An Analysis of the Airbnb Market: A Detailed Look at Four Italian Cities

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Abstract. The Sharing Economy, or the economy of sharing, is an economic phenomenon that has rapidly spread in recent years, transforming the ways in which resources and services are accessed and consumed. This phenomenon has had a significant impact on consumption dynamics, redefining the concept of ownership and promoting the idea of temporary and shared access to goods. An emblematic example is represented by Airbnb, a multinational company founded in 2008 and valued at 35 billion dollars. With over 4 million hosts and 800 million guests in more than 220 countries and regions, Airbnb offers communities the opportunity to make the most of their cultural and scenic heritage, attracting a variety of visitors eager for authentic experiences. In this regard, the present study proposes a methodological model capable of empirically analyzing the Airbnb market in four Italian cities, adopting an integrated approach that combines Principal Component Analysis (PCA) and clustering based on the use of the k-means algorithm, to arrive at a deeper understanding of the data. The results emerging from the research highlight a significantly negative correlation between price and distance from the city center, also revealing a negative correlation between reviews and price, as well as between reviews and distance from the city center. Through the analysis of the research results, it aims to make a relevant contribution to academic literature, providing new perspectives and insights for further studies on Airbnb dynamics, as well as on the economic and social implications of resource and service sharing in the context of the Sharing Economy.

Keywords: Airbnb · Real Estate Market · Short-Term Rent

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1 Introduction

In the last decade, the Sharing Economy has gained increasing relevance as a social and economic phenomenon, generating a significant impact on consumption dynamics and shaping the contemporary economic landscape [1]. This innovative economic model, based on the sharing of resources, goods, and services among individuals through digital platforms, has exerted a remarkable influence in various economic sectors. Services such as carpooling with BlaBlaCar, household task management through TaskRabbit, culinary experiences offered by EatWith, pet hospitality with DogVacay, bicycle and sports equipment rental through Spinlister, along with platforms like Uber for private transportation and Airbnb for accommodation, have all contributed to shaping this new mode of sharing and economic collaboration. The Sharing Economy, or the economy of sharing, can be defined as an economic model in which individuals or businesses share access to resources, goods, or services through digital platforms, either for free or for a fee. This approach fosters collaboration among individuals, enabling them to mutually benefit from underutilized resources or offer services directly to peers, often bypassing traditional intermediaries such as companies or organizations [2]. An emblematic example of the sharing economy is represented by Airbnb, one of the leading online accommodation rental platforms worldwide. Three visionary young entrepreneurs, Brian Chesky, Joe Gebbia, and Nathan Blecharczyk, in the vibrant context of San Francisco in 2008, gave life to Airbnb, a company that would revolutionize the way we think about hospitality and travel globally within a few years. The founders of Airbnb had an ambitious goal: to create an authentic travel experience that would allow people to connect with local culture and have unique experiences, going beyond the traditional patterns of the hotel industry. Airbnb offers hosts, who are the owners of the accommodations, the opportunity to make available one or more rooms, an entire apartment, or even just a shared room [3]. The platform's success has been fueled by the growing demand for personalized accommodation solutions from travelers, different from standardized hotel accommodations. The vast differentiation of offerings allows visitors to choose, in line with their tastes, needs, and preferences, from a wide range of options such as designer apartments, rustic countryside houses, or local residences.

Over the years, Airbnb has continued to grow exponentially, expanding globally and establishing itself as a reference point in the home-sharing industry. Just consider that as of 2023, Airbnb had 5 million accommodation listings worldwide, in 191 countries.

The platform has had a significant impact on the global economy, offering new income opportunities to hosts and allowing travelers to discover unique and authentic destinations. Today, Airbnb represents much more than just an online booking platform. It has become a cultural phenomenon and a symbol of global sharing and hospitality. Almost all major urban centers are now affected by the phenomenon, offering advantages for both hosts and guests. For hosts, renting a room or an entire property through Airbnb represents an opportunity to earn extra income by leveraging their real estate resources [4]. For guests, Airbnb offers a flexible and often more affordable alternative to traditional hotels. However, there are also critical aspects of the phenomenon. One of the main disadvantages is the potential unfair competition against traditional accommodation facilities, which must comply with specific regulations and standards regarding safety, taxation, and service quality [5, 6]. Moreover, the Airbnb phenomenon

