METODOLOGICAL PERSPECTIVES ON ESTIMATING AND MODELING HEDONIC PRICING OF RURAL TOURISM ESTABLISHMENTS

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RESEARCH ARTICLE

Abstract

Hedonic pricing is a model used to assess the influence that different characteristics of a product or service affect its price. In tourism, hedonic pricing is used to determine how the attributes of a tourist destination affect the prices of accommodations, activities, and other tourism-related services. Rural tourism can benefit from studies regarding this, as the hedonic price model provides a useful component of the price-setting mechanism employed by rural entrepreneurs.

The main aim of this study is to examine the different methods that can be employed in order to determine hedonic price models, highlighting their characteristics, strengths, weaknesses. Among the statistical methods used are multiple linear regression, geographically weighted regression, and structural equation modelling.

Another methodological consideration addressed in this study is the data collection procedure. Overall, the use of actual market data in hedonic pricing models is preferable because they provides a more accurate and robust picture of the pricing of a product or service. We argue that by employing automated data scraping procedures, future studies on the pricing of rural tourism can address a larger geographical area or that comparisons between models that are appropriate for different markets can become more commonplace. We also note that the data collection procedures should always follow the rules of the source website and general netiquette.

Finally, we present an overview of the independent variables used in previous research on hedonic pricing and their usability in the context of rural tourism. We propose some novel variables that can be useful in future studies.

INTRODUCTION

Hedonic pricing models are powerful analytical tools that allow researchers to assess the impact of different product or service characteristics on pricing (Soler et al., 2019). Although the earliest and most significant applications of the hedonic pricing framework were observed in real estate research, several studies have explored the application of this approach to pricing within the tourism domain (Herath & Maier, 2010; Monson, 2009; Sánchez-Ollero et al., 2014). Within this industry, the hedonic pricing model has proven valuable in understanding how various attributes of a tourist destination influence the prices of accommodations, activities, and other tourism-related services. For rural tourism, studies employing the hedonic price model offer crucial insights into the price-setting mechanisms employed by rural entrepreneurs (Qiao et al., 2021).

This paper aims to explore the diverse methodologies available for estimating hedonic price models, emphasizing their distinct characteristics, strengths, and weaknesses. Statistical methods such as multiple linear regression, geographically weighted regression, and structural equation modeling have been employed in the context of hedonic pricing, and their applicability to rural tourism will be analyzed.

Another critical consideration in this study is the data collection procedure. Utilizing actual market data in hedonic pricing models is preferred as they provide a more accurate and robust understanding of product or service pricing, including non-traditional tourism establishments, as promoted on Airbnb (Gibbs et al., 2018). To enhance future studies on the pricing of rural tourism, we propose the adoption of automated data scraping procedures. By employing such methods, researchers can address a broader geographical area or facilitate comparisons between models appropriate for different markets.

However, it is crucial to emphasize that data collection procedures must strictly adhere to the rules and guidelines established by the source websites, ensuring ethical practices and respect for privacy. Furthermore, it is imperative to maintain proper "netiquette",

respecting the terms and conditions of the websites and platforms from which the data is collected (Scannapieco & Virgillito, 2021).

The data collected through the aforementioned procedures includes both dependent variables (prices) and independent variables (such as accommodation features, room characteristics, and spatial attributes). Therefore, this paper provides an overview of the independent variables employed in prior research on hedonic pricing and examines their applicability within the specific context of rural tourism. Furthermore, this study proposes novel variables that have the potential to enhance future studies in this field.

The findings of this study are expected to benefit various stakeholders involved in rural tourism (Ayazlar & Arslan Ayazlar, 2015). By understanding the factors driving pricing decisions, tourists make informed choices when selecting accommodations and activities. Entrepreneurs and policymakers will gain valuable insights into market trends, enabling them to develop effective pricing strategies and allocate resources optimally. Lastly, researchers will find guidance for conducting future studies, contributing to the advancement of knowledge in rural tourism and associated industries.

