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The Choquet integral supported by a hedonic approach for modelling preferences in hotel selection☆

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ABSTRACT

This paper presents a methodology for modelling the hotel selection process by combining the hedonic pricing method and the Choquet integral, a multi-criteria decision-making approach. The hedonic pricing method is a valuable tool in revealed preference theory, enabling the acquisition of preferential information in a straightforward manner. In this study, we use hedonic pricing to identify the significant criteria that influence the tourism selection process and to evaluate their importance. We combine the hedonic methodology with the Choquet integral to consider not only the importance of each criterion but also the importance of each subset of criteria. This proposed hybrid technique – the Choquet integral supported by the hedonic price method – offers an effective methodology for hotel selection by taking into account the market valuation of the criteria. We apply this methodology to a database of Spanish hotels and demonstrate the validity of our proposal in introducing valuable preferential information into the hotel classification process. This approach holds potential benefits for both tourism companies and travellers.

1. Introduction

The COVID-19 pandemic has presented one of the most significant challenges ever encountered by the tourism sector. Not only has it endangered the survival of many companies within the sector, but it has also had a profound impact on the well-being of tens of millions of employees, local communities, and entire economies worldwide. Tourists have become increasingly demanding when it comes to health and hygiene conditions at destinations while also expressing apprehension about potential future variants of COVID that could lead to border closures and travel disruptions. Moreover, the pandemic has prompted some travellers to contemplate the climate and environmental consequences of their choices. Consequently, governments and tourism businesses have had to reconsider their investment strategies and find ways to mitigate risks in the face of heightened demand volatility. Additionally, the conflict in Ukraine has introduced instability and economic disturbances that could have long-term implications for the sector's development. This means that the objectives of sustainability and resilience within the sector, as well as its role in economic and social development, are of utmost importance in light of the climate emergency, the conflict in Ukraine, and the COVID-19 pandemic (World Economic Forum, 2022 [1]).

The Word Economic Forum assesses and measures the set of policies that facilitate the sustainable development and resilience of the tourism sector, thereby contributing to a country's overall development, through its Travel and Tourism Development Index 2021(World Economic Forum, [1]). This index is composed of five sub-indices and seventeen pillars: Enabling Environment (Business Environment, Safety and Security, Health and Hygiene, Human Resources and Labour Market, ICT Readiness), Travel and Tourism Policy and Enabling Conditions (Prioritisation of Travel and Tourism, International Openness, Price Competitiveness), Infrastructure (Air Transport, Ground and Port Infrastructure, Tourism Service Infrastructure), Travel and Tourism Demand Drivers (Natural Resources, Cultural Resources, Nonleisure Resources) and Travel and Tourism Sustainability (Environmental Sustainability, Socioeconomic Resilience and Conditions, Travel and

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Tourism Demand Pressure and Impact). The Index encompasses a range of objectives, many of which conflict with each other. For instance, improving air transport infrastructure may conflict with achieving environmental sustainability. In this context, multi-criteria decision--making (MCDM) techniques are valuable tools for balancing multiple objectives (for a literature review of MCDM applications to the tourism sector, refer to Vatankhah et al. [2]) where single-objective techniques fail to provide a comprehensive assessment.

Our study aims to further contribute to this field. Specifically, we analyse the process through which tourists select hotels based on the characteristics and services offered. Understanding the value tourists place on hotel characteristics such as health, safety, and sustainability, as well as their interrelationships, can aid in achieving the sector's goals of sustainability and resilience.

MCDM techniques have been applied in this framework by various researchers (Chou et al. [3]; Vu et al. [4]; Li et al. [5]; Işık and AdalıIşik [6]; Zaman et al. [7]; Gülsün et al. [8]; Pahari et al. [9]; Peng et al. [10]; Yu et al. [11]; Liang et al. [12]; Kwok and Lan 2019 [13]; Veloso et al. [14]; Nie et al. [15] Yu et al. [16]; Wang et al. [17]; Andria et al. [18]). These techniques facilitate the explicit identification of relevant criteria for hotel selection by tourists and the integration of these criteria into the decision-making process (Belton and Stewart, [19]). However, most applications in this field suffer from two main shortcomings.

Firstly, many studies rely on information gathered from tourists through personal interviews or from hotel and travel websites to determine tourist preferences. However, preferences expressed through these channels are hypothetical and only represent stated tastes, which may not align with the actual behaviour of consumers in the market (Cropper and Oates, [20]). The hedonic price method (HPM) has therefore been presented to address this gap in the literature as it relies based on consumer preferences revealed through the market rather than a hypothetical evaluation of alternatives (Baranzini et al. [21]). The HPM belongs to the family of approaches that utilises market information to infer consumer preferences. The central idea of the HPM is to decompose the price of a good or service into the prices of its individual characteristics. A hedonic price function is used for this purpose, describing the equilibrium relationship between the price of the good or service and its characteristics. Consequently, the market price of the good or service depends on inherent characteristics rather than the price itself. If the market is equilibrium and operates under perfect competition, the partial derivative of the hedonic function with respect to a specific characteristic represents the marginal or hedonic price associated with that characteristic. In this research, we take advantage of this interpretation of the hedonic price. Specifically, we use marginal prices to determine the weights of the criteria in our multi-criteria modelling. Moreover, methods using information obtained from tourists through personal interviews or information published by hotel and travel websites, provide ranking and/or text comments on the preferences of tourists. In contrast, HPM provides a quantitative value for these preferences through the monetary valuation of characteristics made by the market (Rosen, [22]). Consequently, this supports the identification of the criteria's importance.

Secondly, most MCDM studies applied to the hotel selection process assume that the criteria are mutually independent. However, it is important to acknowledge that in practice, the independence of criteria cannot always be assumed, and various interactions such as independence, complementarity, and correlation exist amongst different criteria exist (Li et al. [5]). Only a few studies take into account these interrelationships (Tseng,[23]; Vu et al. [4]; Li et al. [5]; Peng et al. [10]). The presence of interactions between criteria implies that the contribution of a criterion to the overall valuation of a hotel varies not only with respect to its own performance but also with the performance of other criteria that it interacts with. For instance, when there is a redundant relationship between a pair of hotel evaluation criteria (i.e. substitutability between them), the individual values of a hotel under these two criteria can compensate each other. Conversely, in the case of a synergistic relationship (i.e. irreplaceability between them), the compensation effect between the individual values under these two criteria is small because each criterion plays a unique role in the minds of tourists. To address this, aggregation operators based on non-additive value functions allow for the characterisation of interactions between criteria (Wu and Liao [24]).

A variety of non-additive value functions have been proposed in the literature to tackle complex aggregation problems. One such function is the Choquet integral (CI) (Choquet [25]), which is constructed based on the weight assigned to any subset of criteria. The CI is defined based on capacities (Kojadinovic [26]) to model the importance of every subset of criteria and employs the weighted average operator for aggregation. In this approach if two criteria are synergistic, the weight of the coalition comprising these two criteria should exceed the sum of their individual weights. Conversely, for redundant criteria, the weight of the coalition becomes smaller. The Sugeno integral [27], similar to the CI, accounts for interactions between criteria using capacities and aggregates with minimum and maximum operators.

Another non-additive aggregation function worth mentioning is the multilinear model (Keeney and Raiffa [28]; Owen [29]). This approach involves a polynomial aggregation of the criteria evaluations (Pelegrina et al. [30]). In addition, Greco et al. [31] introduced an alternative approach to the CI, the bonus and penalty-based value function, that provides a method to handle interacting criteria. Its central idea is to add a bonus to the additive component of the additive value function when a given pair of criteria exhibit synergy. Conversely, if they are redundant, a penalty is subtracted from the additive component of the additive value function.

It is important to note that applying capacity-based aggregation methods can present difficulties in real-world scenarios. Determining the coefficients associated with all the subsets of criteria is a complex problem, and extensive research has been conducted in this area. In situations where we lack either further information about these parameters or preferences given by the decision maker, the unsupervised approaches are suitable for identifying capacities (Pelegrina et al. [32]). We hypothesise that using the CI (Grabisch and Labreuche [33], Angilella et al. [34], Corrente et al. [35]) offers the possibility to include interactions between criteria in the aggregation process, thereby improving the modelling of tourist preferences.

In this study, we employ the hedonic price method to identify the decision criteria and their importance in hotel assessment. Each selected hotel is characterised by a profile consisting of scores on the identified criteria. From this information, we use a two-phase hotel evaluation process using CI aggregation. The first phase involves applying unsupervised methodologies, while a supervised method is implemented in the second phase.

It should be noted that the application of a supervised method requires information on a set of alternatives and their associated global values. However, such information is not available in our framework. Therefore, we employ a prior process (first phase) to obtain an overall value for each hotel based on its profile of scores on the criteria. This intermediate information serves as input for the supervised method.

The first phase is based on correlation coefficients between criteria, and we apply two alternative unsupervised methodologies. Rowley et al. [36] work with Pearson correlation matrices and the coalition coefficients are determined by the ratios of non-interacting criteria. By applying algebraic results (Hwang [37]) they demonstrate that their method achieves a capacity function. Alternatively, Duarte [38] uses Spearman correlation to obtain interaction indices. His-proposal leads a 2-additive capacity (Grabisch, [39]), which simplifies the model by only considering interactions amongst pairs of criteria and the parameters associated with singletons. This approach reduces the number of parameters that need to be identified. The output of this first phase is a global valuation for each hotel represented by its CI score.

In the second phase, we incorporate the preferential information provided by hedonic regression into the construction of a capacity. Here, we use two inputs: the hedonic prices of criteria and the CI valuations of the hotels obtained in the first phase. A least squares model is applied to search for a capacity that generates a CI with a minimum L2 distance from the one obtained in the first phase while satisfying certain linear constraints on the Shapley values. These constraints are derived from the preferential market information revealed by the hedonic regression. In summary, the hedonic method serves as an ideal tool for use in a CI-based aggregation process to obtain a market-adjusted ranking of hotels.

To the best of our knowledge, no previous study has combined the hedonic pricing methodology with the CI for this specific topic. Furthermore, this combination provides a framework for optimal investment by firms. This is particularly relevant given that the study market comprises hotels located in the south of Tenerife (Canary Islands, Spain), a sun and beach tourist destination that is facing serious economic challenges resulting from the COVID-19 pandemic. Moreover, this study is of interest to policymakers as it identifies tourist preferences towards sustainable policies and serves as a guide for tourists themselves in their selection processes.

The significant relevance of the hedonic methodology for practitioners in various diverse areas, covering housing (Gaur and Lang [40]), education (Yang et al. [41]), labour market (Kniesner and Viscusi [42]), finance (Bilbao-Terol and Cañal-Fernández [43]) and environmental quality (Gao et al [44]) amongst others, along with its strong theoretical foundation, makes it an attractive addition to MCDM problems. In summary, the novelty of this research lies in proposing hedonic regression to obtain the necessary information on the relative importance of the criteria considered in the ranking. This approach could be applied in any field where it is feasible to have an economic valuation from the market of the alternatives to be ranked. Our approach presents a novel solution to the dilemma between objective and subjective weighting.