can lead to an increase in long-term rental prices and gentrification in certain areas, with a negative impact on the social fabric of local communities [7, 8]. This study aims to empirically examine the Airbnb phenomenon in four Italian cities: Rome, Milan, Naples, and Bologna, over the course of a single year, using a dataset consisting of 62.810 property listings. The conducted analysis, along with a review of the growing literature on the sharing economy, contributes to understanding the functioning of the tourist accommodation sector. Specifically, it provides an interpretive framework of the Airbnb market in the four Italian cities under study, using the combined application of Principal Component Analysis (PCA) and K-means clustering. The work is organized as follows. The second section presents a review of case studies from the literature regarding the expansion of Airbnb and its impact on various sectors of society. The third section illustrates the case study, defining the areas under examination, the data, the applied methodology, and a summary of the results. Finally, the fourth section draws the conclusions of the study and outlines possible future developments.

2 Literature Review

The expansion of Airbnb has generated significant implications in the tourism industry and the practice of home sharing, triggering a series of complex dynamics that have permeated various spheres of society, sparking widespread academic interest. Numerous studies have been undertaken to examine the different facets of this phenomenon, analyzing how Airbnb impacts the economy, the real estate market, the environment, the social cohesion of local communities, and the visitor experience. Each of these facets represents a specific perspective that contributes to a deeper understanding of the overall effects of Airbnb on various aspects of society and the economy. Oskam & Boswijk (2016) consider Airbnb as a tool for optimizing real estate resources [9]. This innovative home-sharing model presents itself as a potential source of additional income for property owners. Many owners have found that making their homes available on Airbnb can be a true "gold mine." The platform offers them the opportunity to make the most of their properties by generating income through sharing available spaces. For owners who have a second home or vacant rooms in their residences, Airbnb provides a convenient way to monetize otherwise unused spaces. This represents an advantageous opportunity to generate additional revenue, which can be used to cover property management expenses such as utilities or mortgage payments [10]. In addition to the possibility of generating extra income by allowing property owners to monetize their properties more flexibly, Airbnb gives owners greater control over the management of their assets. They are able to determine rates, choose when to make their homes available, and engage in direct communication with guests. This level of control holds considerable appeal for those who wish to personally oversee their short-term rental activity [11]. This is particularly effective in places where tourism represents a significant source of income. Airbnb offers communities the opportunity to make the most of their cultural and scenic heritage, attracting a variety of visitors seeking authentic experiences. The unique and authentic properties, often offered by local residents, constitute a strength that sets Airbnb apart from traditional models of accommodation [4]. Airbnbs often have more affordable prices compared to hotels and offer a more intimate experience, along with household

amenities that are not available in hospitality establishments. These factors can attract a significant portion of the clientele that traditionally chose hotels [5]. This comparison between hospitality establishments and Airbnb reflects the complexity of a constantly changing market. While Airbnb offers new economic opportunities for property owners, traditional hotels must face the challenge of adapting to an evolving market, seeking to differentiate themselves and offer experiences that meet the changing expectations of modern travelers. According to studies conducted by Zervas, Proserpio, and Byers [6], Airbnb's entry into the Texas market had a negative impact on the hotel industry, revealing that a 1% increase in Airbnb listings resulted in a 0.05% reduction in quarterly hotel revenues. Other authors [12], using a large dataset comprising 28 cities in the United States, have highlighted that a 1% increase in hotel room rates led to a 1.397% increase in the availability of accommodations on Airbnb. This demonstrates the close substitutability relationship between the two markets, even though the services offered by Airbnb differ significantly from those of the hotel industry, targeting distinct customer segments [13]. Scholars describe users of traditional hospitality establishments as a particularly demanding category of consumers with high expectations for the services offered. Tussyadiah (2015), while acknowledging that Airbnb has lower costs compared to traditional hospitality establishments, shows that Airbnb guests are typically highly educated individuals characterized by frequent travel and a propensity for choosing less conventional accommodation solutions [14]. This suggests a user profile that, in addition to being cost-conscious, is motivated by an interest in more authentic and personalized travel experiences. Guttentag et al. (2018) and Adamiak et al. (2019) conducted in-depth investigations into the motivations that drive travelers to prefer Airbnb, highlighting the importance of experience authenticity, value for money, and the opportunity to interact with the local community [4, 11]. These elements have not only shaped travelers' preferences but have also significantly influenced market dynamics, amplifying the change in consumer perspectives regarding traditional accommodations such as hotels. On one hand, the advent of Airbnb has represented a promising source of income for many property owners. However, it has also triggered an increase in rental costs and consequently a reduction in the availability of long-term accommodations [15]. Many property owners prefer short-term rentals, renting out their units on platforms like Airbnb and generating significant profits, rather than opting for traditional long-term leases. This inevitably reduces the supply of long-term accommodations in the market, leading to an increase in remaining rental prices [7]. Furthermore, the opportunity to generate additional profits may drive individuals to invest in real estate and acquire new properties for the short-term rental market. The awareness that investors can generate extra income by converting their properties into Airbnb accommodations often leads them to purchase new properties at a higher price than their actual value. They are willing to invest further in property acquisition, seeing the potential that comes from short-term rentals [16]. An analysis conducted by Lee (2016) examined the influence of Airbnb on the real estate sector, highlighting how Airbnb's expansion can contribute to rental price increases and a reduction in the availability of affordable housing [7]. Similarly, Barron, Kung, and Proserpio (2017) analyzed the impact of Airbnb activities on property values and lease contracts. Their findings revealed that a 10% increase in commercial transactions associated with Airbnb listings resulted in a 0.39% increase in long-term rental prices and a

