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Inferring customer heterogeneity for rural tourism: A latent class approach based on a best-worst choice modelling

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Abstract: This research aims to analyse customers' preference heterogeneity for rural tourism in Spain and explore their preferences' personal and socio-demographic factors. To achieve this purpose, latent class analysis with the best-worst choice modelling has been applied through conducting a survey on 452 customers in Madrid and Barcelona. The results show that there are five classes in the Spanish rural tourism market: 'all-around seeker', 'leisure activist', 'culture explorer', 'comfort-driven user', and 'basic value pursuer'. The contribution of this investigation is that it is the first study that applied the latent class analysis with best-worst choice modelling to explore customers' preference heterogeneity for rural tourism.

Keywords: customers' preference; heterogeneous choices; tourism experiences

In Spain, rural tourism emerged as an alternative to overcoming the tendency to concentrate on beach and sun tourism (Campón-Cerro et al. 2017). As the rural area outside the city was perceived by urban residents as a place where new experiences were possible, the demand for rural tourism has steadily increased, and investments in natural heritage and culture have been made in response (Albaladejo-Pina and Díaz-Delfa 2009). With this increase in demand, the number of rural tourism destinations in Spain has skyrocketed, and many jobs related to it have been created (Martins--Almeida et al. 2014). However, 75% of the owners have not specialised in any type of demand and continues to contemplate broad segments such as families, couples, and groups (Albaladejo-Pina and Díaz-Delfa 2009). Each of them seems to be too heterogeneous to meet its specific needs. As a consequence, Spain's rural tourism sector faces a somehow undifferentiated supply. On the other hand, the increase in tourist destinations made it difficult to distinguish between them by blurring their unique characteristics (Garrod et al. 2006).

Grasping customers' needs related to selecting tourist destinations and drawing up strategies to satisfy them is an essential task for increasing the competitiveness of rural tourism in Spain (Albaladejo-Pina and Díaz--Delfa 2009). In other words, understanding customers' preference heterogeneity for rural tourism can provide insights for rural development, which might be worthy for local firms and policymakers. Promotion and communication campaigns will improve if more information on distinct groups of clients is available (Park and Yoon 2009). By targeting specific segments, accommo-

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dation owners, restaurants and leisure activity providers could differentiate their establishments and services and create additional value (Eusébio et al. 2017).

In the quantitative market research literature, studies on preference heterogeneity have been mainly conducted in two directions. The first approach identifies homogeneous segments by applying factor analysis and cluster analysis based on the rating with the Likert scale. It has the advantage that it is easy for respondents to understand and respond. Several applications show its usefulness for characterising rural tourists belonging to each segment based on benefits (Frochot 2005; Martins-Almeida et al. 2014) or motivation (Park and Yoon 2009; Polo Peña et al. 2014; Rid et al. 2014). However, it has the disadvantage that respondents do not consider the trade-offs between individual alternatives and apply the same weight to all alternatives.

The second approach is choice experiments. It has been applied to a wide array of rural tourism-related research because it can effectively reflect actual customers' behaviour as they consider multiple attributes at the same time in the purchasing decision process (Hearne and Santos 2005; Albaladejo-Pina and Díaz-Delfa 2009; Chaminuka et al. 2012). To become more realistic and accommodate potential differences among respondents, some research in the field of tourism has attempted to explore the customers' preference heterogeneity by applying latent class analysis (LCA) to choice modelling (Wu et al. 2011; Notaro et al. 2019). These studies clearly show preference heterogeneity so that the market can be properly segmented.

Within choice modelling, the best-worst choice has been proposed in order to neither burden the respondents with more choice sets nor increase the sample size and the survey cost. It consists of adding questions about not only the best choice but also the worst one (Louviere et al. 2008). Applying best-worst choice modelling makes it possible to more clearly identify the discriminatory characteristics of customers' preferences by asking their opinions not only on the preference side but also on the non-preference side. In addition, utilising the best choice and the worst choice in the best-worst choice modelling means analysing with twice the tourist preference data compared to choice modelling, and the measurement of statistical significance can be improved (Scarpa et al. 2011). The aim of this research is to analyse customers' preference heterogeneity for rural tourism in Spain and to explore personal and socio-demographic factors of their preferences so that both policymakers in local governments and rural tourism providers can establish strategies. The LCA with the best-worst choice modelling has been applied. This study contributes to the existing literature in various ways. First, while previous studies in the field of tourism have applied choice modelling to exploring tourists' preference heterogeneity, this study applied the best-worst choice approach on tourism for the first time, which permits not only the best choice data but also the worst choice data. Next, most studies in rural tourism exploring tourists' preference heterogeneity have used random parameter logit (RPL), whereas this study applied LCA for the first time in the field of rural tourism to explore it.

