Dynamics in accommodation feature preferences: exploring the use of time series analysis of online reviews for decomposing temporal effects

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Abstract

Purpose - This study explores the use of time series analyses to examine changes in travelers' preferences in accommodation features by disentangling seasonal, trend, and the COVID-19 pandemic's once-off disruptive effects.

Methodology - Longitudinal data are retrieved by online traveler reviews (n=519,200) from the Canary Islands, Spain, over a period of seven years (2015 to 2022). A time series analysis decomposes the seasonal, trend, and disruptive effects of six prominent accommodation features (view, terrace, pool, shop, location, and room).

Findings – Single accommodation features reveal different seasonal patterns. Trend analyses indicate long-term trend effects and short-term disruption effects caused by Covid-19. In contrast, no long-term effect of the pandemic was found.

Practical implications – The findings stress the need to address seasonality at the single accommodation feature level. Beyond targeting specific features at different guest groups, new approaches could allow dynamic price optimization. Real-time insight can be used for the targeted marketing of platform providers and accommodation owners.

Originality - A novel application of a time series perspective reveals trends and seasonal changes in travelers' accommodation feature preferences. The findings help better address travelers' needs in P2P offerings.

Keywords Time series analysis; Text Mining; Seasonality; Accommodation features; Sharing economy

1. Introduction

Accommodation features are known for their enduring assets but exist in a dynamic context with evolving traveler preferences. Accommodation facilities need to cater to a broad spectrum of demand patterns from travelers across different seasons and preferences (Calantone and Johar, 1984). In addition, they need to adapt to shifting traveler preferences due to long-term trends or disruptive incidents, such as the COVID-19 pandemic. Thus, a thorough understanding of the ever-evolving relevance of accommodation features is vital for hosts to effectively meet travelers' needs in the future and make well-informed long-term investments. The use of big data analyses such as machine learning and "feature mining" promises to offer valuable opportunities for personalization (Li *et al*., 2022) and demand forecasting, thereby increasing the hospitality industry's economic performance (Cheng *et al*., 2023b), which has become especially relevant in a post-pandemic world (ibid.).

This is especially true for newly emerging accommodation modes, such as peer-to-peer (P2P) accommodations, where new traveler booking heuristics have been observed (Guttentag and Smith, 2022). Moreover, a more pronounced knowledge of time-specific preferences for single accommodation features may benefit price setting and revenue management, especially since scholars (e.g., Vives and Jacob, 2021) call for more individualized pricing policies.

Research has confirmed the relevance of online reviews in evaluating customer satisfaction, as review comments reflect consumers' experiences (Xiang *et al.*, 2015). Therefore, text mining of user-generated content provides valuable insights into customers' experiences and satisfaction, for both hotel (Cheng *et al.*, 2019; Tussyadiah and Zach, 2016) and P2P environments (Lee et al., 2023). While most of previous studies apply standard methods of static data analysis (Mody *et al.*, 2021), such as topic modeling or sentiment analyses (Cheng and Yin, 2019; Jain *et al.*, 2021), the underlying longitudinal data also allows for deriving insights about the dynamics of accommodation features' importance that may shift with changing seasons, long-term trends, or disruption effects.

Time series data provides a valid tool for measuring cyclical and seasonal effects, as well as long-term upward or downward trends (Burger *et al.*, 2001). Time series analyses offer insights into different components: secular trends, seasonal variations, and irregular variations. This methodology is well-established (Song *et al.*, 2019; Wu *et al*., 2017), especially in the field of econometrics. However, typical longitudinal studies are based on panel studies or "hard" data of revenue or other accounting data generated by companies or tourist organizations. Only recent studies have begun using search engine queries as a forecasting basis (e.g., Li *et al.*, 2017). Few works have used user-generated content or customer reviews in forecasting methods, and those have been limited to price predictions (e.g., Kalehbasti *et al.*, 2021). Thus, we aim to further explore the potential of these methods for analyzing travelers' unstructured online reviews.

This study presents a novel methodological approach: It applies time series analysis in the context of online traveler reviews to investigate the dynamics of single accommodations' feature importance. In a case-study setting (P2P accommodation in the Canary Islands), we use Airbnb reviews between January 2015 and April 2022 to disentangle seasonal, trend, and once-off effects impacting accommodation features' importance by using time series analysis. Grounded in big data research, text mining is used for the analysis (Li *et al.*, 2018). Robust analyses are applied as text data is inherently limited in scaling (nominal scales of verbal data). By applying such a novel method to the P2P field, we aim to bridge the sphere of econometricians with those of statistically less sophisticated users of trend analyses.

