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From host's descriptions to guests' reviews: Semantic similarities

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ABSTRACT

This study investigates the semantic alignment between Airbnb property descriptions and guest reviews. Word2Vec embeddings and affinity propagation clustering are used to identify granular semantic concepts, enabling a detailed comparison of the two text types. A new metric, concept coverage ratio, is introduced to measure the extent to which the guest review content is reflected in property descriptions. Results show that a higher concept coverage ratio is generally associated with more positive sentiment in reviews, suggesting that better alignment between host and guest perspectives contributes to guest satisfaction. However, longer and detailed descriptions may limit the potential for pleasantly surprising guests, as it reduces the chance for positive disconfirmation. These findings offer practical insights for improving communication in peer-to-peer accommodation.

1. Introduction

In recent years, the study of online text through text mining methods in the travel and tourism industry has witnessed continued evolution and refinement. The exponential growth of the Internet has intensified technology integration into the travel experience, making online text, an essential component for understanding tourist behavior/satisfaction (Bi et al., 2024). In the peer-to-peer context, online text plays an even more important role, as it serves as a communication channel, trust-building, and quality assurance, contributing to the overall success and sustainability of peer-to-peer platforms (Tao et al., 2022).

Particularly peer-to-peer text reviews have been extensively studied in the literature to understand tourists' perceptions and identify key service dimensions that directly impact customer satisfaction. These studies contributed to the understanding of customer concerns and the drivers of satisfaction, focusing on dimensions such as service, location, and physical aspects. However, a gap exists in comparing guests' perceptions with host perspectives and evaluating how well these alignments—or misalignments—impact the overall guest satisfaction.

To address this issue, we investigate text reviews (written by guests) and property descriptions (written by hosts) from Airbnb, an online platform with a significant position in the peer-to-peer lodging sector. While property descriptions reflect what hosts consider important to leverage the attractiveness of their property, the reviews provide insights into the relevant attributes for guests in the Airbnb experience. This study aims to measure the alignment of the concepts written in both types of documents (reviews and property descriptions).

Considering the increasing recognition of the role that semantics plays in generating relevant topics (Geeganage et al., 2024; Johnson et al., 2024; Li et al., 2019) our approach to identify concepts is based on semantic models (Mikolov et al., 2013), which allows to understand nuanced relationships, such as synonyms and analogies. Instead of a high-level interpretable list of concepts, our goal is to obtain a large number of semantic clusters (concepts), which allow to uncover a more granular understanding of semantic differences between reviews and property descriptions.

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We propose a text mining approach in which textual data (reviews and property descriptions) is organized into semantic clusters, where similar words are grouped to produce concepts that better capture the semantics of the content while decreasing feature dimension. The clusters are obtained using affinity propagation (Frey & Dueck, 2007) and the similarity between words is computed using a Word2Vec model (Mikolov et al., 2013). Based on these semantic clusters, the overlap of the reviews concepts also present in the respective property descriptions is computed (*concept coverage ratio*). In addition, Sentiment Analysis is used to compute the polarity of reviews (e.g., positive, negative, and neutral), reflecting the level of confirmation/disconfirmation of guests' expectations (Qazi et al., 2017). The relationship between the *concept coverage ratio* and the sentiment is analyzed.

This study makes a significant empirical contribution to understanding the alignment between host and guest perspectives in the peer-to-peer accommodation sector, particularly on Airbnb. The introduction of the *concept coverage ratio*, a metric that quantifies how well property descriptions cover the concepts mentioned in reviews, offers a novel way to measure the alignment between host and guest views expressed in text.

The structure of this article is as follows. Section 2 presents the literature review. Section 3 describes the dataset used. Section 4 presents the methodology applied in this study, while Section 5 presents the experimental results and analysis. Section 6 discusses the conclusions, Section 7 discusses the implications, and finally, Section 8 presents the limitations of this study that should be addressed in future work.

2. Literature review

Although there is not a consensual definition of customer satisfaction, many of the suggested frameworks conceptualize it as derived from a comparison with a standard. Expectation-Confirmation theory is the most widely accepted theory regarding customer satisfaction in hospitality services, where the customer expectation is the standard against which the service/product is compared (Oliver, 1977; Oliver, 1980). The theory states that satisfaction/dissatisfaction results from the customer's comparison of perceived service performance with customer's expectations. While confirmation occurs when perceived service matches customer's expectation, disconfirmation occurs when service is perceived to be better (positive disconfirmation) or worse (negative disconfirmation) than the predetermined expectations. Customers are likely to be satisfied when confirmation and positive disconfirmation occurs. In contrast, negative disconfirmation leads to dissatisfied customers.

Expectation-Confirmation Theory has been widely applied in tourism to understand the relationship between tourists' expectations, experiences, and satisfaction (e.g., Boo & Busser, 2018; Chou et al., 2012). However, in the context of peer-to-peer accommodation, where text (e.g., property descriptions, guest reviews) plays a significant role in shaping expectations, there is a research gap in leveraging automatic approaches to study expectations directly through text analysis. Previous studies have explored the main topics present in reviews and property descriptions, focusing on the identification of broad themes, as opposed to investigating the alignment or congruence between these two types of documents. In the following sections, we summarize the concepts of guest reviews and property descriptions that have been uncovered in the literature through text mining approaches, and then we identify the research gap explored in this study.

2.1. Concepts in guest reviews

In light of the perception of online reviews' value, an increasing number of studies have been using them as the primary data to investigate the significant peer-to-peer service attributes sought by guests. Advances in text mining approaches have contributed to the analysis of this type of unstructured data. Studies exploring key content and themes from online reviews applied different methods such as Topic Modelling (Celata et al., 2020; Ding et al., 2020; Luo & Tang, 2019; Xu, 2020; Zhang, 2019a, 2019b), hierarchical cluster analysis with Jaccard distance based on Term Frequency-Inverse Document Frequency vectors (Tussyadiah & Zach, 2017), co-occurrence of words analysis (Ju et al., 2019; Zhu et al., 2019), or Leximancer concept-mapping algorithm (see Smith and Humphreys (2006) for a detailed explanation on Leximancer's algorithm) (Brochado et al., 2017; Cheng & Jin, 2019; Ranjbari et al., 2020; Zhu et al., 2019).

Although the importance and level of detail of attributes in reviews differ across studies, analyses of guest reviews generally focus on similar themes. These include the relationship with the host, physical aspects of the property, the convenience of the location and general recommendation/complain. Table 1 presents an overview of the main guest review themes reported in the literature regarding peer-to-peer accommodation services, with Airbnb being used as a case study.

Host service is vital in peer-to-peer accommodation, as it provides the personalized, trust-based experience that sets it apart from traditional hospitality. Host communication, as well as host's promptness in offering help and responses are key factors in ensuring guest satisfaction and trust. The ability to make guests feel at home and welcomed fosters a

Table 1
Main reviews themes found in the literature.

