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Business continuity management in the sharing economy: Insights from Airbnb online reviews

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ABSTRACT

The aim of this paper is to demonstrate how text mining of online reviews can support business continuity management in the sharing economy during market turbulence. We use topic modelling and sentiment analysis of Airbnb online reviews to identify specific areas where short-term rental hosts can harness the power of the sharing-economy business model to bounce back from market disruption. The dataset comprises 894,686 online Airbnb reviews from the pre- and post-Covid periods. We approach the pandemic as a paradigm example of a high-impact, external market shock and infer insights and recommendations from the dataset that are relevant to the general understanding of business continuity management in the short-term rental, peer-to-peer sharing economy.

1. Introduction

Business continuity management is a core area of business strategy, business modelling and crisis management (Torabi et al., 2014). Prior literature has investigated how large firms and organisations as well as SMEs respond to major market disruption (Widianti et al., 2024), but business continuity in the sharing economy is currently under-researched. For example, studies have shown that Airbnb has remained resilient during the pandemic with 6.6 and 7.7 million active listing globally in 2022 and 2023, respectively.[1] But we know very little about how individual hosts coped with the pandemic and the strategies they used – or could successfully have used – to bounce back from the crisis (Kourtit et al., 2022; Milone et al., 2023). This is pivotal as the Covid-19 pandemic is a paradigm example of how external conditions can disrupt the entire economy. As such, gaining insight into how consumer preferences in the Airbnb market changed in response to the pandemic provides an opportunity to draw general conclusions about business continuity strategies that can be deployed in response to similar types of disruption in the future (Dolnicar & Zare, 2020). This study investigates how peer-to-peer rental hosts can use customer insights from online reviews to identify specific business areas which are both within their control and where the peer-to-peer business model has distinctive advantages to the traditional service economy.

Business continuity management is the strategic response to internal or external disruptions that pose a substantive risk to critical business operations (Torabi et al., 2014). Widianti et al. (2024) have conducted a review of recent literature in business continuity management and report that strategic frameworks for developing and executing business continuity during disruptions have been studied in certain sectors, e.g. IT (Kutame et al., 2021), banking (Aronis & Stratopoulos, 2016), manufacturing (Torabi et al., 2014) and across specific company types such as multinational companies (Margherita & Heikkilä, 2021), SMEs (Ma et al., 2023), family businesses (Calabrò et al., 2021). Whilst business continuity management in start-ups has also been investigated, there are limited studies specifically focusing on the tourism and hospitality setting, such as peer-to-peer rental market (Kim & Pomirleanu, 2021). Our study bridges this gap. This is a significant contribution because of the size and importance of the short-term rental market to national GDP, but also because the key business agents – individual hosts – are often not business professionals and therefore stand to benefit significantly from recommendations on how to improve their peer-to-peer operations.

Our unit of analysis is London's Airbnb market, which is of interest for two main reasons. First, London's visitor economy contributed £36

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[1] https://news.airbnb.com.

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billion a year in revenue and employed 700,000 people pre-Covid (London & Partners, 2017). Second, London had the highest volume of active rentals in major cities worldwide in 2018 and was previously considered the world's Airbnb capital (Statista, 2021). Therefore, the insights derived from London's Airbnb market can generate general insights into business continuity management in the peer-to-peer rental market.

Specifically, our study utilises datasets comprising the rental and host details of 46,175 Airbnb listings across 33 London boroughs, alongside the corresponding 894,686 online guest reviews spanning from December 21, 2009 to 31 March 2022. Employing text mining techniques, including topic modelling and sentiment analysis, we extract customer opinions and attitudes from these extensive unstructured reviews, and compare the corresponding statistics between the pre- and post-Covid periods. Notable shifts in customer opinions and attitudes are observed, which enable us to identify opportunities for developing business continuity capabilities within the peer-to-peer rental market.

2. Data

Two datasets from Inside Airbnb were used in our analysis: reviews.csv and listing.csv.[2] Inside Airbnb is an open-source project launched in 2016, which reports the web scraped data on Airbnb across major cities worldwide, which have been widely used in different research projects (Chen et al., 2022). Our datasets covered reviews and listing information between December 21, 2009 and 31 March 2022 in London. This period of data allowed us to examine the impact of Covid-19 on the short-term rental market. Specifically, listing.csv is a tabular data that contains the key information related to Airbnb listings which are reviewed by guests in reviews.csv. It includes listing id, name, description, neighborhood, URL, latitude, longitude, room type, facilities, average review rating, host name, host id, host response time, and so on. Reviews.csv contained 1,065,151 reviews in total, which provided detailed review comments from Airbnb guests about their experience in different listings in London. As they were scraped from Airbnb webpages, the review text may contain HTML codes like ⟨br /⟩. These are the noisy information, so we firstly removed them from each review. Emoticons and emojis are the hieroglyphic languages that are used to express emotions. As such, they are important in sentiment analysis and should be properly dealt with in data pre-processing (Novak et al., 2015). To avoid the effects of emoticons and emojis on topic modelling results, we performed topic modelling on text-only reviews but sentiment analysis on text-only reviews, emoticons and emojis.

Languages of guest reviews were detected using the Compact Language Detector 2 (CLD2). It is a pre-trained Naïve Bayesian classifier that can probabilistically detect over 80 languages in Unicode UTF-8 text. We detected 54 languages in our data, including one shown NA, representing the CLD2's inability to detect the language from its database. Non-English reviews were removed from our analysis mainly due to their low representation in the dataset (see Appendix A). Moreover, using English-only reviews can produce more accurate and consistent results from topic modelling and sentiment analysis. In addition, we followed text analysis convention (Silge & Robinson, 2017) and converted all texts into lower case letters. We then removed reviews that contained less than 3 characters or no text because they offered trivial information in text mining. The pre-processed review data was then merged with the corresponding listings and hosts information from the listing.csv dataset. Finally, the pre-processed data in our analysis included 894,686 English reviews posted by 755,524 guests on 46,175 listings from 32,139 hosts in 33 London boroughs over 145 months. Table 1 summarises the dataset for the pre-covid, lockdowns, and reopening periods, where the lockdown and reopening periods are based on the reports from UK Institute for Government.

[2] http://insideairbnb.com.

3. Analysis of results

In addition to the text mining techniques utilised for raw data pre-processing mentioned above, our analysis incorporates several other methods such as statistical inference, topic modelling, and sentiment analysis. This section delves into how these methods were employed and provides a comprehensive analysis of the results.

3.1. Changes in London's airbnb market between the pre- and post-covid periods

This section provides a brief overview of London's Airbnb market between the pre- and post-covid periods. Fig. 2 presents the monthly time series plots for the number of Airbnb listings, hosts, guests, and guest reviews from December 21, 2009 to 31 March 2022. The Airbnb market grew steadily in London since 2009 before the Covid-19 outbreak. The numbers of listings and reviews are slightly more than those of hosts and guests, respectively. In addition, seasonality patterns can be observed with summer months as the peak seasons in London. The impact of the Covid-19 is also apparent as the long-run growth in both supply and demand sides were interrupted during the pandemic. The time points of three lockdowns and the reopening are highlighted in Fig. 1. The data showed a dramatic decrease in the number of Airbnb listings, hosts, guests, and guest reviews during the first three months of the 1st lock-down and a slight recover in subsequent months. During the 2nd lockdown, a slight decrease in the four variables was observed. During the 3rd lockdown, surprisingly, a steady increase in the number of Airbnb listings, hosts, guests, and guest reviews was observed. Finally, the numbers of Airbnb listings, hosts, guests, and guest reviews appeared to bounce back to the "normal" levels after the reopening.

Although the Airbnb market in London shrank after the Covid-19 outbreak, the number of listings per host and the number of reviews per guest were not affected. As Fig. 2 exhibits, there was a steady growing trend for the number of listings per host, and the number of reviews per guest keeps stable around 1 for decades. This may be because although some Airbnb hosts quit the market when the pandemic hit, those remaining were quite optimistic and remained highly visible in the market. This is aligned with Kourtit et al. (2022), which reveals a similar pattern, suggesting that those "professional hosts" are more likely to stay in the sharing economy and thus driving up the number of listings per host.