In our case-study setting, we find that single accommodation features are subject to pronounced seasonal variations and recurring demand patterns. Furthermore, we identify long-term trend effects in single accommodation features' relevance that began well before the pandemic. In contrast, the one-time disruptions caused by the COVID-19 pandemics seem to be limited to temporary effects only.

2. Literature Review

2.1 Applications of Time Series Analyses: A brief overview

Forecasting tourism demand has been a key research endeavor for the past decades. It is primarily applied to predict tourist flows, pricing issues and visitor frequency (Song et al., 2019). Several forecasting methods exist (econometric, AI-based, judgmental models) (Hu and Song, 2020). Time series models are often applied due to their ease of implementation and their ability to capture historic patterns (Song et al., 2019). Time-series models decompose the timely variations of a focal variable by analyzing its own past patterns to explore long-term trends, as well as short-term patterns like seasonality. Recently, forecasting has gained even more relevance as scholars have attempted to predict the recovery of tourism from the pandemic (e.g., Zhang *et al.* (2021)), supported by the wide-spread availability of Internet data (such as search engine data, see e.g. Hu and Song (2020)).

Song *et al.* (2019) report on several new techniques and applications. Time series, among other indicators such as Gini indicator, or Theil index, has also been used to measure seasonality (e.g., Yabanci, 2023). More specifically, Ye et al. (2018) utilize temporal data of online travel reviews and time series to unveil seasonal traveler preferences and Kaya et al. (2022) use hotel features to enhance the time series models of forecasting. However, the combination of forecasting methods based on text mining in the P2P market, as applied in this study, seems to be a relatively unexplored approach. Therefore, our study offers a complementary perspective on demand modeling by using text mining to identify the dynamics of single accommodation features.

Previous studies used time series analyses to forecast demand in P2P setting as well. For instance, Curto *et al.* (2022) investigated the growth rate of Airbnb to predict the market forecast for P2P. Similarly, Ghosh *et al.* (2023) and Peng *et al.* (2020) developed a price prediction model for P2P rentals. Peng *et al.* (2020) also include customer reviews, accommodation features, and geographical data as price predictive factors while other authors predicted Airbnb listing prices using amenities-driven features only (Islam *et al.*, 2022; Kalehbasti *et al.*, 2021). Islam *et al.* (2022) report that the number of bedrooms, accommodations, property types, and the total number of reviews positively influence the listing price.

However, to the best of our knowledge, very little is known about forecasting the demand for specific tourism accommodation features. Insights about the dynamics of single accommodation features could be beneficial for professionals in forecasting and decision-making, thereby improving the performance of their rentals. To gain easy access to the required data, we rely on online reviews as the basis. Hence, this study is the first to apply the time series methodology to forecast single tourism accommodation features. The underlying research question is how time series analysis of online reviews can be used to identify and decompose temporal effects for different accommodation features.

2.2 Seasonal Effects: Recurring importance patterns

Seasonality describes the concentration of tourism flows in relatively short periods of the year due to temporal variation. This issue and its implications are of key concern for the tourism industry (Butler, 1998; Cannas, 2012). Most tourist destinations exhibit systematic and recurring patterns of fluctuation in tourism activities throughout the year (Higham and Hinch, 2002), caused e.g. by weather changes, calendar effects, or (school) holidays (Parrilla *et al.*, 2007; Vergori, 2017). Furthermore, seasonality is influenced by both demand and supply factors. Hereby, scholars typically differentiate between three seasons, with either one (e.g., summer), two (e.g., summer and winter), or no peak season per year (Vergori, 2017). Analyses typically focus on the influence of seasonality on pricing (e.g., Espinet *et al*., 2012)

Studies indicate that Airbnb alters the way seasonal demand is accommodated: While hotels' seasonal pricing dampens the underlying demand, Airbnb's seasonal supply (i.e., more listings during high-demand seasons) helps to resolve the conflict between cyclical demand and fixed hotel capacity to better meet seasonal demand (Li and Srinivasan, 2019). Furthermore, demand in the P2P market is less subject to seasonality than the hotel market (Benítez-Aurioles, 2022) and prices display a smoother seasonal pattern than hotels (Saló *et al*., 2012).