The theme found in guest reviews	References
Host/ Host's service	(Brochado et al., 2017; Cheng & Jin, 2019; Ranjbari et al., 2020; Tussyadiah & Zach, 2017)
host communication	(Ju et al., 2019; Luo & Tang, 2019; Xu, 2020)
feel at home	(Brochado et al., 2017; Celata et al., 2020; Ding et al., 2020; Tussyadiah & Zach, 2017; Zhang, 2019a, 2019b; Zhu et al., 2019)
welcomed	(Celata et al., 2020; Tussyadiah & Zach, 2017)
rental rules (e.g., late check-in)	(Ding et al., 2020; Zhang, 2019a, 2019b)
booking experience	(Ding et al., 2020)
help from host/hosts response	(Ding et al., 2020; Zhang, 2019a, 2019b)
Physical aspects of the property	(Tussyadiah & Zach, 2017)
accommodation and facilities	(Celata et al., 2020; Cheng & Jin, 2019; Luo & Tang, 2019; Ranjbari et al., 2020; Xu, 2020; Zhang, 2019a)
value for money	(Luo & Tang, 2019; Ranjbari et al., 2020; Xu, 2020)
place, apartment, room	(Brochado et al., 2017; Celata et al., 2020; Ding et al., 2020; Ju et al., 2019; Zhang, 2019b)
cleanliness	(Ding et al., 2020; Zhang, 2019a, 2019b)
view	(Ding et al., 2020; Zhang, 2019a, 2019b)
specific amenities (e.g., food in the kitchen, door lock/key, internet connection, pool)	(Ding et al., 2020; Zhang, 2019b)
Location	(Brochado et al., 2017; Cheng & Jin, 2019; Luo & Tang, 2019; Tussyadiah & Zach, 2017; Zhang, 2019b)
features of the neighborhood/city	(Brochado et al., 2017; Ding et al., 2020; Ju et al., 2019; Ranjbari et al., 2020; Xu, 2020)
centrally located; access to transports, services (shops and restaurants), and landmarks	(Celata et al., 2020; Ding et al., 2020; Ju et al., 2019; Xu, 2020; Zhang, 2019a, 2019b)
parking	(Ding et al., 2020; Zhang, 2019a, 2019b)
General recommendation	(Celata et al., 2020; Cheng & Jin, 2019; Ranjbari et al., 2020; Zhang, 2019a, 2019b)
general comment about the stay, experience	(Brochado et al., 2017; Luo & Tang, 2019)
Complaints	(Celata et al., 2020)

sense of belonging, which plays a significant role in influencing guest satisfaction. Additionally, the clarity and flexibility of rental and booking rules reflect the host's professionalism and effort, contributing to a smoother booking process. The literature emphasizes that the host's role extends beyond logistics, being central to the unique appeal of the Airbnb platform.

The physical aspects of the property constitute the second pillar of the factors valued by guests in peer-to-peer accommodation. A well-maintained property with functional amenities and a desirable view can significantly enhance the guest experience, contributing to the perception of value for money. These elements provide the tangible foundation for a comfortable stay, influencing guests' perceptions of value and quality. Location plays a key role in guests' decision-making process, influencing both their initial choice and overall satisfaction with the stay. Guests often prioritize the convenience and accessibility that a property's location offers, as it directly impacts their travel experience. Proximity to public transportation, local attractions, restaurants, and shops makes a property more appealing, allowing guests to easily explore the area. For guests traveling by car, parking is often a major consideration. Additionally, the neighborhood's character and safety are important considerations, as guests often seek areas that are welcoming, vibrant, or offer a unique atmosphere.

2.2. Concepts in property descriptions

Regarding host generated content, there has been a research effort to understand its influence on trust perception and purchase intention/decision (Ert et al., 2016; Liang et al., 2020; Liu & Mattila, 2017; Tussyadiah & Park, 2018; Lz. Zhang et al., 2020). However, few studies have focused on extracting attributes from the description of the properties, written by hosts, which reflects the host primary concerns and preferences when advertising the property. Lutz and Newlands (2018) examined property descriptions for indicators related to demographic characteristics, travel preferences, and social interaction approaches, comparing these with different accommodation types. Their findings revealed that entire home hosts specifically appeal to business travelers, high-income individuals, and couples seeking a romantic experience. In contrast, shared room hosts target younger guests that search for lower-priced experience, emphasizing social interaction as a key element of the experience. Cavique et al. (2022) presents a macro-analysis of the topics presented in property descriptions. Through a topic modelling approach, they identify four main topics: "Location", "Service," "Amenities" and "Accessibility."

2.3. Comparing reviews and descriptions: conceptual gaps

Despite the exploration of reviews and property descriptions attributes, the direct comparison of host and guest textual content is still scarce in the literature (2021). Subroyen et al. (2021) explore the use of Topic Modelling to analyse guest reviews and property descriptions written by hosts on the Airbnb platform in Cape Town, South Africa. By comparing two different Latent Dirichlet allocation models (one based on Airbnb listing descriptions and another based on Airbnb reviews), they conclude that hosts go into more detail about the specifics of the property compared to guests. Nevertheless, it is important to note that comparing the results of different Latent Dirichlet allocation models based on different datasets presents a relevant limitation. The Latent Dirichlet allocation model's stochastic nature implies that comparing different models' results can be subjective. Therefore, a single model incorporating both text data types should be created to identify and compare topics/aspects in both data sources.

On the other hand, Wang et al. (2024) compares sentences with home-feeling-oriented information in the host descriptions and guest reviews and show that congruence between host descriptions and guest reviews leads to higher booking rates. In the given context, we propose a more systematic and comprehensive approach to measure the alignment between host descriptions and guest reviews. To achieve this, our proposed approach leverages word embeddings to consider the semantic relationships between words, thereby improving the effectiveness of the retrieval process.

3. Dataset

The dataset used in this paper is obtained from the Inside Airbnb website (http://insideairbnb.com/), an independent and non-commercial initiative that provides direct download of data collected from Airbnb's Website. Inside Airbnb collects new data periodically for many cities worldwide, including information about the accommodations (*listings* table), the reviews given by the guests for each property (*reviews* table), and the availability calendar for 365 days in the future for each property. This study uses a dataset compiled on January 28, 2020, concerning the guest reviews and respective property descriptions for each accommodation in Lisbon.

As the reviews history for a given property is permanently available on the Airbnb website, the data collection at a certain moment (snapshot of January 2020) also includes older reviews. So, our dataset covers reviews since 2010. Within this set, non-English reviews were detected and removed, as well as automatic reviews in the form of '…This is an automated posting'. In total, 644,038 documents (19,038 property descriptions and 625,000 reviews) were used for training.