Literature review

Preference heterogeneity for rural tourism. Rural tourism is a source of economic development that boosts local initiatives while integrating appropriately into the regional economy (Ruiz-Real et al. 2020). Better knowledge of the market, more professional management, and modern marketing methods can lead to a more specialised supply that increases added value (Lane and Kastenholz 2015). To this end, it is necessary to identify the characteristics of the main rural tourist groups. Based on this, implement promotion and communication actions with clear messages focused on these groups (Park and Yoon 2009).

Within these modern marketing methods, choice modelling is a well-founded alternative that claims that a choice maximises the agent's utility, based on the random utility theory (Louviere et al. 2008). It is conducted with respondents' choice to select the best option and can be applied to draw up the directions for new product development and derive implications for improving existing products (Albaladejo-Pina and Díaz-Delfa 2009). This methodology has been applied in several research fields. In particular, its application has been expanded in the fields of tourism, leisure, and hospitality (a systematic review; Kemperman 2021). Discrete choice modelling requires the subsequent phases: selection of relevant attributes and their levels; establish an experimental design to produce hypothetical profiles and assign them to the choice sets; data collection and model estimation.

The most common attributes considered in choice experiments applied to rural tourism studies are price (Hearne and Salinas 2002; Hearne and Santos 2005; Albaladejo-Pina and Díaz-Delfa 2009; Scarpa et al. 2011; Chaminuka et al. 2012), infrastructure, type of building or diverse facilities (Hearne and Salinas 2002; Albaladejo-Pina and Díaz-Delfa 2005, 2009), location (Hearne and Salinas 2002; Albaladejo-Pina and Díaz-Delfa 2005,

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2009), experiences related to farming (Albaladejo-Pina and Díaz-Delfa 2005, 2009), craft activities (Chaminuka et al. 2012), landscape/diversity (Scarpa et al. 2011) or local festivals (Kim 2018), information type (Hearne and Salinas 2002; Hearne and Santos 2005).

Several rural tourism studies have applied multinomial logit (MNL) or RPL based on discrete choice experiments to explore customers' preferences for rural tourism. Hearne and Santos (2005) confirmed the high preference for attributes such as the use of professional guides and management of rural ecotourism areas by allowing stakeholders to choose their preferences for several options related to ecotourism. Chaminuka et al. (2012), applying choice modelling, showed that customers prefer village tours and crafts experiences. Albaladejo-Pina and Díaz-Delfa (2005) applied discrete choice experiments to find customers' preferences for rural tourism accommodations and found that various types and sizes of accommodation are important attributes that affect tourist preferences. Albaladejo--Pina and Díaz-Delfa (2009) explored customer preferences for rural tourism using both MNL and RPL based on discrete choice experiments. The findings show that important attributes in choosing rural tourism were the number of rooms, quality certification, and location.

Although no research specifically in rural tourism has been done with LCA with choice modelling, some tourism studies have explored tourists' preference heterogeneity more clearly by applying the latent class model with discrete choice experiments. Wu et al. (2011) found that by applying choice modelling with a latent class approach, the number of tourism spots, the attractiveness of the destination, and travel time were important attributes in the destination choice and derived two groups that were heterogeneous for preference. Notaro et al. (2019) investigated tourists' heterogeneity in preference for Alpine landscapes using a latent class approach and derived two heterogeneous segments using four attributes such as forests, grassland use, extra cost, and agricultural land use. Shoji and Tsuge (2015) identified tourists' preference heterogeneity for tours in subfrigid climate zones applying four attributes (a fee for a tour, the possibility of visiting eagles, interpretation, and purpose of tour) and derived three heterogeneous segments: 'adventure-based ice tour pursuer', 'wildlife observation tour pursuer', and 'balanced tour pursuer'.

Best-worst choice modelling. While the best-worst choice modelling is similar to the choice modelling in that respondents choose one of the alternatives in each choice set to provide information about their preferences, one is different from the other in that respondents not only choose the best alternative but immediately follow with the next worst alternative (Marley and Louviere 2005). In addition, through this, more information about respondents' preferences can be obtained, and the significance in statistical aspects can be improved (Louviere et al. 2008).