0.64% increase in housing prices [17]. In France, a study by Ayouba K et al. (2019) in eight cities highlighted that the increasing number of Airbnb listings for tourism purposes exerts upward pressure on the long-term rental market in Lyon, Montpellier, and Paris, with respective percentage increases of 0.3851%, 0.3982%, and 0.5242% [18]. These phenomena, including rental price increases, pressure on the long-term rental market, reduced availability of affordable housing, and property value increases—all attributable to the intensification of Airbnb listings—contribute to distorting the real estate market through two interconnected mechanisms: conversion and gentrification.

Considering the opportunity for property owners to generate additional profits, there is an authentic process of conversion where dwellings that were previously intended for long-term rentals or residential use are now absorbed by the Airbnb market, representing units that are taken away from the residential rental market and primarily transferred to the tourism and hospitality sector [8]. This phenomenon is not limited to peripheral areas of cities but mainly occurs in historical centers and central neighborhoods, which are considered attractive for tourists or those seeking short-term accommodations. The conversion of residential units into Airbnb properties has caused a substantial increase in property values and long-term rental prices, gradually contributing to the so-called urban gentrification. This process is associated with the arrival of new residents with higher purchasing power, who progressively replace low-income groups or pre-existing historical communities. Due to rising prices, low-income residents are forced to move elsewhere, making room for new high-income inhabitants [19]. It is important to emphasize that financial aspects are not the sole determining factors in gentrification, as socio-cultural dynamics can also come into play. While the profits derived from sharing economy operations contribute to revitalizing the local economy, there is also a phenomenon of touristification closely related to gentrification [3]. Many historical centers are literally overwhelmed by tourist flows, causing a series of issues related to the inability of these neighborhoods to cope with such a situation. Research conducted by Jordan & Moore (2018) highlights the intricate relationships between residents and tourists. The significant increase in tourist flows in specific urban areas puts additional pressure on local communities. This phenomenon brings about a change in the demographic composition, with an increase in short-term tourist presence and a decrease in long-term resident population. A massive presence of visitors can compromise the quality of life for local residents, causing disturbances, excessive noise, overcrowding neighborhoods, and creating tensions between residents and visitors [20]. Moreover, the significant increase in visitor flow has a direct impact on the surrounding environment. While the sharing economy in the tourism sector offers a considerable opportunity to promote sustainability through the utilization of underutilized assets and the expansion of services without further constructions or acquisitions, thus reducing the sector's environmental impact, it is equally true that increased travel and the use of short-term accommodations can contribute to increased energy consumption and carbon emissions [21–25]. It is crucial to consider these dynamics in formulating appropriate policies and regulations to manage the impact of Airbnb on local communities. On the other hand, the growth of Airbnb has raised fundamental questions regarding the need for specific regulations concerning its governance. In order to counter the phenomenon of indiscriminate conversion, many countries and urban centers have adopted specific regulations aimed at addressing the