In order to avoid the bias of the COVID-19 pandemic effect on Airbnb activity (Dolnicar & Zare, 2020), the time span selected for analysis is between July 2010 and December 2019. Only reviews with the respective property description available in the snapshot of January 2020 were considered. In total 554,276 reviews and the respective property descriptions were selected for our analysis.

The documents used in this study, representing property descriptions, are the result of the concatenation of eight textual attributes related to the property description (summary, space, neighborhood_overview, notes, transit, access, interaction, house_rules) available at *listings* table. These documents have an average length of 415 words (terms), varying between 6 and 1261 words, while reviews present a smaller size and content, with an average length of 54 words (terms), varying between 1 word and 1008 words.

4. Methodology

The framework of the proposed method is illustrated in Fig. 1, which consists of two main parts: assessing the semantic overlap between concepts mentioned in reviews and their corresponding property

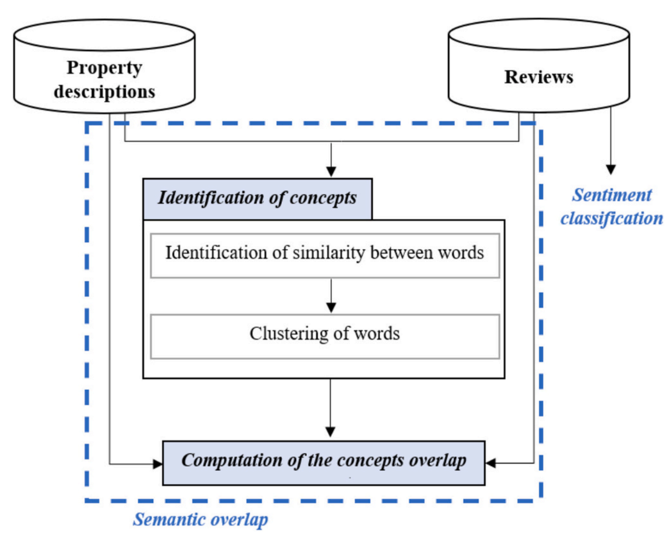

Fig. 1. Research framework.

descriptions, and determination of reviews sentiment. In the following sub-sections, each step of the framework is detailed.

4.1. Semantic overlap between property descriptions and reviews

Semantic overlap between property descriptions and reviews entails identifying the concepts present in both documents and then calculating the degree of overlap between these concepts. The following sub-sections describe the methods used to identify these concepts and the process for calculating the semantic overlap.

4.1.1. Identification of concepts based on Word2vec and affinity propagation

Although specific keywords identify aspects of the accommodation, searching for words overlap is insufficient as different words have similar meanings. In that sense, we look for concepts, aggregating words with similar meanings. The identification of the concepts includes the determination of similarity between words and then the dimensionality reduction through clustering of words according to their similarity.

4.1.1.1. Semantic similarity between words. Word semantic similarity is a metric of the likeness of words' meaning, a primary stage for sentence, paragraph, and document similarities. Semantic similarity methods can be categorized into four groups: knowledge-based methods, corpus-based methods, deep neural network–based methods, and hybrid methods (Chandrasekaran & Mago, 2021).

In the first group, the similarity is computed using a predefined lexical taxonomy and considering the path distance between the words in the hierarchy. This method is particularly useful for specific applications with highly constrained taxonomies, for example, in the biomedical context. However, it is highly dependent on the underlying source and, thus, not adaptable to different domains.

In corpus-based methods, a large corpus is used to build a statistical model, which can be used to estimate the similarity between words according to their co-occurrence in corpora. These methods create representations of words in the vector space (word embeddings), relying on the idea that words with similar meanings tend to occur in similar contexts.

Deep neural network–based methods are based on deep learning architectures, such as recurrent neural networks, convolutional neural networks, or transformer models, to learn representations on large-scale datasets and capture semantic similarity.

Hybrid methods combine multiple approaches from different groups (e.g., combine knowledge-based and corpus-based features). The goal is to leverage the strengths of each approach to achieve more accurate and comprehensive semantic similarity measurements. The simplicity and accessibility of some corpus-based implementations justify their more frequent use in the literature despite the recent developments in deep neural network–based and hybrid methods, whose results outperform most traditional methods.

This study uses the Word2vec (Mikolov et al., 2013) framework to calculate the similarity between words, an accessible and computationally efficient corpus-based method that provides an acceptable performance. Since the similarity between words is context-dependent, to produce an in-domain model, we have trained our Word2Vec model with Airbnb reviews and property descriptions (a total of 644,457 documents). We have performed a text pre-processing stage that included replacing the pronouns 'I' and 'we' with 'host' on property descriptions, replacing person names with 'host' on reviews, and converting the text to lowercase. Once the word vectors are formed, semantic similarity is calculated using the cosine similarity between these vectors, a commonly used similarity metric in natural language processing (Chandrasekaran & Mago, 2021).

4.1.1.2. Clustering. Since this study aims to search for the interception of concepts, better performance is achieved by grouping similar words. For example, if the host describes the 'apartment', and the guest comments about the 'flat', we want to consider that the host and the guest write about the same concept. For the same reason, misspellings (e.g., 'resturants' instead of 'restaurants') and abbreviations (e.g., 'thx' instead of 'thanks') should be included in the group of words with similar meanings. Hence, the affinity propagation clustering algorithm (Frey & Dueck, 2007) was applied to group different words that are likely to represent a similar concept. The semantic similarity obtained with Word2Vec is used as a metric for measuring the semantic distance between words.

Affinity propagation is an algorithm where each data point is considered a node in a network, and messages are recursively exchanged between data points until convergence occurs and the corresponding clusters are identified. Affinity Propagation automatically calculates the number of clusters, thus surpassing the main drawback of other clustering algorithms (such as K-means), which require the number of clusters as a parameter. Due to its simplicity, general applicability, and performance, this method has increasingly been used in research. This study's clusters are formed based only on nouns, verbs, and adjectives, which correspond to the most meaningful words.

In Affinity Propagation, the preference parameter influences the number of clusters formed, with higher values leading to more clusters and lower values to fewer clusters. Different values of the preference parameter were evaluated with Davies-Bouldin Score and Silhouette Score for accessing clustering quality. The Davies-Bouldin Score offers a global evaluation by measuring the separation and cohesion between clusters, where a lower score indicates better-defined clusters. On the other hand, the Silhouette Score provides both local and global perspectives, assessing how well each point fits within its assigned cluster while also considering the separation from other clusters. Maximizing the Silhouette Score helps ensure that clusters are not only well-separated but also internally cohesive. Our experiments verified that as the preference value increases, the number of clusters also grows and evaluation metrics, Davies-Bouldin Score and Silhouette Score, indicate improvements in the definition and separation of clusters. We set the preference to the median of the similarity matrix as it balances the number of clusters, preventing an excessive number of small clusters or a single large cluster. The values obtained for the Davies-Bouldin Score and Silhouette Score at this setting were 2.18 and 0.012, respectively.