Across seasons, guests have diverse motives for traveling (Calantone and Johar, 1984). Scholars thus suggest to customize tourism products in different seasons to tourists with different motives to attract visitors outside of peak months (Šegota and Mihalič, 2018). In line hereto, we hypothesize that different accommodation features are subject to varying seasonality. We investigate distinct seasonal effects for travelers' preferences of single accommodation features through a time series analysis of online reviews. Linking the influence of seasonality or other timing effects at this fine-grained level has previously not been investigated. While research analyzed overall demand for accommodation features, its seasonality issues are one of the least concerned aspects (Wang *et al*., 2019). Therefore, a clear need arises for differentiating the impact of seasonality across accommodation features.

2.3 Trend Effects: Emerging feature importance

Beyond seasonal effects, accommodation features may also be influenced by trend effects, i.e. patterns of gradual changes over time. This study investigates whether trend effects can be observed in travelers' perceptions of the importance of accommodation features. P2P accommodation offerings have transformed the hospitality industry, and their popularity has grown considerably (Anwar, 2018). While cost benefits initially were a primary motivation to choose P2P settings (Hamari *et al.* 2016), they have become less influential in travelers' decision-making process (Wang and Jeong, 2018) since P2P accommodations became more extravagant and cater to consumers' individualization aspirations (Hardy and Dolnicar, 2018). The desire to immerse oneself in a foreign environment has been identified as a key motivation to use P2P accommodations, which are typically located in more residential, less touristy areas than hotels (Hamari *et al.*, 2016). In addition, the availability of more space and home benefits are driving factors for choosing P2P accommodation (Guttentag *et al.*, 2018). Thus, the importance of various accommodation features may have evolved. This study investigates whether systematic changes can be identified for single accommodation features. By conducting a time series analysis of online reviews, we aim to differentiate the patterns of underlying long-term trends of the importance of single accommodation features.

2.4 Disruption Effects: The COVID-19 pandemic as disruptive event

The relevance of accommodation features can also be influenced by one-time disruptive events. The COVID-19 pandemic had unprecedented effects on the size and structure of travel demand, impacting both the hotel industry and P2P market (Cheng *et al.*, 2023a). Therefore, the COVID-19 pandemic is chosen as an application case for disruption effects. In the specific case of the Canary Islands, the Spanish government was forced to take decisive action (Han *et al*., 2020): On 14 March 2020, the Spanish government declared a nationwide state of alarm, which imposed stringent lockdown measures. This initial lockdown was gradually eased in stages starting in May 2020. Subsequently, the Spanish government adopted a more region-specific approach to manage localized outbreaks, reopening the borders in July 2020. These measures included regional restrictions, curfews, capacity limits in public places, social distancing guidelines, and mask mandates (Frontur, 2019).

The COVID-19 pandemic, therefore, aligns with Kilkki *et al.*'s (2019) definition of disruption. Owing to lockdowns, travel fear, and uncertain quarantine measures, consumers were significantly restricted in their vacationing choices, leading to an adapted decision set for tourism accommodation choices. For instance, travelers were reluctant to book shared flats in late 2020 (Bresciani *et al.*, 2021) and the importance of hotel attributes shifted during different phases of the pandemic (Hu *et al.*, 2021). Enhanced preventive measures provided by hosts positively influenced consumers' attitudes (Qi and Chen, 2022). Ye *et al.* (2022) confirm preference shifts between conventional hotels and P2P accommodation for key accommodation value attributes, such as location.

Since the importance of single accommodation features was clearly influenced by disruption effects, this study examines the effects of the COVID-19 pandemic on the importance of single accommodation features. We aim to distinguish short-term from lasting trend effects that arise from this one-time incident.

3. Methodology

3.1 Case Description: Canary Islands

A dataset of 519,200 traveler reviews from Airbnb accommodations in the Canary Islands was collected through web scraping. The Spanish archipelago located in the Atlantic Ocean offers a highly diverse range of tourism experiences, including sun-and-beach vacations, nature-based holidays, and city trips (Eugenio-Martin *et al.*, 2019). With more than 15 million tourist arrivals in 2018 (Frontur, 2019), it is one of the most popular tourist destinations in Europe. Since it offers mild to high temperatures all year round, it is a non–peak season destination, showing atypical seasonal patterns influenced more by timing and calendar effects in the source market than by climate variations.

For this reason, the Canary Islands were chosen as an “extreme” case in terms of traditional seasonal pattern models to demonstrate the effects of seasonality in atypical, non-peak beach destinations. Due to stable climatic conditions, fluctuations in demand patterns are most likely to be influenced mainly by travelers’ preferences, which change throughout the year. Official tourism statistics (ISTAC, 2018) indicate that more mature travelers visit the Canary Islands in winter, while younger families are expected to visit during the summer school holidays. In the winter, tourists often prefer nature-oriented activities (e.g., hiking), while in the summer, the beaches and pools are the most popular attractions.

