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Machine Learning for short-term property rental pricing based on seasonality and proximity to food establishments

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Abstract

Purpose – Short-term rentals (STRs) (like Airbnb) are reshaping social behaviour, notably in gastronomy, altering how people dine while travelling. This study delves into revenue management, examining the impact of seasonality and dining options near guests' Airbnb. Machine Learning analysis of Airbnb data suggests owners enhance revenue strategies by adjusting prices seasonally, taking nearby food amenities into account.

Design/methodology/approach – This study analysed 220 Airbnb establishments from Madrid, Spain, using consistent monthly price data from Seetransparent and environment variables from MapInfo GIS. The Machine Learning algorithm calculated average prices, determined seasonal prices, applied factor analysis to categorise months and used cluster analysis to identify tourism-dwelling typologies with similar seasonal behaviour, considering nearby supermarkets/restaurants by factors such as proximity and availability of food options.

Findings – The findings reveal seasonal variations in three groups, using Machine Learning to improve revenue management: Group 1 has strong autumn-winter patterns and fewer restaurants; Group 2 shows higher spring seasonality, likely catering to tourists, and has more restaurants, while Group 3 has year-round stability, fewer supermarkets and active shops, potentially affecting local restaurant dynamics. Food establishments in these groups may need to adapt their strategies accordingly to capitalise on these seasonal trends.

Originality/value – Current literature lacks information on how seasonality, rental housing and proximity to amenities are interconnected. The originality of this study is to fill this gap by enhancing the STR price predictive model through a Machine Learning study. By examining seasonal trends, rental housing dynamics, and the proximity of supermarkets and restaurants to STR properties, the research enhances our understanding and predictions of STR price fluctuations, particularly in relation to the availability and demand for food options.

Keywords Seasonality, Dynamic prices, Machine Learning, Short-term rentals, Food establishments

Paper type Research paper

1. Introduction

The short-term rental (STR) market has experienced significant growth in the last decade. This growth has been mainly driven by online platforms, such as *Airbnb*, providing, among other features, the opportunity for households to offer accommodation to visitors

(Koster *et al.*, 2021). Simancas-Cruz *et al.* (2021) also state that the tourism industry and urban space have increased worldwide due to STR and the development of peer-to-peer (P2P) accommodation platforms. This growth in STRs has led to greater competition among owners, therefore, making it difficult to optimise pricing strategies and maximise income.

This competition brings to light a deeper study designed to help owners and professionals better understand the variation of dynamic prices for STRs by analysing variables such as seasonality or the proximity of properties to leisure activities, such as restaurants, food establishments or the urban renewal that results from this boost in the tourism industry (Simancas-Cruz *et al.*, 2021).

To address this challenge, researchers have turned to Machine Learning algorithms to help property owners better understand seasonal trends and dynamic pricing. Casamatta *et al.* (2022), using ordinary least squares (OLS) and double Machine Learning techniques, prove that there is a price difference between professional and opportunistic sellers within the STR market. In this sense, the problem statement studied in this paper explores and contributes to how Machine Learning algorithms can be used to optimise revenue management strategies in the *Airbnb* market, considering the presence and influence of nearby food establishments.

This paper is built on previous investigations that have explored the use of Machine Learning algorithms in revenue management strategies. Other researchers have used Machine Learning algorithms to forecast tourism demand (Zhang *et al.*, 2020) and optimise pricing strategies for ridesharing services (Song *et al.*, 2020). However, there are fewer studies focused specifically on the STR markets located near supermarkets and restaurants, which are pivotal factors influencing consumer decisions, especially with regard to food choices.

The central argument and context framing the question of this research relates to a Machine Learning algorithm that involves calculating average prices for tourism apartments in Madrid over 24 months. In calculating specific seasonal prices for each apartment, we applied factor analysis (FA) to define three groups of months (autumn-winter, spring and summer) and implemented cluster analysis to outline typologies of STR apartments, then cross-checked this data with nearby supermarket/restaurant variables with homogeneous seasonal behaviour, thus, helping to identify these groups and variables.

As STR platforms continue to spread, they generate an effect on the local economy. Hidalgo *et al.* (2024) underscore how STR guests prefer to stay and consume near their accommodation, going to restaurants and cafes in the immediate vicinity, in addition to visiting other small retail shops. They consider that since STRs are spread throughout the city, unlike traditional accommodation, the benefits of tourist activities can thus extend beyond traditional tourist areas. According to these authors, the emergence of *Airbnb* has promoted food and drink establishments in Madrid. As an example, they state that an increase of 10 *Airbnb* rooms in a given area can translate into the creation of one additional restaurant, and Basuroy *et al.* (2020) calculated an increase of 12% in restaurant income due to these types of apartments in the area.

The findings of this paper give theoretical, empirical and methodological insights with an interdisciplinary approach, with implications for property owners looking to optimise their revenue management strategies in the face of seasonality and dynamic pricing, as well as in light of the presence and influence of neighbouring grocery stores and dining establishments. By using Machine Learning algorithms to better understand seasonal trends and group properties with similar seasonal behaviour, property owners can make more informed pricing decisions that maximise revenue while remaining competitive.

In the past decade many studies have focused on STRs, addressing, for example, the situation and development in 167 countries of this type of rental (Adamiak, 2022), the price strategy regarding seasonality (Aznar *et al.*, 2018), perceived market power (Casamatta *et al.*, 2022), dynamic pricing (Gibbs *et al.*, 2018) and factors affecting rental prices, such as restaurants and supermarkets (Basuroy *et al.*, 2020; de Jaureguizar Cervera *et al.*, 2022; Hidalgo *et al.*, 2024). This study aims to bridge the existing gap in the literature by exploring the impact of seasonality and proximity to restaurants and nearby leisure activities on consumer behaviour. By integrating these two approaches within the same study, we can gain a comprehensive understanding of how factors like food availability and recreational options influence individuals' choices and preferences.

The main goal of this research is to analyse the price dynamics in *Airbnb* tourist apartments, by gauging whether seasonal variables or the proximity of supermarkets and restaurants influence them. We also categorise months into groups and cluster apartments by type. This results in the formulation of several hypotheses, including (1) whether there are variations in the average price of tourist apartments during a year; (2) whether there are specific seasonal price patterns with large fluctuations or stability; (3) how can we group them into three seasonal categories that reveal associations between tourist apartment characteristics and environment variables, including food availability, or by behavioural group; and (4) the behaviour analysis of this grouping.