In the MNL to which the best-worst choice modelling is applied, both the best choice and the worst choice derived from the choice set are analysed (Louviere et al. 2008). While MNL has the advantage that model estimation and result analysis are relatively easy, it has the limitation that it does not sufficiently reflect the preference heterogeneity of respondents because it has a firm assumption that their preferences are homogeneous. There is a high probability that meaningful information acquired from a variety of behaviours regarding consumer choices is lost (Hynes et al. 2008).

LCA is a method of analysing unobserved heterogeneity through a non-parametric approach. Heterogeneity in LCA is expressed through a finite number of different classes with individual parameters. LCA divides unobserved heterogeneity by distinguishing latent segments in a discrete manner without assumptions about the distribution of the coefficients. In the LCA, each individual belongs to one of the segments called classes (Boxall and Adamowicz 2002). All classes have different characteristics, but within the same class, members' preferences are considered homogeneous (Bujosa et al. 2010). LCA allows for investigating and identifying groups of people with the same preferences (Bujosa et al. 2010). The probability (P_{ijm}) of the class m being related to alternative j, in which individual i chooses in a choice set, is explained as follows:

$$P_{ijm} = \frac{e^{\beta_m X_{ij}}}{\sum_j e^{\beta_m X_{ij}}} \quad (1)$$

where: P_{ijm} – probability; e – Euler's number; β_m – set of coefficients related to alternative attributes X_{ij} belonging to class m; i –individual; j – alternative

Classifying individuals (H_{im}) into one of the m classes, which is related to latent structures or the characteristics of the individual being observed, can be expressed as a probabilistic model as follows:

$$H_{im} = \frac{e^{Z_i \theta_m}}{\sum_m e^{Z_i \theta_m}} \quad (2)$$

where: H_{im} – classifying individuals; θ_m – set of coefficients related to latent observable factors Z_i; m – class.

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MATERIAL AND METHODS

Deriving attributes and determining their levels is the most important procedure in a best-worst choice study. In this study, attributes and levels were determined through three-step processes, such as the analysis of rural tourism experiences directly mentioned by customers, literature research, and expert interviews (Kim and Park 2017). First, by analysing the texts and photos left by about 1 002 customers in the rural tourism online community, what rural tourism experiences were considered important by them was analysed (An and Alarcón 2021). Next, by filtering literature research, a pool of important rural tourism experiences was derived. Finally, interviews with ten experts, consisting of rural tourism owners, rural tourism association representatives, and professors in related fields, were conducted to identify the seven attributes influencing customers when choosing rural tourism (An and Alarcón 2020). The seven attributes are shown in Figure 1.

The levels of each attribution were also determined through expert interviews. The levels were designed in three stages in consideration of the quantitative and qualitative characteristics of the seven attributes mentioned above. The derived levels are shown in Figure 1.

Since it is less realistic to induce the respondent's response by applying all of these alternatives, to overcome this problem, this study created a total of 18 choice sets through the application of an optimal design (Aizaki et al. 2014). In addition, by using the block design, two versions of the questionnaire, each of which applied nine choice sets differently, were created to reduce the respondents' burden. Figure 2 shows an example of the best-worst question applied to the survey. Each choice set has four options, and the respondents were asked to choose the best choice from the four options ('Which of the four op-

Attributes	Levels	Specification	Definition	Code
Location	3	– Town – Farming area – Nature	– Located in town – Located in a fruit and vegetable growing area – Located near nature like a mountain, river, or lake	– Status quo – Location1 – Location2
Outdoor activities	3	– None – Some – Many	– There is no activity – Some activities like hiking and climbing – Many activities like horse riding, cycling, fishing, hiking, and climbing	– Status quo – Activity1 – Activity2
Cultural experiences	3	– None – Some – Many	– There is no cultural experience – Some cultural experiences related to crafts and food – Many cultural experiences related to cultural heritage like ruins/castles/churches, crafts and food	– Status quo – Culture1 – Culture2
Room quality	3	– Basic – Good – High	– Room with basic/functional bedding and furnishings – Room with good quality bedding, furnishings, and coffee service – Room with luxurious bedding, furnishings, and wine service	– Status quo – Room1 – Room2
Additional facilities	2	– None – Some – Many	– It does not have any additional facilities – Some facilities like a barbecue, or chimney – Many facilities like a pool, spa, garden, recreation area, barbecue, or chimney	– Status quo – Facility1 – Facility2
Staff hospitality	2	– Basic – Good – High	– Hospitality only while greeting guests – Hospitality through offering local information – Hospitality through continuous care, offering local information, and a good breakfast	– Status quo – Hospitality1 – Hospitality2
Price per room for one night	2	– Low – Medium – High	– EUR 60 per room for one night – EUR 120 per room for one night – EUR 180 per room for one night	– Price (continuous)

Figure 1. Attributes and levels used in the choice experiment design

Source: Authors' own processing

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	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 does not have any additional facility	**Some** Barbecue and chimney	**None** It does not 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	EUR 60	EUR 60	EUR 120	EUR 180
Best choice	◯	◯	Ⓥ	◯
Worst choice	Ⓥ	◯	◯	◯

Figure 2. Example of a best-worst question

◯ – unselected option; Ⓥ – selected option

Source: Authors' own processing

tions would you most likely choose?') and then select the worst choice from the remaining three options ('Which of the three remaining options would you least likely choose?').