4.1.2. Identification of concepts based on BERTopic approach

BERTopic (Grootendorst, 2020) is a Topic Modelling algorithm based on contextual embeddings. This method comprises four phases to produce a topic's distribution for a set of documents. Initially, it creates document embedding to generate representations in vector space that can be compared semantically using the Sentence-BERT (SBERT) framework (Reimers & Gurevych, 2019). Then, the dimensionality of the resulting embeddings is reduced through Uniform Manifold Approximation and Projection (UMAP) (McInnes et al., 2018). This reduction process aims to address the issue of sparsity in high-dimensional space, which can interfere with identifying dense clusters within the data. One of the key advantages of UMAP is its ability to preserve both local and global structures in the data. Moreover, UMAP's computational approach does not restrict or assume any embedding dimensionality, making it compatible with a wide range of language models. Subsequently, BERTopic clusters the documents using Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN) (McInnes et al., 2017) to find the densest areas of the semantic space while identifying outliers. HDBSCAN builds a hierarchical representation of the data by creating a density-based tree, which connects the data points based on their densities, with higher-density points being connected first. This hierarchical structure allows HDBSCAN to capture clusters of varying densities. Finally, the class-based TF-IDF (c-TF-IDF) procedure extracts the top keywords from each cluster. These keywords represent each topic as the set of its most important words.

BERTopic applies soft HDBSCAN, a modification of the HDBSCAN clustering algorithm, to compute the topic distribution for each document in the corpus. This algorithm allows soft assignments of data points to clusters rather than hard assignments, meaning that each data point (i.e., each document) is assigned to a probability distribution over the identified clusters, reflecting the degree to which the document belongs to each cluster. The number of topics (clusters) is automatically determined based on stability and coherence using a minimum cluster size parameter. In contrast to traditional Topic Modelling techniques that often require extensive preprocessing of the input text data, BERTopic can generate topic distributions without the need for tokenization, stemming, or stopword removal. This makes BERTopic a straightforward tool for analyzing large and complex text corpora (Grootendorst, 2020).

4.1.3. Computation of the concepts overlap

At this step, we verify the intersection of concepts (clusters) between the two documents (review and respective property description) and the coverage of reviews concepts by the respective property description, named *concept coverage ratio*. This ratio is computed by dividing the number of clusters in common by the number of reviews clusters, as illustrated in Eq. 1.

$$concept\ coverage\ ratio = \frac{|Clusters(review) \cap Clusters(description)|}{|Clusters(review)|} \quad (1)$$

Fig. 2 exemplifies the computation of the *concept coverage ratio* for the review/property description shown below. We have highlighted the words in the text that represent the concepts in common.

Property description

*"[…] Taxi's are very affordable in Lisbon. You can walk to a taxi stand or call one that arrives within 10 minutes. They are very **reliable**. CHECK-IN 15h -00h (3pm – midnight) CHECK-OUT 11h (host try to accommodate your schedule whenever host can.) There is parking 5 minutes walk from the house Public transportation is excellent! host do not have private parking, Lisbon airport is 15 minutes by taxi and less than 15€. The famous #28 Tram is a 1 minute walk from the house. There is a grocery store across the street open until midnight. There are lots of cafe's Fado clubs (Portuguese folk music) Restaurants, supermarkets. A 3 minute walk will take you to the river (Tejo) with lots of places to sit and enjoy the river view. The famous number '28 Tram' is just on the corner – you can take it across the city. One of Lisbon's treasures. 5 minute walk to the Castle of Saint Jorge. Very central **location**. You will certainly enjoy being here in this area. host am available by email (or in person if host am there in Lisbon) to help you with every aspect of your stay in Lisbon. Directions, tips of places to go, best places to eat, hear Fado, get to the beaches. 20 years of experience of this beautiful city. No smoking. No pets. Only booked guests are entitled to be in the apartment. Quiet after 10PM until 8AM."*

Review

*'All is good. Ellie is really **flexible**. It was a good **localisation**.'*

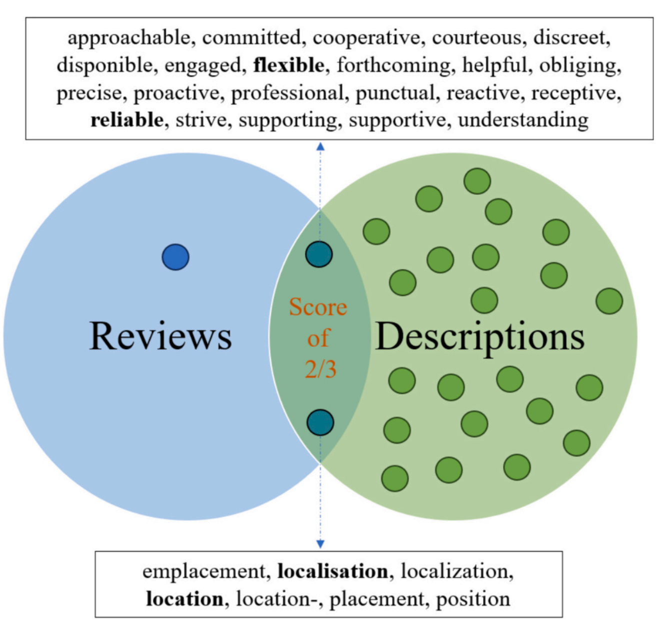

Fig. 2. Illustration of the concept coverage score calculation.

4.1.4. Concepts overlap: comparing the two methods for concepts identification

In order to assess the most appropriate method for calculating the concepts overlap, we have conducted experiments on an independent dataset comprising Airbnb property descriptions and their corresponding summaries written by hosts. This dataset was selected because the concepts present in the descriptions are expected to be reflected in the summaries. As such, the concept coverage score, which measures the alignment of concepts between descriptions and summaries, is used to assess the performance of the methods, with a score closer to 1 indicating better coverage. To compare the methods, for each summary/description pair, one method is considered to outperform the other if it achieves a higher concept coverage score.

For our experiments, we used the Python implementations of Word2Vec provided by Gensim (Rehurek & Sojka, 2011) and Affinity Propagation provided by scikit-learn (Pedregosa et al., 2011). The hyperparameters of Word2Vec were fixed to default values. We set 100 to the size of the word embedding vector. The minimum frequency of a word in the entire corpus to be considered in Word2Vec training (min_count) was set to 5, meaning that a word will be excluded from the model if it appears 4 or fewer times across all documents. The window size determines the maximum distance in a sequence of two tokens that can interact in training, which was set to the default value of 5 (Levy & Goldberg, 2014). In our experiments, affinity propagation converged with a damping factor of 0.7.