2. Literature review

In this study, we have analysed the relationship between the seasonality, the proximity and the price of STRs, suggesting clusters of different characteristics of the asset and generating a model of this evolution. The results of companies will be optimised through digitisation, aligned with Saura *et al.* (2023), who state that the internal structure and organisation of companies have changed to evolve towards a digital environment influenced by internet business models and digital marketing (DM) techniques.

Several factors may arise which affect this seasonality, hiring trends, study terms, bank holidays, economical fluctuation in the family, business fairs or events and others. However, the impact studies in the literature do not accurately assess the relevant relationships with nearby stakeholders in the area (Wang *et al.*, 2020). In this sense, there are different variables, such as the location, proximity and influence exerted by neighbouring grocery stores and eateries; the size of the apartment or the distance from the centre are also relevant variables when users choose accommodation (Sainaghi *et al.*, 2021; Tong and Gunter, 2022; Yilmaz *et al.*, 2022).

The aim of this paper is a Machine Learning study, focusing on how the seasonality and the proximity of supermarkets and restaurants affect this type of STRs.

2.1 Dynamic price trends: examining fluctuations in STR apartments

Tourism is a vital component of Madrid's economy, and understanding the dynamic factors influencing the pricing of STRs is of paramount importance for both property owners and policymakers. The scientific literature establishes differences between STR and long-term rental (LTR), as do Shabrina and Morphet (2022), who compare STR and LTR price patterns. They conclude that: "STR prices tend to be higher overall with an indication of higher volatility (less stability) compared to LTR; there is statistical evidence supporting the arguments that STR and LTR markets are indeed in competition; STR pattern with a characteristic that higher-priced short-term properties are found to be geographically concentrated in the core city areas and those surrounding residential areas with easy access to popular tourist attractions (among others, supermarkets and restaurants)."

In this sense, research in tourism economics, exemplified by Sánchez-Pérez *et al.* (2019), has observed fluctuations in tourism apartment prices over time, bolstering the anticipation of substantial variations. Regarding dynamic pricing, Abrate *et al.* (2019) point out that it involves the strategic use of price fluctuations across various time intervals within the booking horizon. This pricing strategy has garnered substantial recognition within the STR and LTR accommodation platforms of the sharing economy, as underscored by Oskam *et al.* (2018), and Xie and Kwok (2017). Essentially, dynamic pricing empowers hosts to promptly adapt their rates in response to a multitude of influential factors. This data-driven methodology equips hosts with the means to efficiently optimise the revenue potential of their rental properties in real-time.

Focusing on STR, heuristic rules can be a practical solution if a decision-maker wants to set the dynamic price of a new product or of a product whose past price variation is low (i.e. STR property), and budget limitations prevent the use of marketing experiments or customer surveys (Gahler and Hruschka, 2022). However, dynamic prices in STRs have been frequently updated with automated models, depending on changing supply/demand conditions; these changes are consistent across customers (Abrate *et al.*, 2019). Hence, Adamiak's (2022) findings regarding the dynamics of *Airbnb*'s platform usage and the geographical variations in its supply and impact are highly relevant when considering the implementation of dynamic pricing strategies, showing that the *Airbnb* platform is most commonly used to rent entire apartments by multi-hosts. Adamiak adjusts a dynamic pricing method with the cost of a product or service in real-time, based on various factors, including demand, supply and different location patterns (the proximity of commercial services, such as supermarkets and restaurants).

Dynamic pricing of STRs offers a valuable way to set prices efficiently, especially when budget limitations hinder extensive marketing research. Dynamic pricing enables property owners and managers to optimise revenue by adjusting prices in response to market changes, ensuring competitiveness and profitability while reducing the need for costly and time-consuming research.

2.2 Monthly pricing by season for STR apartments

Seasonality plays a pivotal role in shaping pricing dynamics and performance disparities among STRs, as noted by various researchers. Several authors (Aznar *et al.*, 2018; Magno *et al.*, 2018; Falk *et al.*, 2019; Sainaghi *et al.*, 2021; Casamatta *et al.*, 2022; Yilmaz *et al.*, 2022; Alrawabdeh, 2022) consider seasonality one of the most important factors explaining price and performance differentials among *Airbnb* properties. They find that during the summer or peak season, for example, when school starts, a higher degree of market power is more probable, impacting pricing and performance within the *Airbnb* market.

Deboosere *et al.* (2019) and Casamatta *et al.* (2022) have specifically investigated the impact of seasonality on nightly prices and revenue for *Airbnb* listings in New York. They discovered that hosts adjust their prices according to the holiday calendar and seasonal demand, meaning they often charge higher rates during long summer holidays, compared to shorter winter holidays. Casamatta *et al.* (2022) further examined how demand seasonality affects price differentials between professional hosts and opportunistic homeowners. They found that professionals tend to have a greater degree of market power during peak seasons, which allows them to enhance their earnings.

However, it is important to note that not all *Airbnb* hosts respond to seasonal fluctuations in the same way. Some hosts do not practice dynamic pricing, which means they miss out on revenue opportunities. Hosts who do adjust their prices more frequently, both upward and downward, tend to improve the revenue performance of their listings (Li *et al.*, 2016; Chen and Xie, 2017; Gibbs *et al.*, 2018; Oskam *et al.*, 2018; Kwok and Xie, 2019; Casamatta *et al.*, 2022).

By frequently adjusting prices upwards during peak periods, hosts capitalise on increased demand and are able to optimise their earnings. Similarly, during off-peak times or to attract budget-conscious travellers, they employ downward price adjustments to maintain high occupancy rates.

Overall, these studies emphasise the importance of seasonality as a significant feature in shaping STR property pricing and performance, as well as the varying strategies adopted by hosts to respond to seasonal demand fluctuations, echoing Mazanec *et al.*'s (2010) comprehensive exploration of FA in revealing patterns within tourism time-series data. Conversely, D'Urso *et al.* (2021) have refined the use of cluster analysis within the tourism domain, demonstrating its efficacy in categorising entities according to a range of characteristics.

