Status quo}}$
	Some	Some activities like hiking and climbing	Activity $^{\text{Some}}$
	Many	Many activities like horse riding, cycling, fishing, hiking, and climbing	Activity $^{\text{Many}}$
3. Cultural experiences	None	There is no cultural experience	Culture $^{\text{Status quo}}$
	Some	Some cultural experiences related to crafts and food	Culture $^{\text{Some}}$
	Many	Many cultural experiences related to cultural heritage like ruins/castles/churches, crafts and food	Culture $^{\text{Many}}$
4. Room quality	Basic	Room with basic/functional bedding and furnishings	Room $^{\text{Status quo}}$
	Good	Room with good quality bedding, furnishings, and coffee service	Room $^{\text{Good}}$
	High	Room with luxurious bedding, furnishings, and wine service	Room $^{\text{High}}$
5. Additional facilities	None	It doesn't have any additional facilities	Facility $^{\text{Status quo}}$
	Some	Some facilities like a barbecue and chimney	Facility $^{\text{Some}}$
	Many	Many facilities like a pool, spa, garden, recreation area, barbecue, and chimney	Facility $^{\text{Many}}$
6. Staff hospitality	Basic	Hospitality only while greeting guests	Hospitality $^{\text{Status quo}}$
	Good	Hospitality through offering local information	Hospitality $^{\text{Good}}$
	High	Hospitality through continuous care, offering local information, and a good breakfast	Hospitality $^{\text{High}}$
7. Price per room for one night	Low	60 euros per room for one night	
	Medium	120 euros per room for one night	
	High	180 euros per room for one night	

Expert interviews were conducted in order to specify the levels of the attributes. In this study, each attribute was designed to have three levels by taking into account the qualitative and quantitative characteristics of the above-mentioned attributes. Seven attributes, each of which consists of three levels, were determined as shown in Table 2.

Experimental design

This study uses seven attributes and three levels for each attribute, so applying a full factorial design leads to 2187 alternatives. It is unrealistic to get respondents' responses through this number of alternatives. Accordingly, this study finally designed 18 choice sets by applying the fractional factorial design to construct a reasonable number of alternatives (Aizaki et al., 2014). In addition, by constructing the questionnaire into two versions using the block design technique to reduce the burden on respondents, only nine choice sets were placed in each version-specific questionnaire.

Each choice set was designed to include not only four options; option 1, option 2, option 3, option 4, but also option 5 as "no choice" option with additional purchase intention question asking whether to choose in order to reflect the characteristics of customers who can give up their purchases without actually choosing any alternative in the real market (Blamey et al., 2002). The use of the "no choice" option to reflect reality makes it possible to minimize the difference between the results through the real experiment based on the revealed behavior and the hypothetical experiment based on the hypothetical behavior, thus it allows for understanding whether respondents prefer the alternatives or are not interested in any of the options (Hensher, 2010). When a respondent selects 'no' for the purchase intention question, the "no choice" option (option 5) becomes the first best option, and the order of the four options previously selected is then naturally placed. However, if a respondent responds 'yes' for the purchase intention question, the option chosen as best is treated as the first best option among the four presented options. The location of the "no choice" option is still unknown. Thus, this study decided to apply the "no choice" option only to the first best data analysis, similarly to discrete choice experiments. Accordingly, the number of options per choice set is four in the analysis of rank-based data and sequential best-worst data or five in the analysis of the first best data, and the number of attributes per option is seven. A sample of the choice set applied in this investigation is shown in Fig. 1.

Administration of survey

In this investigation, an online survey was conducted considering merits such as speed, high response rate, and an interactive survey asking questions again with the remaining alternatives after respondents' selection of an alternative (Caussade et al., 2005). The questionnaire was comprised of three parts: (1) screening questions to select the people who are subjected to the survey, (2) preferences in rural tourism, and (3) demographic characteristics such as region, gender, civil status, education level, and income level, and general behavior in rural tourism such as frequency of visiting rural tourism over the previous three years, and trip type. In preferences in rural tourism, four steps of questions were asked as follows: (Step 1) Which of the four options would you MOST likely choose, (Step 2) Which of the three remaining options would you LEAST likely choose, (Step 3) Which of the two remaining options would you MOST likely choose, (Step 4) Would you buy the option that you considered the most interesting for you if it were available. On the online questionnaire, when one alternative was selected at each step, the remaining alternatives were automatically displayed on the screen to select in the next step.