In the subsequent sections, we will delve into the theoretical foundations of hedonic pricing, review the relevant literature, discuss methodological approaches, examine data collection procedures, and present an overview of independent variables. Through this comprehensive analysis, our aim is to contribute to the existing research literature and advance knowledge in the field. ultimately fostering sustainable development and growth within this vital sector.

MATERIAL AND METHOD

This paper presents a comprehensive review of the existing literature on hedonic pricing, both in general and in the context of rural tourism establishments. The aim is to analyze and synthesize the methodological perspectives employed in estimating and modeling hedonic pricing. To achieve this, a systematic literature review methodology was followed, involving a thorough search across the most widely used academic databases accessible: Scopus, Web of Science, and Google Scholar.

The search utilized keywords related to "hedonic pricing in tourism", "rural tourism pricing", "agritourism pricing" and similar terms. Relevant articles were selected based on their alignment with the research topic, publication in peer-reviewed journals, and availability of full text. Additionally, the reference lists of selected articles were reviewed to identify additional relevant studies.

Data extraction and analysis were conducted to gather key information from the selected articles. The extracted data focused on research objectives, methodology, variables examined, statistical techniques used, and major findings. Thematic organization was applied to synthesize the data and identify common methodological perspectives, challenges, and trends in estimating and modeling hedonic pricing of rural tourism establishments.

The synthesized data were analyzed using a narrative synthesis approach, enabling a comprehensive overview of the literature on hedonic pricing in rural tourism establishments (Lisy & Porritt, 2016). Through this analysis, common themes, methodological variations, and emerging trends were identified and discussed.

By following this systematic review methodology, this paper provides an in-depth analysis of the existing literature on hedonic pricing in the context of rural tourism establishments. The findings contribute to our understanding of the methodological approaches employed in estimating and modeling hedonic pricing, while also identifying research gaps and providing directions for future studies in this field.

RESULTS AND DISCUSSIONS

The research findings include a comprehensive examination of the strengths and weaknesses associated with hedonic price models. The following advantages were identified:

- Availability of online data: One of the key strengths of the hedonic pricing model is the availability of data online, particularly for hotel room prices and characteristics. This accessibility allows researchers to easily access relevant information for their analysis (Soler & Gémar, 2017; Tong & Gunter, 2022).

- Adequately structured data: The data used in hedonic pricing models tends to be well-structured, reducing the time needed for data cleaning and preparation. This efficiency enables researchers to focus more on the

analysis and interpretation of the data. However, this is a result of well-written programs used to data scrape. As such, a sub-optimal data collection algorithm will impact the quality of the data negatively (Sanchez-Lozano et al., 2021).

- Utilization of market data: The hedonic pricing model directly utilizes data from the market, which contributes to high levels of confidence in the results. By using real-world market information, researchers can capture actual pricing dynamics and consumer preferences(Chau & Chin, 2003).

- No need for questionnaires: Unlike methods that rely on willingness-to-pay measures, which typically involve questionnaires or experimental setups, the hedonic pricing model bypasses the need for such direct interactions with consumers. It leverages existing market data instead, eliminating the necessity of additional data collection efforts and potential biases associated with survey responses or experimental conditions (Gordan & Goje, 2021; Song et al., 2021). This distinguishing feature allows for a more convenient and less intrusive approach to estimating price influences within the hedonic pricing framework.

- Support for decision-making: The hedonic pricing model provides valuable insights for both entrepreneurs and authorities involved in decision-making processes. Entrepreneurs can better understand the factors that influence pricing decisions, while authorities can utilize the model's findings to inform policy and regulatory decisions.

Our research also delves into a detailed exploration of the associated disadvantages and limitations. Those identified by us are:

- Assumption of perfect information symmetry: The hedonic pricing model assumes perfect information symmetry or transparency in the market. However, in reality, information asymmetry can exist, leading to potential limitations in accurately capturing all relevant factors influencing prices (Pope, 2008). In a related note, some tendencies in the tourism industry might be problematic for the research endeavor, for example the inaccurate portrayal of hotel amenities and features, cherry-picked photos, and astroturfing (Harris, 2012; Self et al., 2010). Astroturfing consists of artificially inflated review scores, obtained through fake reviews(Alallaq et al., 2019).