legal and financial aspects associated with the use of Airbnb. According to arguments put forward by Guttentag (2015), Schneiderman (2014), and Streitfeld (2014), a significant amount of short-term rentals operate illicitly in numerous cities, as hosts, those who provide properties on platforms like Airbnb, may not comply with the associated tax obligations [5, 26, 27]. Just a few months ago, it was reported that Airbnb in Italy was fined a massive amount for not paying taxes on nearly 4 billion euros in short-term rentals. In response to this issue, various countries and urban centers have introduced specific regulations to address the legal and tax-related issues associated with Airbnb [28]. Research conducted by Wachsmuth et al. (2018) examined the different regulations introduced to address the legal and tax-related issues associated with Airbnb, analyzing the impacts of these policies on the market and the community, and highlighting the complexity of regulation in a continuously evolving sector like Airbnb [19]. For example, Quattrone et al. (2016) focused their attention on the regulation of Airbnb in London, highlighting the lack of effective rules to adequately manage the phenomenon and proposing innovative policies based on in-depth analysis of spatial and economic patterns of housing supply and demand [1]. A similar approach was followed by Lee (2016), who, through the use of legal and statistical analysis, explored the impact of short-term rentals on the residential rental system in Los Angeles, offering suggestions on how local authorities and policymakers can adequately regulate the phenomenon [7]. The analyses developed on the Airbnb market in four major Italian cities and the obtained results show some peculiar aspects of the short-term rental market that differentiate it from other segments of the real estate market in relation to the specific needs of users.

3 Case Study

3.1 Research Areas

The cities under study, situated within the Italian urban context, are Rome, Milan, Naples, and Bologna. In 2023, Airbnb continued to consolidate its presence in Italy, becoming one of the most widely used accommodation rental platforms in the country. Data for that year shows a significant increase in the availability of accommodations on Airbnb in various Italian cities. In Rome, the number of listings registered on Airbnb exceeded 29.000, representing a notable increase compared to the approximately 12.000 listings in 2017. The Italian capital continues to be one of the preferred destinations for tourists, and Airbnb has contributed to meeting the demand for alternative accommodations. Milan has also experienced considerable growth in the availability of Airbnb listings. In 2023, the number of listings on the platform reached 24.936, representing an increase of about 10.000 listings compared to 2022. The city of Milan, renowned for its vibrant nightlife and its status as a financial center, has attracted an increasing number of tourists and business travelers. Naples and Bologna, albeit to a lesser extent than Rome and Milan, have also seen an increase in the availability of accommodations on Airbnb. Naples witnessed an increase from 7.175 to over 10.000 listings in 2023, while Bologna saw an increase from approximately 3.685 to over 4.700 listings during the same period [29]. These data confirm the important role that Airbnb has assumed in the Italian real estate market, offering a wide range of accommodation options for travelers.

3.2 Data Description

For our research, we used a dataset consisting of 62.810 listings of housing units published on the renowned Airbnb platform during 2020, pertaining to the cities of Rome, Milan, Naples, and Bologna. The data was collected through the Inside Airbnb website (http://insideairbnb.com/), a platform founded by Murray Cox with the aim of analyzing the Airbnb phenomenon and its impact on the real estate market and urban social fabric. The website provides access to raw data concerning property listings on Airbnb, allowing users to examine trends, supply patterns, and prices. By accessing the data, scholars, journalists, activists, and the general public can explore how Airbnb influences the rental market, gentrification, and much more. In order to ensure accurate, homogeneous, and meaningful analysis, some restrictions were applied to the collected data. Specifically, Airbnb listings with more than 4 bedrooms and 6 bathrooms were excluded, as properties of such large sizes could have significantly higher prices compared to the average, making them incomparable to more common accommodations and distorting the analysis results. Subsequently, listings with more than 15 reviews per month were removed, as they were considered extreme values or outliers. These listings potentially represent accommodations subject to aggressive marketing strategies, which may not be representative of the average Airbnb listings. Additionally, listings with prices exceeding 300 euros per night were excluded, as they represent luxury or highly exclusive accommodations. Following these preprocessing steps, the dataset included 23.956 listings for Rome, 15.019 for Milan, 5.792 for Naples, and 3.203 for Bologna.

To empirically examine the Airbnb market in the four Italian cities under study, the analysis focuses on four main variables: price, number of bedrooms, number of reviews per month, and distance from a reference point in the city center. These variables are considered crucial for analyzing the Airbnb market as they have the potential to influence the dynamics of short-term rentals. An exploratory data analysis of the available data is presented in Fig. 1. It should be noted that the number of reviews is a proxy variable for the employment rate.

3.3 Methods

The interpretative framework of the Airbnb market in the four Italian cities under investigation was empirically delineated using a combined approach of Principal Component Analysis (PCA) and cluster analysis based on the k-means algorithm.