3.2 Data collection and processing

The raw data was obtained from AirDNA, an Airbnb data provider, and included publicly accessible review comments between November 2014 and April 2022. This dataset contained a total of 1,043,112 review comments. The Cdl2 *R* package (Ooms, 2022) was used to identify and select English language reviews only, as language processing tools for English are more robust. For estimation stability, the sample was limited to reviews published after January 2015, as very few reviews were available before this date. Finally, 519,200 comments were selected. As shown by Smironva *et al*. (2020), online accommodation reviews do not suffer from more pronounced non-response bias in comparison to offline reviews.

Using the text mining software *R*, time series analyses were performed to investigate changes over time (seasons, trends, and the disruptive event that was COVID-19) on the occurrence (i.e., mentioning) of different accommodation features since we assumed that the frequency of mentions of single accommodation features indicates the importance travelers give to these attributes, as it is common practice in examining customer opinions in mined text (e.g., Hu *et al.*, 2021; Liu *et al.*, 2017). Similarly to other studies, this study used the mentioning frequency within a specified period to identify an attribute's importance within that period. We manually checked reviews to ensure the mentioning of single accommodation features was indeed related to aspects of relevance and not occurring randomly. Table 1 presents the distribution of reviews over the specified time period and reveals that review comments are more frequent in winter than in summer. Notably, a disruptive effect of COVID-19 is evident.

[insert Table 1 about here]

3.3 Variable Selection

To identify suitable features for the analysis, the authors performed a literature review on accommodation attributes, which covered both traditional and P2P perspectives, as previous studies (e.g., Cheng and Yin, 2019) found that travelers consider both traditional hotel and specific P2P attributes when choosing P2P accommodations. Mody *et al.* (2022) find evidence supporting the convergence of attributes considered important to consumers across accommodation segments (hotels and P2P). The most crucial attributes are quality and service factors, followed by amenities (i.e., kitchen, pool) and accessibility and safety.

However, for P2P accommodations, the concept of accommodation experiences expands beyond the room's interior. It also includes aspects such as the overall facilities of the whole apartment or the local neighborhood (Guttentag *et al.*, 2018). Furthermore, P2P guests perceive their stay as providing a more authentic local experience than staying in a hotel (Birinci *et al.*, 2018). For our analysis, we adopt a framework comprising four dimensions: (1) interior (room, cleanliness, household furnishings and equipment, etc.), (2) exterior dimension of the room(s) (e.g., facilities such as a terrace and view), (3) the overall complex of the accommodation (e.g., pool), and (4) the surroundings (relating to the location and accessibility of tourist attractions). To select appropriate feature examples for each dimension, the authors conduct a frequency analysis to identify key attributes.

3.4 Frequency analysis of key attributes

Text mining was used to identify the key attributes of P2P accommodation feature relevance in the sample. Previous works have shown the effectiveness of text mining in analyzing review data to determine feature relevance in the hospitality industry (e.g., Cavique *et al.*, 2022). For instance, Liu *et al.* (2017) used user-generated reviews on TripAdvisor to evaluate hotel attributes, Hu *et al.* (2021) used hotel reviews to assess attribute importance during the COVID-19 pandemic, and Hu *et al.* (2019) scrutinized accommodation reviews to investigate repeat patronage.

Before conducting the time series analysis, we carried out a pre-test and a data check. As shown by scholars (e.g., Liu *et al.*, 2017; Vu *et al.*, 2019), the frequency of mentions of single accommodation features indicates the importance travelers give to these attributes. Thus, we regarded the mentioning of specific features in reviews as an indicator of their importance. Consequently, we performed a keyword analysis of absolute incidences of features, screening for proxies with particular prominence in the analysis context. The screening revealed six key features with specific relevance in the dataset: room, terrace, view, pool, location, and shop.

The authors then examined the mean occurrence of each feature in all reviews, indicating how often each feature was mentioned in the sample. As shown in Table 2, “location” was mentioned most often (approximately 25 percent of reviews), while “terrace” and “shop” were mentioned in about 10 percent of the reviews in the sample. In the context of COVID-19, it is worth acknowledging that two exterior (terrace, view) and two surrounding dimension features (location, shops) demonstrated relatively high relevance of features outside the interior dimension.