This study conducted a pretest of 30 customers who had experience with rural tourism in the previous three years to test whether they understand the best-worst choice scenario well, and the length of the survey is appropriate. The pretest showed that customers had no problem understanding and responding to the survey.

The survey was conducted for 452 customers over 20 years old who had experienced rural tourism in the last three years and lived in either Madrid or Barcelona. In order to select a reliable representative sample, the survey employed Ikerfel, a Spanish panel research company. Respondents who would participate in the survey were selected from 8000 panels who were highly relevant to this survey. In June 2019, 452 respondents (Madrid 227, Barcelona 225) completed the survey. This resulted in 4068 (452 * 9) first choice observations and 12,204 (452 * 9 * 3) repeated best-worst choice observations.

Respondent characteristics such as region, gender, age, civil status, whether he/she has children, education level, household income, frequency of rural tourism in 3 years, and trip type for rural tourism were shown in Table 3.

Estimation of best-worst discrete choice experiments

This investigation utilized the R package 'mlogit' (Croissant, 2012) and 'Rchoice' (Sarrias, 2016) to analyze multinomial logit, mixed logit, rank-ordered logit, mixed rank-ordered logit, sequential best-worst multinomial logit, and sequential best-worst mixed logit models. Especially, the mixed logit series such as mixed logit, mixed rank-ordered logit, and sequential best-worst mixed logit enabled researchers to consider random heterogeneity in individual preferences (Borgers & Vosters, 2011). Based on random utility theory, it was possible to measure the probable connection between utility and choice by foreseeing customer behavior which could be inferred from the differences of individuals' choice (Albaladejo-Pina & Díaz-Delfa, 2009). In this study, the interaction effects between individuals' utility function and some characteristics of socio-demography and tourists' behavior for rural tourism was evaluated. Accordingly, the seven new variables were included for the best-worst choice experiments model.

For measuring the overall model fit, *Pseudo* R^2 was used as a standard tool. The larger *Pseudo* R^2 value indicates that the proportion of log-likelihood (LL), which the estimated model explains. In accordance with Greene and Hensher (2010), it is defined as '1 - $LL_{\text{Final model}}/LL_{\text{Null model}}$'. Besides, considering that the models estimated have different numbers of parameters and various characteristics of data, *adjusted Pseudo* R^2, which is defined as '1 - $(LL_{\text{Final model}} - K)/LL_{\text{Null model}}$', was applied: where K is the number of parameters in a specific model. By using the *adjusted Pseudo* R^2, the model fit for several models estimated in this study

	OPTION 1	OPTION 2	OPTION 3	OPTION 4
Location	**Nature** Located near nature like a mountain, river, or lake	**Nature** Located near nature like a mountain, river, or lake	**Farming area** Located in a fruit and vegetable growing area	**Town** Located in a town
Outdoor activities	**Some** Hiking and climbing	**Many** Horse riding, cycling, fishing, hiking and climbing	**Some** Hiking and climbing	**None** There is no activity
Cultural experiences	**Many** Related to cultural heritage like ruins /castles/churches, crafts and food	**Some** Related to crafts and food	**Some** Related to crafts and food	**None** There is no cultural experience
Room quality	**Basic** Room with basic/functional bedding and furnishings	**Good** Room with good quality bedding, furnishings, and coffee service	**Good** Room with good quality bedding, furnishings, and coffee service	**Basic** Room with basic/functional bedding and furnishings
Additional facilities	**Some** Barbecue and chimney	**None** It doesn't have any additional facility	**Some** Barbecue and chimney	**None** It doesn't have any additional facility
Staff hospitality	**Basic** Hospitality only while greeting guests	**Basic** Hospitality only while greeting guests	**Good** Hospitality through offering local information	**Basic** Hospitality only while greeting guests
Price per room for one night	**60 €**	**60 €**	**120 €**	**180 €**

(1st BEST) Which of the four options would you MOST likely choose?

○ OPTION 1 ☑ OPTION 2 ○ OPTION 3 ○ OPTION 4

(1st WORST) Which of the three remaining options would you LEAST likely choose?

○ OPTION 1 ○ OPTION 3 ☑ OPTION 4

(2nd BEST) Which of the two remaining options would you MOST likely choose?

☑ OPTION 1 ○ OPTION 3

(INTENTION) Would you buy the option that you considered the most interesting for you if it is available?