2.3 Proximity of food establishments as another factor influencing STR pricing

In addition to seasonality, other variables such as proximity to amenities like swimming pools, parking, supermarkets, restaurants and the size of accommodations in square metres (m^2) have also been identified as important factors in STR and *Airbnb* property pricing (Coenders *et al.*, 2003; Espinet *et al.*, 2003; Rigall *et al.*, 2011; Voltes-Dorta and Sánchez-Medina, 2020; Santos *et al.*, 2021). Collectively, these studies contribute to a comprehensive understanding of the diverse factors shaping pricing behaviour in the rental property market, emphasising the need for stakeholders to consider a broad spectrum of variables beyond seasonal fluctuations. A study conducted by Coenders *et al.* (2003) and Espinet *et al.* (2003) emphasises the importance of amenities in property pricing. Amenities encompass a wide range of features and services, including the availability of swimming pools, parking facilities, nearby supermarkets, restaurants and other recreational areas. Proximity to these amenities can significantly impact a property's desirability and, consequently, its price. For example, an *Airbnb* property with a swimming pool or convenient access to supermarkets and restaurants may command higher prices due to the added convenience and appeal it offers to potential guests.

Similarly, Rigall *et al.* (2011) investigated the effects of beach characteristics and location on hotel prices. Likewise, the location of a given STR, on the beachfront or near a popular tourist destination, for example, can significantly impact its pricing. In this context, the proximity of supermarkets and restaurants can be a critical aspect of location. Rentals near such amenities may be priced higher due to the added convenience they offer guests.

Moreover, Santos *et al.* (2021) developed valuation models for daily holiday rates for STRs. The composition of rental prices was based on factors that influence booking rates. Proximity to supermarkets and restaurants can be a key component of these factors. Guests often prefer accommodations with easy access to dining options and shopping facilities, and property owners may consider this when setting rental prices.

Collectively, these studies demonstrate that STR property pricing is a complex interplay of several factors, extending beyond seasonality. Hosts and property owners must consider variables such as proximity to amenities, supermarkets, restaurants and other location-specific attributes to effectively set competitive prices in the dynamic STR marketplace. Understanding how these factors influence pricing can be pivotal for both maximising returns and enhancing the overall guest experience.

Nevertheless, the literature on seasonality and rental housing, specifically in relation to proximity to supermarkets and restaurants, is still very narrow. This indicates a gap in existing research and a need for further investigation, as literature reviews are a critical part of scientific research (Kraus *et al.*, 2022). By conducting research in this area, we help bridge the knowledge gap and expand our understanding of the relationship between pricing, seasonality, rental housing and amenities like supermarkets and restaurants.

2.4 Machine Learning for pricing STR apartments: unravelling seasonal patterns and proximity factors

The application of Machine Learning models provides companies with a distinct advantage, enabling them to achieve superior price optimisation compared to traditional models. In this sense, a diverse set of modelling techniques, spanning from traditional linear regression to advanced tree-based models, Support Vector Regression (SVR), K-means Clustering (KMC) and neural networks (NN), following the methodology presented by Rezazadeh (2020), have served as crucial Machine Learning elements to predict the outcome of sales opportunities. This is a more concrete and accurate approach than a salesperson's subjective predictions, and it can be applied effectively in the context of STRs and the tourism industry in general.

As demonstrated by Moreno-Izquierdo *et al.* (2018), the use of NN and Machine Learning in the estimation process yields notably more satisfactory results than conventional hedonic models, based on their extensive study of over 10,000 *Airbnb* properties. Priambodo and Sihabuddin (2020) underscore the advantages of Extreme Learning Machine (ELM), including its exceptional generalisation performance, rapid learning speed and high prediction accuracy. Building on this, Ghosh *et al.* (2023a) present a comprehensive Artificial Intelligence-based framework for predicting *Airbnb* listing prices. Their research outcomes emphasise three key aspects: prediction accuracy, homogeneity and the identification of the best and least predictable cities. Hosts can leverage this framework to set rental prices effectively and enhance their service offerings by emphasising key features.

Furthermore, Ghosh *et al.* (2023b) introduce the concept of explainable Machine Learning as an emerging field to provide deeper insights into predictive modelling and to interpret the influence of explanatory features on rental prices at specific locations. In a related study, Garay-Tamajon *et al.* (2022) employed KMC and Machine Learning to investigate the correlation between the concentration of *Airbnb* listings in "highly touristified" and "trendy" neighbourhoods and the corresponding increase in rental prices in these areas.

Building upon the factors discussed earlier, this study endeavours to enhance the predictive model for STR prices by integrating seasonal trends and data related to the proximity of supermarkets and restaurants within a specific radius of these STR properties. This expansion is designed to encompass essential insights that have the potential to significantly elevate the precision of STR price forecasts. Hence, the aim is to contribute to the expanding realm of knowledge within the field of STR apartment pricing. This approach involves harnessing state-of-the-art Machine Learning techniques and delving into the influence of diverse factors (seasonality and proximity of supermarkets and restaurants) on rental prices.

2.5 Research objective and hypotheses of this study

After thoroughly examining the literature in Section 2, this final subsection presents the research objective and hypotheses guiding this study.

The research objective of this study is to analyse the pricing dynamics of *Airbnb* tourism apartments in Madrid, identifying seasonal variations, categorising months into groups and clustering apartments to define typologies while considering nearby supermarket and restaurant variables with homogeneous seasonal behaviour. Through this comprehensive analysis, we endeavour to shed light on the complex interplay of factors shaping pricing strategies in the *Airbnb* sector, particularly in a bustling tourist destination like Madrid.

The following hypotheses serve as guiding principles, allowing us to systematically test and validate our insights, thereby contributing to a deeper understanding of the dynamics driving the *Airbnb* market in Madrid and potentially offering valuable insights for stakeholders in the tourism and hospitality sectors.

H1. There will be significant variations in the average prices of tourism apartments in Madrid over the 24-month period from January 2021 to December 2022.

To support the expectation of significant variations in tourism apartment prices, studies in the field of tourism economics, such as Sánchez-Pérez *et al.* (2019), have documented price fluctuations in the tourism accommodation sector over time.