These experiments employ BERTopic Python implementation, using the default model for the English language "all-MiniLM-L6-v2" due to its speed-performance relation. Regarding the hyperparameters for dimensionality reduction, we studied the influence of the number of nearest neighbors (n_neighbors) on the BERTopic performance. This parameter defines the local neighborhood size for UMAP, controlling how UMAP balances local versus global structure in the data. For low values of n_neighbors, UMAP will focus more on the local structure, while for high values, UMAP will look at broader neighborhoods, resulting in larger cluster size. The hyperparameters for clustering were set to the default values. In order to reduce the noise in the topics, we limited the words to be part of the topic model: setting a minimum for the required word frequency (min_df = 10), indicating that any word that appeared less than ten times in the corpus will not be included in the c-TF-IDF calculation; and removing a predefined wordlist of stopwords.

Table 2 summarizes the four experiments with BERTopic when varying the n_neighbors hyperparameter. For each experiment, Table 2 shows the percentage of summary/description pairs that present a

Table 2
Results of the comparison between Word2Vec and BERTopic based approaches.

n_neighbors (UMAP)	number of resulting topics/clusters	Word2Vec based approach	BERTopic based approach	Equal in both methods
5	681	77,60 %	19,71 %	2,69 %
10	522	63,27 %	34,07 %	2,67 %
50	374	45,41 %	52,39 %	2,20 %
200	309	36,67 %	61,60 %	1,73 %

coverage score higher in the method based on Word2Vec and in the method based on BERTopic, and when the coverage score is equal in both methods.

The method based on Word2Vec, which relies on local language information, generally performs better in examining overlapping concepts. The experiments using the default sentence model "all-MiniLM-L6-v2" have shown that the method based on Word2Vec outperforms the method using contextual word embeddings when we are looking for specific concepts (tendentially composed by interchangeable words). In contrast, when looking for broader concepts (higher value of n_neighbors and larger cluster sizes), the method based on BERTopic (Method 2) outperforms method 1. Although topic modelling methods like BERTopic are valuable for understanding the broader thematic structure of a document, may require additional steps for pinpointing specific words or concepts with certainty due to the inherent probabilities associated with topic assignments. Considering the best results from the Word2Vec-based approach, this methodology was adopted in this study leading to the results presented in the following sections.

4.2. Sentiment classification

Sentiment classification is the automated process of identifying the sentiment polarity (orientation) of a given text, usually consisting of three classes (positive/neutral/negative). Sentiment classification can be performed using rule-based approaches as well as machine learning, and has attracted attention from both academia and industry, in particular for measuring customer satisfaction. This study considers text sentiment as the proxy of confirmation/disconfirmation of expectation, and focus on document-level classification of overall sentiment, distinguishing positive, negative, and neutral reviews.

This study uses VADER (Valence Aware Dictionary for sEntiment Reasoning), a rule-based Sentiment classification tool, specifically adapted to detect sentiments expressed in social media (Hutto & Gilbert, 2014). VADER is based on lists of words associated with valence scores for sentiment intensity and validated by humans. More positive words have higher positive ratings and more negative ones have lower negative ratings. For computing the sentiment polarity, VADER combines a valence-based lexicon attuned explicitly to social media contexts, along with five general rules for changing sentiment intensity: (1) Punctuation, namely the exclamation point, and (2) Capitalization, that increase the magnitude of the sentiment intensity; (3) Degree modifiers (e.g., adverbs such as 'extremely' or 'marginally') that can either increase or decrease the intensity; (4) The conjunction 'but'; and (5) Negation, which changes the sentiment polarity. VADER produces a sentiment score measured on a scale from -1 to $+1$, where -1 is the most negative and $+1$ is the most positive. This work considers the thresholds referred by Hutto and Gilbert (2014), in which scores between -0.05 and $+0.05$ represent a neutral sentiment.

5. Results

After performing the identification of concepts, using the methodology described in the previous section, we have obtained 549 word-clusters, representing concepts of the accommodation experience expressed both in reviews and in property descriptions. The clusters obtained fall in the peer-to-peer accommodation service dimensions mentioned in existing literature: help from host (Ju et al., 2019; Zhang, 2019a, 2019b), socialization and interaction (Moon et al., 2019; Xu, 2020), check-in/out process (Zhang, 2019a, 2019b), household facilities (Xu, 2020; Zhang, 2019a), value for money (Tussyadiah & Zach, 2017), housekeeping (Zhang, 2019a, 2019b), neighborhood safety (Ju et al., 2019), transport (Zhang, 2019b), shops and restaurants (Zhang, 2019b), and home feeling (Zhu et al., 2019).

The sentiment of each review was captured, showing that most reviews (98 %) are positive and confirming the bias towards positivity also perceived in previous studies on Airbnb reviews (Bridges & Vásquez, 2018; Zervas et al., 2018; Zhang, 2019b).

The remainder of this section first presents the most frequent clusters, aligning them to the dimensions of peer-to-peer accommodation services discussed in the literature. It then explores the computed *concept coverage ratio* in relation to review sentiment, offering deeper insights into the relation of property descriptions information and guest satisfaction.

5.1. Top clusters (concepts)

Tables 3 and 4 reflect the most frequent concepts mentioned by guests. The 'Theme' column represents the themes identified in the literature related to the concept discovered. The overlapping of these concepts with the property description concepts is represented in the 'Intersection' column.

Among the most frequent concepts that do not intersect with the description, as shown in Table 3, is the reference to the value for money (e.g., money, value, quality/price), the inaccuracy of the promoted image (e.g., photo, pictures), the communication between guests and hosts (e.g., asked, called, contacted, talked, texted), the occurrence of problems (e.g., delays, difficulties, issues, limitations, problems, challenge) that could be related to general lack of comfort of the house (e.g., cold, humid, moist, hot, smell, lights), unconformity of the facilities (e.g., broken, damaged, unclean, worked, small), and strong negative adjectives (e.g., horrible, bad, terrible, awkward, inconvenient) that naturally do not intersect with the description made by the host. On the other hand, related to positive experiences, the most frequent clusters that do not intersect with the description are concepts related to explicit recommendation (e.g., recommend, suggest), acknowledgment (e.g., thanks, thx), and appreciation (e.g., liked, loved, appreciate, perfect, awesome). The reference to the host is also noticed, including host's adjectives (e.g., caring, communicative, welcoming), host's availability (e.g., guidance, tips, communication) and service provided (e.g., easy, offered, provided).