- Data accuracy is crucial: The accuracy and reliability of the data used in hedonic pricing models are critical. Inaccurate or incomplete data can lead to unreliable results, emphasizing the importance of data quality control and validation.

- Difficulty in assessing true marginal values: Determining the true marginal values of specific attributes can be challenging in hedonic pricing. For example, distinguishing the difference in value between a 2-star and 3-star establishment might be more significant than that between a 4-star and 5-star establishment. Capturing these nuanced differences accurately can be difficult, as it would entail an in-depth analysis of the national legislation regarding tourism classification, as well as the way it is implemented.

- Complex modeling requirements: Hedonic pricing models may require more advanced and complex statistical models to account for autocorrelations (spatial or temporal), non-linear effects, and interaction effects (Latinopoulos, 2018; Yang et al., 2016). These additional complexities can add challenges to the analysis and interpretation of the results.

- Omitted variable bias: Researchers using hedonic pricing models need to carefully consider the inclusion of all relevant factors that may influence prices. Omitted variable bias occurs when important variables are unintentionally left out of the analysis, potentially leading to incomplete or biased results (Guignet & Lee, 2021).

By recognizing and understanding these strengths and weaknesses, researchers can make informed decisions about the appropriate application and interpretation of the hedonic pricing model in their studies.

Following this, the vast majority of research papers written on the subject of hedonic pricing analysis utilize a form of automated data collection procedure.

Web scraping, as an automated data extraction method, offers researchers the opportunity to gather valuable information from various websites. When conducting web scraping for this study, the R programming language (or alternatively, Python) can be employed, along with specific packages like Rvest or RSelenium (R Core Team, 2022).

Rvest is a versatile package suitable for extracting data from relatively straightforward websites. It provides functions and tools to navigate HTML structures, scrape data tables, and retrieve relevant information efficiently (Wickham, 2022). However, when dealing with

websites that heavily rely on JavaScript or fetch content dynamically from external sources, RSelenium becomes a useful alternative. RSelenium allows researchers to control web browsers programmatically and access web pages that require JavaScript execution or user interactions. To run the web browser in headless mode without a graphical user interface, Docker can be utilized, ensuring seamless and efficient web scraping operations (Harrison, 2022).

Prominent online platforms such as Tripadvisor, Booking, or Airbnb can serve as valuable sources of data regarding prices and amenities of accommodation units. By leveraging web scraping techniques, researchers can extract information from these websites, providing insights into the pricing dynamics of tourism establishments. However, it is important to adhere to ethical practices and respect the rules set by the websites. Researchers should consult the robots.txt file to understand any crawling restrictions imposed by the website and implement suitable time-out intervals between fetch requests to avoid overloading the server and disrupting the website's operation.

One challenge researchers may encounter when relying solely on data from these websites is the unavailability of prices if all rooms in a particular hotel are sold out. This limitation should be taken into account during data collection and analysis to ensure accurate and comprehensive findings. Furthermore, it is worth noting that rural accommodations may have a limited presence on these popular booking platforms. As a result, alternative sources of data, such as local tourism boards, regional directories, or direct surveys, may need to be explored to obtain a more representative dataset for rural tourism establishments.

The most commonly used method in estimating hedonic pricing models is multiple linear regression analysis. This method allows for the examination of the relationship between dependent and independent variables, typically employing ordinary least squares (OLS) regression or quantile regression (Masiero et al., 2015; Nadia et al., 2021; Wang et al., 2019).

When utilizing OLS regression analysis, certain criteria need to be satisfied. First, linearity between the dependent and independent variables is required. This can be assessed by examining a residuals versus fitted plot, which helps determine if the relationship follows a linear pattern(Lewis-Beck & Lewis-Beck, 2015).