H2. Specific seasonal pricing patterns will be observed for each apartment, with some apartments exhibiting significant monthly price fluctuations while others remain relatively stable.

To demonstrate the existence of specific seasonal pricing patterns in the tourism industry, Alrawabdeh (2022) highlights that different international and local hotels may exhibit varying price fluctuations throughout the year.

H3. FA will reveal three distinct seasonal groups of months (autumn-winter, spring and summer) based on tourism apartment pricing behaviour.

For the use of FA, the work of Mazanec *et al.* (2010) extensively discusses the application of FA in uncovering patterns and structures in time-series data in tourism.

H4. Cluster analysis will successfully group tourism apartments into typologies with homogeneous seasonal pricing patterns within the three defined groups of months.

To support the use of cluster analysis, the work of D'Urso *et al.* (2021) revises the application of cluster analysis techniques in the tourism field to categorise entities based on various characteristics.

H5. The profile analysis of each cluster will reveal associations between tourism apartment characteristics and environment variables such as proximity to supermarkets and restaurants, providing insights into the factors influencing pricing behaviour across the different typologies of apartments.

Regarding associations between apartment characteristics, environment variables and pricing behaviour, research by Voltes-Dorta and Sánchez-Medina (2020) on *Airbnb* discusses how environmental factors can influence pricing decisions in the real estate and hospitality industries.

3. Methodology

The majority of tourism seasonality research has concentrated on analysing tourism demand, with much less attention paid to examining tourism pricing. Nonetheless, it is reasonable to consider that there exists a correlation between tourism demand and pricing. To fill this gap, data obtained from several databases has been used to focus on the seasonality of prices in STR apartments in Madrid.

The methodology applied for this study is based on Machine Learning, FA and cluster analysis for dynamic pricing as a data-driven approach, given the existence and sway of environment variables (such as supermarkets and restaurants). Cluster analysis is a type of unsupervised Machine Learning technique that involves grouping similar data points (dynamic prices of assets grouped previously by FA in three categories of months) into clusters based on their features or characteristics (environment variables) to identify patterns or structures in the data (seasonal prices), without any prior knowledge of the data labels or categories. In particular, the proposed Machine Learning algorithm of this research has been divided into the following steps:

(1) Average prices have been calculated for 220 tourism apartments in Madrid for 24 months: from January 2021 to December 2022

(2) For every apartment, the specific seasonal price has been calculated month by month. The results show places with strong variations depending on the month and others that hardly vary.

(3) A FA has been applied to define three groups of months.

- Autumn-winter
- Spring
- Summer

(4) Cluster analysis has been implemented to define typologies of STR apartments with homogeneous seasonal behaviour in the three groups of months mentioned in point 3.

(5) A cluster solution of 3 groups has been proposed.

(6) Profile analysis of each cluster has been assessed (characteristics of the tourism apartments cross-checked with environment variables, among them supermarkets and restaurants)

Thus, two Machine Learning algorithms, FA and KMC, were applied in this study. FA is one of the unsupervised Machine Learning algorithms which is used for dimensionality reduction. This algorithm creates factors from the observed variables to represent the common variance, i.e. variance due to correlation among the observed variables. On the other hand, clustering is an unsupervised Machine Learning method of identifying and grouping similar data points in larger datasets without concern for the specific outcome. Clustering or cluster analysis is usually used to classify data into structures that are more easily understood.

3.1 Sampling procedure and database analysis

From the *Airbnb* file, the premises of the Autonomous Community of Madrid, where the average rental prices are known for 24 months: from January 2021 to December 2022, generate a database for analysis with $N = 220$ records. Each record includes:

(1) The average daily rental prices associated with each of the months.

(2) The specific (internal) characteristics of the premises: (number of rooms, capacity, minimum stay, etc.).

A sample of 220 establishments was carefully selected due to their consistent provision of monthly price data for *Airbnb* listings within *Seetransparent*, a technological database containing information about *Airbnb* apartments in the city of Madrid. This sample encompasses 1,063 apartments spanning from January 2021 to December 2022. The remaining 843 *Airbnb* apartments were excluded from this sample selection as they lacked complete monthly price information.

A recent study (Moreno-Izquierdo *et al.*, 2023) collected *Airbnb* price data from Madrid and Valencia over three years from 2018 to 2020 during specific months (May to September), from which we glean an understanding of the effects of the coronavirus disease 2019 (COVID-19) pandemic on tourism. In this research, the 2021–2022 sample reflects a post-pandemic period, providing insights into the recovery and any lasting effects. By examining the pre-pandemic (2018 and 2019) and pandemic (2020) data alongside the post-pandemic (2021 and 2022) data, researchers can draw meaningful conclusions about evolving price trends and the specific impact of COVID-19 on the tourism industry in general, and *Airbnb* apartments in particular.

The *Airbnb* file also provides the coordinates of each location. Through the *MapInfo GIS program*, geolocation has been used to associate the data of each premises with their surroundings (radius of 1,000 metres), such as supermarkets, restaurants and other environment variables, such as the socioeconomic level of the area, percentage of secondary residences, commercial and cultural amenities, etc.

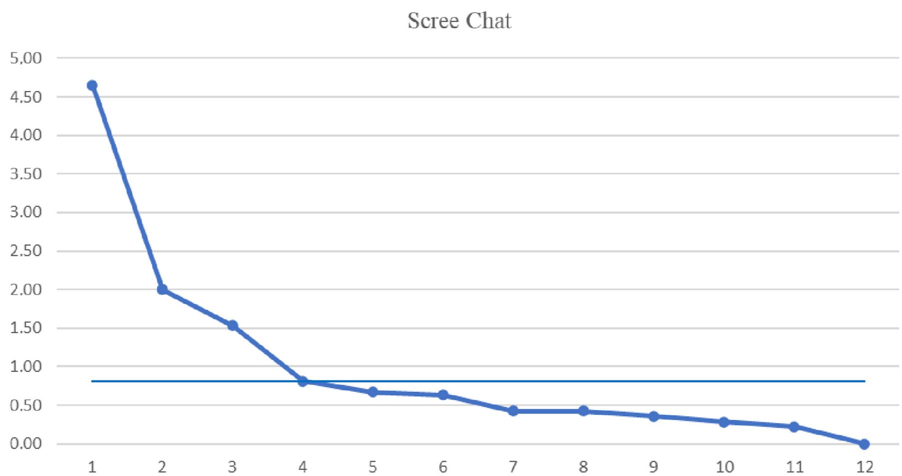
3.2 Seasonality analysis (months) and seasonal season determination

A comprehensive seasonality analysis has been executed. This thorough examination serves as a critical component in understanding patterns and fluctuations within the data. For each of the apartments, the specific seasonal value has been calculated month by month, noting that there are apartments with strong variations depending on the month and others that hardly vary. These specific seasonal values have been integrated into the database as new variables.