○ YES ○ NO

Fig. 1. An example of a choice set and question.

could be compared. The absolute value of *Pseudo* R^2 and *adjusted Pseudo* R^2 is not interpreted independently. Thus, the large or small size of its value does not mean anything in itself (Greene & Hensher, 2010). *Pseudo* R^2 and *adjusted Pseudo* R^2 are meaningful only when relative comparison is made with another *Pseudo* R^2 and *adjusted Pseudo* R^2 of the same type using the same data (Long & Freese, 2006).

Table 3
Summary of data characteristics.

Demographic category	Answers
Region	Madrid: 227 (50.2%), Barcelona: 225 (49.8%)
Gender	Male: 224 (49.6%), female: 228 (50.4%)
Age	Under 30: 81 (17.9%), 30–39: 110 (24.3%), 40–49: 155 (34.3%), 50–59: 77 (17.0%), 60 and older: 29 (6.4%), average: 41.2 years
Civil status	Single: 178 (39.4%), married: 204 (45.1%), in couple: 50 (11.1%), divorced/separated: 17 (3.8%), widowed: 3 (0.7%)
Whether he/she has children (child)	Having son or daughter: 201 (44.5%), no having son or daughter: 251 (55.5%)
Education level (education)	Less than high school: 12 (2.7%), high school: 126 (27.9%), during university: 30 (6.6%), university degree: 166 (36.7%), during graduate school: 19 (4.2%), master or doctor degree: 99 (21.9%)
Monthly household income (income)	Under 2000 euros: 130 (28.8%), 2000–2999 euros: 163 (36.1%), 3000–3999 euros: 84 (18.6%), 4000 and more euros: 74 (16.4%)
Frequency of visiting rural tourism in 3 years (frequency)	1–4 times: 282 (62.4%), 5–9 times: 125 (27.7%), 10 and more times: 45 (10.0%)
Trip type of rural tourism (type)	Family: 135 (29.9%), friends: 150 (33.2%), couple: 167 (36.9%)

Results

Analysis of first best data

The results from the analysis of the first best data are shown in Table 4. In the multinomial logit, all attributes were found to be statistically significant. First of all, the alternative specific constant (ASC) had positive signs. This means that respondents were more willing to choose one of the rural tourism options than the "no choice" option. Concerning location, the attributes' coefficient values were Location $^{\text{Farming area}}$ (−0.745) and Location $^{\text{Nature}}$ (0.661). This means that in terms of the possibility of choosing a location, a farming area is less than a town, and nature is higher than a town. The most crucial attribute of rural tourism, except the location, was Hospitality $^{\text{High}}$. The next most important attributes were Activity $^{\text{Many}}$, Hospitality $^{\text{Good}}$, Facility $^{\text{Many}}$, and Room $^{\text{High}}$. Price has a negative sign, which means that rural tourism is less likely to be chosen as price goes up.

In this study, the mixed logit model's coefficient values tended to be larger than those of the multinomial logit. This is due to the mixed logit model reflecting the heterogeneity of respondent preferences. This study employed simulation based on 100 Halton draws for the mixed logit model estimation. In addition, this study assumed a normal distribution according to McFadden and Train (2000)'s recommendation that the parameters of random variables represent the most reliable estimates in a situation where the normal distribution is assumed. All attributes were found to be statistically significant. In terms of

Table 4
Analysis of first best data.

