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How We Failed in Context: A Text-Mining Approach to Understanding Hotel Service Failures

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Abstract: Service failure is inevitable. Although empirical studies on the outcomes and processes of service failures have been conducted in the hotel industry, the findings need more exploration to understand how different segments perceive service failures and the associated emotions differently. This approach enables hotel managers to develop more effective strategies to prevent service failures and implement more specific service-recovery actions. For analysis, we obtained a nine-year (2010–2018) longitudinal dataset containing 1224 valid respondents with 73,622 words of textual content from a property affiliated with an international hotel brand in Canada. A series of text-mining and natural language processing (NLP) analyses, including frequency analysis and word cloud, sentiment analysis, word correlation, and TF–IDF analysis, were conducted to explore the information hidden in the massive amount of unstructured text data. The results revealed the similarities and differences between groups (i.e., men vs. women and leisure vs. business) in reporting service failures. We also carefully examined different meanings of words that emerged from the text-mining results to ensure a more comprehensive understanding of the guest experience.

Keywords: text-mining approach; service failure; group difference; gender; purpose of stay; word frequency analysis; sentiment analysis; word correlation; TF–IDF analysis

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1. Introduction

The development of global competition requires effective approaches to reduce failures and attain error-free processes in service industries [1]. However, errors are inevitable in the service industry [2]. Service in the hospitality industry involves multiple interactions between the service providers and customers, and a high risk of service failures accompanies these interactions. Once failures occur, service providers must act to effectively offset customers' adverse reactions to prevent post-consumption customer dissatisfaction [3,4], passive recommendation behavior [5], increased switching [6], and decreased revenue [7]. An appropriate service-recovery mechanism allows service providers to alleviate these potentially adverse consequences and restore customers' positive attitudes and confidence. However, studies conclusively show that even with excellent service recovery, restoring customer satisfaction is not as promising as preventing service failure in the first place [8]. Thus, taking a proactive approach to understand how service failures occur and planning to prevent service from failing is of greater importance in sustaining customer satisfaction than focusing only on better service recoveries.

Prior research has categorized different types of service failures in the hotel industry. For instance, researchers have identified 26 service problems, which can be further grouped into six broad categories, including staffing issues (the most serious), as well as (in descending order of importance) security, food and beverages, check-in/out, room, and facilities for business and leisure guests [9]. Additionally, other scholars identified 50 keywords related to service failures, which can be clustered into eight aspects, including guest arrival and departure, room amenities, food services, variety of choices, service personnel, banquet services, general food and beverage services, and communication [10]. However, the existing studies either considered guests homogenous and thus mainly focused on hotel guests' overall service-failure experiences or used quantitative survey questions to measure how different segments evaluate the importance of service-failure dimensions. What is missing is an in-depth analysis of how different groups respond to unsatisfactory hotel services, especially by examining guests' stories.

Researchers have suggested the importance of identifying group differences. For instance, different cultural groups (i.e., Asian and non-Asian guests) perceived specific service-failure items differently when using hotel services, and it is suggested that more research can be conducted by adding the impact of the purposes for travel [11]. In addition, future research on service failures in the hotel industry can benefit from actively listening to consumer reviews and hotel responses from OTAs [12]. Hence, this study attempts to demonstrate how hotel guests perceive service-failure experiences and explore the similarities and differences between groups (i.e., gender (female vs. male) and purpose of stay (leisure vs. business)) using customer comments on service failure. If service providers can identify which segments incoming customers belong to and match them with the appropriate service strategies, the probability of service failure could be diminished.

Notably, previous studies on service failures typically used data from third parties, such as TripAdvisor.com [13]; experimental design [14]; or surveys from online panels over a short period of time [10]. However, limited studies provided evidence from the longitudinal perspective even though various studies have proven that longitudinal data are more effective in determining patterns and the validity of variables [15]. To overcome the current limited availability of longitudinal studies, this present study provides insights into a nine-year (2010–2018) longitudinal dataset from an internationally recognized hotel chain. These real-world data are unstructured and stored as natural-language text, which cannot be thoroughly analyzed using conventional quantitative and qualitative techniques. Text mining is a particular data mining method that can automatically extract information from unstructured data (i.e., raw texts) [16]. Text mining helps to discover the underlying structure of textual data and generate more implicit meanings from the hidden information.

In summary, this study aims to identify critical issues related to service failures and explore similarities and differences between groups when reporting service failures in the hotel industry based on a longitudinal dataset via a text-mining approach.

2. Literature Review

2.1. Service Failure and Service Recovery

Service failure has been explored in detail in terms of service recovery in service marketing literature. The literature has identified two types of service failures [17,18]: (a) while generating outcomes and (b) during the consumption process. Consumers who encounter the outcome dimension of service failure might deal with a third party, whereas those experiencing the process dimension of service failure deal with the service provider directly. In this study, we specifically focus on the process dimension, which denotes that service failures happen during the consumption process of a hotel stay. This approach is in line with previous research, which identified that service failure occurring in the consumption stage contributed most to determining whether a customer would return or recommend a restaurant to others [19]. Therefore, understanding how service failures happen during the consumption stage is critical.