Principal Component Analysis

Principal Component Analysis (PCA) is a technique used in the field of multivariate statistics to address complexity and redundancy in data, especially when dealing with datasets that have a considerable number of variables [30, 31]. The primary purpose of this model is to reduce the dimensionality of the dataset while preserving most of the information contained in the original data. Essentially, PCA examines and simplifies the data to understand the structure of the covariance matrix of a group of variables through a reduced set of linear combinations. The model is able to transform a set of correlated variables into a new set of uncorrelated variables, called principal components, which are arranged in such a way that the first component explains the maximum variance in

the data, the second component explains the maximum remaining variance, and so on. This is achieved through a linear transformation of the variables that projects the original variables onto a new Cartesian coordinate system, where the variables are arranged in descending order of variance.

Formally, given n observations of a set of features $X_1, \ldots, X_p$, the first principal component can be defined as the normalized linear combination of the original features as:

$$Z_1 = \phi_{11} X_1 + \cdots + \phi_{p1} X_p \tag{1}$$

where the vector $\phi_1 = (\phi_{11}, \ldots, \phi_{p1})^T$ is referred to as the principal component loading vector, and $\sum_{j=1}^{p} \phi_{j1}^2 = 1$ to ensure not to have an arbitrarily large variance. Hence, given an $n \times p$ dataset $\boldsymbol{X}$, and assuming the features to be centred to have zero mean, PCA search for the linear combination of the values as:

$$Z_{i1} = \phi_{11} X_{i1} + \cdots + \phi_{p1} X_{ip} \tag{2}$$

that has the largest variance under the constraint that $\sum_{j=1}^{p} \phi_{j1}^2 = 1$. The first principal component loading vector therefore results from the optimization:

$$\underset{\phi_{11}, \ldots, X_{ip}}{maximize} \left\{ \frac{1}{n} \sum\nolimits_{i=1}^{n} \left(\sum\nolimits_{j=1}^{p} \phi_{j1} x_{ij} \right)^2 \right\} subject\ to \sum\nolimits_{j=1}^{p} \phi_{j1}^2 = 1 \tag{3}$$

Notice that one can write $\frac{1}{n} \sum_{i=n}^{n} z_{i1}^2$, and that since $\frac{1}{n} \sum_{i=n}^{n} x_{ij} = 0$, the average of $z_{11}, \ldots, z_{n1}$, which are usually called as the scores of the principal component, will also be 0. Therefore, the objective to maximized is equivalent to the sample variance of the n values of z_{i1}. Operationally, the problem is solved via an eigen decomposition or via singular value decomposition [32, 33]. Moreover, principal component analysis (PCA) can reveal relationships among data that were not previously evident, enabling new interpretations. Despite involving minimal loss of initial information, PCA is widely used because it confines such loss within acceptable margins. It is worth noticing that PCA can be also extended for its application to spatio-temporal data [34–36], in which case is often referred at as Empirical Orthogonal Functions Decomposition [37]. In such case data are decomposed into fixed temporal scores and their corresponding spatial loadings [38].

K-Means Clustering

Clustering refers to a set of unsupervised learning techniques aiming at finding subgroups, called cluster, into a dataset. While with PCA the aim is identifying a low dimensional representation of the data explaining a sufficiently large fraction of the data variance, with clustering the aim is determining homogeneous subgroups among the available observations. K-means is a popular clustering algorithm partitioning the dataset into K distinct and non-overlapping clusters [39]. Given a desired number of clusters to be identified into the data, K-means assigns the $i - th$ observation to a cluster C_k, for $k = 1, \ldots, K$, minimizing the within-cluster variation. For a cluster C_k the latter

is defined as the measure $W(C_k)$ of the amount by which the observations within a cluster differ from each other. This implies solving the optimization function:

$$\underset{C_1,\ldots,C_K}{minimize}\left\{\sum_{k=1}^{K} W(C_k)\right\}. \tag{4}$$

Here within cluster variation was defined based on Euclidean distance so that

$$W(C_k) = \frac{1}{|C_k|}\sum_{i,i'\in C_k}\sum_{j=1}^{p}(x_{ij} - X_{i'j})^2 \tag{5}$$

in which $|C_k|$ is the number of observations in the $k - th$ cluster. The solution to the defined optimization problem is algorithmically found as in Algorithm 1 [40] Table 1.