The remainder of this study is organised as follows. The following section provides a literature review that motivates our research. Section 3 outlines the methodology employed in the study. We then proceed to describe the empirical application to the Spanish market in Section 4. Finally, in Section 5, we provide our concluding remarks.

2. Previous studies

Various studies have applied MCDM to the tourism sector (see Mardani et al. [45] and Vatankhah et al. [2] for a review). These studies are diverse in terms of objectives and the methodologies used, but they all face a common challenge, which is the selection, valuation, weighting, and aggregation of criteria to identify the most suitable alternatives. The information for these studies is typically derived from personal surveys of tourists, online hotel reviews, hotel and travel websites, expert opinions, or official statistical data. Extracting the selection criteria, determining their importance weights, and understanding their interrelationships from this extensive information is crucial.

Prominent discrete multi-criteria methods have been employed to address problems in this domain. Many studies combine multiple multi-criteria techniques and, in some cases, statistical techniques (e.g., principal component analysis, Markov chains, etc.), efficiency models, graph theory, and fuzzy logic techniques are hybridised with multi-criteria methods. Furthermore, the integration of multi-criteria and machine learning methods is a growing trend in current research. Therefore, multi-criteria methods are not in competition with other technologies but rather complement them when decision-making, prioritisation, selection, and evaluation based on conflicting criteria are required. The scope of application for multi-criteria methods is broad, encompassing areas such as tourist destinations, selection of tourist attraction locations, evaluation of hotel websites, assessment of evaluation services, resilience in the tourism sector, and more.

Examples of MCDA outranking methods applied to the tourism context include the work of Boti and Peypoch [46] who implemented an application of method Elimination et Choix Traduisant la Realité (ELECTRE) I to tourism destinations. The case of four Hawaiian islands is used to show how ELECTRE I enables the analysis of tourism destination relative competitiveness. Andrades-Caldito et al. [47] analysed the perceived destination image amongst visitors to Andalusia (Spain) and its provinces. They employed a slightly modified Bray–Curtis dissimilarity index to synthesise the evolution of the destinations' image into a single value during the studied period. ELECTRE II methods were also applied to rank the provinces based on their levels of attractiveness, as perceived by tourists.

Ishizaka et al. (2013) [48] evaluated the alternatives in a location selection problem using the weighted sum method (WSM), the technique for order of preference by similarity to ideal solution (TOPSIS) and the preference ranking organization methods for enrichment evaluations (PROMETHEE) methods. They concluded that PROMETHEE and WSM are more suitable than TOPSIS for solving this problem. TOPSIS provides a different recommendation as it tends to favour extreme alternatives. Akincilar and Dagdevien [49] developed a model to evaluate the quality of hotel websites. They proposed a hybrid model that combines two multi-criteria decision-making approaches, namely the analytic hierarchy process (AHP) and PROMETHEE, to achieve the study's objectives. AHP was utilised to weight the criteria, and the ranking of the alternatives was determined through PROMETHEE. Their case study involved the analysis of the websites of five-star hotels in Ankara.

Ostovare and Sahahraki [50] evaluated the status of websites and e-services provided by five-star hotels. They employed the fuzzy Delphi method to establish initial criteria and subcriteria for evaluation and the Shannon entropy method to calculate the weights of the criteria. Finally, PROMETHEE and geometrical analysis for interactive aid (GAIA) methods were utilised to rank the websites and develop visual aids.

Tseng [23] proposed a combined fuzzy TOPSIS and decision-making trial and evaluation laboratory (DEMATEL) method using linguistic preferences to evaluate service quality expectations in hot spring hotels. The weights of the criteria are expressed using linguistic preferences with triangular fuzzy numbers. TOPSIS was used to obtain the ranking order of all alternatives, while DEMATEL was employed to model the interdependency relationships and combine them into the TOPSIS method.

Gülsün et al. [8] applied three MCDM methods: AHP, TOPSIS, and *vlsekriterijumska optimizacija i kompromisno resenje* (VIKOR). The main objective of their study was to determine the optimal hotel alternative by assigning weights to the selection criteria and assessing the relationships between criteria and alternatives. Surveys were conducted with a hundred participants to determine the criteria weights. Five criteria were specified for hotel selection, including the room fee, food diversity, cleaning service, security service, and proximity to the sea.

Kwok and Lau [13] proposed the vague set (VS) TOPSIS algorithm as a decision support tool that is more applicable to help travellers rank options during the hotel selection process. The central idea of the VS-TOPSIS method is to rank alternatives based on their proximity to the positive ideal solution, taking into consideration the potential negative impacts of the negative ideal solution.

Işık and AdalıIşik [6] presented an integrated decision-making approach that combines step-wise weight assessment ratio analysis (SWARA) and operational competitiveness ratings analysis (OCRA) methods to address the hotel selection problem. The authors used the SWARA method to determine the weights of the criteria, while the OCRA method was employed to determine the ranking of alternatives and selection of the best hotel.

MCDM methods have also been combined with other techniques such as Data Envelopment Analysis (DEA) and an adaptive neuro-fuzzy inference system (ANFIS). Shirouyehzad et al. [51] proposed a DEA model that includes five service quality gaps as inputs and customers' perceptions as single output. Experts fill out a pair-wise comparisons questionnaire to determine the weights of input criteria. The hotels are then ranked based on the integrated AHP/DEA model and the service quality approach.

Another example of hybridisation of several techniques is the work of Gómez-Vega & Picazo-Tadeo [52]. Their paper developed a weighted composite indicator of competitiveness for 136 world tourist destinations by combining DEA and MCDM techniques with raw indicators of the Travel & Tourism Competitiveness Report by the World Economic Forum (WEF). The weights were endogenously generated, and the role played by several variables was assessed using truncated regression and bootstrapping. The ranking of world tourist destinations obtained by the weighted composite indicator aligns closely with the ranking derived from the unweighted indicator provided by the WEF. Furthermore, the authors found that several economic, geographical, cultural, and political features were significant determinants of the competitiveness of tourist destinations.

Nilashi et al. [53] proposed a new hybrid method for hotel recommendation that combines dimensionality reduction and prediction techniques. Accordingly, they have developed a multi-criteria Collaborative Filtering (CF) recommender systems for hotel recommendations, enhancing predictive accuracy by using Gaussian mixture model with an Expectation Maximization (EM) algorithm and an ANFIS.

In the context of applying MCDM methodology to the tourism sector, a literature review of relevant studies that utilise the CI as an aggregation operator is presented below.

2.1. The Choquet integral in the tourist context

Vu et al. [4] are pioneers in introducing CI for assessing the tourist industry. Specifically, they analysed the process of hotel selections by travellers to Singapore in 2011, considering different traveller profiles based on both the type of trip (business, family, or couple) and their continent of origin. They propose the use of the CI through sentiment mining systems to support the business planning process. The data was collected from online reviews on the TripAdvisor website, involving a total of 8790 stays, and six hotel criteria ratings were employed (value for money, hotel location, quality of sleep, quality of room, room cleanliness, and additional services). The Shapley value (Shapley [54]) was used to determine the overall importance of each hotel criteria as a contribution to the final decision from different travel groups while the Interaction Index assessed the interaction between the criteria in the decision making process for each travel group. The results indicate that the CI performs better than other aggregation operators, such as weighted arithmetic mean (WAM), ordered weighted averaging (OWA) (Yager [55]) and unrestricted linear model (LM) operators.

Similarly, Li et al. [5] analysed the hotel selection process of travellers to Hong Kong in 2011 using the same methodology, data source, traveller profiles, and hotel criteria as the study by Vu et al. [4] study. The results were consistent with the study of Vu et al. [4] .

Zhang et al. [56] evaluated the performance of fifteen US airlines in terms of service quality during 2012. They employed Marichal entropy (Marichal [57]) and CI with respect to the capacity with monthly data extracted from the Air Travel Consumer Report 2012, spanning a period of 10 years. Four criteria were considered: on-time arrivals, mishandled baggage, involuntarily denied boarding, and consumer complaints. The results demonstrate that the methodology used is more effective than dealing with MCDM standard applications because it considers the interrelationships between criteria.

Estêvão et al. [58] applied MCDM to construct a ranking of tourism regions in Portugal based on their level of sustainability. Within the MCDM method, cognitive mapping was employed to determine the key evaluation criteria and the CI was utilised to assess the interdependencies between criteria. The information for the study was gathered through group meetings with a panel of sustainable tourism experts and a senior representative of the Portuguese Tourism Confederation.

Bidoux et al. [59] presented a theoretical framework to address the problem of planning preferences. They proposed a model that combines multi-attribute utility theory (MAUT) with CI. Their model is applied to optimise trajectory preferences and several numerical preferences for a road trip.

Sabri et al. [60] proposed a mathematical model of non-additive measures and their fuzzy integrals (Sugeno integral, Choquet integral, and Shilkret integral) to apply to tourism management. Their model measures the degree of satisfaction of the Iraqi tourists visiting five cities in Turkey, presenting a ranking of the five cities.

Table 1 provides an overview of related studies that apply MCDM in conjunction with CI. Only two of the six studies that applied the CI within MCDM to the tourist market analysed the problem of hotel selection, while none specifically focused on the Spanish tourist market. Furthermore, no studies have applied the hedonic price method together with the CI for this specific topic.

2.2. The hedonic price method and the hotel industry

The hedonic method was first applied in the hotel industry in the early 1990s. The initial studies aimed to analyse how the various characteristics related to comfort, services, and location influence hotel prices. The seminal work of Sinclair et al. [61] analysed the coastal hotel market in Malaga and Clewer et al. [62] studied the competitiveness of inclusive tour holidays in London and Paris. Jaime [63] differentiated between city and vacation hotels in Spain, and Ferri et al. [64] used the hedonic price method to estimate price indices in the Spanish tourist sector after excluding price increases due to improvements in service quality. Espinet et al. [65] examined the price of hotel characteristics along the coast of Girona, and Mangion et al. [66] assessed different tourist destinations in the Mediterranean. Thrane [67] applied the hedonic method to the tourism sector, paying attention to the endogeneity problem between the category variables and other services offered by the establishment. Chen and Rothschild [68] studied the impact of the characteristics of Taipai hotels on their prices, differentiating by weekdays and weekend.

In later studies, attention shifted towards analysing the impact of environmental characteristics on accommodation prices. Le Goffe [69] included the surrounding land uses of rural accommodation in Brittany in the hedonic estimation. Similarly, Vanslembrouck et al. [70] and Bilbao-Terol et al. [71] quantified the influence of agricultural activities on the price of rural accommodations, in different parts of Flanders and the Asturian region of northern Spain, respectively. Taylor and Smith [72] explored how environmental characteristics can be a source of market power, both theoretically and empirically. Similarly, Mollard et al. [73] examined the possibility of market power from rural accommodation providers based on environmental characteristics. Hamilton [74] assessed the impact of coastal characteristics on the price of tourist accommodation in northern Germany. Rigall-I-Torrent and Fluvià [75] analysed the influence of local public goods on hotel prices, while Rigall-I-Torrent et al. [76] studied the impact of beach characteristics on the price of the surrounding hotels, both focussing on the Catalan coast. Bilbao-Terol et al. [77] investigated the effect of the construction of an artificial beach on the prices of nearby hotels in the city of Gijón, Spain. Latinopoulos [78] applied a spatial hedonic model to evaluate the impact of sea views on hotel prices in Halkidiki, Greece.