From June 1 to June 30, 2019, this study conducted an online survey for adults aged 20 years or older who have had at least one rural tourism visit within the last three years and reside in Madrid and Barcelona. Since the tourists of Madrid and Barcelona, the largest cities in Spain, are representative customers of rural tourism in Spain, it was decided to use them as the target of the survey. Quotas were applied for age, region, income, and educations level to get a representative sample. Finally, a total of 452 customers participated in the survey, consisting of 227 Madrid residents and 225 Barcelona residents. Through the best-worst choice survey of these 452 customers, a total of 8 136 observations were obtained, including not only 4 068 observations related to the best choice but also 4 068 observations related to the worst choice.

This study utilised the R package 'Rchoice' (Sarrias 2016) and the Latent GOLD® version 5.1 (Vermunt and Magidson 2016) software to analyse the latent class MNL model.

RESULTS AND DISCUSSION

Table 1 shows the overall respondents' profiles.

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Table 1. Socioeconomic variables of the total sample

Sample characteristic		Number	Percentage (%)
Gender	female	228	50.4
	male	224	49.6
Age (year)	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
Region	Madrid	227	50.2
	Barcelona	225	49.8
Civil status	non-married	248	54.9
	married	204	45.1
Whether he/she has children (child)	without children	251	55.5
	with children	201	44.5
Education level (education)	below university	168	37.2
	university degree and higher	284	62.8
Monthly household income (income)	under EUR 2 000	130	28.8
	EUR 2 000–2 999	163	36.1
	EUR 3 000–3 999	84	18.6
	EUR 4 000 and more	74	16.4
Frequency of visits 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 (trip type)	family	135	29.9
	friends	150	33.2
	couple	167	36.9
Total		452	100.0

Source: Authors' own processing

To determine the number of potential latent classes, the goodness of fit is measured by log-likelihood (LL), Bayes information criterion (BIC), and Akaike information criterion (AIC). Table 2 shows the results with an increasing number of latent classes. A model with five latent classes was deemed optimal since the LL, BIC, and AIC decreased sharply up to the five-latent class model but very smoothly in the six-latent class model.

Table 3 shows the estimated parameters for latent class regression, and Table 4 indicates the class membership on socio-demographics. The size of the five latent classes ranges from at least 15.7% to at most 31.4%. In the first class, the estimated parameters of all attributes except 'Facility1' were significant at a 5% significance level. It included 31.4% of respondents, the highest rate among the five classes. It was named 'all-around seeker' because they take into account a variety of attributes little by little when deciding on rural tourism. In the first class, the percentage of the male

Table 2. Statistical indicators to determine the optimal number of classes

Number of clusters	Number of parameters	LL	BIC	AIC
1	15	–20 911	41 914	41 852
2	31	–20 711	41 611	41 484
3	47	–20 538	41 363	41 170
4	63	–20 429	41 244	40 985
5	79	–20 353	41 189	40 864
6	95	–20 300	41 180	40 789

LL – log-likelihood; BIC – Bayes information criterion; AIC – Akaike information criterion

Source: Authors' own processing

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Table 3. Estimated parameters for latent class regression