Earlier studies on service failures concentrated on categorizing different types of service failures [7,17,20], sources of failure [21], or the typology of problematic customers [22]. Later, scholars focused on exploring the consequences of service failure. They found that the inability to properly cope with service failure might result in consumer dissatisfaction [3,23,24], negative word-of-mouth behavior [5], increased switching behavior [6], diminished customer loyalty [25], and decreased revenue [7].

A recent study on customers' coping strategies when experiencing service failures found that the coping mechanism customers use varies depending on the different levels of service-failure severity [26]. Moreover, there is an interaction between the levels of service-failure severity (high vs. low) and brand reputation (high vs. low). When a highly reputed brand and a high-severity service failure occurs, a customer's positive thinking is significantly reduced. Another area that scholars have devoted efforts to is the antecedents that lead to service failures. Previous studies identified consumers' expectations of service quality [9,27], service stages [19], recovery efforts [17,18], the role of gender [28], external providers and service [29], and the identity of service agents [30] as critical factors that impact the severity of service failures.

2.2. Group Differences in Hotel Services

Previous studies have contributed significantly to various aspects of service failures in the hotel industry. Although few studies have explored whether customers' behavior in handling service failures would be different if the group characteristics were different, some previous studies provide some hints. For example, different levels of customer–organizational relationships reflect different customer reactions to service recovery [23]. Specifically, customers with a loyal relationship with the service provider have a lower service-recovery expectation and associate service failures with a less stable cause [23].

Individuals can be put into different groups according to specific characteristics [31]. In the hospitality industry, typical group differences examined include travelling purpose, age, gender, loyalty program, culture, and past experience. As previous studies have only briefly examined certain types of group difference, gender and travelling are the focus of this study based on stereotype accuracy [32]. The following sections discuss these factors in more depth.

According to one of the bestselling books of the 1990s, *Men Are from Mars, Women Are from Venus*, there are inherent psychological differences between men and women [33]. In the marketing literature, the role of gender has been well researched. For example, various studies found that female customers generally care about relationships, compromise, and negotiation with others for conflict resolution. In other words, females emphasize interpersonal relationships with service providers more than males [34]. As they put more weight on interpersonal relationships, females may expect more affective or sensitive elements than males when dealing with service failures [35,36].

Gender differences exist in many aspects of hotel studies, such as evaluating service quality [37,38]; selection of lodging accommodations [39,40]; customer dissatisfaction [41]; and more specific issues, such as sleep quality [42] and hotel room design [43]. For instance, one study showed that functional service quality (service-delivery efficiency) better predicts satisfaction and loyalty among men; however, women's satisfaction and loyalty toward brands are more likely to be influenced by relational service quality (guests' emotional benefits, beyond the core performance, social interaction between customers and employees) [28]. Another study examined the relationship between the five dimensions of service quality (i.e., assurance, reliability, responsiveness, tangible and empathy) and guest satisfaction toward hotel service delivery, and the results showed that empathy predicts satisfaction across two gender groups, tangibility only predicts satisfaction among male guests, and reliability and responsiveness predict satisfaction among female guests [38]. Besides, women and men report differently on sleep quality, although it is generally perceived that sleeping quality in hotels is not as good as that in the home. For instance, one study confirmed that individual differences exist among guests; more specifically, men, younger people, and guests with insomnia tend to sleep better than others [44]. However, when identifying factors that influence hotel sleep quality, another study found that the likelihood of women reporting better sleep quality was higher than their male counterparts [42].

The extant research also suggests differences among men and women in handling service failures. For instance, compensation strategy is more effective for male customers in increasing post-recovery satisfaction with humans rather than self-service technologies, whereas it does not influence female customers [45]. Researchers directly tested and proved that responses to positive and negative affective displays from men and women are different in that women were less satisfied when a display was emotionally negative [14]. Besides, it is suggested that female customers care about their voice being heard, whereas male customers could be satisfied by the compensation outcome [46]. Therefore, we propose that a gender difference exists in reporting service failures encountered at hotels.

Motivation literature has treated the purpose for travel synonymously with motivation [47]. When individuals have different motivations to travel, their pursued experience and service selections might differ [48,49]. Hence, groups with different purposes for travel might seek and focus on different experiences.

Prior research in travel literature supports that group behaviors differ according to purpose for travel. For instance, it was found that business travelers seek a more rational experience in airline services than leisure travelers [50]. In other words, leisure travelers tend to focus more on the emotional aspects of their flying experience than business travelers. Sleep quality is also reported differently by business and leisure travelers. For instance, researchers found that business travelers reported lower sleep quality than leisure travelers [51]. In terms of in-room technology amenities, business travelers have higher technology needs for high-speed Internet access and guest-device connectivity compared to leisure travelers [52]. Not surprisingly, when a hotel customer's purpose of stay is different, it is proposed that they focus on different things when encountering service failures.