	Multinomial logit			Mixed logit		
	Coefficient			Coefficient		
Mean						
ASC	2.360	***	(0.119)	3.364	***	(0.270)
Location $^{\text{Farming area}}$	−0.745	***	(0.062)	−1.492	***	(0.289)
Location $^{\text{Nature}}$	0.661	***	(0.105)	1.011	***	(0.172)
Activity $^{\text{Some}}$	0.562	***	(0.059)	0.624	***	(0.181)
Activity $^{\text{Many}}$	1.053	***	(0.107)	1.425	***	(0.220)
Culture $^{\text{Some}}$	0.404	***	(0.058)	0.543	***	(0.097)
Culture $^{\text{Many}}$	0.417	***	(0.109)	0.372		(0.216)
Room $^{\text{Good}}$	0.596	***	(0.060)	0.711	***	(0.203)
Room $^{\text{High}}$	0.613	***	(0.062)	0.716	***	(0.166)
Facility $^{\text{Some}}$	0.351	***	(0.062)	0.372	**	(0.128)
Facility $^{\text{Many}}$	0.956	***	(0.066)	1.372	***	(0.136)
Hospitality $^{\text{Good}}$	1.050	***	(0.060)	1.414	***	(0.126)
Hospitality $^{\text{High}}$	1.455	***	(0.074)	1.580	***	(0.195)
Price	−0.546	***	(0.038)	−0.879	***	(0.095)
Standard deviation						
Location $^{\text{Farming area}}$				1.358	**	(0.447)
Location $^{\text{Nature}}$				0.156		(0.720)
Activity $^{\text{Some}}$				0.833		(0.608)
Activity $^{\text{Many}}$				0.881		(0.498)
Culture $^{\text{Some}}$				0.117		(0.282)
Culture $^{\text{Many}}$				1.071	**	(0.398)
Room $^{\text{Good}}$				1.245	**	(0.382)
Room $^{\text{High}}$				1.355	***	(0.322)
Facility $^{\text{Some}}$				0.481		(0.393)
Facility $^{\text{Many}}$				0.061		(0.315)
Hospitality $^{\text{Good}}$				0.051		(0.219)
Hospitality $^{\text{High}}$				2.171	***	(0.304)
Price				0.124		(0.136)
Interaction						
Location $^{\text{Nature}}$:Age	−0.022		(0.034)	−0.037		(0.050)
Activity $^{\text{Many}}$:Age	−0.043		(0.034)	−0.052		(0.053)
Culture $^{\text{Many}}$:Age	0.045		(0.034)	0.059		(0.056)
Room $^{\text{High}}$:Frequency	0.014	**	(0.005)	0.021	**	(0.008)
Facility $^{\text{Many}}$:Frequency	−0.013		(0.007)	−0.018		(0.010)
Hospitality $^{\text{High}}$:Income	0.009		(0.036)	0.019		(0.065)
Price:Income	−0.011		(0.021)	−0.017		(0.031)
N. of respondents	452			452		
N. of observations	4,068			4,068		
Null log-likelihood	−10,180			−10,180		
Final log-likelihood	−8,932			−8,899		
Pseudo R^2	0.1226			0.1258		
Adjusted Pseudo R^2	0.1205			0.1225		

Notes: parentheses: standard errors. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

location, the attributes' coefficient values were Location $^{\text{Farming area}}$ (−1.492) and Location $^{\text{Nature}}$ (1.011). The top three most important attributes except location were Hospitality $^{\text{High}}$, Activity $^{\text{Many}}$, and Hospitality $^{\text{Good}}$.

The results of interaction effects show that in the multinomial logit and mixed logit, only Room $^{\text{High}}$ with the frequency of visiting rural tourism over the previous three years was significant. This means that for tourists with more rural tourism experience, 'room quality' was considered essential. Additionally, in the mixed logit, it is possible to identify the existence of heterogeneity for individual preferences through statistically significant coefficients for the standard deviations. It suggests preference heterogeneity in Location $^{\text{Farming area}}$, Culture $^{\text{Many}}$, Room $^{\text{High}}$, Room $^{\text{Good}}$, and Hospitality $^{\text{High}}$ across respondents.

In terms of the model fit, concerns the *adjusted Pseudo* R^2, the multinomial logit had 0.1205, and the mixed logit had 0.1225. The latter had a larger *adjusted Pseudo* R^2 than the former. This means that the mixed logit had a better model fit than the multinomial logit.

Analysis of best-worst data

Results from both models with rank-based data (rank-ordered logit and mixed rank-ordered logit) and models with sequential best-worst data (sequential best-worst multinomial logit and sequential best-worst mixed logit) are shown in Table 5. In the rank-ordered logit among models with rank-based data, the main effects of all attributes were significant. Its order was slightly different from the multinomial logit. Hospitality $^{\text{High}}$ is a remarkable attribute. It means that the more deeply tourists consider the preference for rural tourism, the more critical staff hospitality is. Concerning location, the attributes' coefficient values were Location $^{\text{Farming area}}$ with a negative coefficient and Location $^{\text{Nature}}$ with a positive coefficient. This shows that tourists' preferences for location in order from most important to least are nature, town, and farming area. The next most essential attributes arranged from most to least were Hospitality $^{\text{Good}}$, Activity $^{\text{Many}}$, and Facility $^{\text{Many}}$. Like the relationship between the multinomial logit and mixed logit, the coefficient values of the mixed rank-ordered logit tended to be higher than those of the rank-ordered logit. Hospitality $^{\text{High}}$ was the most important attribute, while Location $^{\text{Farming area}}$, Hospitality $^{\text{Good}}$, Activity $^{\text{Many}}$, and Facility $^{\text{Many}}$ were the second most important attributes.