Table 1. K-means clustering.

Algorithm 1
1. Randomly assign to each observation an initial cluster from 1 to $\boldsymbol{K}$.
2. Until the cluster assignment stop changing:
• For each of the $\boldsymbol{K}$ clusters, compute cluster centroid as the vector of the $\boldsymbol{p}$ feature means for all the observations included in the $\boldsymbol{k-th}$ cluster;
• Assign each observation to the cluster whose centroid is closest, based on Euclidean distance.

Notice that Algorithm 1 provides a local optimum and depends on the initial random assignment of observations from step 1. To limit the bias induced by such randomness, the algorithm is generally executed multiple times and only the solution resulting in the minimum value of the objective function is selected as final clusterization. The solution also depends on the number K of clusters to be identified in the data. Multiple approaches can be used to determine the optimal number of clusters for the data at hand [41]. Here the Within-Cluster Sum of Squares (WSS) was used to quantify the compactness of clusters by measuring the sum of squares of distances between each data point and its assigned cluster centroid [42]. By evaluating WSS across different numbers of clusters it is possible to identify the point at which further partitioning of data into clusters does not significantly decrease the within-cluster variance, indicating an appropriate number of clusters for the dataset.



Fig. 1. Exploratory data analysis: Pairwise plots among the considered features, including correlations.

3.4 Results and Discussions

The results of the principal component analysis and subsequent clustering have revealed some interesting correlations among the variables under investigation. It should be noted that the analysis of the data, being limited to the territorial boundaries of the cities under study, is evidently influenced by the geographical extent of the municipal administrations as well as the size of the real estate market. In particular, according to the 2011 ISTAT census, the city of Rome had a total number of dwellings of 1.259.649, Milan 643.053, Naples 361.966, and Bologna 206.689. It is therefore normal that the total number of accommodations on Airbnb is higher for Rome, followed in the same order by Milan, Naples, and finally bologna. However, when measuring the percentage of Airbnb's impact on the total residential property, the percentage varies between 2% and 3% for all cities, with the following values: Milan 3%, Rome 2.4%, Naples 2.1%, Bologna 2%. Regarding the prices of accommodations, it has been observed that Rome is the most expensive city, followed in descending order by Milan, Bologna, and finally Naples. This finding contrasts with the long-term rental market, where Milan is at the forefront, surpassing Bologna by approximately 30% (based on the average value of the

entire municipal territory), followed closely by Rome and then Naples. The demand for accommodation by university students certainly has a significant impact on the long-term rental market in Milan and Bologna. This, however, demonstrates the independence of the two market segments (short-term and long-term rentals). This independence is even more evident when looking at the distribution of values within each city. for example, in the case of the Western Area of Naples (Posillipo), despite higher rental prices in the city for long-term leases, low-priced Airbnb accommodations from cluster 1 are found, indicating a distance from the city center. From the results of the clustering (see Figs. 1, 2, 3 and 4), Bologna, Milan, and Rome show a significantly negative correlation between price and distance from the center. Therefore, the prices of Airbnb listings follow the normal trend of the residential real estate market, where urban rent decreases from the center towards the outskirts. Location is also a determining factor for Airbnb users in their choice of accommodation. Accommodations located further from the center require visitors (for tourism or work) to spend more time and effort to reach the main attractions, points of interest, or business areas of the cities. This correlation is reversed for the city of Naples. This different trend can likely be justified by considering that Naples is in a territorial context with numerous tourist attractions outside the historic center and administrative boundaries of the city. Think of the Sorrento Coast, Pompeii, Mount Vesuvius, and the Islands (Ischia and Capri). Therefore, the choice of accommodation serves as a logistical base for visiting the city as well as other destinations. This is clearly evident when observing the map (see Fig. 4), where cluster 1 "low prices, far from the center" concentrates in the Western area, which has the lowest accessibility both to the city center and other tourist destinations. The same rationale explains why Naples has the greatest distance of Airbnb accommodations from the Center, Followed by Rome, Milan, and Bologna. This finding is also justified by the different spatial distribution of the cities. Bologna and Milan are monocentric cities, with a well-defined historic center as the main focal point. On the other hand, Rome, especially, but to some extent Naples as well, can be considered polycentric cities with multiple areas of interest and therefore a greater spatial dispersion of Airbnb listings. The analyses also show a negative correlation between reviews and price, as well as between reviews and distance from the center. This implies that cheaper accommodations located in less central areas tend to have a higher number of reviews. This corresponds to a higher occupancy rate for peripheral accommodations, which are often chosen for economic reasons. This is in line with the results of other studies that have already highlighted the particularity of the typical Airbnb guest, who is usually cost-conscious, motivated by an interest in personalized and authentic travel experiences, and inclined to opt for unconventional accommodation solutions.