Fig. 3 shows the changes in the types of listings over time. Private room and entire place are two dominant types of listings. Before the Covid-19 pandemic, there were more than 50% listings offered in terms of private rooms while about 40% were entire places. During lockdowns, the percentage of entire places increased to nearly 60% while private rooms decreased to about 40%. Such pattern seemed to prevail after the reopening as our results showed that upon reopening, the percentage of private rooms slightly increased but was still less than 50%. The results are in line with Bresciani et al. (2021), which further suggests that due to customers' needs for physical distance during the Covid, entire place was preferred over shared accommodation on Airbnb and over hotel rooms.

3.2. Major topics in online guest reviews

This study implemented the structural topic model (STM), one recent advancement from machine learning techniques that has been widely used in the tourism and hospitality literature (Ding et al., 2020; Hu et al., 2019), with the R package 'stm' (Roberts et al., 2019). The listing price per night, the number of minimum nights, the total number of reviews, and the number of reviews per month were used as covariates in topical prevalence. Following Geva et al. (2016, pp. 501–524), several automated tests were performed to search for the optimal number of topics K

Table 1
Summary of the Airbnb data into the pre-Covid, during lockdowns and upon reopening periods.

Period	Year	Dates	No. of months	No. of listings	No. of hosts	No. of reviews	No. of reviewers
Pre-Covid	2009–2016	[2009-12-21, 2016-12-31]	82	9,921	8,485	152,205	139,378
	2017	[2017-01-01, 2017-12-31]	12	12,554	10,169	114,586	105,312
	2018	[2018-01-01, 2018-12-31]	12	16,765	13,068	163,618	148,401
	2019	[2019-01-01, 2019-12-31]	12	21,442	15,789	220,756	199,023
	2020	[2020-01-01, 2020-03-22]	3	12,451	9,150	40,697	37,681
During lockdowns	2020	[2020-03-23, 2020-12-31]	9[a]	9,358	6,422	31,550	28,099
	2021	[2021-01-01, 2021-07-18]	7	9,827	6,292	40,407	35,601
Upon reopening	2021	[2021-07-19, 2021-12-31]	5[b]	17,803	11,000	97,869	87,189
	2022	[2022-01-01, 2022-03-31]	3	12,011	7,887	32,998	30,133

[a] On 2020-03-23, PM announces the first lockdown in the UK, so the 9 days from 2020 to 03–23 to 2020-03-31 are not accounted for a full month.
[b] Since 2021-07-19, most legal limits on social contact removed in England, and the final closed sectors of the economy reopened so the 13 days from 2021 to 07–19 to 2021-07-31 are not accounted for a full month.

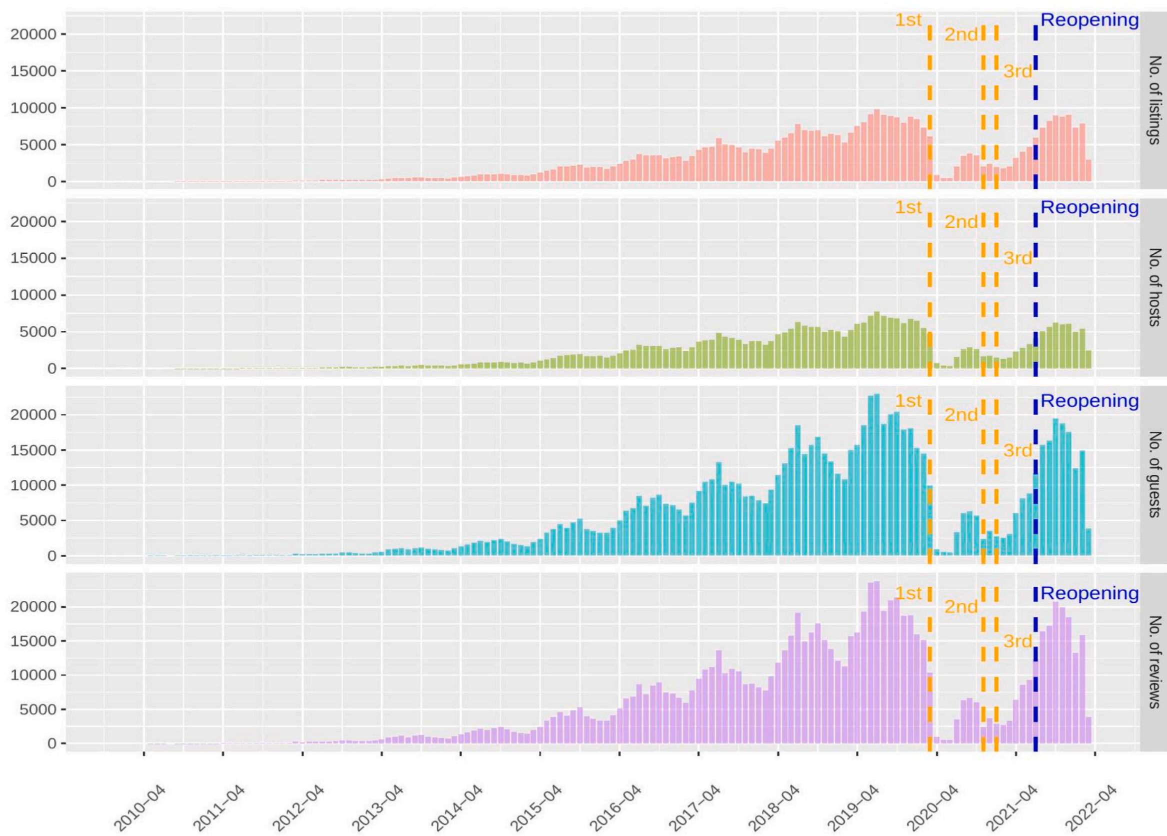

Fig. 1. Monthly time series plots, where the vertical dashed lines (in orange colour) show the time that UK government announced national lockdowns and the vertical dashed line (in blue colour) shows the reopening. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

from the range between 5 and 30 (Appendix B). We found that $K = 11$ could achieve the best trade-off between the model's predictive power and the average semantic coherence of the model's topics. Therefore, we used $K = 11$ to generate topics from the STM for our analytics.

Table 2 summarises the identified 11 topics of Airbnb guest reviews. The most representative words within each topic are also presented, which have the highest probabilities inferred from the topic-word distribution parameter. Given that each review is a mixture of corpus-wide topics, we further analysed the representative reviews for each topic, in which the proportion of the focal topics was the largest (Appendix C). Thereafter, we labelled each topic based on those representative words and reviews. Our labelled description of topics (see the second column "Description" in Table 2) is consistent with previous literature, particularly in hospitality or service industry (Hu et al., 2019; Zhang, 2019).

Specifically, Topic 1 is about a guest's check-in or check-out experience. When the topic is mentioned, most of the representative reviews are associated with negative sentiments, such as disappointments. Topic 2 is about public transportation as all the representative reviews mention the walking distance or time to bus or tube stations. Topic 3 is related to host communications, with a special focus on the timely responses to guest queries. Topic 4 is about the cleanliness of the accommodation. The representative reviews show that guests would appreciate clean accommodation provided by hosts as they are predicted with a bit higher sentiment score than other topics. Topic 5 is also related to the Airbnb listing location. Different to Topic 2 which discusses the detailed walking distance or time to specific bus or tube stations, the representative reviews in Topic 5 only mention good transportation links and local areas. Following Hu et al. (2019), we refer Topic 5 to describe if a listing has a decent location in general. Topic 6 describes room facilities such as toilet, sofa, shower, and kitchen. Topic

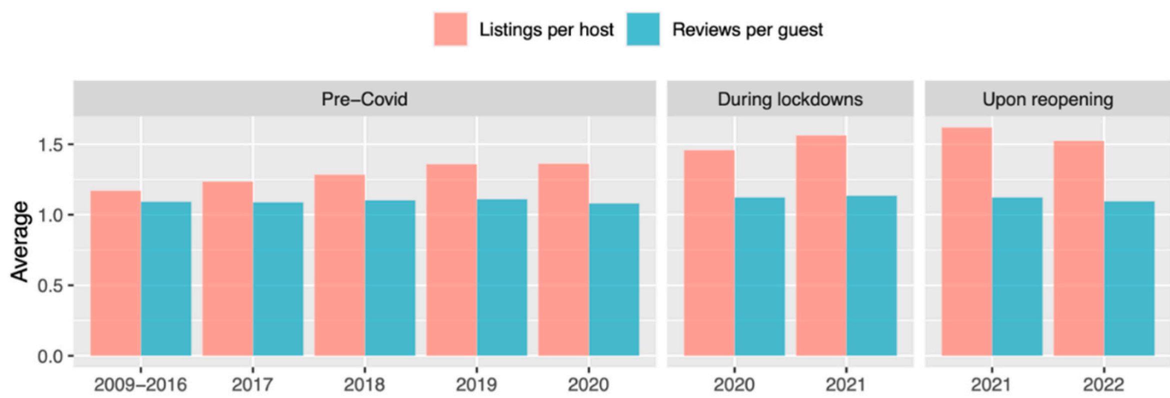

Fig. 2. Listings per host vs reviews per guest over time.