Results from both sequential best-worst multinomial logit and sequential best-worst mixed logit revealed that their order of attribute importance is similar to that of the rank-ordered logit, despite the slight difference. The attributes related to Hospitality $^{\text{Good}}$ and Hospitality $^{\text{High}}$ were noteworthy and Activity $^{\text{Many}}$, Facility $^{\text{Many}}$, and Location $^{\text{Farming area}}$ followed after them. This means that when respondents choose the worst choice in addition to the best choice, the relative importance of these attributes was increased.

The results of the interaction effects show that in both models with rank-based data and models with sequential best-worst data, Activity $^{\text{Many}}$ with age, and Facility $^{\text{Many}}$ with frequency of visiting rural tourism tended to be significant with negative signs. This means that the older the tourist, the less the preference for outdoor activities, and the fewer visits to rural tourism, the higher the demand for additional facilities. Besides, Culture $^{\text{Many}}$ with age, and Room $^{\text{High}}$ with the frequency of visiting rural tourism were significant with positive signs. This means that as tourists get older, they pursue cultural experiences, and the more visits to rural tourism they make, the more importance they put on room quality.

Additionally, in the mixed rank-ordered logit model, in terms of the standard deviations, Location $^{\text{Farming area}}$, Activity $^{\text{Some}}$, Culture $^{\text{Many}}$, Room $^{\text{High}}$, and Hospitality $^{\text{High}}$ had statistically significant coefficients. In contrast, in the sequential best-worst mixed logit, Location $^{\text{Farming area}}$, Location $^{\text{Nature}}$, Activity $^{\text{Many}}$, Culture $^{\text{Some}}$, Room $^{\text{Good}}$, Room $^{\text{High}}$, and Facility $^{\text{Many}}$ were statistically significant. This suggests preference heterogeneity in the attributes.

The appendix indicates the number of best choices and worst choices by attribute levels and the relative difference in preference between the best and the worst. Through this resource, it is possible to see how many more times the respondents chose the worst choice for each attribute level than the best choice. In this study, it can be seen that Hospitality $^{\text{Status quo}}$, Location $^{\text{Farming area}}$, Price $^{\text{High}}$, and Facility $^{\text{Status quo}}$ were selected as worst, much more than the number of times selected as best. This means that the mentioned attribute levels are important factors in shaping negative preferences among respondents.

Compared to utilizing only the first data, methods of using more data related to best-worst choice enabled us to get estimates with lower standard errors, because the statistical efficiency is increased due to the additional preference information (Huber & Zwerina, 1996; Sándor & Wedel, 2001). In terms of goodness of fit, it is necessary to note that it's impossible to compare these measures across the tables because the amount and composition of the data utilized in each table is different. The first best model uses less data than the other two methods.

The model fit to compare the estimated models was evaluated through *adjusted Pseudo* R^2. In terms of it, the rank-ordered logit had 0.0566, and the mixed rank-ordered logit had 0.0578. By contrast, the sequential best-worst multinomial logit had 0.0592, and the sequential best-worst mixed logit had 0.0604, showing a better model fit. The overall model fit of models with sequential best-worst data (sequential best-worst multinomial logit and sequential best-worst mixed logit) was better across the board than that of models with rank-based data (rank-ordered logit and mixed rank-ordered logit). In addition, the series of mixed logit such as mixed rank-ordered logit and sequential best-worst mixed logit was statistically better than the series of multinomial logit such as rank-ordered logit and sequential best-worst multinomial logit.

Conclusions and implications

This study was conducted with the goal of analyzing overall tourist preferences for rural tourism and the exploring individual determinants of these preferences, by applying best-worst discrete choice experiments. In this study, it was found that tourists

Table 5
Analysis of best-worst data.