Regarding monthly variations, “view” exhibits the highest fluctuation (delta=0.186) over the analyzed period, while “shop” shows the lowest fluctuation (delta= 0.0866). These meaningful variances in the mentioning frequency of each specific feature allowed for a longitudinal data analysis of relative changes in reviews over time. This analysis focuses on relative rather than absolute numbers, thereby overcoming possible limitations of text mining, such as sample selection or omission biases (Humphreys and Wang, 2018).

[insert Table 2 about here]

3.5 Data Decomposition

A decomposition analysis of the time series is conducted for each of the variables. This statistical technique is used to disentangle a time series into its underlying components, including trend, seasonal, and irregular or random variations. The decomposition of a time series provides valuable insights into the data’s patterns and behavior, which can be useful in forecasting, anomaly detection, and decision-making (Hyndman and Athanasopoulos, 2018).

Multiscaling (Zhang *et al.*, 2022) is commonly used in tourism demand forecasting due to its ability to capture the nonlinear and non-stationarity characteristics of time series through several steps, combining decomposition and prediction. Examples of such methods include empirical mode decomposition (EMD) and seasonal trend decomposition (STL). Multiscaling methods have been found suitable for demand forecasting as well (Li and Law, 2020, Xie *et al.*, 2020), although filtering methods have also shown their suitability for forecasting tourism demand in the world’s top 20 destinations (Liu *et al.*, 2023). Given its extensive use (Cleveland *et al.*, 1990), we choose STL as the decomposition method for the time series of the review comments.

First, the researcher has to choose between an additive or multiplicative model. The choice between these models depends on the nature of the underlying time series components. Typically, an additive model is appropriate when the seasonal fluctuations or the random variation around the trend remain constant over time, regardless of the level of the time series. To test this point, we regressed the standard deviation as a function of the mean for the six accommodation features. The results show that the relationship between standard deviation and mean is null at the 99% level of significance for all features, justifying the use of the additive model. It can be written as follows:

$y(t) = Trend(t) + Seasonal(t) + Residual(t)$,

where $y(t)$ is the value of the time series at time t, $Trend(t)$ is the trend component at time t $Seasonal(t)$ is the seasonal component at time t, and $Residual(t)$ is the residual or random component at time t, calculated by subtracting the estimated seasonal and trend components.

In the STL method, the trend and seasonal fluctuations are calculated by using local weighted regression. Results are visualized by locally estimated scatterplot smoothing (LOESS). The decomposition analysis was conducted by using the *R* package “stats”, which allowed the authors to separate the temporal development of accommodation features into trend and seasonal development. In addition, we inspected the remaining data (i.e., the fluctuations that cannot be explained by seasonal or trend aspects). Figure 1 presents the results of this variance decomposition.

[insert figure 1 about here]

Subsequently, we analyze the occurrence of features based on seasonal and trend decomposition. Figure 2 illustrates the seasonal occurrence for each feature. The results show that specific recurring patterns can be identified for each feature. Some features (i.e., shop, location) exhibit high fluctuations throughout the year, while others (i.e., room, pool) show only moderate changes in occurrence. Therefore, we proceeded to further analyze seasonal effects at the level of single features.

[insert figure 2 about here]

4. Findings and Discussion

4.1 Seasonal Effects

Seasonal patterns across each 12-month period for different accommodation features are summarized in Figure 3. The analysis reveals that the seasonality patterns for each feature differ significantly. The importance of "pool" reaches its peak during the summer, while other features such as "view" and "terrace" peak in spring and autumn, and "room" peaks in the winter period. This indicates that an aggregated (shared) view of seasons is not applicable. Instead, it emphasizes the need to separately assess and evaluate the seasonal effects for each of the six accommodation features.

For the features "view" and "terrace," we observe recurring peaks in spring (March, April, and May) and autumn every year, with a low point in June. One interpretation thereof may be that, in spring and autumn, active, nature-seeking travelers value the view from their accommodation relatively more than beach-seeking families on their summer holidays. The "pool" category shows the highest peak during the summer months of July and August, with above-mean occurrence in the shoulder seasons on either side of the summer season (April to June and September to October). The relevance of a pool seems to be highest for summer vacationers (as well as travelers) to the Canary Islands during Easter and fall holidays (e.g., families with school children). These findings are in line with previous research that reports a high preference for swimming pools among children on holiday and highlights that their preference is taken into account by their parents (Curtale, 2018).