2.3. Text Mining and Longitudinal Studies in Tourism and Hospitality

Text mining, which focuses on knowledge discovery (e.g., patterns and relations) from text-based databases [53], has been applied in different textual data analyses since the late 1990s. Considering the number of observations in our database, a text-mining approach allows us to deal with the massive unstructured and fuzzy raw text data. Besides, information on clustering, categorization, visualization, and information extraction could be obtained to better understand the results.

Nevertheless, studies in hospitality and tourism started applying this approach in the mid-2000s. For instance, researchers have conducted various studies on hotel profiles, room prices, and customer demographic information with a text-mining approach, demonstrating the potential use of this technique [54]. When applying the text-mining approach to cluster service failure and service recovery, researchers identified eight service-failure clusters and seven service-recovery clusters [10]. This approach was also used to analyze online reviews collected from TripAdvisor.com, and study results showed that satisfied customers are more likely to mention intangible elements of their stay, whereas dissatisfied customers discuss more the tangible aspects [13]. In summary, the text-mining approach has great potential to help hotels to understand their customers.

Although various studies have proven that longitudinal data are more effective in determining patterns and validity of variables [15], few studies have provided longitudinal evidence on service failure or service recovery. This outcome is mainly due to the fact that collecting longitudinal data takes a long time and involves significant costs. In tourism and hospitality, a few studies have validated the effectiveness of longitudinal data. For instance, Qian et al. [55] conducted a longitudinal study to explore the pattern of research in sustainable tourism. Some other applications include identifying the attributes of innovation and productivity in tourism enterprises [56]; in social media management [57]; in tourism demand patterns and segmentation of tourism markets [58]; or in tourists' behavior patterns [59]. Nevertheless, no known study on service failure and recovery has applied longitudinal data evidence.

In summary, although the current service literature extensively explores various antecedents and consequences of service failure in hotels, limited studies have examined the differences among groups of guests. Moreover, no known research has leveraged evidence from longitudinal data related to service failure and service recovery.

The following research questions were designed to close the current research gap: Why does the same service fail in some groups but not in others? What are the main attributes when guests make a complaint? During service recovery, what are the main elements that guests care about?

3. Methodology

3.1. Data Collection

We used the secondary data collected over a nine-year period from 2010 to 2018 by a property affiliated with an international hotel brand in Canada. The brand used a pre-designed customer survey and sent out the survey invitation via email to every guest after their stay. The survey contained a total of eight sections: experience with loyalty programs, overall guest experience, facilities/amenities experience, check-in experience, problem incidence, brand promise experience, past experience, and demographic information. The dataset contained 8337 responses. Considering our focus on service failures using the text-mining approach, we started the data-cleaning process by screening respondents who indicated "problem incidents" (answered "Yes"). This step resulted in 1,618 observations. We further narrowed the scope by focusing on those who provided comments on "what could we have done" (problem), excluding other languages (e.g., French, Japanese), and deleting invalid samples. The final dataset contained 1224 respondents, with 73,622 words of textual content or 322,048 characters (excluding spaces).

We utilized the selected key variables for descriptive analysis, including satisfaction ("On this stay, how satisfied were you with your overall experience as a guest?"), intention to return ("How likely would you be to stay at this hotel again if you were to return to this area (for the same purpose)?"), recommendation ("How likely would you be to recommend this hotel to someone else, if they were to require a hotel in this area in the future?"), and value for money ("Please rate the value that you received for the price paid. Was it . . . "). Although we did not design the survey questions, these measurement items were used in previous studies with satisfactory reliability and validity [60,61]. Gender and the purpose of stay (i.e., leisure vs. business) were used for group comparison, and a qualitative variable (i.e., service failure or "what could we have done" (wrong)) was utilized for text-mining analysis.

3.2. Data Analysis

Text-mining and natural language processing (NLP) approaches were employed for data analysis. Examples of natural language include books, texts from websites, and spoken words [62]. A recent study analyzing hotel guest complaints posted on TripAdvisor supported the appropriateness of NLP in dealing with customer reviews [11]. Text mining aims to discover the underlying structure of textual data and generate more implicit meanings from the hidden information. This method is gaining in popularity for understanding customer experience [63], in particular in tourism and hospitality studies [13,64].

On the one hand, by combining machine learning and data mining, the text-mining approach can effectively and efficiently reveal new information when dealing with large volumes of unstructured data [16,53]. This approach allows researchers to quickly identify keywords and their relationships for a more in-depth analysis. On the other hand, the traditional coding of qualitative data is usually accompanied by coding inconsistencies due to the subjectivity of human decision making, and the analysis becomes more challenging as the data volume increases [62,63]. To deal with the large volume of unstructured data (i.e., 73,622 words of textual content), we adopted a text-mining method to allow research themes to emerge from the data and reduce coding inconsistencies. We were aware of the need for manual intervention, so we also checked the accuracy of the text-mining results by comparing them to the original reviews. We followed similar text pre-processing steps used in previous studies [62,65,66]. The process included tokenization, lowering cases, removing digits and stop words, and more. Then, we conducted a word frequency analysis, sentiment analysis, word correlation, and term frequency–inverse document frequency (TF–IDF), following the guidelines suggested by existing research [62].