Mean	Latent class-multinomial logit (LC-MNL)				
	class 1 (all-around seeker)	class 2 (leisure activists)	class 3 (culture explorer)	class 4 (comport-driven user)	class 5 (basic value pursuers)
Location1	–0.137* (0.061)	–0.966*** (0.103)	–1.511*** (0.195)	–0.267* (0.109)	–0.276* (0.107)
Location2	0.154* (0.061)	1.592*** (0.113)	0.135 (0.175)	0.656*** (0.112)	0.423*** (0.107)
Activity1	0.148** (0.054)	0.760*** (0.108)	0.427** (0.134)	0.150 (0.094)	0.412*** (0.089)
Activity2	0.300*** (0.058)	1.468*** (0.110)	0.684*** (0.096)	0.082 (0.107)	0.870*** (0.099)
Culture1	0.134* (0.055)	0.398*** (0.087)	0.620*** (0.096)	0.444*** (0.103)	0.005 (0.089)
Culture2	0.182** (0.062)	0.232* (0.094)	1.128*** (0.137)	0.381*** (0.086)	–0.207* (0.099)
Room1	0.244*** (0.055)	0.471*** (0.091)	0.310* (0.128)	0.159 (0.090)	0.660*** (0.099)
Room2	0.268*** (0.057)	0.805*** (0.107)	0.532*** (0.091)	–0.025 (0.100)	1.181*** (0.113)
Facility1	0.095 (0.057)	–0.457*** (0.104)	0.493*** (0.118)	0.051 (0.103)	0.123 (0.102)
Facility2	0.140* (0.063)	0.567*** (0.108)	0.941*** (0.166)	1.183*** (0.122)	0.472*** (0.119)
Hospitality1	0.268*** (0.059)	0.890*** (0.089)	0.584*** (0.093)	1.863*** (0.191)	0.884*** (0.091)
Hospitality2	0.493*** (0.063)	1.371*** (0.089)	1.313*** (0.121)	2.148*** (0.180)	1.118*** (0.099)
Price	–0.091** (0.031)	–0.381*** (0.057)	–0.008 (0.052)	–0.524*** (0.054)	–1.076*** (0.071)

*, **, ***Statistical significance at $P < 0.05$, $P < 0.01$, $P < 0.001$, respectively; parentheses indicate standard errors (SE)
Source: Authors' own processing

is slightly higher than that of female. The proportion of respondents who have visited rural tourism five to nine times at the medium level in the past three years was high. Compared to other classes, the percentage of the couple trip type is higher.

In the second class, the estimated parameters of all attributes were significant at the significance level of 5%. 20.1% of respondents belong to the second class, which is the second-largest among the five classes. It was named 'leisure activists' because the ratio that considers the possibility of various activities in rural tourism to be the most important is higher than in other classes. In the second class, younger, non-married, low education, and low earners are relatively high. The percentage of the friends' group trip type is higher.

In the third class, the estimated parameters of all attributes except 'Location2' and price per room for one night were significant at the significance level of 5%. 16.6% of respondents were in this class. It was called 'culture explorer', reflecting the importance of higher cultural experiences compared to other classes. In this class, the proportion of unmarried and low-educated respondents was relatively high, and the ratio of those who had practised rural tourism ten and more times in the past three years was the highest compared to other classes. Their trip type was centred on the family.

In the fourth class, the remaining attributes except for the attributes such as 'Activity1', 'Activity2', 'Room1', 'Room2', and 'Facility1' were significant at the significance level of 5%. This class includes 15.7% of respon-

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Table 4. Multinomial logit for class membership on socio-demographics

Socio-demographics		Class 1 (all-around seeker)	Class 2 (leisure activists)	Class 3 (culture explorer)	Class 4 (comfort-driven user)	Class 5 (basic value pursuers)
Gender	female	–0.132*** (0.011)	–0.017 (0.013)	–0.005 (0.014)	0.273*** (0.014)	–0.119*** (0.014)
Age (category number)		–0.018 (0.011)	–0.188*** (0.013)	0.040** (0.014)	0.024 (0.015)	0.141*** (0.015)
Region	Barcelona	0.068*** (0.010)	0.120*** (0.012)	–0.243*** (0.013)	0.071*** (0.014)	–0.016 (0.013)
Civil status	married	0.054*** (0.014)	–0.226*** (0.018)	–0.192*** (0.019)	0.181*** (0.019)	0.183*** (0.018)
Child	with children	0.040*** (0.016)	0.016 (0.019)	0.047* (0.020)	0.188*** (0.021)	–0.290*** (0.020)
Education	university degree and higher	0.063*** (0.012)	–0.129*** (0.013)	–0.145*** (0.014)	0.043** (0.015)	0.167*** (0.015)
Income	less than EUR 2 000	–0.168*** (0.019)	0.116*** (0.021)	0.021 (0.023)	0.234*** (0.024)	–0.203*** (0.024)
	EUR 2 000~2 999	0.116*** (0.016)	0.151*** (0.020)	0.071*** (0.021)	–0.143*** (0.023)	–0.196*** (0.022)
	EUR 3 000~3 999	–0.153*** (0.021)	–0.165*** (0.026)	–0.025 (0.027)	0.169*** (0.025)	0.174*** (0.025)
	EUR 4 000 and more	0.205*** (0.021)	–0.103*** (0.028)	–0.067* (0.030)	–0.260*** (0.032)	0.225*** (0.026)
Frequency	1~4 times	0.010 (0.016)	0.029 (0.019)	–0.117*** (0.019)	0.233*** (0.022)	–0.156*** (0.019)
	5~9 times	0.063*** (0.018)	0.161*** (0.022)	–0.056* (0.022)	–0.088*** (0.026)	–0.079*** (0.022)
	10 and more times	–0.073** (0.024)	–0.190*** (0.030)	0.173*** (0.027)	–0.145*** (0.035)	0.235*** (0.028)
Trip type	family	–0.110*** (0.018)	0.042 (0.022)	0.358*** (0.022)	–0.122*** (0.023)	–0.168*** (0.024)
	friends	–0.006 (0.016)	0.078*** (0.018)	–0.118*** (0.020)	–0.006 (0.020)	0.051* (0.020)
	couple	0.116*** (0.015)	–0.121*** (0.018)	–0.241*** (0.020)	0.128 (0.020)	0.117*** (0.020)