It is worth noting that studies have applied the hedonic methodology to examine the impact of sustainable tourism certifications on hotel prices. Rivera [79] analysed the impact of Costa Rican Certification for Sustainable Tourism, while Bilbao-Terol and Bilbao-Terol [80] investigated the effects of the voluntary sustainable certification, Eco-Management and Audit Scheme (EMAS), for coastal hotels in Tenerife (Canary Islands, Spain). Both studies addressed the methodological

Table 1
Related studies that apply MCDM methods together with CI.

Literature	Objective	Data Source	Method	Site	Year	Criteria
Vu et al. 2012	Hotel selection by different types of travellers and their continent of origin	TripAdvisor web site	Shapley Values, Interaction Index, CI	Singapore	2011	Six criteria hotel: value for money, hotel location, quality of sleep, quality of room, room cleanliness and additional service
Li et al. 2013	Hotel selection by different types of travellers and their continent of origin	TripAdvisor web site	Shapley Values, Interaction Index CI	Hong Kong	2011	Six criteria hotel: value for money, hotel location, quality of sleep, quality of room, room cleanliness and additional service
Zhang et al. 2015	Evaluate airline service quality	Air Travel Consumer Report 2012	Marichal entropy and CI	US	2012	Four criteria: on-time arrivals, mishandled baggage, involuntary denied boarding and consumer complaints
Estêvão et al. 2019	Ranking of tourism regions according to their degree of sustainability	Panel tourism expert	Cognitive mapping and CI	Portugal		Six fundamental points of view: 1. Religion, Society and Culture, 2. Safety, 3. Marketing and Services, 4. Environmental Factors, 5. Political-Economics Factors, 6. Infrastructure and Accessibility
Bidoux et al. 2020	Organise a road trip	NA	Multi-attribute Utility Theory (MAUT) and CI	NA	NA	Trajectory preferences (points of interest to visit before and culinary specialities to try). Numeric preferences (travel duration, financial cost, comfort, entertainment, and cultural scores)
Sabri et al. 2020	Evaluate grade gratification of tourist of staying in a particular town	Al-Massal Company.	Non-additive measures, Sugeno integral, Shilkret integral and CI	Irak	2018	Five Turkish cities: Istanbul, Ankara, Bursa, Antalya, Trabzon.

NA: Not Applicable.

challenges associated with sample selection by implementing propensity score-matching methodologies prior to the hedonic analysis.

Rigall-I-Torrent et al. [76] evaluated the impact of Blue Flag certification on the beach hotels along the Catalan coasts, while Sánchez-Ollero et al. [81] examined the impact of environmental sustainability measures on hotel prices in Andalusian establishments located in southern Spain.

3. Methodology

In this study, an MCDM methodology, namely the Choquet integral supported by the hedonic price method (CI-HPM), is used to model the hotel selection process by tourists. The hedonic price method is first applied to understand the selection criteria employed by tourists when choosing accommodation. This method provides valuable information for calculating the criteria weights. One distinct advantage of this methodology is its ability to capture tourist preferences as revealed by the market. Secondly, MCDM methods are employed to determine the best choice amongst various hotel alternatives, using the information obtained from the hedonic estimation. The Choquet integral is also employed to consider the interrelationships between criteria.

3.1. Hedonic price method

The hedonic price method (Rosen [22]) departs from the theoretical assumptions of the New Approach Consumer Theory (Lancaster [82]). According to this theory, the consumer does not derive utility from the goods or services themselves, but from their characteristics, called criteria in the context of MCDM. The hedonic method aims to obtain a market valuation for a characteristic of a good or service and to calculate its supply and demand functions.

The market value assigned to each characteristic is referred to as its hedonic price (HP), which cannot be directly observed in a real market. The mapping that determines the market price of a good or service based on these characteristics is known as the hedonic price function (HPF). The model assumes the existence of a large number of differentiated goods or services and that the choice amongst different combinations of the characteristics is treated as a continuous process. This enables the estimation of the implicit price relationship (i.e. the HPF) for any given characteristic. The partial derivative of the HPF with respect to a characteristic provides its implicit marginal or hedonic price (i.e., the HP) (Landajo et al. [83]). In the present study, the hedonic price method is applied to the hotel accommodation service.

From a hedonic perspective, when a tourist selects the *k-th* hotel accommodation service, H_k, she observes the vector of its characteristics, $\bar{c}_k$, which includes aspects such as comfort category, location, and equipment provided by the hotel. The tourist makes her decision by maximising her utility while considering budget constraints that influence their choices. Any choice is, therefore, conditional on the price of each of the characteristics. In equilibrium and a perfectly competitive hotel market with enough variety of accommodation options featuring different combinations of characteristics, the hedonic prices can be estimated.

We assume that the dataset under analysis (comprising m hotel accommodation services) represents a finite realisation of the independent identically distributed (i.i.d.) random process $\{\bar{c}_k, P_{H_k}; k = 1, 2, ..., m\}$ where P_{H_k} is the observed price and $\bar{c}_k$ is a n-dimension row vector of characteristics. The hedonic relationship is as follows:

$$P_{H_k} = f(\bar{c}_k; \theta) + u_k, \ k = 1, 2, ..., m \tag{1}$$

where u_k represents the random error, normally distributed with $E(u_k) = 0$ and $var(u_k) < \infty$. The processes $\{\bar{c}_k\}$ and $\{u_k\}$ are assumed mutually independent and θ is the vector of coefficients that include all free parameters for estimating the hedonic regression surface, f.

Estimating the HPF, according to (1), allows us to determine the hedonic price for each characteristic. The HPF represents an equilibrium between the average marginal amount of money a tourist is willing to pay for an additional unit of a particular accommodation characteristic and the amount of money that a firm is willing to receive for this unit (Rigall-I-Torrent and Fluvià [76]).

Thus, the HP of the continuous characteristic, c_i, denoted by p_i is defined as the partial derivative of the HPF, f, with respect to c_i,

$$p_i = \frac{\delta f(\bar{c}_k; \theta)}{\delta c_i} \tag{2}$$

Hence, p_i quantifies the increase in the price of the hotel accommodation service if one wishes to obtain an additional unit of that particular characteristic, c_i, holding all other factors constant.

The HP of the dummy characteristic, modelled by a binary variable, c_i, is calculated from the HPF as follows:

$$p_i = f\left(c_i = 1, \bar{c}_{\{-i\}}; \theta\right) - f\left(c_i = 0, \bar{c}_{\{-i\}}; \theta\right), \tag{3}$$

where $\bar{c}_{\{-i\}}$ is the vector of all characteristics but the i th. The HP, p_i, indicates the increase in the price of hotel accommodation service due to the presence of the dummy characteristic, c_i, everything else being constant.

Once the hedonic prices are calculated, they are used in the selection process amongst different hotel accommodation services to determine the best selection. For this purpose, the Choquet integral is employed as an MCDM technique that allows for the aggregation of interacting criteria.

3.2. Choquet integral

Let $H = \{H_1, ..., H_m\}$ be a set of hotels and $C = \{c_1, ..., c_n\}$ be a set of characteristics/criteria that represent qualities of the hotels upon which tourists base their choice. The performance of each hotel H_k w.r.t. the set of criteria C is measured by the vector $(c_1(H_k), ..., c_n(H_k))$ where $c_i(H_k)$ is the individual performance value of H_k on criterion c_i. For aggregation purpose, the value $c_i(H_k)$ is transformed into a normalised value s_i^k ranging from 0 to 1.[1]

In this context, each hotel H_k is identified with its *profile of partial scores* $s^k = (s_1^k, ..., s_n^k)$ where, for any $i = 1, ..., n$, s_i^k is the valuation of the hotel H_k with respect to characteristic c_i.

In MCDM, the goal to obtain a global value, $M(s^k)$, that assigns a real number to each hotel $H_k \in H$. The form of the global value function M depends on the assumptions underlying the MCDM model. When mutual preferential independence (see e.g. Vincke [84] and Kojadinovic [26]) for criteria is assumed, the global value function is often additive and takes the form of a weighted arithmetic mean (WAM).

The WAM operator provides a global score for the profile $(s_1, ..., s_n)$ according to the following expression:

$$M_w(s) = \sum_{i=1}^{n} w_i s_i$$

where $w_i \geq 0$ is the *weight* of criterion c_i and $\sum_{i=1}^{n} w_i = 1$.

However, mutual preferential independence is rarely verified in real-world applications (Grabisch [85]; Keeney and Raiffa [28]). To model interactions amongst criteria, a monotonic set function on C, called capacity (Choquet [25]) or fuzzy measure (Sugeno [27]), has been proposed to obtain the global value of each alternative. Using a capacity function involves considering the importance of each subset of criteria. A natural extension of the WAM in such a context is the Choquet integral w.r.t. the defined capacity (Labreuche & Grabisch [86]).

A fuzzy measure or capacity is defined as a set function with the monotonicity property with respect to the inclusion.

Fuzzy measure or capacity. Let $P(C)$ be the power set of C, a fuzzy measure on the set C is a set function $\mu : P(C) \rightarrow [0, 1]$ with $\mu(\emptyset) = 0$, $\mu(C) = 1$ and for any $S \subseteq T \subseteq C$ implies $\mu(S) \leq \mu(T)$.

For any subset of criteria S, $\mu(S)$ can be interpreted as a measure of the weight of the coalition S (Duarte [38]). By replacing the vector of weights w with a fuzzy measure μ, we can effectively represent the importance of each subset of criteria, allowing us to move beyond considering only the individual importance of each criterion.

As mentioned previously, the Choquet integral serves as an appropriate aggregation operator for modelling the criteria interaction, and it generalises the weighted average.

The Choquet integral. The Choquet integral of the vector s^k with respect the capacity μ is defined by the expression:

$$C_\mu(s^k) = \sum_{i=1}^{n} \left(s_{(i)}^k - s_{(i-1)}^k\right) \mu\left(A_{(i)}\right) = \sum_{i=1}^{n} s_{(i)}^k \left(\mu\left(A_{(i)}\right) - \mu\left(A_{(i+1)}\right)\right) \quad (4)$$

where $s^k = (s_1^k, ..., s_n^k)$ represents the profile of hotel H_k on n criteria; and the sub-index (i) is a permutation of the indices $i = 1, ..., n$ such that $s_{(1)}^k \leq ... \leq s_{(n)}^k$ with $s_{(0)}^k = 0$ and where $A_{(i)} = \{c_{(i)}, ..., c_{(n)}\}$.

[1] In this work we have used the max-min normalisation.

We present below several indices associated with a capacity that are useful for interpreting the interactions between criteria and enabling alternative formulations of the Choquet integral. The importance of a criterion is not solely determined by its individual contribution but also by the impact it has on other criteria with which it interacts. The relevance of the criterion is not solely determined by its capacity, but also by the capacities of all the subsets that contain the criterion. Therefore, it is necessary to introduce definitions for the importance of a criterion and the interaction index for subset of criteria. Shapley [54] proposed a coefficient known as the Shapley value to measure this importance.