The data were analyzed by R version 3.5.2. Researchers have recommended R for its versatile statistical computing environment [67]. The R software is an open-source tool with various statistical and graphical techniques and can be easily expanded via packages [68]. There are 18,976 packages in the CRAN package repository as of 17 February 2021 [69]. We slightly modified the existing R codes [62] that contain all details on the packages (e.g., dplyr, tidyr, tidytext, ggplot2, forcats, stringr, widyr) and functions (e.g., unnest_tokens, anti_join, count, get_sentiments, group_by, ggplot, bind_tf_idf, bigram_counts, pairwise_count, pairwise_cor, filter) for analysis. For sentiment analysis, four existing approaches were summarized, including (1) NLP and pattern-based approaches, (2) unsupervised learning, (3) machine learning, and (4) hybrid classification [70]. Following the existing research [62], we used the Bing lexicon, which is based on unigrams (i.e., single words) and belongs to the NLP and pattern-based approaches. The Bing lexicon groups words into positive and negative sets.

4. Results

4.1. Descriptive Analysis

We first conducted a descriptive analysis among 1224 respondents. The gender distribution was relatively balanced, with 47% female and 53% male. Regarding the purpose of stay, results showed that leisure travelers (60%) outweighed business travelers (40%). In terms of respondents' overall experience of the stay, on a 10-point Likert scale (1 = extremely dissatisfied/unlikely, 10= extremely satisfied/likely), the mean values fell between 6 and 7: satisfaction ($\bar{x}$= 6.6, SD = 2.4), intention to return ($\bar{x}$ = 6.4, SD = 2.9), recommendation ($\bar{x}$ = 6.3, SD = 2.9), and value for money ($\bar{x}$ = 6.5, SD = 2.6).

4.2. Frequency Analysis and Word Cloud

The importance of a word can be measured by term frequency (tf) (i.e., how frequently a word is used in a document). Table 1 displays the 10 most commonly used words in all groups, females vs. males, and leisure vs. business. In Figure 1, a word cloud shows a visualization of the word importance. The data visualization technique presents the textual data in a visual format, showing each word's importance (i.e., word frequency) using its size [62]. Specifically, a word with a higher frequency of usage in the dataset appears larger in data visualization; for instance, hotel, staff, stay, breakfast, and desk were the top five most frequently used words by hotel guests responding to "what could we have done" (wrong). Although term frequency and word cloud give an overall idea of guest experience regarding service failure, more in-depth analyses are needed to explore the themes and emotions among groups, as discussed in the following sections.

Table 1. The top 10 most commonly used words.

All		Female		Male		Leisure		Business	
Word	**N**	**Word**	**N**	**Word**	**N**	**Word**	**N**	**Word**	**N**
hotel	450	hotel	219	hotel	199	hotel	236	hotel	161
staff	368	staff	184	staff	154	breakfast	214	staff	116
stay	333	breakfast	174	stay	140	staff	204	stay	109
breakfast	319	stay	170	breakfast	131	stay	199	breakfast	79
desk	233	desk	132	desk	89	time	132	night	70
time	210	front	109	time	88	pool	131	service	68
front	200	time	108	bbrand	85	desk	127	time	61
night	175	told	97	night	85	front	115	desk	60
told	166	night	79	front	80	told	102	bbrand	51
pool	160	pool	79	water	77	check	90	water	50

Note: the name of the hotel brand is replaced with the word "bbrand" for confidentiality.

Figure 1. Data visualization of the service-failure comments.

4.3. Sentiment Analysis

This section investigates a different topic: opinion mining or sentiment analysis [71,72]. This step helps to understand the emotional intent of words existing within the textual data. Sentiment analysis aims to extract text by categorizing it into positive or negative opinions [73,74]. We focused on words related to negative emotions, as this study aims to explore issues related to service failure. Not surprisingly, as shown in Figure 2, the word "issues" ranked number one in the negative group. The horizontal axis indicates the frequency for the word appearances in customers' reviews. For example, the word "issues" was mentioned more than 125 times across all groups. We also reviewed the original comments to understand the issues related to the negative words.

Cold. This word was used to describe food and beverage (e.g., coffee, water, pancake, salad, breakfast), spaces (e.g., air, room, fitness center, gym, dining area, lobby, hallway), water temperature (e.g., shower, swimming pool), or "everything" in the hotel. The word "cold" is ranked the highest among all groups, and not much difference can be identified between groups (i.e., gender, travel motives). The textual data revealed that guests in all groups are very sensitive to temperatures and intolerant of a "cold" environment, which indeed implies an eagerness for a "warm" stay at the hotel.

The lobby was cold, doors open for construction.

The heating system in the room continuously blew cold air even when we turned the heat up.