Furthermore, to determine if there are seasonal seasons, an exploratory FA has been carried out using the specific monthly seasonal values. Once the suitability of the correlation matrix was verified (KMO = 0.786 and simple random sampling adequacy measures greater than 0.7 in all variables), the sedimentation chart (see Figure 1) was used (to determine the three-factor solution as suitable).

In multivariate statistics, Figure 1 shows a sedimentation chart (or scree plot) that is a line graph of the eigenvalues of the principal factors or components in an analysis (Lewith *et al.*, 2010). The scree plot is used to determine the number of factors to retain in an exploratory FA or principal components to retain in a principal component analysis (PCA). The procedure of finding statistically significant factors or components using a scree plot is also known as the scree test (Cattell introduced it in 1966).

The three-factor solution explains 68.2% of the variance and has allowed us to identify three seasons:



Source(s): Authors

Figure 1.
Sedimentation chart

(1) Autumn-winter (October to February)

(2) Spring (March to June)

(3) Summer (July to September)

The specific seasonal values of the seasons were calculated for each location as the mean of the seasonal values of the months included in each one. These were then integrated into the analysis database as new variables.

3.3 Typologies of listings according to their seasonality and descriptive analysis of the clusters

To identify types of apartments based on their seasonal behaviour, a k-means cluster analysis has been carried out using the seasonal values of the three seasons as grouping variables.

Solutions of 2, 3 and 4 groups have been analysed, finally selecting the one with 3 groups as it is the one that generates the most robust results:

(1) The three groups have significantly different seasonality indicators (ANOVA analysis), both in the three seasons and in each of the 12 months.

(2) Carrying out a discriminant analysis with affiliation to the groups as a dependent variable and seasonality by seasons as independent variables, obtaining that 97.3% of the cases are correctly classified.

Finally, we have delved into a descriptive analysis of the distinctive traits defining each cluster of apartments. This scrutiny encompasses both internal features, including room count, capacity and minimum stay requirements, as well as external factors within a 1,000-m radius. These external considerations range from the presence of supermarkets and restaurants to the socioeconomic fabric of the area, including the proportion of secondary residences and the availability of commercial and cultural amenities.

3.4 Algorithm formula applied in this study

This section underscores the robust foundation upon which the study stands, fortifying its connection to well-established concepts and setting the stage for the development of the subsequent algorithmic formulation. Through the integration of references to cited authors and relevant studies in the literature review within the hypotheses outlined in section 2.5, the theoretical framework of the methodology is solidified. Hence, the proposed formula is:

$$R(P, M, F, A, E) = H1(P) + H2(M) + H3(F) + H4(A) + H5(E)$$

Where:

R represents the research objective.

P represents the monthly price data.

M represents the monthly price fluctuations for each apartment.

F represents the apartments' FA for seasonal groups of months.

A represents the apartment data for clustering.

E represents environment variables (nearby supermarkets and restaurants) and apartment characteristics (bathrooms, bedrooms, beds, capacity and minimum stay).

H1, H2, H3, H4 and H5 are the specific research hypotheses.

4. Findings

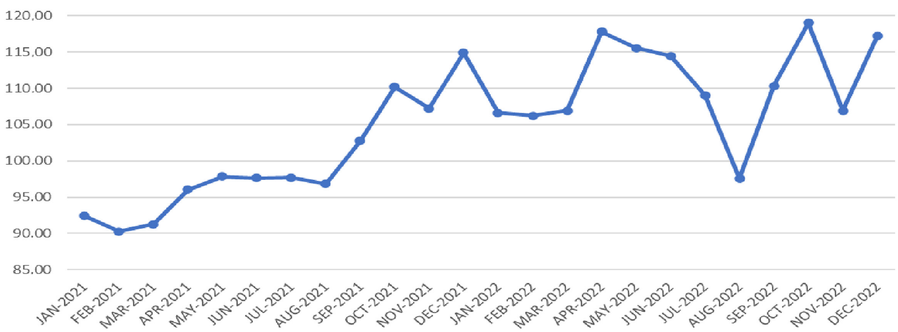
4.1 Seasonality analysis (months)

Figure 2 illustrates the listing average price over 2021 and 2022. The line represents the average price, which is calculated by summing up the prices for every day and dividing by the number of days for each month. By observing the direction of the line, prices have risen from January 2021 (92€) to December 2022 (117€). It shows how the average price has changed over time, highlighting whether prices have generally increased, decreased or remained relatively stable.

Figure 3 depicts the seasonality graph for the pattern of price fluctuations over 2022 within the short-term property rentals, based on the 2021–2022 average annual price. It illustrates how prices tend to vary in a recurring manner based on the season. In December prices are 9% higher than the annual average price. In August, prices are 6% lower than the annual average price. However, this behaviour is not homogeneous; therefore, typologies will be developed in the following sections.