Autocorrelations, which refer to the presence of correlation among the residuals, should be avoided. The Durbin-Watson test can be employed to assess the presence of autocorrelations and ensure their absence for accurate regression results (Lewis-Beck & Lewis-Beck, 2015).

Another important consideration is the absence of multicollinearity among the independent variables. Multicollinearity occurs when the independent variables are highly correlated with each other, which can lead to unstable regression estimates. The Variance Inflation Factor (VIF) is a commonly used metric to detect multicollinearity and ensure that the independent variables are not strongly correlated(Lewis-Beck & Lewis-Beck, 2015).

The assumption of normal distribution of errors is another requirement for OLS regression. This assumption can be assessed using a Q-Q plot, which compares the distribution of the residuals against a normal distribution (Lewis-Beck & Lewis-Beck, 2015). However, it is worth noting that this assumption can be relaxed by utilizing quantile regression, which allows for a more flexible approach to the error distribution (Koenker et al., 2017).

Finally, homoskedasticity, which refers to the assumption that the variance of the residuals is constant across different levels of the independent variables, should be considered. A scale-location plot can be employed to evaluate the presence of heteroskedasticity and ensure that the variance of the residuals is consistent (Koenker et al., 2017).

If the assumptions of ordinary least squares (OLS) regression are not fully met, alternative modeling approaches can be employed to account for specific complexities. Generalized least squares (GLS) or mixed-effect models are useful options in such cases, allowing for more flexible modeling while accommodating deviations from the assumptions of OLS. The "nlme" package in R provides tools for implementing these models, enabling researchers to incorporate varying levels of fixed and random effects (Pinheiro et al., 2022).

Geographical features play a crucial role in the pricing of accommodation units, particularly in rural tourism. To incorporate these spatial considerations, Geographically

Weighted Regression (GWR) can be employed. GWR allows for modeling spatially varying relationships between variables, accounting for the heterogeneity of effects across different geographic locations. In R, packages such as "gwrr" and "spgwr" offer tools for implementing GWR analysis (Wheeler, 2022). Alternatively, distance variables can be included in the regression model as a proxy for geographical features, capturing the influence of proximity on pricing dynamics (Portolan, 2013).

In certain cases, structural equation modeling (SEM) can be a valuable alternative to regression analysis, particularly when assessing the effects of latent variables. SEM allows for modeling complex relationships among observed and latent variables, providing a comprehensive understanding of the underlying factors influencing the pricing of rural tourism establishments (Freeman & Zhao, 2019; Ullman & Bentler, 2012). Popular software packages such as SPSS-AMOS, Stata, or R packages like "lavaan" and "sem" facilitate the implementation of SEM. However, it is important to note that SEM is not commonly used in hedonic pricing research.

In hedonic pricing research within the domain of tourism, various independent variables are frequently employed to capture the attributes and characteristics of tourism products or services that contribute to pricing variations in the market (Sharaan et al., 2020).

One important independent variable is the spatial dimension, particularly the location of the tourism establishment. The geographic placement of the establishment, in terms of its proximity to prominent attractions, beaches, or urban centers, can significantly influence pricing dynamics (Espinet et al., 2003; Somphong et al., 2022).

Accommodation features are another significant facet in hedonic pricing models. Variables such as the number of rooms, room sizes, available amenities, and room types contribute to the overall value perception of the accommodation (Gordan et al., 2023).

Service quality constitutes an integral independent variable frequently integrated within hedonic pricing research. Indicators of service quality, such as customer ratings, reviews, or satisfaction scores, serve as proxies for the overall experiential dimension that tourists can anticipate (Cró et al., 2019; Lorde et al., 2019; Wang et al., 2019).

The accessibility of the establishment represents another important aspect incorporated in hedonic pricing models. Factors such as proximity to transportation hubs or the availability of parking facilities can influence pricing dynamics (Portolan, 2013).