Dining room temperature was very cold.

Noise. Noise can be very disturbing and especially negatively impacts guests' sleep quality. First, guests frequently reported an unpleasant experience due to noise caused by other guests, especially group guests, families with kids, or drunken guests in public areas, such as hallways, lobbies, elevators, and swimming pools. These incidents happen more often during holidays, such as Christmas and Thanksgiving. Even without disturbing guests, noise can come from hotel facilities and amenities, such as heating/cooling systems, refrigerators, toilets and plumbing, and bathroom sinks, making it impossible to rest in noisy environments. Some guests even reported hearing guests in the next room talking because of thin walls. Besides, room location is highly related to guest noise complaints. Guests likely encounter noises when their room is near public areas, such as the elevator or the swimming pool. We did not find much difference between females and males, but "noise" ranked much higher among leisure travelers than business groups. The difference might be caused by the fact that more leisure travelers stay in hotels during holidays. Additionally, the leisure group uses hotel facilities, such as swimming pools, more often than their counterparts, which is why they perceive a higher noise level.

With the lobby and the pool the noise went on quite late.

Gatherings in rooms with doors open added to noise.

Enforce the noise rules more effectively.

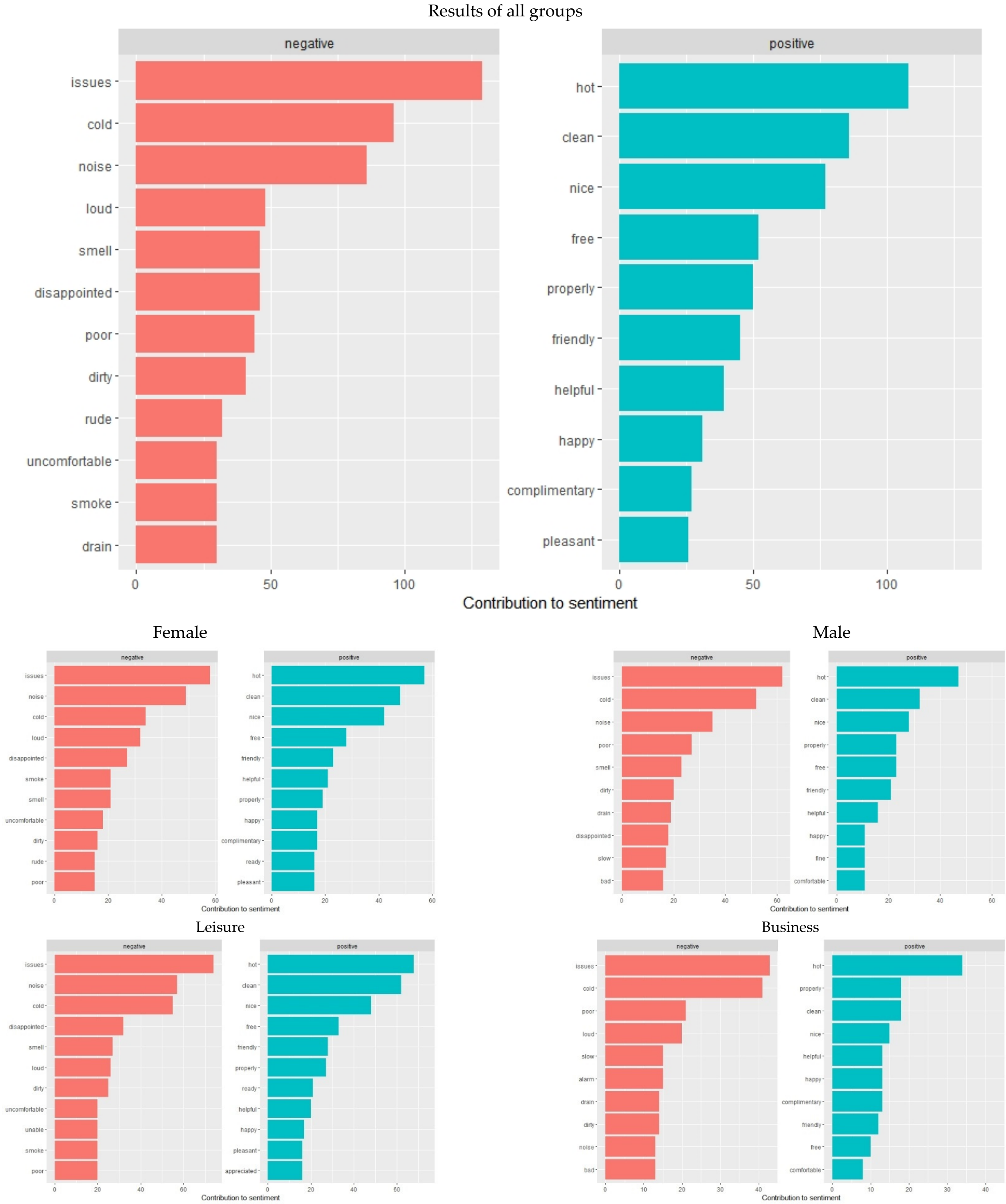

Figure 2. Contribution to sentiment.