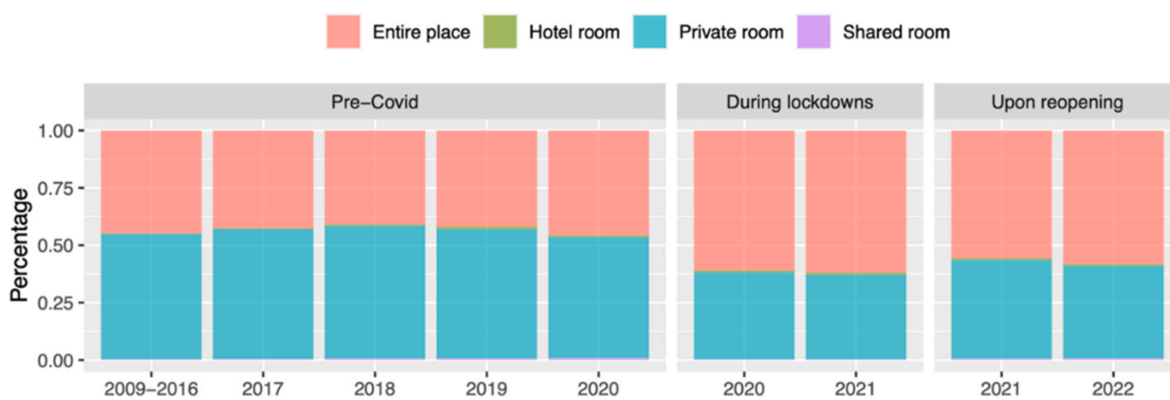

Fig. 3. Changes in the types of places over time.

Table 2
Summary of topics in guest review comments.

Topic	Description	Top words [a]	Topic proportion
1	Check-in & check-out	evening, day, arrive, time, get, first, didn't	6.77%
2	Public transportation	station, nice, london, bus, walk, minute, city	7.50%
3	Host communication	host, great, location, help, friend, excellent, accommod	12.33%
4	Cleanliness	stay, place, recommend, clean, definitely, really, comfortable	15.28%
5	Decent location	great, location, easily, london, close, flat, love	11.47%
6	Room facilities	bed, room, bathroom, kitchen, small, bedroom, shower	8.00%
7	Local amenities	walk, park, restaurant, shop, tube, street, minute	7.74%
8	Accuracy	everything, apart, perfect, need, thank, flat, well	9.34%
9	Value	good, room, value, price, money, hotel, check	4.81%
10	Food service	home, house, love, welcome, room, feel, beautiful	13.47%
11	Room size & good feeling	space, well, airbnb, place, clean, comfortable, flat	3.30%

[a] Words within each topic with the highest probability inferred from the topic-word distribution parameter.

7 is another location-related topic, with a special focus on local amenities such as park, restaurant, and shops. Topic 8 is about accuracy - if the listing is as described in adverts or meets the expectations. Topic 9 discusses if the listing is good value for money. Topic 10 is related to food services as many representative reviews mention nice teas and breakfast. Compared to other topics, Topic 11 is slightly more mixed and covers terms related to room size and good feeling.

The network structure of the 11 topics was then estimated using the Meinshausen-Buhlmann method (Zhao et al., 2012). As Fig. 4 shows, Topic 2, Topic 5, and Topic 7 are highly correlated as they all pertain to the location and convenience of the Airbnb listing. Guests frequently mention the ease of access to public transport, the general desirability of the location, and the availability of nearby amenities such as parks, restaurants, and shops. This is consistent with the findings of Hu et al. (2019) and Zhang (2019), who highlight that location-related factors are crucial in guest decision-making and satisfaction. Topic 1, Topic 6 and

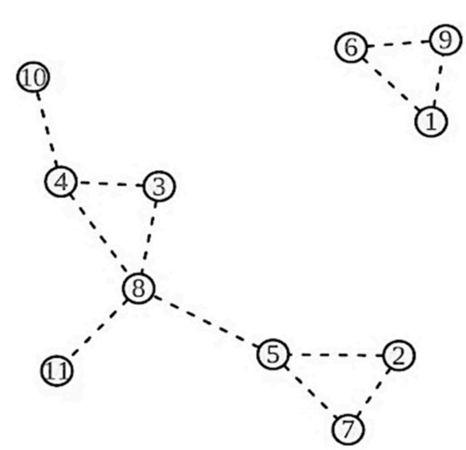

Fig. 4. Graphical representation of topic correlations.

Topic 9 are interconnected as they address fundamental aspects of the guest experience. Efficient check-in and check-out processes, adequate room facilities, and perceived value for money are basic expectations that influence overall guest satisfaction. This aligns with the expectancy-disconfirmation theory (Abrate et al., 2021) and the concept of service quality (Ding et al., 2020), which suggest that meeting or exceeding basic service expectations is crucial for positive guest reviews. Other studies (Gavilan et al., 2018; Hu et al., 2019) also support the idea that operational efficiencies and perceived value are key determinants of customer satisfaction in the hospitality industry.

3.3. Changes in guest review topics before, during, and after the pandemic

The comparison of topic proportions between the pre- and post-Covid periods involved further division of the post-Covid phase into two segments: during lockdowns and upon reopening, as illustrated in Table 1. Given that the pre-Covid period spans over 10 years of data, significantly longer than the post-Covid timeframe, we specifically examined the most recent pre-Covid period (2018–2020) to allow more reliable comparison. This timeframe, from 16 March 2018 to 22 March 2020, matches the 738 days of observations in the post-Covid period. In total, we analysed 607,469 reviews, including 404,645 reviews from the pre-Covid period, 71,957 reviews during lockdowns, and 130,867 reviews upon reopening. Fig. 5 presents plots of the topic proportion