*, **, ***Statistical significance at $P < 0.05$, $P < 0.01$, $P < 0.001$, respectively; parentheses indicate standard errors (SE)
Source: Authors' own processing

dents, the lowest among the five classes. It was named 'comfort-driven user' because customers belonging to this class compared to other classes highly value the importance of hospitality provided by staff and additional facilities provided by rural tourism accommodation. In this class, the proportion of women was relatively high. The proportion of married people and those having children was relatively high. There were many low-income households, and the proportion of customers who had visited rural tourism at a low level was high.

Finally, in the fifth class, all attributes except 'Culture1' and 'Facility1' were significant at the significance level of 5%. This class includes 16.2% of respondents. Since customers belonging to this class favour the basic values provided by rural tourism, such as price and room quality, they were named as 'basic value pursuers'.

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In this class, the proportions of men, elderly, married, and high-income earners were relatively high. In this class, relatively more customers had carried out rural tourism ten and more times in the past three years.

Discussion. This study aimed to analyse tourist preference heterogeneity for rural tourism in Spain and explore personal and socio-demographic factors of their preferences. Best-worst choice modelling with LCA was applied to achieve this goal. In terms of customers' preference heterogeneity, our study revealed that there are five classes in the Spanish rural tourism market (Table 5).

The first class, named 'all-around seeker', has the characteristic its members consider various attributes little by little when selecting rural tourism. It presents some similarities with the 'want-it-all' found in the study by Park and Yoon (2009), although socio-demographic characteristics are quite different. The Korean 'want-it-all' is composed by less educated and wealthy tourists that do not mind doing housework when they travel, while the Spanish 'all-around seeker' includes, to a greater extent, couples with higher living standards.

The second class, named 'leisure activist', is similar to the active visitors from Eusébio et al. (2017) and active rural customers from Molera and Albaladejo-Pina (2007). Customers belonging to the second class are characterised by nature and outdoor activities. This segment is connected with ecotourism (Hearne and Salinas 2002; Hearne and Santos 2005; Chaminuka et al. 2012; Fernández-Hernández et al. 2016) and presents promising economic implications. Since their members are more concerned with environmental issues and sustainable development, they can generate a larger economic impact in these areas (Fernández-Hernández et al. 2016; Eusébio et al. 2017).

The third class, called 'culture explorer', tends to seek cultural experiences and a town or nature instead of a farming area located in a fruit and vegetable growing region. This class is consistent with heritage and nature seekers derived from the study of rural tourism market segmentation by Rid et al. (2014). As in the previous case, this type of tourist is also more in tune with the social conditions of the towns they visit, with the depopulation problems that are frequent and with the need to preserve inheritance. Therefore, they are more sensitive to contributing to their economic development. In addition, traditional and cultural values can be interpreted as powerful means to create place branding and to differentiate specific places (Ruiz-Real et al. 2020).

The fourth class, called 'comfort-driven user', has the characteristic that they consider staff hospitality as the most important attribute and prefer to have a lot of additional facilities. This result was consistent with 'enjoying rural destination's services and facilities' reported by Polo Peña et al. (2014), the 'family togetherness' of Park and Yoon (2009), or the 'summer family vacationers' of Eusébio et al. (2017).

Finally, the fifth class, named 'basic value pursuer', valued room quality and price per room for one night.