Loud. This word appeared very often with "noise", indicating issues similar to those mentioned above. Guests were disturbed, especially when sleeping or using hotel facilities, such as the pool and spa. Some said they would like to be informed if they were put on the same floor with guests who were hosting parties or having social gatherings. Not surprisingly, these two words, "loud" and "noise", together demonstrate the importance of a quiet and relaxing environment to ensure guests' privacy. The study results did not indicate a significant difference between leisure travelers and business travelers on this subject. However, females seem to be more sensitive to sound than males, as both words frequently appeared in female guests' comments. This may be because a noisy environment may also be associated with women's insecurity. For instance, female guests may feel insecure and threatened when encountering uncivil guest behaviors, such as guests speaking loudly in public areas or loud drunken guests.

Security was useless the night I checked in. They were at the desk talking to the person, helping me check-in. Not controlling any of the loud people all over the hall way.

I could hear a woman screaming then what sounded like a sexual assault next door.

Smell. Smell can be associated with a hotel's cleanliness. For instance, guests said their room did not "smell clean" or that they could smell odors coming from shower curtains, fridges, carpets, towels, air conditioners, and chemical cleaners. Another issue is related to the ventilation system. Examples include guests staying in a "non-smoking" room constantly smelling smoke from a smoking room, guests using the gym smelling rubberized flooring, and guests smelling kitchen grease or smoke in the lobby. The study results did not show much difference between females and males reporting smell-related incidents. However, this issue was reported by more by leisure travelers, not business travelers. Since business travelers spend less time in the hotel's public areas than leisure travelers, they are less likely to be exposed to the different smells in the hotel.

As soon as we opened our door we could smell the cigarette smoke in the hall and were concerned that it would start to smell in our room as well.

The general appearance of the room was not inviting nor did it smell clean.

Disappointed. "Disappointed" is used to express guests' evaluation of their overall experience when hotel services did not match their expectations. The hotel failed to meet the service standards on aspects such as room amenities, beds, facilities (e.g., spa, pool), and food quality, although sometimes guests have unrealistic expectations. Guests are more likely to be disappointed when signature items related to the brand are not offered, as it shows a gap between what the brand entails and what is provided. To the guests, it simply means that the service is not worth the money when they compare it to other hotels in the region. A few guests expressed disappointment in the staff, especially the interaction with the front desk. "Disappointed" showed up in both gender groups, and not much difference could be identified. Notably, this word did not appear in sentiment results for business travelers but showed great importance to leisure travelers, as they are paying for all expenses and expecting to ensure perceived value more than their counterparts, whose expenditures are mostly covered by employers.

I was disappointed that you did not have cookies offered at arrival as does other hotels.

I'm very disappointed that my request was not satisfied and apparently a manager was not involved.

Poor. This word is used to describe various experiences at hotel, including "poor conditions", "poor practices", "poor service", "poor customer relations", "poor image", poor taste", "poor facilities", "poor planning", "poor design", "poor management", "poor connectivity", and "poor service." The results showed similar importance of this word for all groups.

Restaurant service and food was very poor.

It was poor management of staff resources.

Wireless connectivity was extremely poor.

Dirty. Similarly, not much group difference can be identified regarding the importance of the word dirty, as cleanliness is one of the essential needs of hotel guests, regardless of gender and purpose of stay. "Dirty" is associated with the accommodation (e.g., room, towels, carpet, bed, bathroom, jacuzzi, toilet, HVAC, door), food services (e.g., table, restaurant, dishes, cutlery, cup), and the facilities (pool, spa).

> *The room was dirty, toilet barely worked.*
>
> *We had to call twice for housekeeping to clean a dirty toilet, the first visit to our room should have gotten the problem taken care of.*

Rude. This word is related to the hotel employees' attitudes, especially those with whom guests have the most contact, such as the front desk staff, as well as the restaurant chef and staff. It is worth mentioning that guests' experience is not only determined by their interaction with hotel employees but is also influenced by the interactions surrounding them. Examples include comments such as that an employee "was rude and insensitive to other races", or the chef "was very rude to our waitress". Surprisingly, "rude" was frequently used by females but did not show up in other groups. This result indicates that female guests care more about attitudes and affections; disrespect is more likely to create a negative impression among female guests. Not surprisingly, during negative emotional displays, female guests tend to be less satisfied compared to males [14] because females pay more attention to interpersonal relationships with service providers [34], and they also have a higher expectation of hotel staff communication skills [37].