	Models with rank-based data						Models with sequential best-worst data					
	Rank-ordered logit			Mixed rank-ordered logit			Sequential best-worst multinomial logit			Sequential best-worst mixed logit		
	Coefficient			Coefficient			Coefficient			Coefficient		
Mean												
Location $^{\text{Farming area}}$	−0.473	***	(0.028)	−0.832	***	(0.116)	−0.525	***	(0.027)	−0.584	***	(0.032)
Location $^{\text{Nature}}$	0.363	***	(0.059)	0.463	***	(0.088)	0.439	***	(0.057)	0.495	***	(0.066)
Activity $^{\text{Some}}$	0.276	***	(0.028)	0.253	***	(0.070)	0.306	***	(0.027)	0.349	***	(0.031)
Activity $^{\text{Many}}$	0.538	***	(0.059)	0.689	***	(0.091)	0.663	***	(0.057)	0.743	***	(0.067)
Culture $^{\text{Some}}$	0.147	***	(0.029)	0.147	**	(0.049)	0.209	***	(0.027)	0.235	***	(0.031)
Culture $^{\text{Many}}$	0.156	**	(0.057)	0.108		(0.099)	0.174	**	(0.056)	0.203	**	(0.062)
Room $^{\text{Good}}$	0.229	***	(0.028)	0.350	***	(0.048)	0.254	***	(0.027)	0.284	***	(0.031)
Room $^{\text{High}}$	0.258	***	(0.032)	0.278	***	(0.071)	0.350	***	(0.030)	0.397	***	(0.036)
Facility $^{\text{Some}}$	0.145	***	(0.028)	0.176	***	(0.048)	0.163	***	(0.027)	0.187	***	(0.030)
Facility $^{\text{Many}}$	0.460	***	(0.033)	0.572	***	(0.060)	0.563	***	(0.032)	0.628	***	(0.038)
Hospitality $^{\text{Good}}$	0.599	***	(0.028)	0.750	***	(0.053)	0.700	***	(0.028)	0.774	***	(0.033)
Hospitality $^{\text{High}}$	0.942	***	(0.039)	1.094	***	(0.089)	1.082	***	(0.038)	1.232	***	(0.049)
Price	−0.266	***	(0.019)	−0.406	***	(0.042)	−0.296	***	(0.018)	−0.321	***	(0.021)
Standard deviation												
Location $^{\text{Farming area}}$				0.944	**	(0.340)				0.451	***	(0.093)
Location $^{\text{Nature}}$				0.374		(0.654)				0.658	***	(0.085)
Activity $^{\text{Some}}$				1.089	***	(0.284)				0.247		(0.189)
Activity $^{\text{Many}}$				0.498		(0.376)				0.646	***	(0.085)
Culture $^{\text{Some}}$				0.322		(0.358)				0.436	***	(0.103)
Culture $^{\text{Many}}$				0.933	***	(0.275)				0.065		(0.165)
Room $^{\text{Good}}$				0.168		(0.269)				0.406	***	(0.111)
Room $^{\text{High}}$				1.246	***	(0.259)				0.665	**	(0.084)
Facility $^{\text{Some}}$				0.284		(0.257)				0.055		(0.153)
Facility $^{\text{Many}}$				0.511		(0.387)				0.666	***	(0.075)
Hospitality $^{\text{Good}}$				0.121		(0.176)				0.302		(0.156)
Hospitality $^{\text{High}}$				1.785	***	(0.285)				0.251		(0.236)
Price				0.178		(0.115)				0.056		(0.238)
Interaction												
Location $^{\text{Nature}}$:Age	−0.027		(0.019)	−0.035		(0.026)	−0.029		(0.019)	−0.034		(0.021)
Activity $^{\text{Many}}$:Age	−0.041	*	(0.019)	−0.049	*	(0.026)	−0.061	**	(0.019)	−0.069	**	(0.021)
Culture $^{\text{Many}}$:Age	0.036		(0.018)	0.048	*	(0.027)	0.047	**	(0.018)	0.055	**	(0.020)
Room $^{\text{High}}$:Frequency	0.006	*	(0.003)	0.008	*	(0.004)	0.006	*	(0.003)	0.007	*	(0.003)
Facility $^{\text{Many}}$:Frequency	−0.007	*	(0.003)	−0.008	*	(0.004)	−0.008	*	(0.003)	−0.009	*	(0.004)
Hospitality $^{\text{High}}$:Income	−0.025		(0.021)	−0.035		(0.035)	−0.016		(0.021)	−0.020		(0.024)
Price:Income	0.004		(0.010)	0.002		(0.013)	0.005		(0.009)	0.005		(0.010)
N. of respondents	452			452			452			452		
N. of observations	12,204			12,204			12,204			12,204		
Null log-likelihood	−23,300			−23,300			−31,070			−31,070		
Final log-likelihood	−21,960			−21,920			−29,210			−29,160		
Pseudo R^2	0.0575			0.0592			0.0599			0.0615		
Adjusted Pseudo R^2	0.0566			0.0578			0.0592			0.0604		