[insert figure 3 about here]

Regarding the "room" variable, we observe a peak in the winter months. During this colder period of the year, travelers spend more time indoors and, consequently, place a higher value on the importance of the interior and amenities. In addition, winter tourists are often pensioners with higher expectations for the quality of the room and its amenities. These interpretations align with research by Ananth *et al.* (1992) and Caber and Albayrak (2014), who find that mature travelers value different accommodation attributes compared with younger travelers. Indeed, these findings confirm the importance of segmentation for hotel attributes (e.g., Wong and Chi-Yung, 2002).

As hypothesized, we were able to identify distinct seasonal effects on travelers' assessment of single accommodation features, in terms of both magnitude and timing, through a time series analysis of online reviews. The only fluctuation that cannot be explained by face validity is the "shop" category with peaks in March, April, July, and October.

4.2 Trend Effects

Next, we analyzed the sample based on a trend perspective. Figure 4 depicts the trend development for each feature between the years 2015 and 2022. We observe both features with enduring downward (shop, room) and upward trends (location), as well as features exhibiting changing trend patterns over the years (pool, terrace, view). Regarding the latter, both the "view" and the "terrace" categories show an initial decline starting in 2016 and a period of stagnation before increasing in 2021, specifically from May 2020 to mid-2021. The initial drop in 2016 can be associated with the establishment of Airbnb in the European market. The increase in the occurrence of “view” and “terrace” in 2021 coincides with the climax of the COVID-19 pandemic and its measures of social distancing.

The “room” and “shop” categories exhibit a persistent downward trend from 2017 onward. Particularly, the “room” feature (e.g., equipment, furnishings, design, size, atmosphere) seems to have lost relevance. Interpreting the data in light of trend effects, one could argue that, during Airbnb’s early years, the rooms were perceived as novelty benefit. Travelers were possibly intrigued by the novelty of the business model and by extravagant or unique accommodations (Guttentag *et al.*, 2018). For instance, Guttentag and Smith (2022) found that early Airbnb adopters were less interested in hotel-like features and more inclined to use alternative, non-hotel lodging options. By contrast, late adopters were seeking less novelty and innovation, suggesting a saturation of Airbnb’s novelty benefits. More professional accommodation offerings as well as travelers’ familiarity with platforms like Airbnb may have led to a decrease in feature relevance.

Moreover, we observe an ongoing upward trend for the “location” feature, which typically refers to the accommodation being conveniently close to tourist attractions, transportation, and points of interest (Shoval *et al.*, 2011). We find a considerable increase of location´s relevance between 2015 and 2019, presumably as travelers seek more individuality and uniqueness (Berrada, 2017). This may be also be explained by an increased spatial distribution of Airbnb rentals over time, transitioning from a concentration in tourist centers to a center–periphery structure (Zhang and Fu, 2022) and, thus, offering travelers more options in terms of locations. In sum, the data shows that the relevance of different accommodation features is indeed influenced by long-term trend effects, as exemplified by Airbnb’s market penetration.

As hypothesized, we could differentiate the patterns of underlying long-term trends of single accommodation features’ importance through a time series analysis of online reviews.

Looking at the first year of COVID-19 (the pandemic's impact on European tourism became palpable in March 2020), we find a steep decline in the occurrence of the "pool" and "location" categories. For "location," the generally consistent increase was interrupted by a brief decline in 2020, but it increased again in 2021 and 2022. The occurrence of "pool" returned already in late 2020. There was also a higher occurrence of "view" and "terrace" in 2020, followed by a decline after 2021. This already hints towards diminishing long-term effects of the COVID-19 pandemics, as will be discussed in section 4.4.

[insert figure 4 about here]

4.3 Single-Time Disruption Effects Caused by COVID-19

An analysis of the remainder is used to identify one-time disruptions in the time series (Figure 5). The residual variance is especially high in the period from April to June 2020, i.e., the first lockdown phase in Europe, when traveling was virtually impossible, and subsequently decreased in the following months of COVID-19 restrictions. Zheng *et al.* (2021) provide a possible explanation, showing that COVID-19 generated an unprecedented level of fear caused by the severity of and susceptibility to the threat. This led to new (protective) travel behaviors immediately after the outbreak of the pandemic.