> *The front desk girl was very rude and the older lady in the restaurant was very rude.*
>
> *There was a young lady that worked during the breakfast buffet and I felt like she was being completely rude to us during our breakfast.*

Uncomfortable. This word is mostly related to sleep quality (e.g., "the bed was extremely uncomfortable", "pull out couch was so uncomfortable", "the mattress for the sofa bed was extremely uncomfortable", and "the pillow was very uncomfortable"). It was also used to describe an "uncomfortable" stay linked to poor room cleanliness, inappropriate room temperature, smells, cold food, and unfriendly staff. This word contributed more to the sentiment results of female business and leisure travelers, which may be due to their higher need for sleep quality compared to their male counterparts. This finding aligns with previous literature, indicating that females' sleep quality in hotels is not as good as that of males based on self-reporting sleep pattern results [44]. However, it contradicts another study, in which business travelers reported lower sleep quality than leisure travelers [51].

> *The bed was extremely uncomfortable, the pillows were terrible.*
>
> *It made me very uncomfortable about the cleanliness level of the room.*

Smoke. "Smoke" indicates similar issues as those covered under "smell" (e.g., the ventilation system not working efficiently, guests staying in a non-smoking room but smelling smoke from "somewhere", "cigarette smoke coming from the vent", or "the floor hallway smelt of smoke"). Another reason for "a very strong odour of smoke" in non-smoking rooms is poor room cleanliness. This word only contributed to the sentiment results of female guests and leisure travelers. Females may be more sensitive to smell than males, or there could be more smokers among males. Compared to business travelers, leisure travelers are more likely to travel with kids and are more annoyed by smoking.

> *It was just the fact that the room smelled strongly of smoke that I was not happy with.*

Drain. This word is related to bathtub/sink drainage issues. Guests mentioned that the most important thing is to "fix the drainage problem with the sink" or "ensure working facilities in rooms as part of the cleaning process". This word only contributed to the sentiment results of male guests and business travelers, maybe because men are usually supposed to deal with such issues or women have many other priorities.

> *The failure of the bathtubs in both bathrooms to drain properly and the need to hold down the handle on the toilet in order to flush properly.*

Slow. This word is mostly associated with Internet speed. Other uses are related to the responsiveness of hotel service quality (e.g., staff being slow to address issues or fix problems). It also refers to issues such as bathtub/sink drainage, elevators, and TV remotes and channels. This word only contributed to the sentiment results of male guests and business travelers, as males may be less patient than their female counterparts and business travelers tend to need high-speed Internet for work. In alignment with previous studies on the areas of dissatisfaction, males are more likely to be upset with Wi-Fi services [41], and business travelers have higher expectations of high-speed Internet compared to their leisure counterparts [52].

> *Internet on this visit seemed very slow and dropped out several times.*

> *Hotel staff was very good except in dining area—unclean & service was very slow.*

Bad. "Bad" is related to an overall bad experience, such as bad value, bad stay, and bad attitude, or specific facility or amenity issues, such as pillows, sofa beds, and smells. This word only contributed to the sentiment results of male guests and business travelers, maybe because they are more rational and critical when evaluating hotel services.

> *The room smelled badly of smoke as did the hallway.*

> *Hair in the bed is a very bad indication of poor conditions*.

Alarm. "Alarm" is related to alarm clocks or fire alarms, and the word only contributed to the sentiment results of business travelers. Business travelers tend to use an alarm clock more often and experience more issues; examples include not having an iPhone-friendly alarm clock, being woken up by an alarm clock set by a previous guest, or an alarm clock not working at all. Regarding fire alarms, guests were woken up by fire alarms unprepared.

> *Not being able to handle the fire alarm shows incompetence of night time staff.*

> *Some hotels have iPhone friendly alarm clocks (with built in charger), and since I forgot my iPhone charger, I was hoping I could charge inside the room.*

Unable. "Unable" is related to guests not being able to perform routine tasks (e.g., taking a shower, using the pool, sleeping, getting service, accessing the Internet) due to the hotel's incapacity to deliver the brand-standard service. This word only contributed to leisure travelers' sentiment results. The result is not surprising, as leisure travelers who pay their own expenses care more about what they receive in relation to how much they pay.

> *The bath tub was clogged and I was unable to take a shower.*

> *When we asked (the next person, on checkout) for it to be applied to both, the desk agent was unable to do so, was unable to find someone to help her do it and did not offer to fix the situation and reverse the charges.*

In summary, the sentiment results can be categorized into three main groups. First, the results showed very unpleasant sensory experiences, as indicated by words such as "cold", "noise", "loud", "smell", "dirty", and "smoke." Second, some words described experiential feelings, such as "poor", "disappointed", "rude", and "uncomfortable." The last word, "drain", is related to a specific issue: bathtub or sink drainage.

Among females, the results showed "issues", "noise", "cold", "loud", and "disappointed" in descending order of importance. Meanwhile, the top five words that contributed to the sentiment score in males are "issues", "cold", "noise", "poor", and "smell." The results revealed that both groups are intolerant of the sound, temperature, and odor, as indicated by words such as "noise", "cold", and "smell." Moreover, words that only appeared for females are "loud", "smoke", "uncomfortable", and "rude." Herein, the words "uncomfortable" and "rude" demonstrate that females are more sensitive to affective feelings, which is in line with the previous studies. Words that only appeared in the top 10 among males are "drain", "slow", and "bad". "Slow" was mainly related to Internet speed, which shows that males tend to be less patient. Moreover, the term "bad" was used in all aspects of services.