Table 5. Latent class interpretation

Name	Class 1 (all-around seeker)	Class 2 (leisure activists)	Class 3 (culture explorer)	Class 4 (comport-driven user)	Class 5 (basic value pursuers)
Size (%)	31.4	20.1	16.6	15.7	16.2
Attributes – high on	all attributes are considered little by little	Location2, Activity2, Hospitality2	Culture2, Hospitality2	Hospitality2, Facility2	Room2, Price
Attributes – low on	Facility1	Culture2	Room1, Activity1	Location1	Culture2
Gender	male	balanced	balanced	female	male
Age	balanced	younger	balanced	balanced	older
Region	balanced	Barcelona	Madrid	balanced	balanced
Civil status	balanced	non-married	non-married	married	married
Child	balanced	balanced	balanced	with children	without children
Education	balanced	low education	low education	balanced	high education
Income	balanced	lower	balanced	lower	higher
Frequency	medium	medium	high	low	high
Trip type	couple	friends	family	balanced	couple, friends

Source: Authors' own processing

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It was similar to those of 'passive tourists' derived from the study of Park and Yoon (2009), but in our case, this segment includes the oldest and highest income tourists, as the 'inactive' of Eusébio et al. (2017). Therefore, in this case, we also identify the possibility of generating added value, targeting a group that seeks relaxing and calming activities, and that on the other hand, has spending capacity. Therefore, this segment can value sustainable tourism and can empathise with rural development.

CONCLUSION

This study has made several contributions in terms of methodology. First of all, the best-worst choice approach that asks for the worst choice in addition to the best choice can offer plentiful information on the individual preferences of customers for rural tourism, as compared to the choice experiments modelling that exclusively utilise best choice data. This was also a way to ensure higher statistical usefulness. In addition, whereas existing choice experiments studies that studied preference heterogeneity in rural tourism focused on single class-based RPL often, this study was able to more clearly confirm the customers' preference heterogeneity by applying LCA to the field of rural tourism.

From a practical point of view, we argue that understanding market heterogeneity leads to better management and a more complete satisfaction of tourist demand. And over time, this can mean a more sustainable development of rural areas (Eusébio et al. 2017; Ruiz-Real et al. 2020). Results show different groups of rural tourists to which rural establishments can be oriented and move away from the great problem of the scarce differentiation of rural tourism in Spain.

Despite the contributions mentioned so far, this study has some limitations. First, this study explored customers' preference heterogeneity for rural tourism based on some large attributes that are considered important in rural tourism. Future research should be conducted by being expanded to include more decision-making factors for customers. Second, in order to generalise the proposed LCA model, it is necessary to consider the cultural context of the region. Future studies could apply the same model derived from this study to other regions after a comparison between regions.

REFERENCES

Aizaki H., Nakatani T., Sato K. (2014): Stated Preference Methods Using R. New York, USA, CRC Press: 1–233.

An W., Alarcón S. (2020): Exploring rural tourism experiences through subjective perceptions: A visual Q approach. Spanish Journal of Agricultural Research, 18: 1–16.

An W., Alarcón S. (2021): From netnography to segmentation for the description of the rural tourism market based on tourist experiences in Spain. Journal of Destination Marketing & Management, 19: 1–13.

Albaladejo-Pina I.P., Díaz-Delfa M.T. (2005). Rural tourism demand by type of accommodation. Tourism Management, 26: 951–959.

Albaladejo-Pina I.P., Díaz-Delfa M.T. (2009): Tourist preferences for rural house stays: Evidence from discrete choice modelling in Spain. Tourism Management, 30: 805–811.

Boxall P.C., Adamowicz W.L. (2002): Understanding heterogeneous preferences in random utility models: A latent class approach. Environmental and Resource Economics, 23: 421–446.

Bujosa A., Riera A., Hicks R.L. (2010): Combining discrete and continuous representations of preference heterogeneity: A latent class approach. Environmental and Resource Economics, 47: 477–493.

Campón-Cerro A.M., Hernández-Mogollón J.M., Alves H. (2017): Sustainable improvement of competitiveness in rural tourism destinations: The quest for tourist loyalty in Spain. Journal of Destination Marketing & Management, 6: 252–266.

Chaminuka P., Groeneveld R.A., Selomane A.O., van Ierland E.C. (2012): Tourist preferences for ecotourism in rural communities adjacent to Kruger National Park: A choice experiment approach. Tourism Management, 33: 168–176.

Eusébio C., Carneiro M.J., Kastenholz E., Figueiredo E., Soares da Silva D. (2017): Who is consuming the countryside? An activity-based segmentation analysis of the domestic rural tourism market in Portugal. Journal of Hospitality and Tourism Management, 31: 197–210.