Although the aspects about location are commonly referred in both reviews and property descriptions, cluster 252, which includes the word 'location' and its synonyms, has a low intersection with property descriptions, as hosts tend to use more specific vocabulary to sell the location of the property (e.g., 'Situated in the heart of the Bairro Alto quarter of Lisbon's most popular [...] the Bairro Alto is also known by the typical restaurants, rooftops and fado restaurants.'). As can be seen in Table 4, among the most common concepts which intersect with the description are the references to locations (e.g., lisboa, city), and accessibility of the neighborhood (e.g., district, walking, center, served, find, restaurants, attractions, nearby).

On the other hand, the references to the apartment/house and its facilities (e.g., bedroom, seaview, essential), the references to the host (e.g., ana, bruno, host), and the positive adjectives (e.g., nice, cozy) have a high intersection with the property descriptions. While in negative reviews, there is a greater prevalence of specific attributes of the house (clusters 151, 135,127), in positive reviews general attributes of the house are most referred (clusters 3, 16). These results suggest that the specific attributes present in clusters 151, 135, and 127 are taken for granted by the guests, resulting in dissatisfaction when not provided. However, they do not cause satisfaction when available. These results are corroborated by Ju et al. (2019), which identifies the Airbnb attributes according to the effect on satisfaction (dissatisfiers, hybrids, and satisfiers) in the light of Kano's three-factor theory (Kano, 1984).

5.2. Concept coverage ratio vs sentiment of review

Fig. 3 illustrates the distribution of the *concept coverage ratio*. On average, 50 % of the reviews concepts overlap with concepts written in property descriptions (*concept coverage ratio* = 0.5). Most of the reviews (70 %) concentrates the *concept coverage ratio* between 0.3 and 0.7, while reviews become less frequent when closer to the extremes (*concept*

Table 3
Most frequent concepts in positive and negative reviews not overlapping with property description.

Theme	Id	Words in the cluster	Frequency	Intersection
Complaints	267	challenges, complications, delays, difficulties, difficulty, involved, issues, limitations, problem, problems, reduced, trouble, troubles	26,301	12 %
	228	assumed, caught, complained, completed, discovered, encountered, entered, experienced, faced, forgotten, found, happened, heard, knew, learned, meant, missed, noticed, notified, realised, realized, requested, reserved, saw, survived, understood, used	21,352	27 %
	179	challenge, challenging, confusing, dangerous, daunting, difficult, hard, harder, hazardous, inclined, nightmare, requires, restricted, squeeze, struggle, tight, tiring, tough, tricky	15,525	9 %
	209	awful, bad, constant, horrible, permanent, poor, proper, solid, somehow, terrible, unacceptable, worst	8882	5 %
	249	annoying, applies, awkward, claustrophobic, complicated, cramped, disappointing, frustrating, inconvenient, odd, pain, pity, problematic, reassuring, stressful, understandable, unfortunate, unlucky, unpleasant	6123	3 %
General recommendation	172	encourage, praise, reccomend, reccommend, recomand, recomend, recommand, recommande, recommed, recommend, recommending, recomment, suggest	122,199	8 %
	40	adored, appreciate, appreciated, enjoyed, liked, love, loved	77,443	19 %
	32	absolute, adorable, amazing, astonishing, awesome, die, epic, exceptional, expansive, exquisite, extraordinary, impeccable, impressive, incredible, outstanding, unbeatable, unbelievable, unreal, wow	59,733	28 %
	22	money, overall, price, price/quality, prices, pricing, rate, ratio, value	30,212	18 %
Host's service	58	accommodating, accomodating, attentive, caring, communicative, considerate, dedicated, generous, gracious, helpful, hospitable, kind, patient, personable, polite, responsive, sweet, thoughtful, welcoming	123,455	18 %
	320	obrigada, thank, thanks, thankyou, thanx, thx	71,976	11 %
	7	advice, guidance, hints, ideas, info, information, insights, knowledge, recommendations, smartphone, suggestions, tipps, tips	46,521	44 %
	12	gave, given, giving, included, offered, offering, provided, provides, providing, supplied	46,234	39 %
	545	communicators, cousins, guys, hostesses, hosts, human, landlords, managers, superhosts	41,875	6 %
	6	comms, communicating, communication, communications, communicator, comunication, interaction, munication, organisation	41,830	4 %
	303	asked, asking, bumped, called, calling, came, chatted, contacted, contacting, emailed, followed, forgot, got, handed, messaged, rang, sending, sent, showered, stopped, talked, texted, texting, wrote	28,780	18 %
Location	252	emplacement, localisation, localization, location, location-, placement, position	155,189	30 %
Physical aspects	4	compact, little, small, tiny	40,019	48 %
	201	fotos, images, photo, photographs, photos, pics, picture, pictures	30,443	6 %
	37	cold, colder, dark, freezing, heated, hot, humid, mild, raining, rainy, stuffy	17,645	7 %
	327	cleaned, featured, function, functioning, functions, operating, work, worked, working, works	17,556	21 %
	197	looked, smell, smelled, smelling, smells, smelt	8376	2 %
	405	cigarettes, damaged, damp, dampness, dirty, disgusting, dusty, filthy, humidity, mildew, moist, moisture, mold, moldy, mould, mouldy, musty, scent, sticky, strange, unclean, weird, wet	6364	5 %
	371	broken, clogged, drain, filter, flood, flooding, flush, fountains, leak, leaked, leaking, leaks, mop, pipe, rain, storm, touching, visible	4761	4 %

coverage ratio = 0 and *concept coverage ratio* = 1).

Fig. 4 illustrates the percentage of positive, neutral, and negative reviews for each interval of *concept coverage ratio*. Although most reviews (98 %) are positive, a clear trend of sentiment polarity can be observed. While the percentage of negative reviews decreases as the *concept coverage ratio* increases (more concepts of the review are written in the property description), the percentage of positive reviews grows. These results can be explained as follows: hosts promote the strengths/advantages of their accommodation, and consequently, it is expected that guests will criticize the attributes that are not described in the advertisement of the property.

However, for higher *concept coverage ratio* values (closer to 1), neutral reviews increase, compensated with a decrease of positive reviews, showing a decline of guests delight (the highest level of customer satisfaction). This can be explained by the increase in the amount of information available in the description, influencing guests' expectations and reducing the potential for positive disconfirmation. As shown in Fig. 4, descriptions' length (number of clusters) is higher for higher *concept coverage ratios*. As descriptions are longer, the gap between expectations and reality is smaller, and reviewers not only tend to write less, but also express more satisfaction, until a certain threshold from which guests express less surprise and joy (positive disconfirmation). Although most neutral reviews express a general satisfaction, (e.g., 'Small, but cozy apartment and very close to the center.', 'The facility is new, the room is big.'), they contrast with positive reviews which express explicit joy (e.g., 'Very nice apartment, lovely neighbourhood', 'This is a brilliant apartment in a great location. […] It's also huge, clean and stylish as well as having hosts who are high communicative. Very much recommended.').