Shapley value. Let μ be a capacity, the Shapley index S_μ for a criterion c_i with respect to μ is defined as follows

$$S_\mu(c_i) = \sum_{A \subseteq C - \{c_i\}} \frac{(n-a-1)!a!}{n!} [\mu(A \cup \{c_i\}) - \mu(A)] \quad (5)$$

where a denotes the cardinality (*card*) of the finite set A. The factorial normalises the values, such that $\sum_{i=1}^{n} S_\mu(c_i) = 1$.

The Shapley index $S_\mu(c_i)$ can be interpreted as an average value of the marginal contribution $[\mu(A \cup \{c_i\}) - \mu(A)]$ of the criterion c_i to a subset A that does not contain it. Therefore, the Shapley index expresses the relative importance of a single criterion within the decision problem.

The information provided by the Shapley importance index should be complemented with additional information on the interaction amongst criteria in order to achieve a good description of the decision problem.

Shapley interaction index (Murofushi and Soneda [87]). Let μ be a capacity, the Shapley interaction index I_μ for the pair of criteria (c_i, c_j) with respect to μ is defined as follows:

$$I_\mu(c_i, c_j) = \sum_{A \subseteq C - \{c_i, c_j\}} \frac{(n-a-2)!a!}{n!} \left[\mu\left(A \cup \{c_i, c_j\}\right) - \mu(A \cup \{c_i\}) - \right. \\ \left. -\mu\left(A \cup \{c_j\}\right) + \mu(A)\right] \quad (6)$$

The sign of the Shapley interaction $I_\mu(c_i, c_j)$ allows us to interpret the type of interaction taking place between c_i and c_j (Grabisch & Labreuche [33]; Pelegrina et al. [32]). When $I_\mu(c_i, c_j)$ is positive, it indicates a complementary interaction between c_i and c_j meaning that both criteria must be satisfied in order to achieve a good global evaluation. Conversely, if $I_\mu(c_i, c_j)$ is negative, it signifies a substitutive interaction, where a high aggregation value can be obtained even when only one of the criteria presents a good score. A value equal to 0 indicates that criteria c_i and c_j do not interact, so that their contribution to the final aggregation is independent.

Grabisch [39] introduced the interaction index amongst a coalition H of criteria as a natural extension of the above case.

Generalised interaction index (Grabisch, 1997).

Let μ be a capacity, the interaction index I_μ of the coalition H of criteria, with $h = card(H)$, respect to μ is defined by the following:

$$I_\mu(H) = \sum_{A \subseteq C - H} \left[\rho(A) \times \left(\sum_{B \subset H} (-1)^{h-b} \mu(K \cup B)\right)\right] \quad (7)$$

where $b = card(B)$ and $\rho(A) = \frac{(n-a-h)!a!}{(n-h+1)!}$.

A capacity is said to be k-additive if $I(H) = 0$ for all coalition H, whose cardinality is greater than k (assuming that there exists at least one coalition G of cardinality k for which $I(G) = 0$). WAM aggregation can be seen as the special case of 1-additive capacity.

The presentation of the basic tools of the Choquet integral highlights the need to have a capacity function. Identifying the appropriate capacity is a challenge in practical applications. Several approaches have been proposed to deal with this problem (see, e.g., Lourenzutti et al. [88], Oliveira et al. [89] and Pelegrina et al. [30] and references therein).

As mentioned earlier, it is important to note that the application of a supervised method requires information regarding a set of alternatives and their associated global values. In our framework, this type of information is not available, and instead, we only have preferential information about the criteria. To address this issue, we propose a solution based on the hotel scores profile. Our approach involves applying an unsupervised method to the matrix of hotel profiles in the first phase to generate global values of the hotels, which will then serve as input for the supervised method.

3.3. Our proposal: identification of a Choquet capacity based on hedonic pricing

To determine the necessary parameters for calculating the CI values, we propose using a supervised method that relies on tourists' preferences, as revealed through the results of hedonic regression, combined with an unsupervised method based on second-order statistics. Specifically, we utilise either the method proposed by Rowley et al. [36] or the method proposed by Duarte [38]. The identification process consists of two steps.

Firstly, we obtain an initial capacity using principal components analysis, following Rowley et al. [36]. This method provides an objective estimation without relying on external information about the desired capacity (unsupervised method).

Rowley et al. [36] use Pearson correlation matrices to describe the correlations between criteria. Let R_S be the correlation matrix between the criteria calculated from a sufficient number of profiles of a coalition $S \subseteq C$. The eigenvalues of R_S are then used to define $\mu(S)$ according to the following ratio:

$$\mu(S) = \frac{J(S)}{J(C)} \tag{8}$$

where $J(S) = \sum_{\lambda_q < 1} \lambda_q + card(\{\lambda_q | \lambda_q \geq 1\})$.

The value $J(S)$ provides an estimation of the number of non-interacting criteria within the coalition S. Rowley et al. [36] demonstrated that the ratios $\mu(S)$ determine a capacity on the set C by applying the Cauchy Interlace theorem (Hwang [37]). The resulting algorithm is very efficient in terms of computational complexity (Duarte [38]).

Alternatively, an initial capacity can be determined using a methodology based on Spearman coefficients. According to Duarte [38], the approach proposed by Rowley et al. [36] only considers the number of correlated criteria without capturing the nature of the interactions between them. To address this issue, Duarte [38] proposed an unsupervised method for estimating the Choquet capacities by associating statistical similarity measures estimated from data with the typical types of interactions (complementarity and substitutivity) modelled by the Choquet integral.

Duarte [38] proposes an alternative approach that avoids using the eigenvalues of a given similarity matrix. Instead, the Spearman correlation coefficient is chosen as the similarity measure. The author provides three justifications for this choice. First, simple estimators for the Spearman correlation can be easily defined. Second, compared to the Pearson coefficient, the Spearman coefficient is more effective in detecting nonlinear correlations between variables. Finally, the Spearman correlation coefficient is more robust against outliers than the Pearson coefficient.

Another important aspect of Duarte's methodology is the class of capacities that is targetted. Duarte focuses on the class of 2-additive capacities (Grabisch and Labreuche [90]) to reduce the number of parameters that need to be adjusted. This choice allows for a more convenient connection between measures of statistical similarity and interaction indexes. In the case of 2-additive capacities, the capacities are completely determined by the Shapley values $S_\mu(c_i)$ and the interaction indexes $I_\mu(c_i, c_j)$. Despite this reduction, 2-additive capacities are flexible enough to model nonlinear interactions, including positive and negative ones (Duarte [38]).

Applying the principle of maximum entropy, Duarte [38] sets the Shapley index for the criterion $c_i$as:

$$S_\mu(c_i) = \frac{1}{n} \tag{9}$$

Additionally, the interaction index between the criteria c_i and c_j is defined as:

$$I_\mu(c_i, c_j) = -Sp(c_i, c_j) \tag{10}$$

where $Sp(c_i, c_j)$ represents the Spearman correlation between the criteria c_i and c_j. Duarte justifies this choice based on the associations between correlation and the interaction modelled by the Choquet integral.

In the case of 2-additive capacities, the Choquet integral takes on a special form (Grabisch and Labreuche [33], Pelegrina et al. [30]):

$$C_\mu(s^k) = \sum_{I_\mu(c_i,c_j)>0} \min\left(s_i^k, s_j^k\right) I_\mu(c_i, c_j) + \sum_{I_\mu(c_i,c_j)<0} \max\left(s_i^k, s_j^k\right) |I_\mu(c_i, c_j)| + \sum_{i=1}^{n} s_i^k \left(S_\mu(c_i) - \frac{1}{2}\sum_{j\neq i} |I_\mu(c_i, c_j)|\right), \tag{11}$$

with the property that

$$S_\mu(c_i) - \frac{1}{2}\sum_{j\neq i} |I_\mu(c_i, c_j)| \geq 0 \quad \text{forall} \quad i, \tag{12}$$

which assures the monotonicity of the 2-additive capacity corresponding to the Shapley values, S_μ and interaction indices, I_μ.

Expression (11) decomposes the Choquet integral into a conjunctive, a disjunctive and an additive part (for further details on the interpretation of this formula, refer to Grabisch and Labreuche [90] p. 46).

However, the application of formulas (9) and (10) to identify a 2-additive capacity does not assure the fulfilment of the property (12). When (12) does not hold, Duarte [38] proposes solving an optimisation problem, specifically a nonlinear programming problem, to search for approximate interaction indexes.

It is worth noting that other unsupervised methods, such as those proposed by Pelegrina et al. [32] could be applied in this first phase. These unsupervised methods should require two features: they effectively model the latent variables in the data while also being computationally efficient.

The second phase of the methodology focuses on identifying a CI that reflects the market information provided by the hedonic method as accurately as possible and is also "close" to the CI obtained in the first phase. In this way, we combine data information with the market valuation.

Our approach is based on a least squares optimisation method. The algorithm takes as inputs the hotel profiles along with their corresponding global values obtained in the first phase, which is the Choquet integral from the unsupervised capacity. Additionally, it incorporates linear constraints that express the importance of criteria.

The least squares capacity identification method (Grabisch et al. [91]) is employed to determines, if feasible, a capacity that minimises the sum of squared errors between the overall scores derived from the data and the output of the CI for those data while satisfying the additional linear constraints. In our proposal, the global value of each hotel is obtained from the Choquet integral using the capacity determined in the first phase.

The optimisation problem to be solved in the second phase is formulated as follows:

$$\left.\begin{array}{l} \min_{\mu_{lsci}} \sum_{H_k \in H} \left[C_{\mu_{lsci}}(s^k) - C_{\mu_{UNS}}(s^k)\right]^2 \\ s.t. \\ \mu_{lsci}(A \cup \{c_i\}) - \mu_{lsci}(A) \geq 0,\ \forall c_i \in C, A \subseteq C - \{c_i\} \\ \mu_{lsci}(C) = 1 \\ S_{\mu_{lsci}}(c_j) - S_{\mu_{lsci}}(c_i) \geq \delta_{ji} \end{array}\right\} \tag{13}$$

The first set of constraints ensures the monotonicity of the capacity while the second constraint enforces its normalisation. The third set of constraints represents the preferences of the decision maker and captures the relative importance of criteria. Since the Shapley value represents the overall importance of each criterion, these constraints allow for modelling possible monotonic relationships between the criteria.

Schedule of the CI-HPM method (see Fig. A.1 in Appendix)

Stage I: Estimating of hedonic prices

- Inputs: Hotel performance matrix $PM = (c_i(H_k))$ and hotel prices.
- Output: Hedonic prices of the criteria.

Steps:

- [I.1] Estimate Eq. (1).
- [I.2] Detect significant criteria.
- [I.3] Estimate refined Eq. (1).

Stage II: Calculating of unsupervised CI scores

- Input: matrix of hotel profiles $P = (s_i^k)$.
- Output: CI scores of hotels $C_{\mu_{UNS}}(s^k)$.