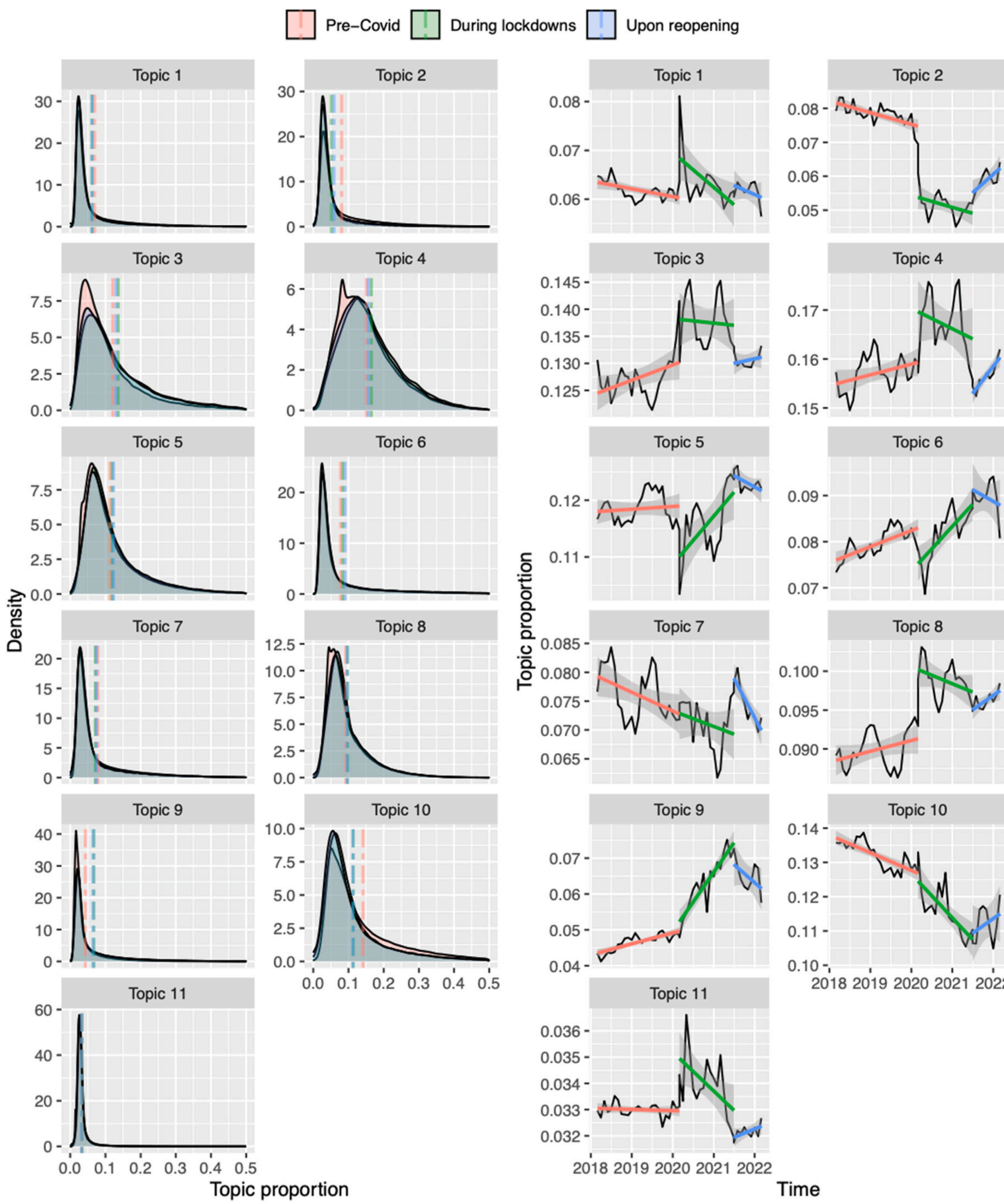

Fig. 5. Topic proportions in the periods of pre-Covid (2018–2020), during lockdowns and upon reopening.

distributions and their evolution over time among the periods of pre-Covid, lockdown and reopening, whereas Table 3 summarises the statistics of the pre- and post-Covid periods and the *t*-test results of comparing their means.

Several findings are worth mentioning. First, in line with other topic modelling studies (Hu et al., 2019; Zhang, 2019), all identified topics exhibit a positively skewed distribution with a long right tail. This characteristic arises because certain topics may encompass a broader range of terms, resulting in a higher probability assigned to a larger number of words, thus leading to the observed skewed distribution. Second, while no single topic overwhelmingly dominates, Topic 3 (host communication), Topic 4 (cleanliness), Topic 5 (decent location), and Topic 10 (food service) consistently exhibit the largest topic proportions (approximately 50% in total) across both pre- and post-Covid periods. Each topic accounts for more than 10% of the total topic proportion in most cases, indicating their prevalence among guest reviewers. Third, Topic 1 (check-in & check out) remains unchanged across all three periods, with no significant difference observed in pairwise hypothesis testing between its means. However, the proportions of the remaining topics vary significantly across the three periods. Notably, the topic proportions between lockdown and reopening periods are significantly different ($p < .001$). Fourth, since the onset of lockdown measures, the proportions of Topic 2 (public transportation) and Topic 10 have notably decreased compared to pre-Covid but they exhibit an upward trend since the reopening phase. Conversely, the proportions of Topic 5 and Topic 6 (room facilities) have shown a steady increase over time. However, despite observing higher proportions of Topic 3, Topic 8 (accuracy), and Topic 9 (value) in the post-Covid periods compared to the pre-Covid period, they display significant decreases upon reopening. This suggests a likelihood of reverting back to pre-Covid levels, similar to the patterns observed for Topic 4 (cleanliness), Topic 7 (local amenities), and Topic 11 (room size & overall satisfaction). Upon reopening, the proportion of Topic 2 and Topic 10 are much lower than the pre-Covid ($p < .001$) but there is an upward trend compared to the lockdown period. On the other side, although the proportions of Topic 5, Topic 6 and Topic 9 in the post-Covid period are much higher than those in the pre-Covid, they show decreasing trends compared to the lockdown period. This suggests that it is very likely that they will drop back to the pre-Covid levels.

3.4. Changes in guest review sentiment before, during, and after the pandemic

The sentiments expressed in guest reviews were analysed using lexical-based sentiment analysis. Specifically, we used the widely used AFINN lexicon (Nielsen, 2011) as it includes sentiment scores for detected emoticons. Additionally, the detected emojis were translated into corresponding text descriptions, facilitating the application of the AFINN lexicon to score sentiment. Consequently, the final sentiment score for each guest review comprised sentiments from text-only content, emoticons, and emojis (Appendix C). It is worth noting that reviews contain mixed topics with varying proportions, while the calculated sentiment score is determined at the review level. Fig. 6 illustrates the distributions of sentiment scores for the periods of pre-Covid (2018–2020), during lockdowns, and upon reopening. Their mean values are recorded 6.36, 6.01, and 6.03, respectively. Notably, there appears to be no significant difference in pairwise hypothesis testing between the means for the periods of lockdowns and upon reopening ($p = .55$). Both periods exhibit significantly lower sentiment scores compared to the pre-Covid period.

Sentiment analysis and topic modelling are different types of analytics. In sentiment analysis, each review comment receives a sentiment score. In topic modelling, each review comment is associated with multiple topics, and each topic with a predicted topic proportion. To gain deeper insights into the potential co-evolution or contribution of each topic to changes in sentiment, we develop predictive models to examine the relationship between topic proportions and sentiment scores. Fig. 7 presents the correlation plots for each examined period. Due to the large number of reviews in the dataset (607,469 in total, with 404,645 reviews from the pre-Covid period, 71,957 reviews during lockdowns, and 130,867 reviews upon reopening), a heatmap graphical representation is used instead of scatter plots. There are noticeable weekly linear correlations among variables across the three periods.

For each period, we develop several predictive models that use all these 11 topic proportions as input feature variables and the sentiment score as the target variable. The benchmarked models include linear regression (LR), lasso regression (Lasso), ridge regression (Ridge), elastic net linear regression (ElasticNet), multilayer perceptron (MLP), random forest (RF), gradient-boosted decision trees (GBDT), and

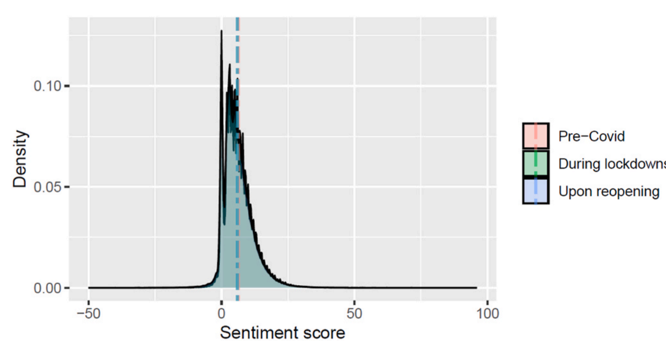

Fig. 6. Sentiment scores in the periods of pre-Covid (2018–2020), during lockdowns and upon reopening.

Table 3
Topic proportion change in the pre- and post-Covid periods.

Topic	Description	Topic proportion			Difference of means (p-value)		
		Pre-Covid (2018–2020)	During lockdowns	Upon reopening	Pre-Covid (2018–2020) vs during lockdowns	Pre-Covid (2018–2020) vs upon reopening	During lockdowns vs upon reopening
1	Check-in & check-out	6.17%	6.19%	6.21%	0.72	0.15	0.51
2	Public transportation	7.82%	5.16%	5.89%	0***	0***	5.75e-157***
3	Host communication	12.68%	13.63%	13.01%	4.85e-101***	7.31e-21***	4.30e-36***
4	Cleanliness	15.69%	16.47%	15.63%	4.20e-109***	0.01*	2.46e-99***
5	Decent location	11.89%	11.89%	12.28%	0.83	1.81e-42***	1.96e-22***
6	Room facilities	8.01%	8.37%	9.03%	5.27e-16***	3.60e-171***	2.40e-36***
7	Local amenities	7.63%	7.14%	7.43%	1.59e-48***	2.27e-13***	4.93e-14***
8	Accuracy	8.96%	9.77%	9.61%	2.48e-229***	3.81e-242***	1.90e-07***
9	Value	4.68%	6.71%	6.46%	0***	0***	2.76e-10***
10	Food service	13.15%	11.36%	11.23%	0***	0***	0.01*
11	Room size & good feeling	3.30%	3.34%	3.21%	1.46e-05***	2.79e-31***	1.99e-32***