6. Conclusions

This is the first study to provide an analysis comparing the differences between the concepts reflected in reviews and the respective property descriptions. Our results show that the main concepts not mentioned in a property description are related to problems during the accommodation, acknowledgment, and appreciation. These concepts that include negative adjectives (e.g., unacceptable, horrible, awesome, terrible), verbs related to guest actions (e.g., liked, stayed) and vocabulary related to issues occurred (e.g., delay, broken, dirty, complained) are expected not to be mentioned by the host. Nevertheless, some negative aspects of the accommodation could be anticipated by the host in the description, such as the information of a 'noisy neighborhood,' helping to manage guests' expectations. On the other hand, some concepts not mentioned in property descriptions refer particularly to the host, suggesting that hosts do not invest in promoting their service and their involvement in the accommodation experience. These results corroborate Cavique et al. (2022), who argue that hosts (through the property descriptions) mainly promote tangible attributes.

This study presents a measure of the coverage of reviews concepts by the respective property description (*concept coverage ratio*) and compares it with the review's sentiment. The findings show that while higher *concept coverage ratios* initially correlate with fewer negative reviews and more positive feedback, there is a threshold beyond which increasing detail leads to more neutral reviews and a decrease in satisfaction intensity. High alignment between property descriptions and guest reviews enhances overall satisfaction by establishing realistic expectations. However, this alignment presents a trade-off, as it diminishes the potential for delight by reducing opportunities for positive disconfirmation. This highlights the complex relationship between

Table 4
Most frequent concepts in positive and negative reviews overlapping with property description.

Theme	Id	Words in the cluster	Frequency	Intersection
General recommendation	8	beat, brilliant, delightful, fab, fabulous, fantastic, good, great, nice, perfect, phenomenal, stellar, superb, terrific, tremendous, wonderful	322,641	72 %
	60	adventure, break, citytrip, holiday, holidays, journey, layover, stay, stay-, stopover, time, travels, trip, vacation, vacations, week, week-end, weekend	196,563	74 %
Host's service	92	ana, augusto, bruno, carla, carolina, christina, claudia, cristina, diogo, felipe, fernanda, filipa, filipe, frederico, goncalo, gustavo, helder, host, host-, hugo, ines, inês, isabel, isabelle, joana, juan, julia, luisa, madalena, mafalda, margarida, maria, marta, nuno, patricia, rita, rodrigo, rui, sandra, sara, sergio, silvia, sofia, sonia, susana, sylvia, sérgio, tania, teresa, theresa, vera	268,917	82 %
	2	catch, commute, connect, enter, find, follow, get, getting, go, locate, navigate, operate, reach	67,959	68 %
	28	afternoon, afternoons, day, dip, evening, evenings, hour, morning, mornings, night	49,383	57 %
	61	check, check-, checked, checking, checking-in, self-check, settling	34,394	62 %
Location	296	city, lisabon, lisboa, lisbon, lisbon-, lisbona, lisbonne, lisbons, lisbon's, lissbon, relation	196,107	96 %
	1	drive, foot, ride, stroll, walk, walkable, walked, walking, walks	100,522	83 %
	13	area, district, environment, hood, locality, neigborhood, neighboorhood, neighborhood, neighbourhood, quarter, suburb, vicinity, área	85,527	85 %
	11	center, centre, core, edge, hart, heart, hearth, hub, middle, midst, outskirts, part, thick	74,598	78 %
	256	centered, connected, deserved, formed, lies, localized, located, locates, metropolitan, nestled, placed, positioned, served, serviced, situated	68,680	78 %
	299	close, close-by, closeby, closest, nearby, nearest, theres	56,004	55 %
	34	atractions, attraction, attractions, destinations, highlights, hotspots, landmark, landmarks, locations, monuments, places, points, sight, sights, sightseeings, sites, spots, things	50,577	61 %
	523	atms, bars/restaurants, cafes/restaurants, discos, eateries, eats, nightclubs, restaurantes, restaurants, restaurants/bars, restos, restuarants, resturants	48,965	66 %
	5	alley, avenue, block, hill, lane, plaza, road, sidewalk, square, street, strip	32,541	61 %
Physical aspects	0	accommodation, apartment, appartement, appartment, apt, condo, flat, guesthouse, hostel, house, place, property, space, studio, unit	453,933	99 %
	15	airy, bright, charming, chic, clean, cosy, cozy, cute, immaculate, inviting, location-wise, modern, neat, new, practical, roomy, spacious, sparkling, spotless, stylish, tidy, well-located	191,345	76 %
	16	bedroom, bedrooms, beds, divisions, dorm, room, rooms, spaces, suites	69,105	87 %
	43	basic, essential, necessary, need, needed, required	54,532	59 %
	3	outlook, panorama, seaview, vantage, view, viewing, views, vue	51,583	79 %
	151	bath, bathtub, bidet, en-suite, ensuite, jacuzzi, kitchen, kitchenette, mat, shower, suite, walk-in	39,041	75 %
	127	bed, bedding, bedlinen, bedsheets, blankets, cotton, crisp, duvet, duvets, fluffy, hotel-quality, linen, linens, mattresses, pillow, pillows, plush, sheets, slippers, soft, towels, weekly	24,424	66 %
	135	attached, basin, bathroom, cabin, counter, curtain, holder, hose, loose, restroom, seat, showering, sink, stall, tank, toilet, unusable, washbasin, washroom, water	22,451	58 %