Steps:

- [II.1.] Identify an unsupervised capacity μ_{UNS} from the hotel profiles, matrix P,using either the Rowley-Geschke-Lenzen (R-G-L) method or the Duarte's method.
- [II.2.] Calculate the Shapley value for each selection criterion corresponding to the capacity determined in Step II.1, $S_{\mu_{UNS}}(c_i)$
- [II.3.] Calculate the Choquet integral of each hotel profile w.r.t. the capacity obtained in Step II.1.: $C_{\mu_{UNS}}(s^k)$

Stage III: Calculating of supervised CI scores

- Input: Matrix of hotel profiles, P, and CI scores of hotels, $C_{\mu_{UNS}}(s^k)$, and hedonic prices of the criteria, $HP(c_i)$.
- Output: CI scores of hotels, $C_{\mu_{lsci}}(s^k)$.

Steps:

- [III.1.] Set preferences from hedonic regression:

Define linear constraints for the Shapley values for significant criteria based on the results of the hedonic regression. To achieve this, we introduce constraints such as: $S_{\mu_{lsci}}(c_i) \leq S_{\mu_{lsci}}(c_j)$ when the hedonic price of criterion c_i is less than or equal to the hedonic price of criterion c_j. These constraints allow for modelling statements like "criterion c_j is more important than criterion c_i".

- [III.2.] Identify a supervised capacity, μ_{lsci} using the least squares capacity identification (l.s.c.i.) method (Grabisch et al. [91]) to minimise the sum of squared deviations between overall scores obtained in Step II.3, $C_{\mu_{UNS}}(s^k)$, and the output of the Choquet integral for those profiles, $C_{\mu_{lsci}}(s^k)$ verifying the constraints set in III.1.
- [III.3.] Calculate the Shapley indexes for the criteria, $S_{\mu_{lsci}}(c_i)$.
- [III.4.] Rank the hotels from the overall scores $C_{\mu_{lsci}}(s^k)$.

4. Empirical study

4.1. Case study

Our empirical study focuses on the hotel market in the southern area of the island of Tenerife, which is one of the seven islands in the Canary Islands archipelago. The Canary Islands archipelago is of volcanic origin and is located in the Atlantic Ocean, southwest of Spain and Northwest Africa, off the coast of Morocco. Tenerife, situated in the central area of the archipelago, is approximately 4° from the Tropic of Cancer, longitude 13° 20′, and 18° 10′ West of the Greenwich Meridian. It has a subtropical climate with an average temperature ranging from 18 °C to 24 °C (64.4°F to 75.2°F).

Tenerife is known for its mature sun and beach tourism, attracting the highest number of tourists in the entire archipelago. In 2019, the island received a total of 6110,838 tourists, with 75 % of them being international tourists, predominantly from the United Kingdom and Germany. The total number of accommodation beds in 2019 was 177,274, of which 100,000 were hotel beds. The overall occupancy rate for the entire island in that year was 75 % (Instituto Canario de Estadística (ISTAC), [92]).

However, the global economic situation resulting from the COVID-19 pandemic has hit the tourism sector hard, and the island of Tenerife has not been an exception. The number of tourists that the island received in 2020 decreased by 70 % compared to 2019, and the number of available accommodation places decreased by approximately 60 % (ISTAC, [93]). This study aims to provide valuable insights to support the future recovery of the tourist sector in Tenerife.

The island is divided into three main tourist areas: the northern zone, which is exposed to the northeast trade winds; the southern zone, covering the southwestern coast of the island; and the metropolitan area, which includes important cities such as San Cristobal de la Laguna and Santa Cruz de Tenerife. The southern area is the most touristic, accounting for 75.9 % of the total tourists visiting the island in 2019. It also has the highest concentration of hotels, with 151 hotels out of a total of 277 (ISTAC, [92,93]).

4.2. Data and variables

To estimate the hedonic price Eq. (1), data on hotels and aparthotel prices in the study area, along with their characteristics, are required. This data was collected from hotel websites as well as from Booking and Trivago websites, which provide hotel prices. Information regarding the characteristics of each establishment was obtained from the official website of the Canary Islands Tourist Government.

The sample used in the study includes all the hotels and aparthotels that were advertised on the latter website in May 2019. This corresponds to 97 hotels and aparthotels out of the total 151 establishments that were open in the study area at that time. While some establishments offer all types of accommodation regimes, others offer only a limited number. Therefore, from the 97 hotels advertised, a total of 132 price observations were obtained (see Table A.1 in Appendix). The data sample was collected during the week of 20–26 May 2019, and the accommodation prices correspond to the second weekend of August 2019.

Table 2
Summary of characteristics of database ($m = 132$).

	Mean	SD	Min	Max
PRICE(€)	185.8	89.4	62.6	727.3
ALLINCLUD	0.36	0.48	0	1
STARS5	0.24	0.43	0	1
NEARBEACH	0.97	0.11	0	1
LABEL	0.41	0.49	0	1

Once the data sample was obtained, the variables included in the hedonic equation were determined. The dependant variable is the price per night in euros of a hotel or aparthotel room, with tax included (PRICE). As noted in the literature review, the studies that apply the hedonic method to the tourism market include explanatory variables related to comfort, services, location, environmental characteristics surrounding the accommodation and sustainable tourism certifications. In our study, we included the category variable (number of stars) to measure comfort, the all-inclusive variable as a characteristic of the services offered, the distance to the beach variable to take into account the location of the establishment, and additionally, a variable to reflect whether the establishment had been awarded a sustainability certification. Since our study focuses on a specific tourist area with similar environmental conditions amongst establishments, no variable of this type was considered. The explanatory variables are defined below[2]:

- ALLINCLUD: takes the value 1 if the accommodation offers all-inclusive services and 0 otherwise.
- STARS5: takes the value 1 if the establishment has been awarded five stars in comfort category and 0 otherwise.
- NEARBEACH: measures the impact of proximity to the beach on the hotel price and is calculated as follows:

$$NEARBEACH_i = \frac{\max D - D_i}{\max D - \min D} \tag{13}$$

where $\max D$ represents the distance of the hotel furthest from the beach in the sample, D_i represents the distance to the nearest beach from each establishment and $\min D$ is the distance from the closest hotel to the beach. Therefore, the variable ranges from zero to one. The distance in kilometres from each establishment to the nearest beach is calculated using Google Maps.

- LABEL: takes the value 1 if the establishment has been awarded any of the following sustainable certification, EMAS (Eco-Management and Audit Scheme), Biosphere certification (granted by Responsible Tourism Institute) and TRAVELIFE (operated by ECEAT-Projects). It takes the value of 0 otherwise.

Descriptive statistics of the study variables for the entire sample are presented in Table 2.

4.3. Hedonic regression

The functional form of the hedonic equation was established using the Box-Cox transformation for the dependant variable. The semi-logarithmic form was chosen since lambda is equal to a value between 0 and 0.5 calculated via the maximum log-likelihood Box-Cox. Therefore, the hedonic equation to be estimated is as follows:

$$\begin{aligned} &LNPRICE_k = \alpha + \beta_1 ALLINCLUD_k + \\ &+\beta_2 STARS5_k + \beta_3 NEARBEACH_k + \beta_4 LABEL_k + u_k \end{aligned} \tag{14}$$

where LN*PRICE* is the natural logarithmic of *PRICE* variable, $k = 1, \ldots,$ 132 and u_k represents the disturbance term that is independent and normally distributed, with zero mean and constant variance. The vector of coefficients θ in Eq. (1) is $(\alpha, \beta_1, \ldots, \beta_4)$ in the case of Eq. (14). The parameter α is the intercept of the regression equation, namely, the value of the natural logarithmic of the accommodation price when the accommodation characteristics are zero.

The hedonic Eq. (14) was estimated through ordinary least squares (OLS) using LIMDEP 9.0 software. To asses multicollinearity, the variance inflation factor test (VIF) was conducted. We assumed a threshold value of 4, based on Fox [94] (see Table 3). None of relationships exceeded this threshold, indicating the absence of multicollinearity for all of the variables.

Table 4 presents the results of the hedonic estimation, which are deemed satisfactory and consistent with findings from other studies in the field. All coefficients are positive and statistically significant at conventional levels, indicating that the market positively values the characteristics represented by the dummy variables and an increase in the quantity for the continuous variable.

Since the functional form of the hedonic equation is semi-logarithmic, the price premium or the impact on the establishment's price due to the presence of a dummy characteristic, on average, is given by $(e^{\beta} - 1)x100$. Similarly, the coefficient of a continuous variable, multiplied by 100, represents the percentage effect on the establishment's price resulting from a unitary change in that continuous variable (Halvorsen and Palmquist [95]).

The comfort category variable had the greatest effect on accommodation prices. The coefficient suggests that the price of a five-star hotel, compared to one with identical characteristics but a lower category is, on average, 72 % higher. While this percentage may appear high, it is consistent with findings in the literature. For instance, Rigall-I-Torrent et al. [76] obtained percentages between 43 and 55 % when comparing four-star hotels to three-star hotels.

Similarly, the price of the hotel increases by 35 % when it offers the all-inclusive regime and by 9 % when the establishment has received any of the sustainability certifications, holding all other characteristics constant. Regarding the coefficient for the distance to the beach, ceteris paribus, a 1 % increase in the distance leads to a 42 % increase in the accommodation price.

Applying the formula shown in Landajo et al. (2012), p.995, hedonic prices were calculated (see Table 5), from results of the hedonic regression (Table 4). The price of a hotel increases, on average, by 95.99€ when it holds the maximum category compared to another of a lower category, and all other characteristics are the same for both hotels. Similarly, the price of a hotel is €52.81 higher when it offers the all-inclusive regime compared to another with the same characteristics but not offering this regime. Regarding the characteristic of the sustainability certification, the price of a hotel increases by €15.84 when it holds a sustainability certification compared to another hotel with equal characteristics but without any certification. Finally, the price of a hotel increases by approximately €7.46 for every 3.1 km in the direction of the beach, since the distance ranges between 0 and 31 km.

Table 3
VIF variables.

ALLINCLUD	STARS5	NEARBEACH	LABEL
1.039	1.027	1.031	1.039

[2] In the first estimates of the hedonic equation, more explanatory variables were included: number of rooms, if the establishment is accessible, if it has a spa, number of swimming pools, number of restaurants, whether the establishment belongs to a chain, and whether it is an aparthotel. However, none of these variables was shown to be significant, which is possibly due to a potential endogeneity problem between the category variable and other services (Thrane [67]). Hence, these additional explanatory variables were excluded from the estimate.

Table 4
Results of the estimate hedonic price equation.

Variable	Coefficient	Price premium (%)
Constant	4.45 (0.166)***	
ALLINCLUD	0.297 (0.054)***	34.58
STARS5	0.540 (0.079)***	71.60
NEARBEACH	0.420 (0.169)**	42
LABEL	0.090 (0.048)*	9.42
R^2 *adjusted*	0.47	
m	132	
p-Value	0.0	
F-ratio	30.54	

SEs (robust to heteroscedasticity White method) are in parentheses. Dependant variable: the natural logarithm price. ***p<0.001, **p<0.05, *p<0.01.