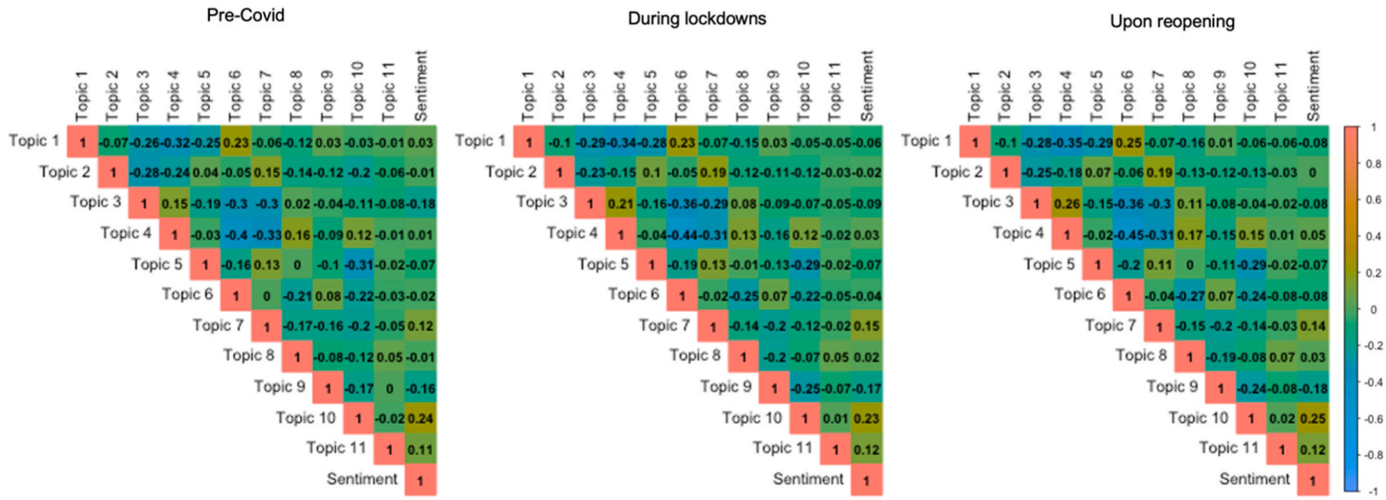

Fig. 7. Correlation plots of topic proportions and sentiment scores across three periods.

extreme gradient boosting (XGBoost) (T. Chen & Guestrin, 2016, pp. 785–794). The LR, Lasso, Ridge, ElasticNet are linear models while the MLP, RF, GBDT and XGBoost excel at fitting non-linear data. Since the topic proportions range between 0 and 1 and sum to 1 for each review comment, further normalisation of the feature variables is unnecessary, which also aids in model interpretation. We adhered to the standard machine learning pipeline (Murphy, 2022), fine-tuning the benchmarked models through randomised 5-fold cross-validation on 70% of the input data for each period. For readers' reference, the hyper-parameter space specification is provided in Appendix D. Fig. 8 presents the performance of all benchmarked models in cross-validation, showing that XGBoost outperforms the other models. Consequently, the fine-tuned XGBoost was also used to predict and test on the test set (30% of the dataset for each period). As depicted in Fig. 8, the XGBoost's test performance are close to its cross-validation perform on all three periods, eliminating the risk of overfitting.

The predictions made by black-box tree-based models like XGBoost can be explained through impurity-based feature importance or feature permutation importance (Murphy, 2022). However, these techniques cannot provide local explanations and do not account for the interactive effects of feature variables. To address these limitations, Shapley additive explanations (in short SHAP) (Lundberg et al., 2020; Lundberg & Lee, 2017) was recently proposed. The SHAP method is based on the concept of Shapley values from cooperative game theory, which provides a way to fairly allocate the contributions of individual features to the overall prediction. We implement SHAP on the fine-tuned XGBoost and present the summary plots in Fig. 9, where the y-axis lists the topics in order of importance (from top to bottom), while the x-axis indicates SHAP values, which reflect the impact of each topic on the model's output, with positive values increasing and negative values decreasing the prediction. The colour gradient represents the feature's value, from low (blue) to high (red), illustrating how each feature's value correlates with its SHAP value. The shape of the points, resembling violin plots, indicates the density of SHAP values for each topic, with wider areas showing higher density.

By comparing these plots across the three periods, we can observe how the influence and importance of each topic changed over time. The topic importance rankings remain largely consistent across different periods, with some exceptions. Notably, Topic 6 (room facilities) and Topic 7 (local amenities) show slight changes in their order, as do Topic 3 (host communication) and Topic 5 (decent location), particularly before and after Covid. Topic 10 (food service) exhibits a wide range of SHAP values, indicating a significant impact on the sentiment score. A high topic proportion is associated with positive sentiment, while a low topic proportion correlates with a low sentiment score. This aligns with studies suggesting that food service quality is a critical factor in customer satisfaction and sentiment (Djekic et al., 2023; Heung & Lam, 2003). Topic 9 (value) and Topic 1 (check-in & check-out) show negative correlations with sentiment scores. A higher prevalence of these topics within customer reviews is associated with decreased customer satisfaction. These findings underscore the pivotal role of value perception and efficient check-in/check-out processes in cultivating positive customer sentiment within the hospitality industry (Li et al., 2020). Topics 7 (local amenities) and 11 (room size and overall

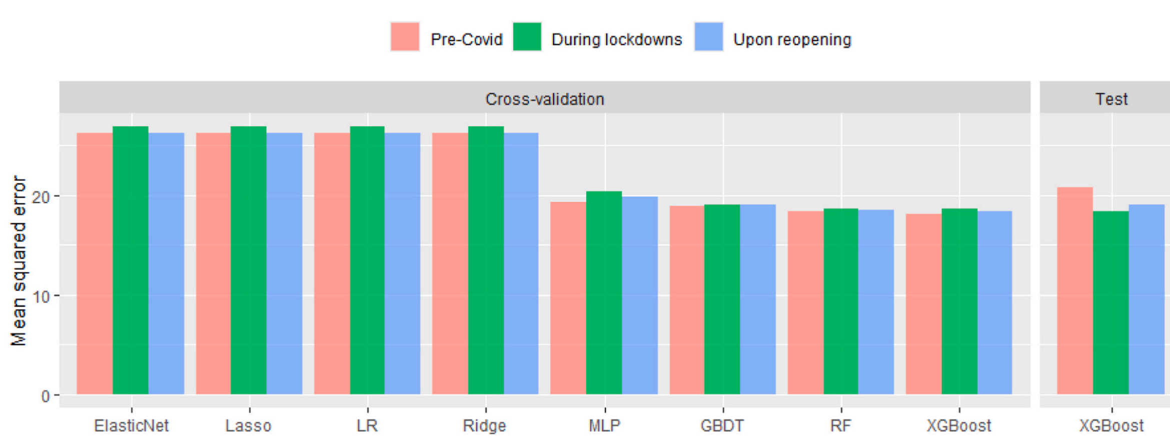

Fig. 8. Model validation and testing.

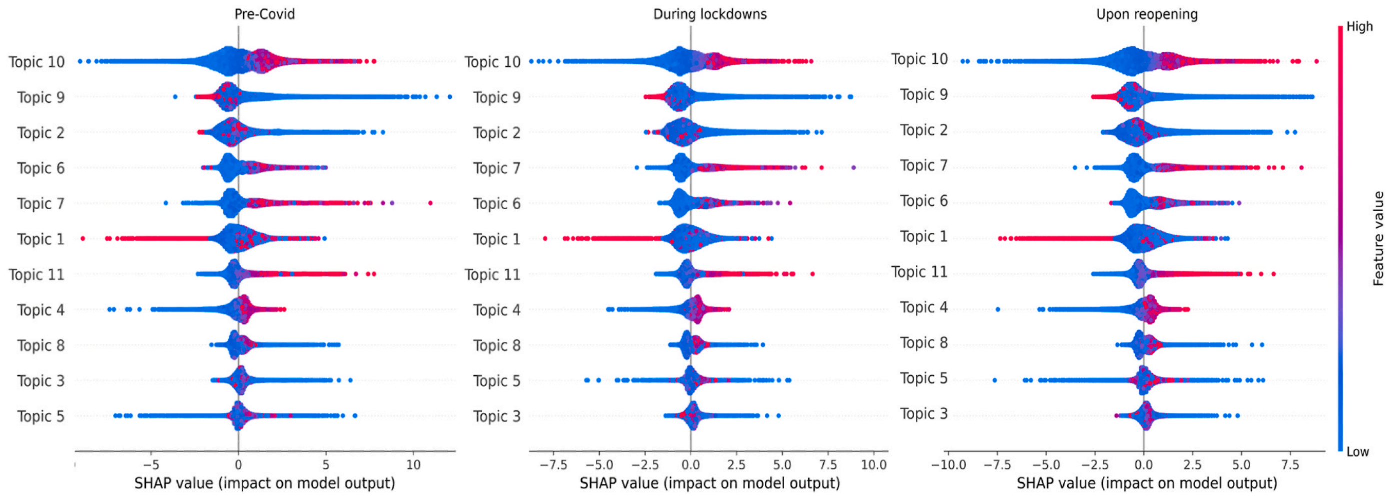

Fig. 9. SHAP summary plots of topic proportion impact on sentiment score.