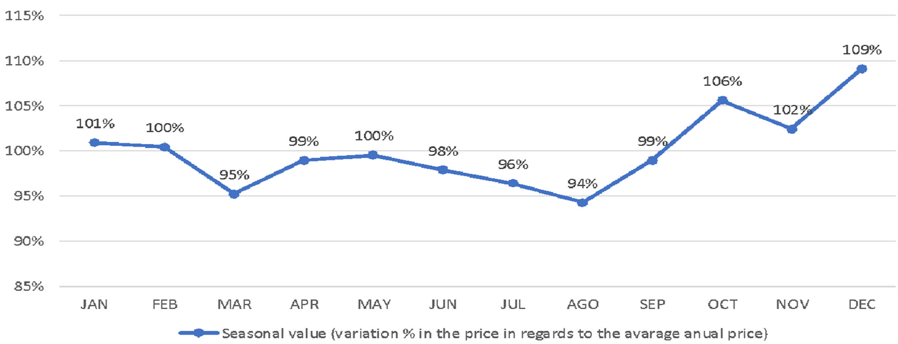
4.2 Seasonal season determination

Table 1 shows the seasonal season determination of 2021–2022 by an Exploratory Factor Analysis using the specific monthly seasonal values. The extracted factors have been examined by the factor loadings. Variables with high loadings on a factor (more than 0.5,



Source(s): Authors

Figure 2.
Average prices through 2021–2022



Source(s): Authors

Figure 3.
Seasonal values (variation % in the price with regards to the average annual price)

Table 1.
Seasonal season determination of 2021–2022 (exploratory factor analysis)

Components matrix without rotation	Component 1	Component 2
Seasonality_DEC	0.778	0.114
Seasonality_NOV	0.751	0.214
Seasonality_JAN	0.647	−0.232
Seasonality_FEB	0.553	−0.295
Seasonality_OCT	0.535	0.336
Seasonality_SEP	0.227	0.668
Seasonality_AUG	0.143	0.687
Seasonality_JUL	−0.266	0.596
Seasonality_JUN	−0.722	−0.017
Seasonality_MAR	−0.750	−0.289
Seasonality_MAY	−0.761	0.057
Seasonality_APR	−0.778	−0.065

Extraction method: Main components analysis for 2 extracted components
Source(s): Authors

positive or negative) are strongly associated with that factor. Three labels can be identified that capture the essence of the underlying seasonal patterns:

(1) First: October, November, December, January and February (Component 1, positive values)

(2) Second: March, April, May and June (Component 1, negative values)

(3) Third: July August and September (Component 2, positive values)

The Exploratory Factor Analysis has identified the underlying factors or dimensions and determined the occurrence and characteristics of seasons in 2021–2022. By examining these loadings, we can determine which variables are more strongly associated with each season or factor and assign three appropriate names to each factor, such as in Table 2:

(1) Group 1: Autumn-winter

(2) Group 2: Spring

(3) Group 3: Summer

4.3 Typologies of the listings according to their seasonality

A K-means cluster analysis was conducted to classify listings into different typologies according to their seasonal behaviour in 2021–2022, using the seasonal values of the three seasons as variables for grouping. After analysing solutions with 2, 3 and 4 groups, the option with 3 groups was chosen due to its ability to produce the most reliable results. Regarding

Table 2.
Seasonal season determination of 2021–2022 (factor analysis)

Factor analysis was useful in suggesting a monthly cluster coherent with the asset behaviour

Group 1	OCT	NOV	DEC	JAN	FEB	Autumn- Winter
Group 2	MAR	APR	MAY	JUN		Spring
Group 3	JUL	AUG	SEP			Summer

Source(s): Authors

percentage, the results show 16% of the listing total in cluster 1, 29% in cluster 2, and 55% in cluster 3 (see Table 3).

The three groups exhibit distinct seasonal indicators in 2021–2022, as confirmed by both ANOVA analysis for the three seasons and individual months within each season. When determining the statistical significance of the centre values of the final clusters, ANOVA statistical tests were conducted to assess whether the observed differences between the groups' seasonal indicators were statistically significant or occurred by chance. It can be determined there are significant differences in the means of the seasonal indicators between the three groups. By comparing the variation between the groups to the variation within the groups, ANOVA calculates the internal reliability of the observed differences in seasonal indicators among the clusters and confirms whether the three groups indeed have significantly different seasonality patterns as follows (see Table 4):

(1) Group 1: Strong seasonality in autumn-winter (seasonal indicator is 1.2, in navy blue)

(2) Group 2: Higher seasonality in spring (seasonal indicator is 1.08, in blue sky)

(3) Group 3: Moderate seasonality (seasonal indicator is 0.98, in green). The prices hardly change

To calculate the seasonal indicators of each cluster by month in the 2021–2022 period, data have been grouped by clusters obtaining the average prices for each month within each season. Based on the filtered dataset, Figure 4 shows the highest seasonal indicators recorded during the winter months for Group 1, that is, October, November, December, January and February (as mentioned in Table 4, statistically significant centre values for Group 1 are around 1.2). In the case of Group 2, the highest seasonal indicators recorded correspond to the spring months, that is, March, April, May and June (as mentioned in Table 4, statistically significant centre values for Group 2 are around 1.08). And for Group 3, seasonal indicators are largely stable, predominantly in July, August and September with some slight

Table 3. Typologies according to their seasonal behaviour in 2021–2022 (cluster analysis)

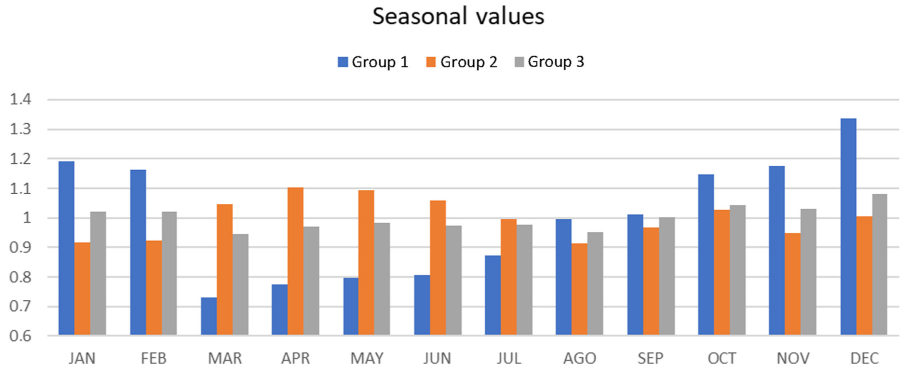
Number of cases per cluster			
Cluster	1	36	16%
	2	64	29%
	3	120	55%
Valid		220	100%
Lost		0	

Source(s): Authors

Table 4. Seasonality patterns (cluster analysis)

Final clusters core	Cluster 1	2	3
Seasonality_autumn-winter	1.2	0.96	1.04
Seasonality_spring	0.78	1.08	0.97
Seasonality_summer	0.96	0.96	0.98
Group 1	High seasonality in autumn-winter		
Group 2	Higher prices in spring		
Group 3	Moderate seasonality (prices barely change)		

Source(s): Authors



Source(s): Authors

Figure 4. Seasonal values of each cluster

fluctuations in other specific months (as mentioned in Table 4, statistically significant centre values for Group 3 are around 0.98).