Table 5
Hedonic Prices (€).

ALLINCLUD (c_1)	STARS5 (c_2)	NEARBEACH (c_3)	LABEL (c_4)
52.81	95.99	74.58	15.84

Table 6
Shapley values obtained in stage II.

Criterion	Shapley importance Index (R-G-L)	Shapley importance Index (Duarte)
ALLINCLUD	0.2484	0.25
STARS5	0.2546	0.25
NEARBEACH	0.25	0.25
LABEL	0.2471	0.25

4.4. Application of the CI-HPM method in the canary Island market

After the hedonic regression determined the significant selection criteria, Stage II was executed using R software, which provides the capacity for calculating the Shapley index of the four criteria (see Table 6). Column 2 of Table 6 shows that the hotel profiles exhibit balanced importance values for the criteria when the R-G-L method is applied. Consequently, the Shapley values obtained using both R-G-L and Duarte's methods are very similar. With respect to the Shapley interaction values, the R-G-L method yields negative results for all pairs of criteria (see Table 7), while Duarte's method identifies two complementary interactions between the pairs (ALLINCLUD, STARS5) and (ALLINCLUD, NEARBEACH) (see Table 7).

Additionally, Choquet scores with respect to the unsupervised capacity for the hotels in our database were available and served as the inputs for Stage III. It is important to note that these scores were obtained independently of the information obtained from hedonic prices.

The Spearman's (resp. Kendall's) rank correlation between the Choquet scores using the unsupervised R-G-L method and those obtained by the unsupervised Duarte's method is equal to 0.95 (resp. 0.87). Sixty-two hotels occupy the same positions with both methods. The first seven positions, positions 40 to 48 and positions 86 to 132 are identical in both methods. The capacities identified by the two unsupervised methods are presented in Table 8. From this, we can conclude that the capacities assigned by R-G-L are more uniform within each cardinality class compared to those detected by Duarte's method.

Table 7
Interaction indexes with R-G-L method (resp. Duarte's method).

	ALLINCLUD	STARS5	NEARBEACH	LABEL
ALLINCLUD	−0.012 (0.10)	−0.007 (0.11)	−0.021 (−0.14)	
	STARS5	−0.012 (0.10)	−0.013 (−0.24)	−0.004 (−0.07)
NEARBEACH	−0.007(0.11)	−0.013 (−0.24)	−0.018 (−0.15)	
	LABEL	−0.021 (−0.14)	−0.004 (−0.07)	−0.018 (−0.15)

Table 8
Capacities obtained in Stage II with R-G-L and Duarte's methods.

Coalitions	R-G-L	Duarte
{1}	0.27	0.22
{2}	0.27	0.36
{3}	0.27	0.39
{4}	0.27	0.43
{1,2}	0.52	0.67
{1,3}	0.52	0.72
{1,4}	0.51	0.51
{2,3}	0.52	0.51
{2,4}	0.53	0.79
{3,4}	0.51	0.67
{1,2,3}	0.77	0.93
{1,2,4}	0.76	0.89
{1,3,4}	0.76	0.86
{2,3,4}	0.77	0.72
{1,2,3,4}	1.00	1.00

The implementation of Stage III was carried out by adding linear constraints, derived from hedonic results, to the Shapley values associated with the sought capacity. Table 5 presents the monotonic relationships between the market values of the characteristics, which are translated into inequalities with corresponding thresholds. Grabisch & Labreuche [86] (p.11) consider that the thresholds have to be fixed arbitrarily.

The constraint $S(c_j) \geq S(c_i)$ is derived from Table 5 when the hedonic price of the characteristic c_j is greater than that of characteristic c_i. It is modelled as follows: $S(c_j) - S(c_i) \geq \delta_{ji}$ where the threshold δ_{ji} is defined based on the hedonic prices by comparing the price premiums of the two criteria. For normalisation purposes, this difference is divided by the sum of the all premiums (see price premiums in Table 4):

$$\delta_{ji} = \frac{(e^{\beta_j} - 1) - (e^{\beta_i} - 1)}{\sum_{l=1}^{4} (e^{\beta_l} - 1)}$$

Consequently, the following constraints are used to find the capacity μ_{lsci}:

$$\begin{array}{rll} S(STARS5) \geq S(ALLINCLUD) & \text{with} & threshold = 0.2 \\ S(STARS5) \geq S(NEARBEACH) & \text{with} & threshold = 0.12 \\ S(STARS5) \geq S(LABEL) & \text{with} & threshold = 0.34 \\ S(NEARBEACH) \geq S(ALLINCLUD) & \text{with} & threshold = 0.07 \end{array} \tag{15}$$

By identification a capacity that minimises the distance to the Choquet scores determined in Stage II while satisfying the above constraints, the Shapley importance indexes are obtained. These indexes (summing up to 1) are presented in Table 9. Comparing them to Table 6, it can be

Table 9
Shapley values obtained in Stage III using Stage II with R-G-L and Duarte's methods.

Criterion	Shapley importance index
ALLINCLUD	0.2063
STARS5	0.4271
NEARBEACH	0.3110
LABEL	0.0556

Table 10
Shapley interactions between criteria obtained in phase II using Phase I with R-G-L method (resp. Duarte method).

	ALLINCLUD	STARS5	NEARBEACH	LABEL
ALLINCLUD		0.045 (0.061)	0.181 (0.129)	−0.039 (−0.05)
STARS5	0.045 (0.061)		−0.284 (−0.447)	−0.059 (−0.016)
NEARBEACH	0.181 (0.129)	−0.284 (−0.447)		0.143 (0.045)
LABEL	−0.039 (−0.05)	−0.059 (−0.016)	0.143 (0.045)	

Table 11
Capacities obtained in Stage III using Stage II with R-G-L and Duarte's methods.

Coalitions	R-G-L	Duarte
{1}	0.10	0.14
{2}	0.55	0.63
{3}	0.32	0.45
{4}	10E−6	0.067
{1,2}	0.70	0.83
{1,3}	0.59	0.71
{1,4}	0.10	0.15
{2,3}	0.58	0.63
{2,4}	0.55	0.67
{3,4}	0.43	0.56
{1,2,3}	0.89	0.96
{1,2,4}	0.70	0.83
{1,3,4}	0.70	0.77
{2,3,4}	0.69	0.72
{1,2,3,4}	1.00	1.00

observed that the importance ranking of the criteria is maintained, but the distances between them are now much larger, reflecting hedonic preferences. Moreover, both supervised methods, R-G-L and Duarte's methods, provide the same Shapley values.

Table 12
The first twenty-five hotels with their average scores and Choquet scores w.r.t. the l.s.c.i. capacity from the R-G-L method (resp. Duarte's method).

Hotel Number	Average Score	Choquet Score	Hotel Number	Average Score	Choquet Score
1	0.5	0.572 (0.629)	14	1	1 (1)
2	0.498	0.572 (0.629)	15	0.75	0.697 (0.724)
3	0.748	0.953 (0.954)	16	0.75	0.697 (0.724)
4	0.498	0.572 (0.629)	17	0.75	0.697 (0.724)
5	0.5	0.572 (0.629)	18	0.748	0.696 (0.723)
6	0.996	0.995 (0.997)	19	0.497	0.572 (0.629)
7	0.746	0.695 (0.723)	20	0.5	0.572 (0.629)
8	1	1 (1)	21	0.736	0.94 (0.948)
9	0.75	0.697 (0.724)	22	0.486	0.572 (0.629)
10	0.744	0.948 (0.952)	23	0.747	0.696 (0.723)
11	1	1 (1)	24	0.495	0.572 (0.629)
12	0.75	0.697 (0.724)	25	0.5	0.572 (0.629)
13	0.998	0.998 (0.999)			

Table 10 displays the values of interaction between each pair of criteria. Three interactions are positive: (ALLINCLUD, STARS5), (ALLINCLUD, NEARBEACH) and (NEARBEACH, LABEL). Thus, the complementary nature of two pairs of criteria detected by Duarte's unsupervised method in Stage II is preserved in this stage.

Table 11 shows the capacities identified in Stage III using Stage II with R-G-L and Duarte's methods. The ranking of the capacities for the singletons is the same for both methods. A monotonic relationship is observed between the two columns. Specifically, column 3 (the capacity obtained from Duarte's method in Stage II: l.s.c.i.[Duarte] method) is always larger than column 2 (capacity obtained from the R-G-L method in Stage II: l.s.c.i. [R-G-L] method). The most important pair of criteria is (ALLINCLUD, STARS5). There is a change in the order of the capacities for the coalitions {2,3} and {2,4} between the two methods. Thus, the l.s.c.i. (R-G-L) method considers the pair (STARS5, NEARBEACH) more important than the pair (STARS5, LABEL), while the opposite is true for the l.s.c.i.(Duarte) method. Differences are also found between the coalitions {1,2,4} and {1,3,4} in the two methods. Furthermore, we can conclude from Table 11 that both identified capacities are non-additive.

Table 12 shows the Choquet scores for first the twenty-five hotels, and a comparison is made with the average scores. Hotels 3 and 16 have very similar average scores, although their Choquet scores are further apart. This difference can be attributed to the greater importance of the ALLINCLUD criterion compared to the LABEL criterion once the identified capacity is assigned (see Table A1 in the Appendix). The same situation is observed when comparing hotels 9 and 10. Similarly, Hotel 21 has a lower average score than Hotel 18, but its Choquet score is higher. This inversion of the ranking can be attributed to the greater importance of the ALLINCLUD criterion relative to the LABEL criterion.

To compare the rankings obtained by the five scoring methods: average, CI applying the R-G- L method, CI using least squares capacity identification with R-G-L prior (l.s.c.i. [R-G-L]), CI based on Duarte's method, CI using least squares capacity identification with Duarte's prior (l.s.c.i. [Duarte]), rank correlation coefficients are shown in Table 13. As expected, the lowest values of the correlation coefficients are obtained when compared with the average of the scores. The highest coefficients are obtained when comparing the two supervised methods. This demonstrates the robustness of the supervised method with respect to the method used in the initial phase.

Regarding the comparison between the two proposed methods, l.s.c.i (R-G-L) and l.s.c.i.(Duarte), we observe that 87 hotels occupy the same places, concentrating on the first and last places. Specifically, the 26 best hotels coincide with both methodologies – l.s.c.i.(R-G-L) and l.s.c.i.(Duarte) – as well as the 61 worst hotels. Therefore, both methodologies identify the same best and worst hotels, while the differences are concentrated in the middle zone.

To analyse the results, four aggregation models were used: the two proposed methods, l.s.c.i.(Duarte) and l.s.c.i.(R-G-L), along with two classical approaches, average scoring and WAM, with the weights corresponding to the Shapley values obtained in Stage III. Table 14 shows the 45 hotels with different rankings in the two l.s.c.i. methods. Each

Table 13
Kendall's Tau and spearman's Rho rank correlation coefficients.