Notes: parentheses: standard errors.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

choose the rural destinations where they are expected to have the highest utility after comprehensive consideration of various attributes. Not only did the respondents assign different importance to each attribute, but they also tried to exchange the attributes in order to select a reasonable alternative. In addition, respondents' preferences for rural tourism were confirmed by applying various models such as multinomial logit, mixed logit, rank-ordered logit, mixed rank-ordered logit, sequential best-worst multinomial logit, and sequential best-worst mixed logit.

The results of the sequential best-worst multinomial logit and sequential best-worst mixed logit were similar to those of the rank-ordered logit and mixed rank-ordered logit. Staff hospitality was the most important attribute that has not been mentioned in the results of the previous choice experiments research for rural tourism by Albaladejo-Pina and Díaz-Delfa (2009), Chaminuka et al. (2012), Hearne and Salinas (2002), and Hearne and Santos (2005). Similarly to findings by Chaminuka et al. (2012), outdoor activities were the second important. Additional facilities were the third important attribute. These results are similar to Hearne and Salinas (2002). The attributes related to location such as farming area followed after it, similarly to Albaladejo-Pina and Díaz-Delfa (2009). These imply that when respondents choose the worst choice as well as the best choice, the relative importance of staff hospitality, outdoor activities, additional facilities, and location is increased.

The findings of this study can help rural tourism workers improve services and products and establish effective marketing strategies. In this investigation, according to tourist segments, different characteristics are shown. For example, the older the tourist, not only the less preference for outdoor activities, but also the more pursuit of cultural experiences. The fewer visits to rural tourism, the higher the demand for additional facilities. In addition, the more visits to rural tourism they make, the more importance they put on room quality. Thus, depending on who the target is, differentiated products and services must be provided, considering the different characteristics of each target population.

From a methodological viewpoint, this investigation applied best-worst discrete choice experiments to explore the effects of choice attributes on rural tourism. Although discrete choice experiments have already been used in many tourism and hospitality fields so far, best-worst discrete choice experiments offer a very useful way to provide much richer data on customer preferences. In the rank-ordered logit of this study, more information about preferences, such as second and third best choice over first best choice, has been obtained. The sequential best-worst multinomial logit also provided more information on not only the best choice but also the attributes to be considered when choosing the worst choice.

In terms of model fit, this study found that models with sequential best-worst data (sequential best-worst multinomial logit and sequential best-worst mixed logit) were better than models with rank-based data (rank-ordered logit and mixed rank-ordered logit). This means that the proportion of log-likelihood explained by the model using additional data in the preference order it was collected, was larger than in the model using additional data in the preference rank. In addition, this study compared the multinomial logit series and mixed logit series in terms of validity. The results revealed that best-worst discrete choice experiments for rural tourism have consistency in both series. As was observed in studies completed by Albaladejo-Pina and Díaz-Delfa (2009) and Kim and Park (2017), this investigation found that the mixed logit series had better model fit measures than multinomial series. Furthermore, through three mixed logit series, which assume that individuals have different preferences, a wealth of information on individual random heterogeneity was obtained.

In terms of statistics, the statistical efficiency of choice models in best-worst discrete choice experiments could be greatly improved, due to generating parameter estimates with lower standard errors for estimating rank-ordered logit and sequential best-worst multinomial logit over discrete choice experiments with only the first choice (Huber & Zwerina, 1996; Sándor & Wedel, 2001). Compared to discrete choice experiments, the results of this investigation show that rank-based model such as rank-ordered logit and mixed rank-ordered logit as well as sequential best-worst model such as sequential best-worst multinomial logit and sequential best-worst mixed logit were statistically more useful in spite of using the same sample. More in-depth analysis of customer preferences is also possible since in best-worst discrete choice experiments, it is possible to identify what are the attributes considered to be important for the worst choice as well as the best choice.