ambiance) exhibit positive correlations with sentiment, indicating their critical role in shaping guests' positive experiences and overall sentiment towards their stay. Local amenities, in particular, have become increasingly important post-Covid. Many people now prefer local or regional travel over long-distance or international trips. This shift increases the significance of local amenities as guests rely more on the immediate surroundings for dining, shopping, and entertainment. Additionally, with heightened awareness of health and safety, guests are more likely to seek out destinations with high-quality local amenities that adhere to stringent hygiene standards. Nearby medical facilities, outdoor spaces, and wellness centres have gained importance.

4. Conclusion and implications

Managing business continuity during external market disruption requires strong dynamic capabilities within the firm (Buzzao & Rizzi, 2023). Compared against traditional hotels as the main competition, individual hosts who offer accommodation through commercialised peer-to-peer platforms such as Airbnb benefit from an unrivalled business agility. This is vital because individual hosts can respond very rapidly to changes in the external market conditions and to sudden changes in customer preferences. However, one key barrier that hosts face is the lack of deep consumer insight, which is difficult to obtain without access to powerful tools of marketing analytics that are usually not available for them. By revealing the changes in customer review sentiment and topic proportions before and after the pandemic, this study not only addresses the recent call for understanding Airbnb customers' preferences before and after the Covid (Gao et al., 2022) but also provides guidelines for peer-to-peer rental providers to enhance their business agility via data mining.

Moreover, whilst previous literature has explored the nature, extent and design of business continuity frameworks across different business sectors (e.g. banking, manufacturing, IT) and business types (e.g. multinationals, SMEs, family businesses), this study is innovative in demonstrating how data mining of large, unstructured datasets of customer reviews can be used to enhance business continuity management by individual, peer-to-peer, short-term rental providers. We have shown how consumer trends and customer preferences can be inferred from online Airbnb reviews and how hosts can use this to enhance business continuity during external market disruption. This is an important contribution both to the general literature on business continuity management but also, crucially, to tourism management (Kim & Pomirleanu, 2021). This research aligns with the growing call for studies that explore the continuity of economic agents (e.g., hosts) within the peer-to-peer rental market (Fan et al., 2023). As the peer-to-peer model has undergone significant commercialisation and third-party monetisation through platforms such as Airbnb, we recommend that platform owners provide individual rental providers (hosts) with access to these insights. This is a win-win situation as it will benefit the business continuity capabilities of hosts and, thereby, also enhance the robustness of the commercialised, third-party-facilitated, peer-to-peer business model which is now predominant in the sharing economy.

Our results have identified three areas where peer-to-peer hosts can quickly reconfigure their services in response to rapidly changing market conditions and consumer preferences. Whilst these insights are derived from a Covid-related dataset, they are generalisable to other types of market disruption as they point to long-term consumer trends that can be served in different ways.

Transportation. A substantial change in the perception of public transportation is evident in Topic 2 (public transportation). The significant decrease in topic proportion after the pandemic is indicative of consumers' worry about using public transportation as this is perceived to be a high-risk environment of potential contagion, even after the pandemic is largely under control and when cities and transportation networks have reopened and resumed operations (Dong et al., 2021). The change in topic proportion also reflects consumers' growing awareness of sustainability and an increasing preference for environmentally friendly tourism. Peer-to-peer hosts can enhance business continuity management by strategic incorporation of micro-mobility (e.g. bikes, e-bikes, e-scooters) and advice on e-car sharing into their service offerings. There is additional evidence that enhancing the value proposition with customised opportunities for and advise on environmentally friendly micromobility would provide emotional and psychological consumer benefits, as well as being conducive to more sustainable cities (Nikiforiadis et al., 2022). Hosts can again harness the sharing economy business model by incorporating their own unused micromobility assets into the service offering, thus capitalising on own possessions that have been acquired for personal use. The ability to incorporate own transportation-related assets into the service offering (e.g. bike, roller skates, skateboards, and e-scooters) enhances business continuity management because it can be delivered during times of external disruption and personalised to meet individual preferences.

Cleanliness and healthy eating. Topic 4 (cleanliness) and Topic 10 (food service) exhibit a shift in sentiment post pandemic, with sentiments negatively correlated to topic proportion, indicating a propensity for consumer complaints when discussing these topics. Topic 4 demonstrates a notable increase during the lockdown period followed by a decrease after reopening, a finding supported by Shen and Wilkoff (2022). Cleanliness assumes heightened importance during the lockdown period as an effective measure to prevent the spread of diseases, maintain public health standards, and promote overall well-being amidst challenging circumstances. On the other hand, Topic 10 experiences a significant decrease in proportion size during the lockdown period, with a gradual increase observed after reopening, albeit still notably lower than pre-Covid levels. This suggests that consumers are concerned about eating healthily in safe and clean service environments post-pandemic. This again offers hosts a competitive advantage in terms of business continuity management because they can configure their own capabilities to continue delivering on these consumer preferences during times of external market disruption in ways that are not available to traditional hotels. For instance, by actively encouraging 'home cooking' and ensuring that the kitchen is inviting, well-equipped and very clean, hosts can nudge guests to consider cooking 'at home' and eat healthily during their visit. This again is an example of capitalising on existing under-used assets in the host's personal possession and being able to personalise the service to individual preferences by stocking specific foods based on individual customer preferences.

Technological innovation. Topic 1 (check-in and check-out) is particularly noteworthy as it is the only topic that remains unchanged in terms of topic size across all three periods. The negative correlation between sentiment and topic proportion suggests that guests often express dissatisfaction in this category. This highlights a functional service area that is ripe for innovation and experimentation. Interestingly, the check-in and check-out process is one that can be partly or fully automated, using self-service technology as evidenced in the hospitality setting (Yoganathan et al., 2021). This implies that peer-to-peer rental hosts can offer personalised and hybrid check-in services which enhances both business continuity management and personalisation of the service offering. If, for example, a host has to offer self-check in or if this is the preference of the guest, then the host can still personalise this with real-time customer support through instant messaging or by phone.

Limitations. We would like to draw attention to two limitations of our study, which open avenues for future research. On the one hand, due to the small percentage of non-English languages, excluding these reviews from the raw data is unlikely to significantly affect our results. However, their inclusion would enable further investigation into cultural differences among customers. This necessitates the use of advanced natural language processing techniques in future studies to accurately translate guest reviews from different languages into English. On the other, our current datasets lack guest background information due to ethical considerations. This limitation could be addressed by exploring alternative datasets containing guest nationality or data from major tourism cities globally. Such an approach would allow for an examination of city-specific factors, government policies, cultural influences, and a comparison of how Covid-19 affected Airbnb listings versus local hotels.

Impact statement

The Covid-19 pandemic severely disrupted industries worldwide, with the short-term rental sector being especially impacted. This research investigates the challenges faced by the peer-to-peer rental market and provides crucial insights into strategies for ensuring business continuity during such disruptions. By leveraging techniques like topic modeling and sentiment analysis, the study examines shifts in customer opinions and behaviors before and after Covid-19, based on a large set of customer reviews. The findings offer practical recommendations for Airbnb hosts and platform operators on how to strengthen business continuity and better prepare for future crises.

CRediT authorship contribution statement

Bowei Chen: Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Thomas Boysen Anker:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Xiaoning Liang:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization.

Declaration of competing interest

None.