The surrounding environment of the establishment emerges as a significant independent variable in hedonic pricing research. Natural or built elements, such as scenic views, proximity to parks or natural attractions, or noise levels, can shape consumer preferences and influence prices (Kim et al., 2020; Tapsuwan & Polyakov, 2016). In this sense, a recent study employed machine learning algorithms in order to assess several streetscape variables: greenery, walkability and enclosure (Wang & Rasouli, 2022). Another study, which is considerably older than the other ones referred to in the literature, utilized as independent variables the land use and development of agriculture in the territory adjacent to the accommodation unit (Vanslembrouck et al., 2005). This is of considerable interest to agritourism and rural tourism.

Temporal factors, including seasonality, also warrant attention in hedonic pricing research. Variables related to peak or off-peak seasons, holidays, or special events can impact pricing dynamics (Guizzardi et al., 2020; Wang et al., 2019).

Lastly, market demand-related variables provide insights into the overall demand for tourism services within a specific area. Measures such as occupancy rates or tourist arrival data enable researchers to discern the level of demand and its influence on pricing decisions (Sanchez-Lozano et al., 2021). At the same time, a spatial autocorrelation effect might be accounted for by assessing the prices of other accommodation units in the vicinity of the studied businesses.

An overview of the variables presented in the literature is provided in table 1. An essential factor to consider when selecting variables is the presence of the dummy variable trap. This arises when a set of dummy variables exhibits multicollinearity, such as in the case of the multiple classifications of hospitality units (e.g., star ratings). For instance, if there are five potential categories, we should avoid including five binary variables, each representing one category. To avoid multicollinearity, it is necessary to reduce the number of dummy variables pertaining to a specific feature to the number of categories minus one (Pal et al., 2019).

We consider that an adaptation of the streetscape features set, adapted to the rural environment would be a welcome addition to future research. Furthermore, machine learning algorithms, particularly those employed in semantic segmentation or object recognition, should become more prevalent in the hedonic pricing literature, as they allow for large-scale classification of both scenery features (which might be of interest to tourists, and that can be obtained from Google Maps Street View), as well as architectural features of the accommodation units themselves (as guests might be more interested in traditional architecture, or conversely they might prefer modern architecture) (Mo et al., 2022). Another variable of considerable interest would be the proximity of popular touristic attractions, which can be easily assessed using Google Maps or websites such as Tripadvisor. In the former case, an API is made available to researchers and other interested parties, allowing for the automated large-scale collection of data in this regard.

Furthermore, we consider that a study examining the impact of tourism vouchers on accommodation prices would be of interest for the Romanian policymakers in particular, as a way of assessing the impact of this policy on accommodation prices, complementing the already existing literature on revenue and arrivals.

Table 1

Independent variables utilized in studies employing hedonic pricing methods

Variable category	Variable	Variable type
Accommodation and room attributes	Capacity	Discrete numeric
	Star rating	Discrete numeric
	Room type	Dummies
	Room amenities	Dummies
	Chain affiliation	Dummies
Service quality	Review scores	Continuous numeric
	Number of reviews	Discrete numeric
Accessibility	Parking	Dummy
	Proximity to access routes and mass transit routes	Continuous numeric
	Location	Dummies
Environmental factors	Land use	Continuous numeric
	Streetscape features	Continuous numeric
Time-related factors and seasonality	Weekday or weekend	Dummy
	Month	Dummy
Market demand and competition	Number of arrivals in locality	Discrete numeric
	Prices of concurrent accommodation units in the vicinity	Continuous numeric

CONCLUSIONS

In conclusion, hedonic pricing models are valuable for assessing the impact of product or service characteristics on pricing in rural tourism. The review highlighted different estimation methodologies, recommended automated data scraping procedures, and suggested additional variables for investigation. The findings inform decision-making for stakeholders and emphasize the advantages and limitations of hedonic price models. Multiple linear regression, geographically weighted regression, and structural equation modeling were discussed as common analysis methods.

Key independent variables, including spatial dimension, accommodation features, service quality, accessibility, surrounding environment, temporal factors, and market demand, were identified. This study contributes to the literature on hedonic pricing in rural tourism, guiding future research and promoting sustainable development.

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