4.4 Descriptive analysis of the clusters

To conduct a descriptive analysis of the three clusters, the *Airbnb* database (the coordinates of each location for each listing) has been crossed with the MapInfo GIS program (environment variables in the surroundings of each dwelling). Geolocation techniques have been used to associate environment and equipment characteristic data from their surroundings with each dwelling (radius of 1,000 metres), such as supermarkets, restaurants, socioeconomic level of the area, percentage of secondary residences, commercial, cultural equipment, number of bathrooms, number of beds, etc. Table 5 and Table 6 analyse both characteristics, Table 5 analyses environment issues and Table 6 analyses equipment issues.

	Total	Cluster 3 groups: Cluster 1 of 3	Cluster 2 of 3	Cluster 3 of 3
N (cases)	220	36	64	120
Environment characteristics (radio 500 m.)				
Socioeconomic level (0–10)	6.55	6.48	6.40	6.65
Seasonality of residents: % of secondary homes (over/ total homes)	13%	11%	15%	13%
No. of active shops × 1,000 inhabitants	81.89	64.87	84.81	85.47
No. of active offices × 1,000 inhabitants	56.81	36.65	66.92	57.40
No. of supermarkets (and hypermarkets)	2.92	3.63	2.83	2.75
No. Restaurants/bars/coffee	177.69	124.63	216.25	172.71
No. of hotels, pensions	7.69	5.23	9.24	7.59
No. of train/bus stations	1.90	1.77	2.05	1.85
No. of suburban stations	4.77	4.06	5.21	4.74
Universities	0.01	0.00	0.02	0.01
Number of premises dedicated to shows	10.41	7.54	12.48	10.16
No. of clothing stores	4.16	2.86	4.78	4.22

Source(s): Authors

Table 5. Descriptive analysis of the clusters (according to the environment characteristics)

(1) Group 1: This cluster with strong seasonality in autumn-winter is located in areas of Madrid with more supermarkets/less restaurants (3.63/124.63) than Group 2 (2.83/216.25) and 3 (2.75/172.71). It has the smallest relation in the number of beds.

(2) Group 2: This cluster with higher seasonality in spring is in areas of Madrid with the largest quantity of restaurants (216.25), active offices, and trains, and seems to have the largest number of hotels, which suggests a more seasonal or touristic area.

(3) Group 3: This cluster with moderate seasonality all-the-year-round is located in areas of Madrid with the lower number of supermarkets (2.75), the highest socioeconomic level and the largest quantity of active shops. It can be also observed how this cluster is not only the most stable in price but also the largest among the three in the average number of overnight stays.

5. Discussion

We maintain that STR pricing is affected by the proximity of restaurants and supermarkets, as per this paper. Whereas Voltes-Dorta and Sánchez-Medina (2020) discuss how environmental factors affect the price, other authors, such as Hidalgo *et al.* (2024), highlight how guests prefer to consume near their accommodation, extending the benefits of the tourism market to other areas, finding that an increase of 10 *Airbnb* rooms translates into the creation of one new restaurant. Meanwhile, in calculating the impact of this type of accommodation, Basuroy *et al.* (2020) estimate an increase of 12% in the restaurant income. de Jaureguizar Cervera *et al.* (2022) study the influence of pricing on different aspects that may affect the price of the listing, such as the proximity of supermarkets and restaurants, relevant factors that affect prices considerably.

The distribution and characteristics of listings suggest that Group 1 is more likely situated in residential areas with more supermarkets and fewer restaurants, such as Chamartin and Moratalaz. These districts have a mix of middle-to upper-class neighbourhoods, with a variety of food shops and services catering to different socioeconomic levels. Whereas Group 2 seems to be located in very touristy, centrally located areas with plenty of restaurants, as well as in business centres. These are commercial districts or zones within the city that are known for their vibrant business activities. Examples include downtown areas, shopping districts or areas with popular markets, such as Retiro, Salamanca and Justicia, which have a similar outcome, as suggested by Soler-García and Gémar-Castillo (2017), who defend that the proximity to a historic city centre with an abundance of dining options has a great impact on revenue.

	Total	Cluster 1 of 3	Cluster 3 groups Cluster 2 of 3	Cluster 3 of 3
N (cases)	220	36	64	120
Apartment characteristics (equipment)				
Num. bathrooms	1.24	1.17	1.23	1.27
Num. bedrooms	1.36	1.22	1.33	1.42
Num. beds	2.09	1.39	2.28	2.20
Capacity (pax)	3.82	3.67	3.81	3.87
Min stay (days)	4.95	4.14	4.38	5.49

Source(s): Authors

Table 6.
Descriptive analysis of the clusters (according to the equipment characteristics)

We maintain that seasonality and rental housing affect the daily price of listings. Also, to better understand and analyse this seasonality, we propose grouping the listings into clusters of similar behaviour; D'Urso *et al.* (2021) defend this technique in analysing the tourism field based on various characteristics. A seasonality observed specially in Group 1 as well as in Group 2, aligned with Aznar *et al.* (2018), Magno *et al.* (2018), Falk *et al.* (2019), Sainaghi *et al.* (2021), Casamatta *et al.* (2022) and Yilmaz *et al.* (2022), who consider certain seasons with a higher degree of market power, as well as Deboosere *et al.* (2019) and Casamatta *et al.* (2022), who find a significant impact of seasonality or Coenders *et al.* (2003), Espinet *et al.* (2003), Rigall *et al.* (2011), Santos *et al.* (2021), who consider seasonality one of the main factors affecting the price.