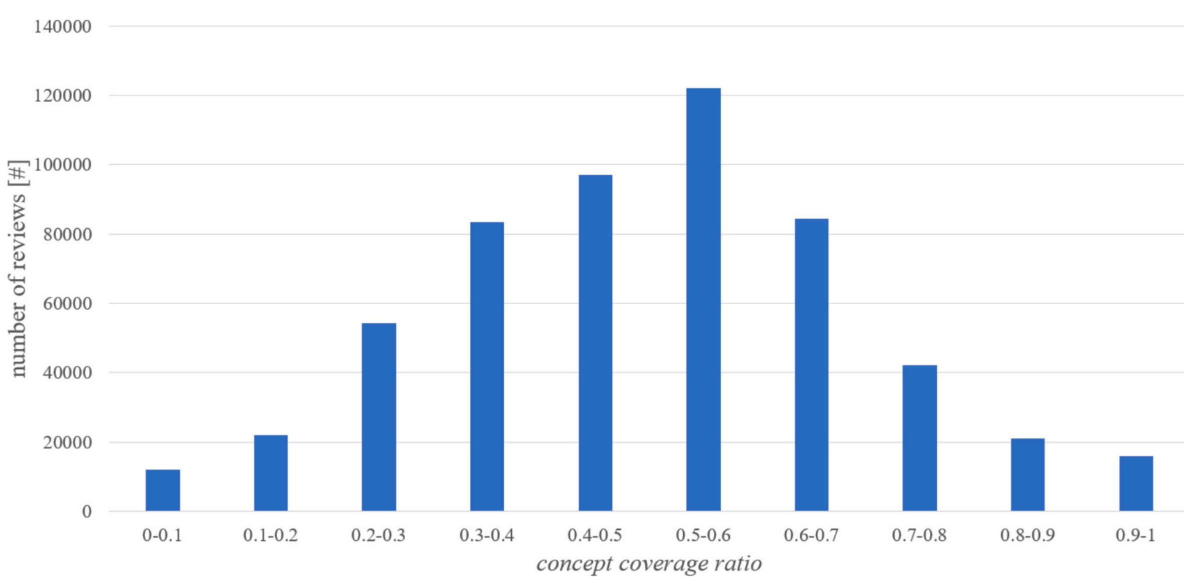

Fig. 3. Distribution of the *concept coverage ratio.*

transparency in property descriptions and guest satisfaction, suggesting that while clarity is essential, hosts should also consider the potential benefits of leaving some aspects of the guest experience to be discovered upon arrival.

7. Implications

Drawn upon Expectation-Confirmation theory, this study contributes to a better understanding of the alignment between hosts and guests and its relationship with the confirmation/disconfirmation of that expectation, ultimately contributing to their satisfaction. While property descriptions are the primary source of expectations, the sentiment of the

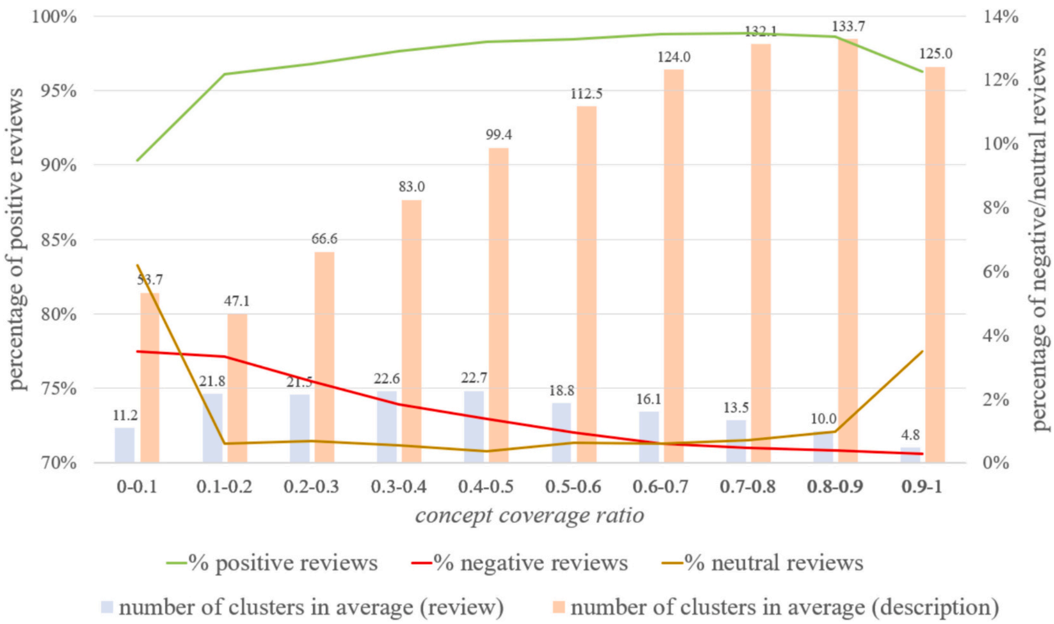

Fig. 4. Percentage of reviews per polarity and number of clusters of reviews and descriptions for each interval of *concept coverage ratio*.

review reflects the confirmation/disconfirmation of that expectation. By applying this framework to peer-to-peer accommodation, the study extends our understanding of how hosts manage and communicate expectations through property descriptions, and how those descriptions align (or fail to align) with the reality expressed in guest reviews. The ability to measure this alignment through the *concept coverage ratio* also contributes to the broader literature on service quality and customer satisfaction, offering new insights into how online platforms like Airbnb manage user-generated content.

The introduction of the *concept coverage ratio* as a measure in this study expands existing frameworks for analyzing online text. By quantifying the alignment between guest reviews and property descriptions, we provide a methodological tool that can be utilized in future research to examine the effectiveness of communication strategies in different service industries. Furthermore, the *concept coverage ratio* introduced in this study could be implemented as a feedback mechanism on platforms like Airbnb.

For individual hosts, leveraging concept coverage analytics can lead to more accurate and engaging property descriptions that set realistic expectations. For instance, if guest reviews frequently highlight positive aspects—such as a well-equipped kitchen or a cozy atmosphere—but the listing does not emphasize these features, hosts can update their descriptions to showcase them more prominently. Conversely, if reviews indicate recurring complaints — such as noise levels or limited parking— hosts can preemptively address these concerns in their listings to manage expectations and reduce negative feedback. Regularly updating descriptions based on guest feedback can foster transparency, improve guest satisfaction, and ultimately drive higher ratings and repeat bookings.

For Airbnb platform designers, integrating the *concept coverage ratio* into host dashboards as an automated analytics feature could provide actionable insights. A scoring system could alert hosts to gaps between descriptions and reviews, offering recommendations on key areas to update. From a platform-wide perspective, Airbnb could use aggregated concept coverage data to identify broader trends in guest expectations and inform best-practice guidelines for hosts. This data-driven approach would not only improve individual host performance but also enhance trust and satisfaction across the platform.

By implementing the *concept coverage ratio* as both an individual feedback mechanism and a platform-wide optimization tool, Airbnb and similar services can strengthen their communication strategies, resulting in better guest experiences, improved booking conversions (Wang et al., 2024), and greater overall platform credibility.

8. Limitations and future work

Although the current study provides notable contributions, it has some limitations that should be addressed in further research. Firstly, the present work is based on data collected from the Inside Airbnb website, which offers direct access to data compiled from Airbnb's website. This dataset is widely used in academic research but lacks investigations regarding its quality. Although the issues found by Alsudais (2021) in the dataset do not suggest compromising published research using the Inside Airbnb dataset, future work should be done regarding the quality of these data.

Secondly, this study proposes an unsupervised method that does not consider supervised labels with expert knowledge. Future research could incorporate manual independent expert labels to improve the alignment of the resulting model with human expectations.

Finally, besides property descriptions, the reviews from other customers have a significant effect on user's expectations, and ultimately, on satisfaction. Therefore, future research could replicate our methodology to understand the alignment between the reviews of a certain property.

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CRediT authorship contribution statement

Mariana Cavique: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Data curation, Conceptualization. **Ricardo Ribeiro:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Fernando Batista:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Antónia Correia:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Declaration of competing interest

None.

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