In Fig. 2, the first component explains 35% of the data variability, while the second explains 28%. The first component discriminates based on price and number of rooms, while the second discriminates based on distances and reviews.

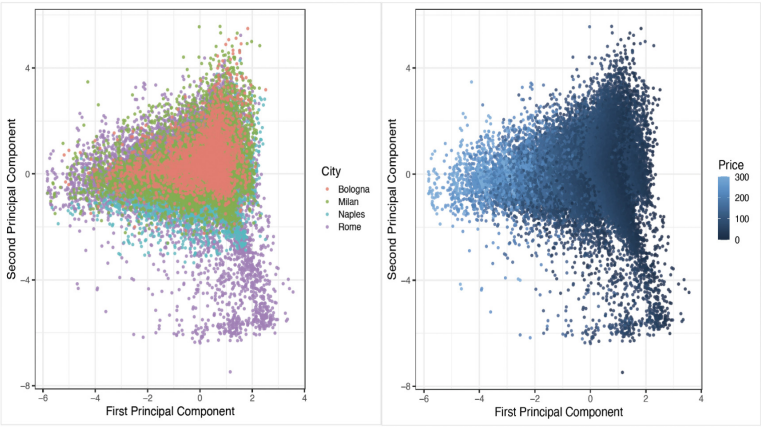


Fig. 2. PCA: Data are plotted in a two-dimensional projection based on the values of the two first principal components. Each point corresponds to a single Airbnb location. Points are colored based on the city the Airbnb belongs (left) and based on price (right).

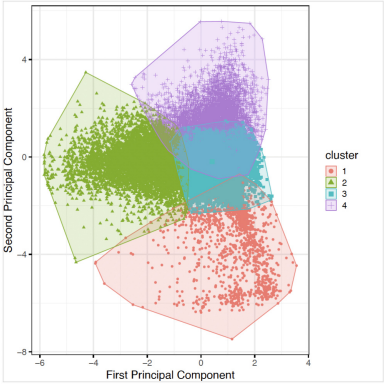


Fig. 3. PCA: K-means clusters: Results of K-means are visualized in the two-dimensional representation of the feature space obtained using the two first principal components derived from PCA. Cluster 1: Low prices, far from the center; Cluster 2: Medium-high prices, not far distances, mostly 2 rooms; Cluster 3: Low prices, average distances, 1 room, few reviews; Cluster 4: Low prices, short distances, 1 room, many reviews.