Both the "view" and "terrace" categories exhibit notably large unexplained deviations in May 2020 and June 2020. These values indicate that neither seasonality nor trend effects were responsible for the change in keyword occurrence in the reviews. Simultaneously, a shift in the long-term trend can also be observed with steep increases as of May 2020 (Figure 4). This hints at the influence of external factors in the early stages of the COVID-19 pandemic on European tourism in the spring of 2020. These findings enrich findings of enhanced seasonal fluctuations in tourism demand due to COVID-19 (Yabanci, 2023). They align with previous studies that claim customers' preferences for specific hotel attributes changed, such as increased demand for hotels and rooms with access to or views of blue spaces due to COVID-19, while the importance of location decreased (Srivastava and Kumar, 2021). However, they contradict more recent findings by Ye *et al.* (2022).

The remaining data of the "pool" category suggests a non-explicable development in April, May, and June 2020, indicating a significant impact of COVID-19. Similar effects are observed in the trend development for the relevance of shops close to accommodation facilities, with the lowest point in the spring of 2020 and an increase in 2021. Consequently, we can conclude that COVID-19 caused one-time disruption effects on the relative importance of accommodation features, with the effects varying in terms of magnitude and duration.

[insert figure 5 about here]

4.4 Long-Term Effects Caused by the Pandemic

Trend shifts before and after the spreading of COVID-19 indicate possible long-term effects caused by the pandemic. However, no definitive effect could be observed. By contrast, several non-lasting effects are revealed as almost all trend patterns reverse after the immediate COVID-19 situation, and the old trends are re-established. For instance, the occurrence of the "view" category decreased before COVID-19, then increased again to peak in May 2021 before becoming less relevant. This suggests a non-persistence in the disruption effect. With the onset of the COVID-19 pandemic, tourists who traveled again after experiencing containment and various regional lockdowns may have felt a stronger desire for nature and a sense of freedom of movement, as reported e.g. by Jarrat (2021). The decline in popularity of the "view" category after 2021 might indicate a changed interest among people after most restrictions were removed. Comments then focused on reinstated social activities, such as enjoying the pool, shopping, and seeking a good location.

The same could be assumed for the “terrace” category, which shows a slow decline after a potential novelty effect in 2016, followed by a steep increase from May 2020 to mid-2021 during the pandemic. During the time, guests possibly placed a higher value on outdoor space, perhaps half-expecting quarantine measures due to changing travel restrictions. However, data suggests that access to a terrace became less relevant after 2021, when most restrictions and quarantine measures were lifted.

The “pool” feature (e.g., private or shared pool) experienced its lowest occurrence in the spring of 2020, coinciding with the advent of the pandemic in Europe. We assume that preventative and protective measures, such as physical distancing and mask-wearing, along with pool closures, led to the diminished relevance of pools. According to the data, travelers seemed to be more comfortable using pools in 2021, which may be attributed due to the general availability of COVID-19 vaccines in Europe (Gössling and Schweiggart, 2022).

The relevance of “location” declined at the beginning of the pandemic, which can be interpreted as an indication that the location’s proximity to sightseeing spots or city centers became less relevant to travelers. During that time, travelers preferred more secluded areas where it was easier to maintain physical distance and manage their fear of contamination. With fewer restrictions in 2021, “location” became more relevant again since attractions in the surroundings were once again accessible. These findings align with the research of Park *et al.* (2021), who show that travelers had a diminished preference for crowded places during the pandemic.

5. Discussion and conclusions

5.1 Summary and conclusion

In this case study application, we demonstrate how time series can disentangle different temporal effects by decomposing seasonal, trend, and disruption effects. A new perspective on seasonality is provided by showing that accommodation features possess different seasonality patterns. Findings also identify several trend effects which can be linked to the diffusion of P2P accommodation offers. Finally, in the context of the COVID-19 pandemic in the Canary Islands, our case study reveals notable short-term disruption effects, however no lasting long-term effects.

Method-wise, we present a novel application of the time series analysis method. While established decomposition/forecasting analyses rely on “hard data” such as revenue or sales data (see e.g, Song *et al*., 2019), our study applies robust analyses to investigate “soft data” of written reviews. In so doing, we explore the method’s potential for unstructured content, specifically user-generated online reviews by travelers.

5.2 Theoretical implications

The findings demonstrate the need to look beyond the traditional two-peak seasonality and show that different seasonal effects influence individual preferences for accommodation features. This highlights the need for a more nuanced approach to seasons, based on different guest groups and their motives for traveling. Scholars like Ananth *et al.* (1992) have already shown that accommodation features´ relevance differs between age groups. Researchers could further assess single accommodation features’ temporal relevance for different guest groups (segments) throughout the year.