This study has some limitations despite the aforementioned contributions. Above all, this study was conducted on tourists from Madrid and Barcelona in Spain. Although tourists from Madrid and Barcelona are representative of Spain, it is not appropriate to apply the results of this study to all regions. Therefore, it may be necessary to further investigate tourists of different regions in the future.

Next, there are various typologies of accommodations such as rural houses, rural hotels, campsites, and rented houses in the rural tourism market. In future studies, it may be required to clarify the scope of the analysis depending on the characteristics of the typology in detail to get accurate information for each typology of rural accommodations.

Additionally, only seven attributes were applied in order to prevent the survey from burdening the respondents, even though there are more detailed attributes that can affect the preference of rural tourism. It is necessary to develop more sophisticated attributes to more closely reflect the needs of respondents in the future. Since attributes and levels were determined based on qualitative methods such as literature reviews and expert interviews in this study, some of the derived attributes have qualitative characteristics that are difficult to quantify (e.g., location, outdoor activities, cultural experiences, room quality, additional facilities, staff hospitality). Thus, this study has been expressed through steps in degree, because it is difficult to quantitatively and accurately represent the levels of these attributes (e.g., none, some, many). Future studies will need to consider expressing levels more precisely.

There are some interesting future research issues related to this study. First, since best-worst discrete choice experiments enable us to obtain statistically significant results from a smaller sample size, it could be applied to some studies where access to respondents is difficult, such as foreign visitors, high-class visitors, and visitors to destinations that are difficult to visit. Second, in the case of analyzing interaction effects by cross-resolving the other socio-demographic and trip behavioral attributes not applied in this study such as gender, civil status, education level, and trip types, etc. with the seven attributes that influence rural tourism choices, the factors that lead to preference heterogeneity can be identified in detail. Finally, the attributes related to rural tourism destination choices applied in this study only explain some of the tourists' preference heterogeneity for rural tourism. Thus, it is necessary to elaborate ways of introducing rational criteria to segment to identify potential preference heterogeneity among respondents and its cause more closely. A complementary study should be conducted to compare the respondents' preference patterns after segmenting them through applying a method like latent class analysis.

Funding

Strengthening the agri-food innovation system in food chain actor, I + D + i project RTI2018-093791-B-C21, Ministry of Science, Innovation and Universities, Spain.

Declaration of competing interest

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

Appendix A. Attribute levels ranked in accordance with best, worst and BW difference

Specification	First best	Second best	Second worst	First worst	BW diff.	B/W	Weighted BW diff.[a]	Weighted B/W[b]
Location Status quo	1325	1444	1451	1204	114	1.043	235	1.061
Location Farming area	806	1212	1460	1946	−1388	0.592	−2528	0.528
Location Nature	1937	1412	1157	918	1274	1.614	2293	1.766
Activity Status quo	1005	1292	1462	1655	−820	0.737	−1470	0.692
Activity Some	1362	1412	1387	1283	104	1.039	183	1.046
Activity Many	1701	1364	1219	1130	716	1.305	1287	1.370
Culture Status quo	1121	1353	1474	1496	−496	0.833	−871	0.805
Culture Some	1502	1260	1159	1443	160	1.061	219	1.054
Culture Many	1445	1455	1435	1129	336	1.131	652	1.177
Room Status quo	1005	1361	1486	1562	−682	0.776	−1239	0.731
Room Good	1428	1336	1428	1262	74	1.028	240	1.061
Room High	1635	1371	1154	1244	608	1.254	999	1.274
Facility Status quo	1129	1195	1446	1644	−766	0.752	−1281	0.729
Facility Some	1148	1463	1460	1333	−182	0.935	−367	0.911
Facility Many	1791	1410	1162	1091	948	1.421	1648	1.493
Hospitality Status quo	767	1024	1521	2132	−1862	0.490	−3227	0.442
Hospitality Good	1433	1394	1354	1183	290	1.114	540	1.145
Hospitality High	1868	1650	1193	753	1572	1.808	2687	1.996
Price Low	1773	1425	1221	1015	962	1.430	1720	1.529
Price Medium	1208	1417	1448	1321	−144	0.948	−257	0.937
Price High	1087	1226	1399	1732	−818	0.739	−1463	0.699

[a] Weighted BW diff.: (2·First best + Second best) – (Second worst + 2·First worst).
[b] Weighted B/W: (2·First best + Second best)/(Second worst + 2·First worst).

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