We argue that, depending on the behaviour of tourist apartment prices, the FA will reveal three different seasonal month groups (autumn-winter, spring and summer). Others consider seasonality to be one of the most important factors explaining the difference in *Airbnb* prices and yields and find that the summer period or peak season, such as when the academic term begins, the probability of a higher degree of market power can impact prices and performance within the *Airbnb* market (Aznar *et al.*, 2018; Magno *et al.*, 2018; Falk *et al.*, 2019; Sainaghi *et al.*, 2021; Casamatta *et al.*, 2022; Yilmaz *et al.*, 2022). Deboosere *et al.* (2019) and Casamatta *et al.* (2022) found that hosts adjust their prices based on the holiday calendar and seasonal demand.

Alrawabdeh (2022) highlights that different international and local hotels may exhibit varying price fluctuations throughout the year. We find there is a difference between professional and opportunistic owners. Comparing findings with the existing literature, the research presented here focuses on seasonality and professional host skills versus non-professionals and how these variables affect the reservation of a STR and the price that is set. All these are in comparison with Group 3, which is more likely to be in mixed residential areas, trendy streets and commercial zones with a limited selection of eateries and a moderate number of grocery stores. Higher-income areas tend to have a greater quantity of active shops and a higher socioeconomic level (Chamberí, Moncloa, Aravaca and Ciudad Universitaria, which are known for their high-quality properties and proximity to universities).

We consider that there will be significant variations in the average price of tourist apartments in Madrid, as has been observed in the study by Sánchez-Pérez *et al.* (2019) of tourist accommodations over time. But this situation varies depending on whether it is a professional who adjusts the price in the calendar. Some hosts do not practice dynamic pricing, which means they miss out on revenue opportunities. On the other hand, hosts that adjust their prices more frequently, both upward and downward, tend to improve the revenue performance of their listings (Li *et al.*, 2016; Chen and Xie, 2017; Gibbs *et al.*, 2018; Oskam *et al.*, 2018; Kwok and Xie, 2019; Casamatta *et al.*, 2022).

6. Conclusion

In conclusion, three Madrid clusters were identified based on seasonality and location: Group 1, with strong autumn-winter patterns and fewer restaurants; Group 2, showcasing higher spring seasonality and likely catering to tourists with abundant restaurants; and Group 3, characterised by year-round stability, fewer supermarkets and active shops, potentially influencing restaurant dynamics in the area. This study underscores the existing void in accessible literature concerning the intersection of seasonality, rental housing and the proximity to essential amenities like supermarkets and restaurants. This highlights a gap in current research and emphasises the necessity for additional investigation on tourism-location impact to provide insights to apartment owners and managers and professionals who work in the food/hospitality industry. By undertaking this study, we aim to bridge this knowledge gap and enhance comprehension of the interplay of seasonality, rental housing, and amenities such as supermarkets and restaurants. The integration of seasonality, dynamic pricing and proximity factors enables property owners to maximise their revenue while providing guests with competitive rates.

6.1 Theoretical contributions

The theoretical underpinnings of this investigation, aligned with Hypothesis 5 (H5), elucidate the intricate associations between STR pricing and environment variables. This cluster analysis reveals discernible responses to the proximity of apartments to supermarkets and restaurants within behavioural groups. This analytical framework synthesises the insights from the seminal work of Voltes-Dorta and Sánchez-Medina (2020) on *Airbnb*, establishing a theoretical nexus between apartment characteristics, environment variables and pricing dynamics. Consistent with H5, the role of nearby establishments in dynamic pricing augments an understanding of pricing mechanisms, specifically in the context of STRs and includes environment variables in the theoretical discourse.

Drawing on H5, this empirical examination of seasonality's impact on pricing dynamics, notably within the ambit of Group 1, underscores the pivotal role of environment variables in active revenue management. The discerned associations between seasonality, pricing strategies, and environmental factors enrich the theoretical framework, positing an imperative to integrate external influences, such as the proximity of supermarkets and restaurants, into the comprehension of the seasonality-pricing relationship within distinct behavioural cohorts.

This study focuses on enhancing the predictive model for STR prices by incorporating seasonal trends and data related to the proximity of supermarkets and restaurants within a specific radius of the STR properties, enriching the understanding of the contextual factors influencing pricing and occupancy patterns in the *Airbnb* market. The goal is to contribute valuable insights that can significantly improve the accuracy of STR price forecasts. This new approach involves utilising Machine Learning techniques to explore the influence of diverse factors, such as seasonality and proximity to amenities, on rental prices.

6.2 Managerial implications

In line with H5, the discerned associations offer pragmatic insights for apartment owners and managers concerning the influence of environmental variables on pricing dynamics. The actionable intelligence derived from these associations provides nuanced guidance for professionals within Group 1, advocating a strategic focus on the proximity of supermarkets and a dearth of restaurants to optimise active revenue management. Non-professional owners in Groups 2 and 3 stand to benefit by refining their pricing strategies, cognizant of the stability observed in pricing behaviour vis-à-vis environment variables.

This study's ramifications extend beyond property management, proffering cogent insights for the food and hospitality industry. By elucidating the nexus between environment variables and pricing behaviour, this research presents opportunities for symbiotic collaborations between property owners and nearby local businesses. The insights garnered can function as a strategic compass for restaurants and supermarkets, enabling them to strategically position themselves in locales with potential demand for STRs, thereby fostering mutually beneficial partnerships and influencing pricing strategies across both sectors.

6.3 Limitations and future research directions

The acknowledgement of study limitations, specifically its exclusive focus on the STR market in Madrid, is indispensable in the context of H5. The uncertain extrapolation of findings to markets with disparate environment variables, pricing dynamics, or seasonal trends underscores the necessity for future research endeavours to embrace diverse contexts. This serves as a clarion call for the validation and refinement of the identified associations across varied market landscapes.

With regard to H5, future research trajectories may scrutinise the adaptability of the identified associations in this study across diverse contexts. The investigation of how environment variables interact with apartment characteristics and concomitantly influence pricing decisions in disparate markets would contribute substantively to an enriched theoretical framework. Building upon the seminal contributions of Voltes-Dorta and Sánchez-Medina (2020), a more granular exploration of the intricate connections between environmental factors (nearby supermarkets and restaurants) and pricing behaviour could crystallise and extend the theoretical edifice, thereby beckoning forth novel avenues for exploration in this evolving scholarly terrain.

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