Appendix A. | Distribution of languages detected in Airbnb guest reviews

Figure A1 shows the percentages of the top 25 detected languages, in which English reviews account 88.4%, followed by reviews in French (3.68%), Spanish (1.74%), NA (1.64%) and German (1.26%). Due to the small percentage and the diversification of non-English languages, removing non-English guest reviews from the raw data will not significantly affect our analysis results in the current study.

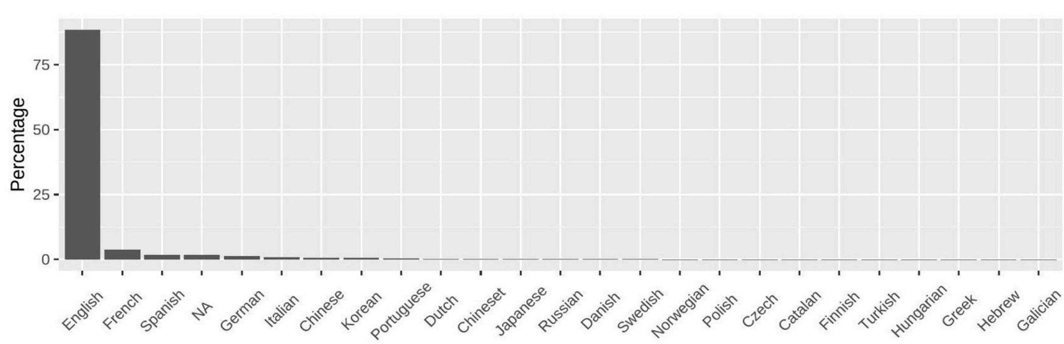

Fig. A1. Top 25 detected languages in Airbnb reviews.

Appendix B. | Determining the optimal number of topics in the STM

In topic modelling, the number of topics K is the hyper-parameter that can be set manually based on domain knowledge or be determined using data-driven approaches. We perform several automated tests to search for the optimal K from the range between 5 and 30. The trade-off between the model's predictive power and the average semantic coherence of the model's topics is considered. The former is measured by the held-out log-likelihood (Wallach et al., 2009). The idea is to train a topic model using the training set and then test the model on a test set that contains held-out reviews. Thus, a better model would give rise to a higher probability of held-out reviews on average. The semantic coherence is a metric proposed by

Mimno et al. (2011), which estimates the conditional likelihood for the combination of words for which the document contains the first few of the topic words at the same time. Models that produce topics with high semantic coherence are desirable as it can better aid topic interpretability. Mathematically, for a list of the M most probable words in topic k, the semantic coherence for the topic C_k can be computed as

$$C_k = \sum_{i=2}^{M} \sum_{j=1}^{i-1} \log \left\{ \frac{D(v_i, v_j) + 1}{D(v_j)} \right\},$$

where $D(v_i, v_j)$ represents the number of times that words v_i and v_j appear together in the review.

Our selection of the optimal K for the STM is presented in Figure B1. The first two subplots show the smooth line graph of the held-out log-likelihood and the semantic coherence against K, respectively. More complex models (higher values of) have a better fit at the expense of using on average. However, on the other hand, they produce less semantically coherent topics that can be more susceptible to incorrect interpretation. The third subplot illustrates the resulting trade-off between these two metrics. While no single topic model can simultaneously generate the highest goodness of fit and the semantic coherence, it highlights a subset of models that forms the Pareto frontier (i.e. models that produce the highest values of held-out likelihood for a fixed level of semantic coherence). The topic model with $K = 11$ seems to flatten out for higher values of $K > 11$. This means that a further increase in K beyond 11 does not add much explanatory power to the STM-generated topics per unit loss in model semantic coherence (interpretability). Therefore, we use $K = 11$ to generate topics from the STM for our analysis

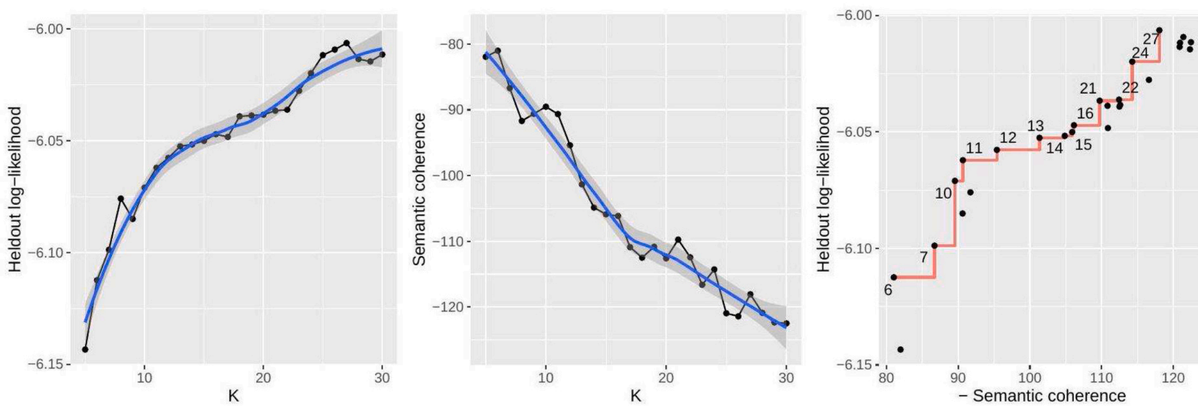

Fig. B1. Selection of the optimal number of topics for the STM.

Appendix C. | Examples of Airbnb guest reviews

Table C1 presents representative examples of Airbnb guest reviews. For each topic, the reviews are sampled from the top 20% highest topic proportions. The sentiment score is the sum of sentiments from text-only review, emoticons and emojis.

Table C1
Examples of Airbnb guest reviews and their sentiment scores

Topic	Review ID	Review comments	Sentiment
1	3.513E+08	very disappointed when it came to check out due to a cleaner (who didn't introduced himself) who knocked repeatedly 30 min before the check out time to inform us we had to leave when we were already preparing to check out. previous guests' rubbish still in the bin on our arrival.	−1
1	4.752E+17	lock didn't work, couldn't lock the door for the entire stay. they have a emergency number but they didn't help. seems like they knew about and just don't want to fix it. it's now a couple of weeks after and i still haven't heard back or gotten an explanation	−2
1	5.643E+17	for an accidental late check out they want to charge me around 600gbp! we had constant communication about the delay and headed back as soon as we could. but they lie to airbnb with fake invoices claiming that the changed locks etc … avoid these.	−7
1	4.780E+17	was told after i booked that they couldn't have me but the ¬£35 had already left my account. i then get a confusing message saying they look forward to seeing me and when i asked them to call to clarify they never did. i'm now out ¬£35.	−2
1	5.107E+17	worst check-in process, i was left on hold for 20 odd minutes while trying to find the key box. i hang up and call again, then no one ever picked up the phone again so i had to figure it out myself and my partner in the freezing cold.	−5
2	3.124E+08	it takes 15 min from the imperial wharf station, which is the overground line in london.there's a big supermarket near this apartment, so you can buy whatever you want there!	0
2	4.371E+08	good localisation in 3 zone of london. i have travelled from london stansted airport using stansted express and then buses and whole trip took about 50 min underground is located 10 min by foot or you can take a bus.	0
2	2.763E+08	carlos and celia's place was great.close to big ben and london eye.the bus station and underground are also close to the house.the neighborhood is quite and all people have disposition to help you.carlos and celia were so kind.	0
2	5.620E+08	the appartment is really close to the overground station which gets you to the center of the city in 15 min, the appartment is really clean and confortable and viki is really nice.	5
2	2.750E+08	very good location, best for family, easy commutation to piccadilly line.only 5 min walk to bust stop & 2 station from osterley train station.12–13 min walk to islewarth train station.host is very good, helpful,always available to guide.thanks a lot.	2
3	4.048E+17	a fantastic property. great location and bob an excellent, thoughtful and responsive host. highly recommend.	13
3	1.843E+08	katija is a great host. friendly and helpful! communication is great and she always responds quickly.	4
3	5.758E+08	great accommodation in a great location. anastasis was very helpful & responded quickly to messages. highly recommend!	4
3	4.868E+08	excellent and friendly communication with quick responses - an excellent host and very nice accomodation.	11
3	2.673E+08	thao was a great host. she replied very quickly to my queries. the room was very clean. the location was fantastic. would highly recommend this accommodation.	8

(continued on next page)

Table C1 (*continued*)