	Spearman's Coeff.	Kendall's Coeff.
(R-G-L,l.s.c.i.(R-G-L))	0.968	0.903
(Average, l.s.c.i.(R-G-L))	0.944	0.848
(R-G-L, Average)	0.964	0.889
(l.s.c.i.(R-G-L),l.s.c.i.(Duarte))	0.977	0.934
(Duarte, l.s.c.i.(Duarte))	0.977	0.930
(Duarte, R-G-L)	0.950	0.867
(Duarte, Average)	0.926	0.812
(Average, l.s.c.i.(Duarte))	0.932	0.828
(R-G-L,l.s.c.i.(Duarte))	0.977	0.922
(Duarte,l.s.c.i.(R-G-L))	0.926	0.864

Table 14
Hotels with their different ranks in Stage III.

Hotel Number	Hotel	Ranks (a, b, c, d)
101	Green Garden Resort-AI	27,37,37,50
78	Sunlingt Bahía Principe Tenerife Resort	28,38,38,51
9	Iberostar Hotel Anthelia	29,27,6,10
12	Bahía del Duque	30,28,7,11
15	Roca Nivaria Gran Hotel	31,29,8,12
16	Sheraton la Caleta Resort and Spa	32,30,9,13
17	Jardines de Nivaria	33,31,10,14
26	IberostarGran Hotel El Mirador	34,32,11,15
27	Barceló Royal Hideaway Corales Suites	35,33,15,16
18	Hotel Gran Tacande Wellneess and Relax	36,34,20,17
23	La Plantación del Sur Vincci	37,35,24,18
7	GF Gran Costa Adeje	38,36,27,19
68	Spring Hotel Bitácora-AI	39,52,48,52
66	Hotel Troya-AI	40,53,49,53
52	Catalonia Punta del Rey-AI	41,54,51,54
36	Sol Tenerife-AI	42,55,54,55
42	Guayarmina Princess-AI	43,56,55,56
113	Hotel Sol Arona Tenerife-AI	44,57,58,57
115	Hotel Europea Park Club	45,58,59,58
Hotel Number	**Hotel**	**Ranks (a, b, c, d)**
73	Hovima Costa Adeje-AI	46,59,62,59
48	Labranda Isla Bonita	47,60,67,60
93	Olé Tropical Tenerife-AI	48,61,69,61
70	Allegro Isora-AI	49,62,73,62
89	Hotel Aguamarina Golf	50,63,74,63
107	Grand Hotel Callao-AI & Spa	51,64,75,64
122	Bahía Flamingo-AI	52,65,76,65
75	Melía Jardines Teide-AI	53,66,81,66
82	Hotel Paradise Park-AI	54,67,83,67
49	Gara Suites Golf and SPA-AI	55,68,84,68
92	Dreamplace Tagoro Family & Fun Costa Adeje	56,69,85,69
104	Kn Hotel Arenas Del Mar Beach-AI & Spa	57,70,86,70
124	Palia Don Pedro	58,71,88,71
1	Hard Rock Hotel Tenerife	59,39,39,20
5	The Ritz-Carlton, Abama	60,40,40,21
20	Hotel Europe Villa Cortes	61,41,41,22
29	Sir Anthony	62,42,42,23
25	Barceló Royal Hideaway Corales Beach Adults Only	63,43,50,24
4	Iberostar Sábila	64,44,57,25
2	Gran Meliá Palacio Isora	65,45,60,26
32	Iberostar Grand Salomé	66,46,61,27
28	Royal Hideway Corales Resort	67,47,66,28
19	GF Victoria	68,48,71,29
24	Baobab Suites	69,49,77,30
30	Las Madrigueras	70,50,89,31
22	Grand Muthu Golf Plaza Hotel and Spa	71,51,90,32

a: l.s.c.i. (Duarte), b: l.s.c.i. (R-G-L), c: Average, d: WAM.

Table 15
The twenty-five best hotels according to their Choquet scores w.r.t. the l.s.c.i capacity associate to R-G-L method.

Ranking	Number	Hotel	Choquet Score
1	8	Iberostar Hotel Anthelia	1
2	11	Bahía del Duque	1
3	14	Roca Nivaria Gran Hotel	1
4	13	Sandos San Blas	0.998
5	6	GF Gran Costa Adeje	0.995
6	3	Iberostar Sábila	0.953
7	31	Iberostar Grand Salomé	0.953
8	10	Fantasía Bahía Principe	0.948
9	21	Grand Muthu Golf Plaza Hotel	0.940
10	38	H10 las palmeras	0.725
11	44	Iberostar Bouganville Playa	0.725
12	64	H10 Gran Tinerfe	0.725
13	86	Be Live Experience La Niña	0.723
14	119	Hotel apartamentos Parque la Paz	0.723
15	59	Barceló Santiago	0.721
16	80	Bahía Princess	0.720
17	55	GF Fañabe	0.719
18	99	Hotel Vincci Tenerife Golf	0.717
19	97	Coral Ocean View	0.716
20	40	Be Live Family Costa los Gigantes	0.715
21	41	ClubHotel Riu Buena Vista	0.715
22	46	H10 Costa Adeje Palace	0.713
23	57	Iberostar Las Dalias	0.712
24	34	H10 Conquistador	0.709
25	87	Marylanza Suites and Spa	0.709

Table 16
The twenty-five worst hotels.

Ranking	Number Hotel	Choquet Score	Ranking	Number Hotel	Choquet Score
108	74	0.27140	121	76	0.2665
109	33	0.27104	122	83	0.2661
110	62	0.27095	123	50	0.2648
111	79	0.27095	124	118	0.2648
112	106	0.27095	125	121	0.2648
113	94	0.2701	126	105	0.2639
114	71	0.2692	127	125	0.2621
115	112	0.2692	128	103	0.2604
116	129	0.2692	129	109	0.2445
117	108	0.2687	130	132	0.2206
118	123	0.2687	131	110	0.0794
119	117	0.2683	132	111	0.0000
120	126	0.2683			

hotel's rank obtained by the four approaches under study is provided in the table. For example, "Green Garden Resort 27,37,37,50″ means that the Green Garden Resort Hotel was ranked 27th, 37th, 37th, and 50th by Duarte's method, the R-G-L method, the average, and WAM, respectively.

It is noteworthy that the number of matching positions has considerably increased compared to the situation found in Stage II, where there were 62 matches. Cases where the rankings of the two proposed CI scores differ significantly from the average scores, such as Iberostar Hotel Anthelia to Hotel Gran Tacande Wellness and Relax in Table 14 (rows 3 to 10), are a consequence of the influence of the preferential constraints in the process of obtaining CI scores. In the eighth referenced case, the differences in the rankings provided by the two l.s.c.i. methods compared to the average are due to the substantial difference between the importance of the ALLINCLUD and LABEL criteria. An interesting example is the case of Hard Rock Hotel Tenerife (hotel number 1 in Table 15). This hotel was ranked 59th and 39th by Duarte's method and the R-G-L method, respectively. Such a difference can be explained by the scores of this hotel, represented by the vector [0 1 1 0] and the different treatment given by the two methods to the pair (2,3), as mentioned above. Similar situations are observed for the hotels Ritz-Carlton Abama, Hotel Europe Villa Cortes, and Sir Anthony.

Moreover, these four hotels achieve favourable rankings when the WAM is used, leveraging the Shapley values of the most important criteria (STARS5 and NEARBEACH), which account for more than 70 % of the Shapley values (see Table 9). Another observation from these four scores on these hotels is the non-additivity of the Choquet aggregations and the effect of negative interactions between these two criteria (see

Table 10). Similar comments are applicable to hotels below these (i.e. hotels 25, 4, 2, 32, 28, 19, 24, 30, and 22) where differences in the scores in the NEARBEACH criterion alter the averages and, consequently, the values in the third component of the rankings.

The twenty-five best hotels ranked according to their lsci-CI scores are shown in Table 15. The top three hotels in the ranking, hotels 8, 11 and 14, have been awarded five stars, are situated on the beach, offer the all-inclusive regime, and possess a sustainable certification. Hotels 13 and 6, which follow, differ from the previous ones in that they are not located directly on the beach, though they are in close proximity. The next four, hotels 3, 31, 10, and 21, do not have beachfront locations and do not hold any sustainability label. This result is expected since the LABEL criterion is the one with the least weight. The subsequent five hotels, hotels 38, 44, 64, 86 and 119, differ from the first three by not having the maximum five stars category. The remaining hotels on the list also lack beachfront locations.

Table 16 shows the twenty-five lowest-ranked hotels based on their Choquet scores. These hotels lack the highest category, do not offer an all-inclusive regime, and do not hold any sustainability certifications. The first twelve hotels on the list are situated in close proximity to the beach. The following five are located at a mid-distance from the beach. Subsequently, the listed hotels are progressively farther away from the beach, with the last hotel being the furthest. The ranking of the 25 worst hotels does not change when Duarte's method is employed as an unsupervised method.

5. Conclusions

The modelling of travellers' preferences is an appealing research question that we have addressed through the application of a new hybrid methodology called CI-HP. This methodology combines revealed preferences with a multi-criteria technique, allowing us to model the interaction between criteria, which is an important aspect of research.

Existing literature has primarily focused on a set of functions that substitute weight vectors in the calculation of the weighted arithmetic means. However, our approach goes beyond this by considering not only the importance of each criterion but also the importance of each subset of criteria. We achieve this by utilising the Choquet Integral as an alternative tool to the weighted arithmetic mean that incorporates the preferential priority of each subset of criteria. The Choquet Integral is used as an aggregation operator that is able to combine hedonic information, on the consumer side, with information about hotels, on the provider side.

Our proposed approach overcomes several drawbacks found in other methodologies: interactions between criteria, partial and expensive information, and the use of subjective valuations. Our approach enables us to generate a hotel ranking tailored to a specific market. The new methodology we propose utilises knowledge that has been demonstrated to be more reliable for the hotel selection process than other techniques. This, in turn, allows firms to develop improved planning strategies to enhance aspects of their hotels. Additionally, the implementation of the method is cost-effective as it is based on publicly available information that is accessible to the modeller and can be applied to any market.

In this paper, we presented a case study focusing on hotels in Tenerife, which represents a mature tourist market known for its sun and beaches. Tenerife is an important travel destination in Spain, but it has been significantly impacted by the COVID-19 pandemic. Our database contains of 132 observations and 97 hotels analysed in the year 2019. As a result of our study, we observed some interest amongst travellers in ecological labels. However, the importance of environmental concerns was still relatively low compared to other hotel characteristics.

CRediT authorship contribution statement

Amelia Bilbao-Terol: Methodology, Software, Formal analysis, Writing – original draft, Writing – review & editing. **Celia Bilbao-Terol:** Conceptualization, Methodology, Investigation, Writing – original draft, Writing – review & editing.

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.

Data availability

Data will be made available on request.