Fernández-Hernández C., León C.J., Aranã J.E., Díaz-Pére F. (2016): Market segmentation, activities and environmental behaviour in rural tourism. Tourism Economics, 22: 1033–1054.

Frochot I. (2005): A benefit segmentation of tourists in rural areas: A Scottish perspective. Tourism Management, 26: 335–346.

Garrod B., Wornell R., Youell R. (2006): Re-conceptualising rural resources as countryside capital: The case of rural tourism. Journal of Rural Studies, 22: 117–128.

Hearne R.R., Salinas Z.M. (2002): The use of choice experiments in the analysis of tourist preferences for ecotourism development in Costa Rica. Journal of Environmental Management, 65: 153–163.

Hearne R.R., Santos C.A. (2005): Tourists' and locals' preferences toward ecotourism development in the Maya Bio-

https://doi.org/10.17221/56/2021-AGRICECON

sphere Reserve, Guatemala. Environment, Development and Sustainability, 7: 303–318.

Hynes S., Hanley N., Scarpa R. (2008): Effects on welfare measures of alternative means of accounting for preference heterogeneity in recreational demand models. American Journal of Agricultural Economics, 90: 1011–1027.

Kemperman A. (2021): A review of research into discrete choice experiments in tourism: Launching the Annals of Tourism Research Curated Collection on Discrete Choice Experiments in Tourism. Annals of Tourism Research, 87: 103–137.

Kim D., Park B.-J.R. (2017): The moderating role of context in the effects of choice attributes on hotel choice: A discrete choice experiment. Tourism Management, 63: 439–451.

Kim H.N. (2018): The economic valuation of change in the quality of rural tourism resources: Choice experiment approaches. Sustainability, 10: 1–17.

Lane B., Kastenholz E. (2015): Rural tourism: The evolution of practice and research approaches – Towards a new generation concept? Journal of Sustainable Tourism, 23: 1133–1156.

Louviere J.J., Street D., Burgess L., Wasi N., Islam T., Marley A.A.J. (2008): Modelling the choices of individual decision-makers by combining efficient choice experiment designs with extra preference information. Journal of Choice Modelling, 1: 128–164.

Marley A.A.J., Louviere J.J. (2005): Some probabilistic models of best, worst, and best-worst choices. Journal of Mathematical Psychology, 49: 464–480.

Martins-Almeida A.M., Correia A., Pimpão A. (2014): Segmentation by benefits sought: The case of rural tourism in Madeira. Current Issues in Tourism, 17: 813–831.

Molera L., Albaladejo-Pina I.P. (2007): Profiling segments of tourists in rural areas of South-Eastern Spain. Tourism Management, 28: 757–767.

Notaro S., Grilli G., Paletto A. (2019): The role of emotions on tourists' willingness to pay for the Alpine landscape: A latent class approach. Landscape Research, 44: 743–756.

Park D.B., Yoon Y.S. (2009): Segmentation by motivation in rural tourism: A Korean case study. Tourism Management, 30: 99–108.

Polo Peña A.I., Frías Jamilena D.M., Rodríguez Molina M.Á., Rey Pino J.M. (2014): Online marketing strategy and market segmentation in the Spanish rural accommodation sector. Journal of Travel Research, 55: 362–379.

Rid W., Ezeuduji I.O., Pröbstl-Haider U. (2014): Segmentation by motivation for rural tourism activities in the Gambia. Tourism Management, 40: 102–116.

Ruiz-Real J.L., Uribe-Toril J., de Pablo Valenciano J., Gázquez-Abad J.C. (2020): Rural tourism and development: Evolution in scientific literature and trends. Journal of Hospitality and Tourism Research: 1–25.

Sarrias M. (2016): Discrete choice models with random parameters in R: The Rchoice package. Journal of Statistical Software, 74: 1–31.

Scarpa R., Notaro S., Louviere J., Raffaelli R. (2011): Exploring scale effects of best/worst rank ordered choice data to estimate benefits of tourism in alpine grazing commons. American Journal of Agricultural Economics, 93: 809–824.

Shoji Y., Tsuge T. (2015): Heterogeneous preferences for winter nature-based tours in sub-frigid climate zones: A latent class approach. Tourism Economics, 21: 387–407.

Vermunt J., Magidson J. (2016): Upgrade Manual for Latent GOLD 5.1. Belmont, MA, USA, Statistical Innovations Inc.: 1–17.

Wu L., Zhang J., Fujiwara A. (2011): Representing tourists' heterogeneous choices of destination and travel party with an integrated latent class and nested logit model. Tourism Management, 32: 1407–1413.

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