Topic	Review ID	Review comments	Sentiment
4	6.282E+08	second time we have stayed and we will be definitely staying again! love place, clean and tidy, comfortable. we really enjoyed our stay!	7
4	4.713E+08	we had a pleasant stay at lucien and chris's place. both of them are really friendly and the place was clean and cozy. would definitely recommend it!	9
4	4.733E+08	it was really indeed a homely stay at ellen's place. sparkling clean homeellen is so kinde, humble and helpful really ellen it was my pleasure staying hererightly a superhosti will highly recommend her place	12
4	1.561E+08	had a wonderful time staying with brigid! place was lovely and clean, really enjoyed my stay at her place. she is very accommodating and will definitely stay with her again when i come back next time! would really recommend her place.	11
4	3.439E+08	theodoros' place is a wonderful place to stay in london. it's clean, homey, and spacious. i highly recommend anyone visiting london to stay with theodoros.	8
5	2.035E+08	flat is located very close to public transport. the local area was quiet and the checking in/out process was very easy. we attended a gig at the hammersmith and this was ideally located.	1
5	5.368E+08	chloe and alejo's flat is very comfortable and handy for transport links. brixton is a fun area with loads of good options to eat out	6
5	3.599E+08	it is a great flat in a great location - in the middle of london. easy access to multinational food and easy transportation.	2
5	4.518E+08	a lovely cosy apartment in a great location. communication with nursel was easy and check in was a breeze. all in all, a great option for london, with easy access to the city.	5
5	4.114E+17	great base for exploring east london snd wider afield. great transport links, restaurants and cafes.	0
6	5.354E+17	less than a full toilet roll, sofa bed was broken, not enough blankets or sheets, mattress dirty, not enough towels, mold on the bathroom walls and ceiling, lots of stairs if that matters for you.	−2
6	5.920E+08	nice enough room with poor entrance and for instance it is not possible to open windows as the sash chord is broken, so room over heats. the room is pleasant enough but have to fill kettle by going down one floor and have to shower three floors up.	3
6	5.115E+17	very very small and not like the pictures. it's only one small room with the kitchen and the bed inside, no more than 9m2. there's no product, it was very cold, the hair dryer didn't work. the pillows weren't comfortable at all.	2
6	1.494E+08	2 separate bedrooms (both with american queen-sized beds) plus each bedroom had their own toilet, sink and shower. additional toilet room off the hallway. additional beds were mattresses placed on floor of living room. clean and very comfortable.	4
6	5.766E+17	bathroom was very dirty, wouldn't dare use the shower. mold and pubic hair in there. front door for the building was extremely hard to open. bit of a dodgy building with windows that don't lock properly.	−5
7	3.466E+08	it's about 15 min walk to harrods and 5 min walk to victoria and albert museum, natural history museum is right across the street. very very convenient.	1
7	7.671E+08	this is a superb flat in a period building, beautifully recently renovated. very convenient for paddington and westbourne grove shops with tubes and buses nearby. despite being on a main road it's very quiet.	8
7	4.780E+08	modern well equipped apartment within close proximity to gloucester rd tube, hyde park, kensington gardens, museums, university. two major supermarkets nearby. plenty of good restaurants within walking distance.	0
7	4.905E+17	lovely weekend in notting hill with a family group. apartment is 5 min walk from ladbroke grove or notting hill gate. two minutes from portobello road. notting hill has loads of bars and restaurants in easy walking distance.	4
7	1.546E+08	very convenient for supermarkets (waitrose, sainsbury m&s food hall), varied bars (islianton pub and the angelic) and restaurants from mexican to pizza and upmarket steaks houses or takeaways. but a quiet courtyard location too. 5 mins from angel tube station	0
8	8.951E+07	stephen was very available and answered very quick to my question. the apartment is very clean and confortable according to the description. everything worked perfectly.	5
8	1.030E+08	experience was great. soner communicated ahead of time to make sure we had everything we needed. checkin went fine and soner was there to ensure everything went well. the place was well furnished and met the expectations.	3
8	5.757E+08	the place is perfect. so much better than what you see in the photos. super cosy, you have absolutely everything you need and michael is always available and ready to help. couldn't have asked for anything better.	6
8	5.708E+08	exactly as pictured and described. met my needs perfectly. thanks for everything, sophie … see you again soon!	3
8	5.308E+08	the flat and its location is just perfect! also savannah is very helpful with everything, she provided us all the info we needed and replying to messages very fast. thank you!	5
9	5.194E+17	the location is excellent, but the room is very basic and was pretty run-down. okay for a base if you're not after anything fancy.	4
9	5.209E+17	accommodation was not as advertised and was a hostel not a hotel or air bnb. nothing extremely poor about it but was not what we expected.	−2
9	4.563E+17	we came for one night before the flight. it was a conveniently located and the staff was nice. overall good value for money.	3
9	1.916E+08	all i'm going to say is this: no, there is no boutique hotels in walthamstow. but there is this very special air bnb, for the fraction of the price of a hotel room. i couldn't rate it higher!	0
9	4.795E+17	terrible experience!!! wouldn't recommend this place at all. do your homework and check the reviews on other platforms before booking. shame on the owner!!! shame on him.	−5
10	6.682E+07	quite frankly my best airbnb experience. annie and belinda are so warm and welcoming. the breakfast they provide in the morning is generous and their house tastefully furnished. it feels like you are coming home to family.	3
10	4.092E+17	we had a lovely time at claire's home and were made to feel very welcome. breakfast a particular highlight with loganberries from the garden and homemade marmalade. such a treat! thank you claire.	5
10	6.152E+08	lucille is kind and warm woman.her loving smile made me happy!the room was clean and comfortable.the garden was pretty.i felt here is home or more than my home.the teas and breakfast was all nice.i can't hope for anything more.thank you!	12
10	4.222E+07	jacqueline went above and beyond in making us feel welcome and at home the entire time we were there. jacqueline's kind and caring nature made our first experience at a bed and breakfast environment unforgettable. thank you.	0
10	6.602E+08	nice room in delightful home, made to feel very welcome, loved the healthy fresh breakfast. heather goes the extra mile.	9
11	4.468E+08	if you prefer (website hidden by airbnb).clea (website hidden by airbnb).ne (website hidden by airbnb).saf (website hidden by airbnb).optimum level luxur (website hidden by airbnb).easy/smiley peopleand cost effective holiday, this is your home	3
11	5.368E+08	the flat is nice clean tidy.it is even too big for 1 (website hidden by airbnb) enough for 3–4 persons.ausra is very kind guy and give me lots of help.really appreciate.	5
11	6.083E+08	mike's place is beautiful, incredibly comfortable, so well furnished, and the communication is top notch. one of my favorite ever experiences via airbnb!	9
11	7.054E+08	this is one of the best airbnb experiences i have had! the flat is spacious, well lit and very well maintained.	0
11	7.036E+08	spacious apartment in a very central location. all the necessities you (email hidden by airbnb) munication was top notch private balcony is an added bonus would highly recommend	4

Appendix D. | Examples of Airbnb guest reviews

Table D1 presents the hyper-parameters settings for benchmarked models used in cross-validation during model tuning.

Table D1
Hyper-parameter settings for tuning machine learning models.

Type	Model	Hyper-parameter settings
Linear model	Linear regression	NA
	Ridge regression	"alpha": [0.001, 0.01, 0.5, 1]
	Lasso regression	"alpha": [0.001, 0.01, 0.5, 1]
	Regularized linear regression with L1 and L2 penalties (ElasticNet)	"alpha": [0.001, 0.01, 0.5, 1], "l1_ratio": [0.001, 0.01, 0.5, 1]
Neural network	Multi-layer perceptron (MLP)	"hidden_layer_sizes": [(100, 100, 100), (200, 200, 200), (200)], "activation": ["relu", "tanh", "logistic"]
Tree-based ensemble method	Random forest (RF)	"max_depth": [10, 25, 50] "min_samples_leaf": [1, 5, 10] "min_samples_split": [2, 5, 10] "n_estimators": [300, 400, 500]
	Gradient boosting decision tree (GDBT)	"learning_rate": [0.05, 0.1, 0.15] "n_estimators": [300, 400, 500]
	Extreme gradient boosting (XGBoost)	"max_depth": [10, 25, 50], "learning_rate": [0.05, 0.1, 0.15], "min_child_weight": [2, 3, 4], "n_estimators": [300, 400, 500]

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