By examining accommodation features’ relevance over multiple years and differentiating between temporary and permanent importance shifts, we identify long-term trend effects and one-time disruption effects due to COVID-19. Trend analyses indicate important shifts in accommodation features' relevance well before the COVID-19 pandemic's disruption effects. In contrast, the pandemic's effects seem to be limited to short-term temporal changes in accommodation features' relevance, since no long-lasting effects were verified.

Our study demonstrates the potential of time series analysis for analyzing unstructured content from user-generated content. The data and the methodology indicate fluctuations in and trend effects of accommodation features´ importance. As such, the latter is applicable to a larger data sample, which allows more long-term changes to be interpreted.

Since accommodation managers specifically aim to promote "green" practices (Yan *et al.*, 2023) to address and monetarize current consumer preferences (Gupta *et al*., 2023), our time series approach could be extended to also investigate sustainability features. Forecasting travelers' needs in a temporal dimension could include pro-environmental attitudes, thereby differentiating specific target groups. However, caution should be maintained regarding not engaging in greenwashing practices (Majeed and Kim, 2023).

5.3 Practical implications

This study has valuable insights for both practitioners and students. They can use our method to identify accommodation features' seasonal dependencies by examining the guest reviews of these features closely to infer specific seasonal patterns. While many accommodation providers might have intuitively applied this practice, a more structured approach could potentially increase profits. Improving time-specific advertising campaigns for accommodation and highlighting distinct features across different communication channels could help differentiate between target groups.

On a more conceptual level, the results address an important, but underexplored, issue in pricing research by indicating seasonal demand issues (Vives *et al.*, 2018). The evidence of seasonal variations at the attribute level might offer new approaches to price optimization: Future models might include seasonal discrepancies between static supply and seasonally varying demand for different accommodation features. Price differentials between two market offerings, for example, a room with a view and one without, should not be fixed the entire year, but depend on the feature's seasonal relevance for travelers. That is, a higher price should be charged for a room with a view in spring and fall (important months for "views"), while asking a (relatively) smaller surcharge in the summer months (less important for "views"). Hence, future price optimization techniques could include an attribute-based seasonal price discrimination.

P2P platforms could leverage this knowledge further and develop a tool for accommodation providers that monitors trends based on guest reviews or searches continuously (see Haldar *et al.*, 2020 for initial ideas). This allows real-time recommendations derived from trend and seasonal analyses to be used for demand optimization, price and product management in P2P networks (e.g., Benítez-Aurioles, 2022). In turn, accommodation providers can better address customers' seasonal wants and needs, as well as market and highlight specific seasons' accommodation features. Daily marketing can even be used to target insights (e.g., "*Demand for pools is currently rising. You should now highlight this feature in your house description*"). Consequently, we consider our work an initial step toward the implementation of a real-time forecasting model for tourist accommodation features.

5.4 Limitations and Future Research

Despite its novel contributions, our study also has limitations. While the authors selected relevant accommodation features based on a literature review, they only examined six features due to their respective prominence in the sample data. Future research could build composite models across different accommodation features (Pan and Yang, 2017) and add other data sources, as e.g. website traffic, weather (Li *et al.* (2017), to create a joint model for assessing temporal variations of accommodation feature preferences.

While there are multiple variants of time series analysis (Song *et al*., 2019), the contingency principle implies that used methods need to fit to study objectives. Our decomposition of traveler reviews sought to identify temporal variations of accommodation features´ relevance. Future studies can further insight by addressing forecasting issues with more sophisticated methods.

This study examined seasonality for a limited geographic area and specific climate conditions, being P2P accommodations in the Canary Islands. Future studies could expand the trend and seasonality analyses of accommodation features to hotel settings and other destinations with different seasonal characteristics (one-peak, two-peak, or multiple-peak), climate conditions, or target groups. Finally, keyword occurrence is neutral and does not provide a positive or negative assessment of the specific feature. To link this research to satisfaction studies, consumer sentiment needs to be integrated (e.g., Wang *et al.*, 2018), while potential non-response biases have to be addressed. Such future analyses might provide insights into the dynamics of consumer satisfaction.

Despite these limitations, this study lays the groundwork for scholars and practitioners aiming to better anticipate tourist accommodations according to the preferences of different guest structures and target groups. Time series analysis can be a valuable tool for tourism forecasters, allowing them to observe both long-term and cyclical trends in visitor behavior. Future research could use this first application case to build more elaborate models for analyzing and even forecasting demand for specific accommodation features. Continuous implementation of more elaborate forecasting through text mining of time-series data could significantly enhance real-time monitoring and management of tourist accommodation.

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