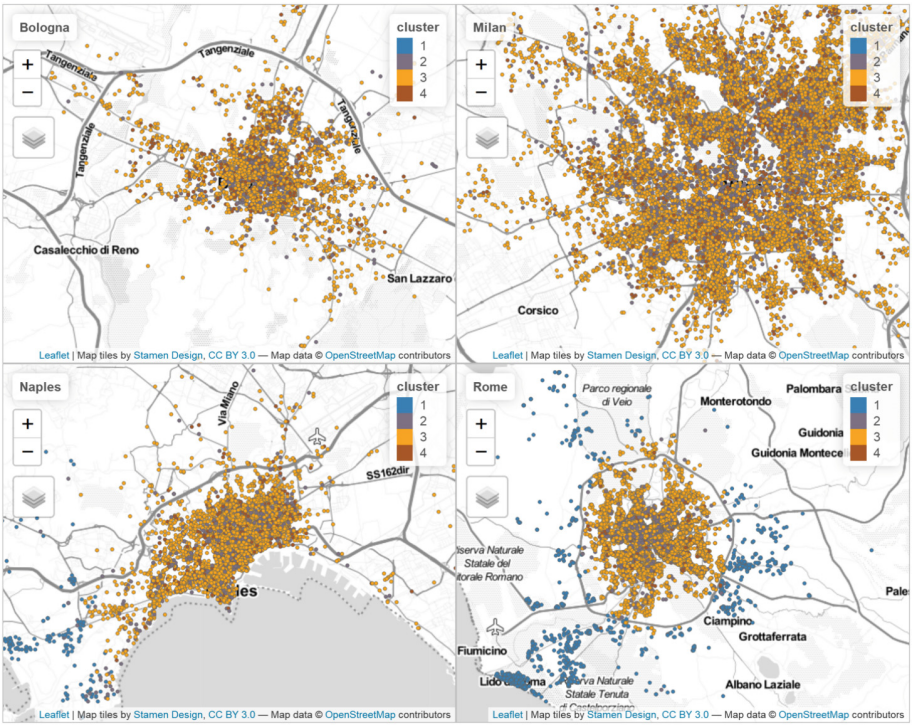


Fig. 4. Spatial distribution of clustered Airbnb listings in the metropolitan areas under study.

4 Conclusions

Airbnb has revolutionized the tourism accommodation sector and the way people approach travel. Firstly, it introduced a new form of lodging that goes beyond traditional hotels and bed and breakfasts. People can now choose to stay in private homes, apartments, or rooms within residences, offering a wide range of accommodation options to fit the needs and preferences of travelers. This has led to the spread of the sharing economy concept, where individuals can make their own properties or unused living spaces available to earn extra income. Additionally, Airbnb has promoted a more authentic and intimate experience for travelers. Choosing to stay in residential neighborhoods rather than tourist areas allows travelers to immerse themselves in the local culture and interact with residents, providing a more authentic and meaningful experience. Flexibility and personalization are other key aspects of Airbnb. People can select accommodations that meet their specific needs in terms of location, size, comfort, and budget, offering greater freedom of choice compared to traditional hotels. This shift in the accommodation landscape has had a significant impact on the traditional hotel industry. Hotels have had to adapt and improve their services and marketing strategies to remain competitive in an increasingly diverse market. However, in addition to its advantages, Airbnb has also raised concerns about its effects on local communities. Increased long-term rental prices and mass tourism in residential neighborhoods have become significant issues in many

cities, prompting greater attention to short-term accommodation regulation policies. By combining Principal Component Analysis (PCA) and clustering analysis using the k-means algorithm, this research aims to empirically examine the Airbnb phenomenon in four Italian cities. The focus is on four key variables: price, number of bedrooms, number of reviews per month, and distance from a landmark in the city center. To achieve this, a dataset consisting of 62.810 listings of properties used as accommodations in the four cities under investigation - Rome, Milan, Naples, and Bologna - over the course of a single year was examined. The results suggest a significantly negative correlation between price and distance, except for the city of Naples. This indicates that while in cities like Rome, Milan, and Bologna, prices tend to decrease as the distance from the center increases, Naples, renowned for its natural beauty, breathtaking coastlines, historic neighborhoods, and numerous cultural and artistic attractions scattered throughout the entire metropolitan area, being a polycentric city, has numerous tourist attractions outside the historic center and administrative boundaries of the city. Therefore, the variety of points of interest outside the historic center can influence the demand and perceived value of Airbnb accommodations, keeping prices relatively stable even in peripheral areas. This is why Airbnb listings in the city of Naples have a higher average distance from the historic center compared to the other cities under study. The results also highlight a negative correlation between reviews and price, as well as between reviews and distance from the center. The negative correlation between reviews and price, as well as between reviews and distance, suggests that cheaper Airbnbs and those located slightly further from the center tend to be more popular and utilized by guests. This could indicate that travelers are willing to sacrifice the convenience of a central location to save money or have a greater choice of accommodations with more reviews, which are considered more reliable. Furthermore, the results revealed that the Airbnb supply in the cities under study is primarily concentrated on accommodations with 1 or 2 bedrooms, which could reflect the prevalent demand for smaller accommodations suitable for couples or solo travelers, rather than larger groups. Finally, the comparable prices among the cities indicate that there is a certain uniformity in Airbnb costs between Rome, Milan, Bologna, and Naples, although Naples shows slightly lower average prices compared to the other cities. Although our study has enriched the emerging literature on home-sharing by offering significant theoretical contributions and improving academic understanding of the sharing economy and the dynamics of home-sharing activities, a limitation should be noted. The methodology adopted is not dynamic, as it is based solely on cross-sectional data collected in a single time period. This approach may not fully capture the variations and evolutions over time in home-sharing practices and their socioeconomic implications. Therefore, future methodological approaches could benefit from an analysis that captures the long-term dynamics and trends of home-sharing activities, as well as exploring how real estate markets, including informal ones, are changing due to the presence of Airbnb.

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