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Appendix

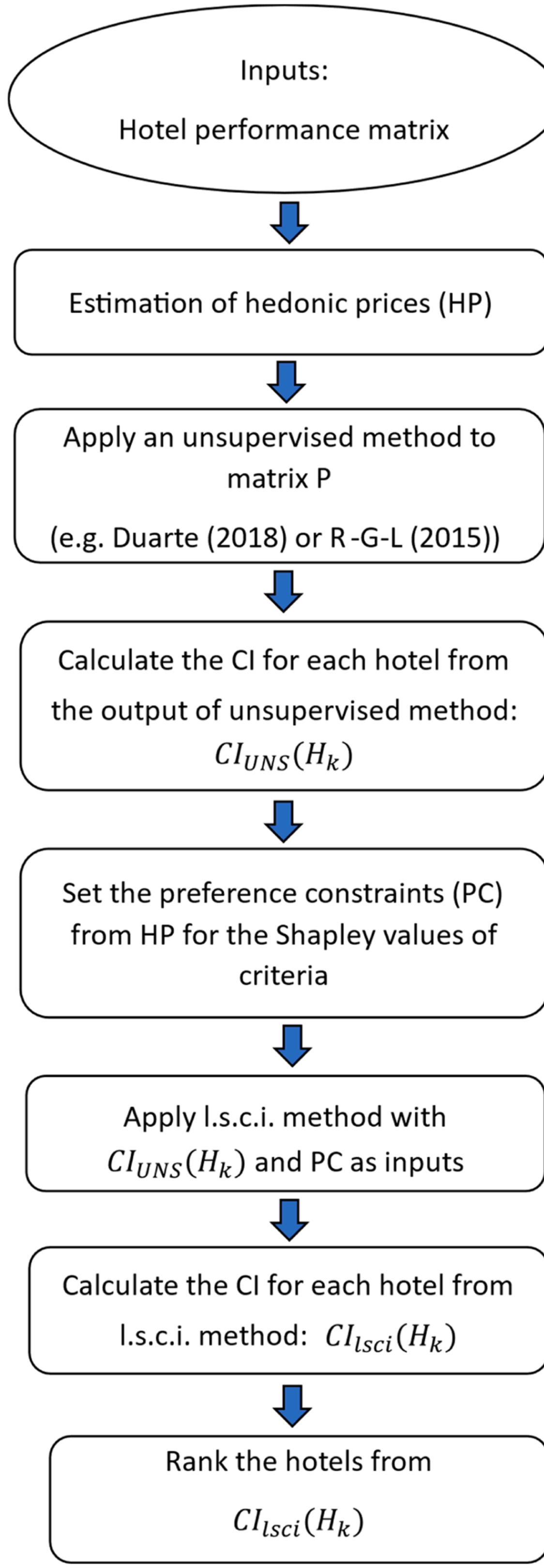

Fig. A.1. The flowchart of the model.

Table A1

No	HOTEL	ALL INCLUD	STARS5	NEAR BEACH	LABEL
1	Hard Rock Hotel Tenerife	0	1	1.00	0
2	Gran Meliá Palacio Isora	0	1	0.99	0
3	Iberostar Sábila-AI	1	1	0.99	0
4	Iberostar Sábila	0	1	0.99	0
5	The Ritz-Carlton, Abama	0	1	1.00	0
6	GF Gran Costa Adeje-AI	1	1	0.98	1
7	GF Gran Costa Adeje	0	1	0.98	1
8	Iberostar Hotel Anthelia-AI	1	1	1.00	1
9	Iberostar Hotel Anthelia	0	1	1.00	1
10	Fantasía Bahía Principe	1	1	0.97	0
11	Bahía del Duque-AI	1	1	1.00	1
12	Bahía del Duque	0	1	1.00	1
13	Sandos San Blas	1	1	0.99	1
14	Roca Nivaria Gran Hotel-AI	1	1	1.00	1
15	Roca Nivaria Gran Hotel	0	1	1.00	1
16	Sheraton la Caleta Resort and Spa	0	1	1.00	1
17	Jardines de Nivaria	0	1	1.00	1
18	Hotel Gran Tacande Wellneess and Relax	0	1	0.99	1
19	GF Victoria	0	1	0.99	0
20	Hotel Europe Villa Cortes	0	1	1.00	0
21	Grand Muthu Golf Plaza Hotel and Spa-AI	1	1	0.95	0
22	Grand Muthu Golf Plaza Hotel and Spa	0	1	0.95	0
23	La Plantación del Sur Vincci	0	1	0.99	1
24	Baobab Suites	0	1	0.98	0
25	Barceló Royal Hideaway Corales Beach Adults Only	0	1	1.00	0
26	IberostarGran Hotel El Mirador	0	1	1.00	1
27	Barceló Royal Hideaway Corales Suites	0	1	1.00	1
28	Royal Hideway Corales Resort	0	1	0.99	0
29	Sir Anthony	0	1	1.00	0
30	Las Madrigueras	0	1	0.95	0
31	Iberostar Grand Salomé-AI	1	1	0.99	0
32	Iberostar Grand Salomé	0	1	0.99	0
33	Mediterranean Palace	0	0	0.99	0
34	H10 Conquistador-AI	1	0	0.97	1
35	H10 Conquistador	0	0	0.97	1
36	Sol Tenerife-AI	1	0	1.00	0
37	Sol Tenerife	0	0	1.00	0
38	H10 las palmeras-AI	1	0	1.00	1
39	H10 las palmeras	0	0	1.00	1
40	Be Live Family Costa los Gigantes	1	0	0.98	1
41	ClubHotel Riu Buena Vista	1	0	0.98	1
42	Guayarmina Princess-AI	1	0	1.00	0
43	Guayarmina Princess	0	0	1.00	0
44	Iberostar Bouganville Playa-AI	1	0	1.00	1
45	Iberostar Bouganville Playa	0	0	1.00	1
46	H10 Costa Adeje Palace-AI	1	0	0.98	1
47	H10 Costa Adeje Palace	0	0	0.98	1
48	Labranda Isla Bonita	1	0	0.99	0
49	Gara Suites Golf and SPA-AI	1	0	0.97	0
50	Gara Suites Golf and SPA	0	0	0.97	0
51	Cleopatra Palace	0	0	1.00	0
52	Catalonia Punta del Rey-AI	1	0	1.00	0
53	Catalonia Punta del Rey	0	0	1.00	0
54	Hotel Tigotan Lovers and Friend	0	0	0.99	0
55	GF Fañabe-AI	1	0	0.99	1
56	GF Fañabe	0	0	0.99	1
57	Iberostar Las Dalias	1	0	0.98	1
58	Sensimar Arona Gran Hotel	0	0	1.00	1
59	Barceló Santiago	1	0	0.99	1
60	Hotel Jardín Tropical	0	0	1.00	1
61	GF Isabel	0	0	0.97	1
62	Spring Hotel Vulcano	0	0	0.99	0
63	Hotel Riu Arecas	0	0	0.99	1
64	H10 Gran Tinerfe-AI	1	0	1.00	1
65	H10 Gran Tinerfe	0	0	1.00	1
66	Hotel Troya-AI	1	0	1.00	0
67	Hotel Troya	0	0	1.00	0
68	Spring Hotel Bitácora-AI	1	0	1.00	0
69	Spring Hotel Bitácora	0	0	1.00	0
70	Allegro Isora-AI	1	0	0.98	0
71	Allegro Isora	0	0	0.98	0
72	Gala Tenerife	0	0	1.00	0
73	Hovima Costa Adeje-AI	1	0	0.99	0
74	Hovima Costa Adeje	0	0	0.99	0
75	Meliá Jardines Teide-AI	1	0	0.97	0
76	Meliá Jardines Teide	0	0	0.97	0

(*continued on next page*)

Table A1 (*continued*)

No	HOTEL	ALL INCLUD	STARS5	NEAR BEACH	LABEL
77	Hotel Riu Palace Tenerife	0	0	0.99	1
78	Sunlingt Bahía Principe Tenerife Resort	1	0	0.93	1
79	Hotel la Siesta	0	0	0.99	0
80	Bahía Princess-AI	1	0	0.99	1
81	Bahía Princess	0	0	0.99	1
82	Hotel Paradise Park-AI	1	0	0.97	0
83	Hotel Paradise Park	0	0	0.97	0
84	Hotel Apartamentos Club Atlantis Hovina	0	0	1.00	0
85	Hotel Hovima La Pinta Beachfront	0	0	1.00	0
86	Be Live Experience La Niña	1	0	1.00	1
87	Marylanza Suites and Spa-AI	1	0	0.97	1
88	Marylanza Suites and Spa	0	0	0.97	1
89	Hotel Aguamarina Golf	1	0	0.98	0
90	Gran Oasis Resort-AI	1	0	0.95	1
91	Gran Oasis Resort	0	0	0.95	1
92	Dreamplace Tagoro Family & Fun Costa Adeje	1	0	0.97	0
93	Olé Tropical Tenerife-AI	1	0	0.99	0
94	Olé Tropical Tenerife	0	0	0.99	0
95	H10 Big Sur	0	0	1.00	1
96	Colón Guanahani	0	0	1.00	1
97	Coral Ocean View-AI	1	0	0.99	1
98	Coral Ocean View	0	0	0.99	1
99	Hotel Vincci Tenerife Golf-AI	1	0	0.99	1
100	Hotel Vincci Tenerife Golf	0	0	0.99	1
101	Green Garden Resort-AI	1	0	0.95	1
102	Green Garden Resort	0	0	0.95	1
103	Royal Sun Resort	0	0	0.95	0
104	Kn Hotel Arenas Del Mar Beach & Spa-AI	1	0	0.96	0
105	Kn Hotel Arenas Del Mar Beach & Spa	0	0	0.96	0
106	Vanilla Garden	0	0	0.99	0
107	Grand Hotel Callao & Spa-AI	1	0	0.98	0
108	Grand Hotel Callao & Spa	0	0	0.98	0
109	Regency Country Club, Apartements Suites	0	0	0.89	0
110	Hotel Spa Villalba	0	0	0.29	0
111	La Casona del Patio	0	0	0.00	0
112	Hotel Apartamentos Santa María Hovima	0	0	0.98	0
113	Hotel Sol Arona Tenerife-AI	1	0	0.99	0
114	Hotel Sol Arona Tenerife	0	0	0.99	0
115	Hotel Europea Park Club	1	0	0.99	0
116	Annapurna Tenbel Tenerife	0	0	1.00	0
117	Oro Negro Catalonia	0	0	0.98	0
118	Hotel apartamentos Jardín Caleta Hovima	0	0	0.97	0
119	Hotel apartamentos Parque la Paz-AI	1	0	1.00	1
120	Hotel apartamentos Parque la Paz	0	0	1.00	1
121	Hotel Apartamentos Panorama Hovima	0	0	0.97	0
122	Bahía Flamingo-AI	1	0	0.98	0
123	Bahía Flamingo	0	0	0.98	0
124	Palia Don Pedro	1	0	0.95	0
125	Hotel Apartamentos Malibú Park	0	0	0.96	0
126	Hotel Apartamentos Andorra III	0	0	0.98	0
127	Hotel apartamentos Los dragos del Sur	0	0	1.00	0
128	Hotel Playa Sur Tenerife	0	0	1.00	0
129	Ona Sueño Azul	0	0	0.98	0
130	Hotel Médano	0	0	1.00	0
131	Hotel Apartamentos Atlantic Holiday centre	0	0	1.00	0
132	Hotel Ucanca	0	0	0.81	0

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