Concerning contribution to the sentiment score, leisure and business travelers differed in four words. Words such as "smoke", "disappointed", "uncomfortable", and "unable" contributed more to the sentiment score among leisure travelers, mainly related to affection. It is worth noting that business travelers focused on efficiency and functionality, as indicated by words such as "slow" and "alarm."

4.4. Word Correlation

Furthermore, a pairwise correlation was conducted to extend the meanings of negative words. Word correction examines the relationship between words (i.e., how often two words occur together compared to separately) [62]. We selected the top six negative words in all groups and those that only appeared in females vs. males, as well as leisure vs. business travelers (Figure 3).

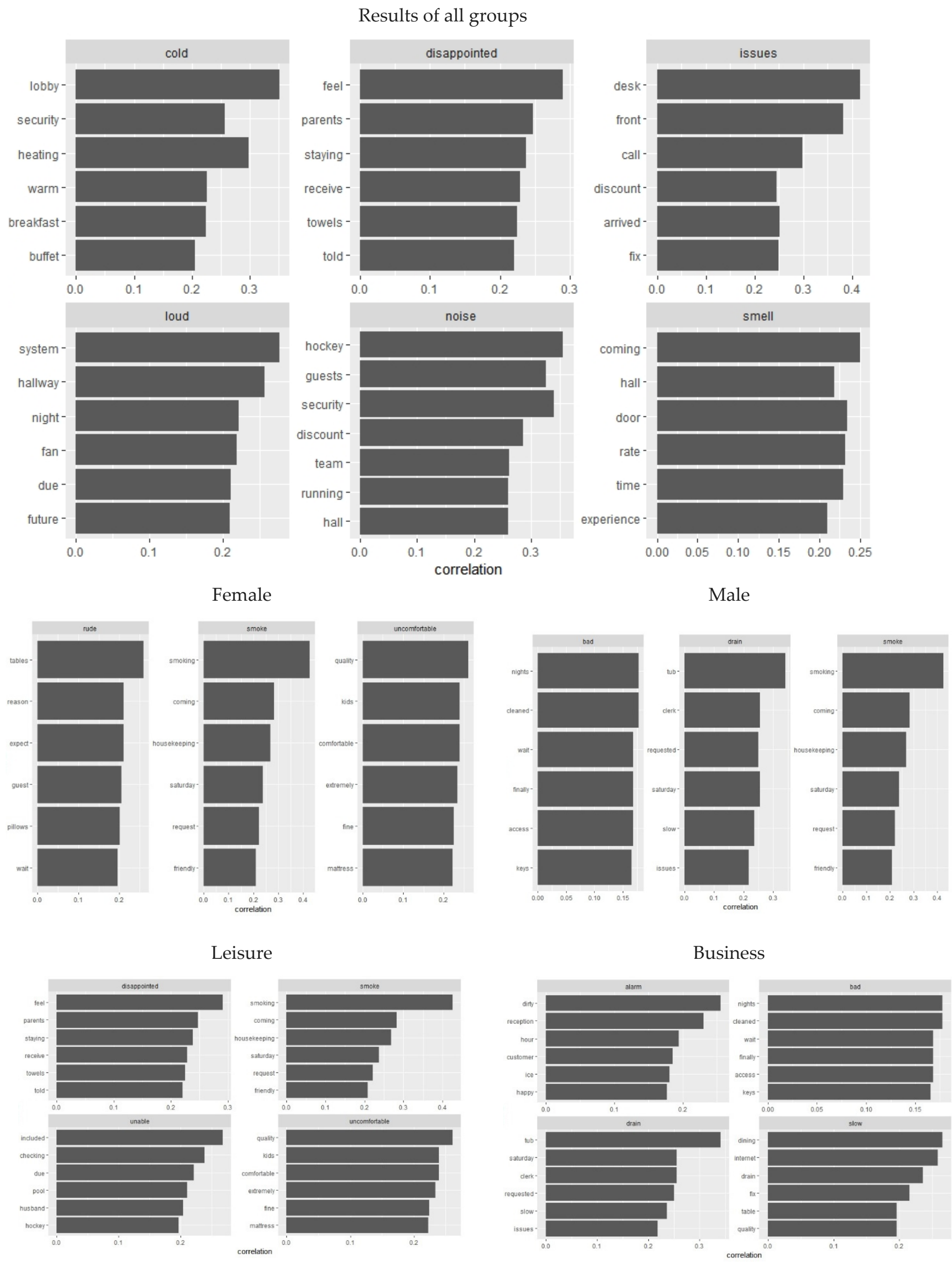

Figure 3. Pairwise correlation.

We visualized pairs of words which often showed up together in the text data, as shown in Figure 4. Examples include Internet + access, extremely + disappointed, towels + clean, and staff + housekeeping.

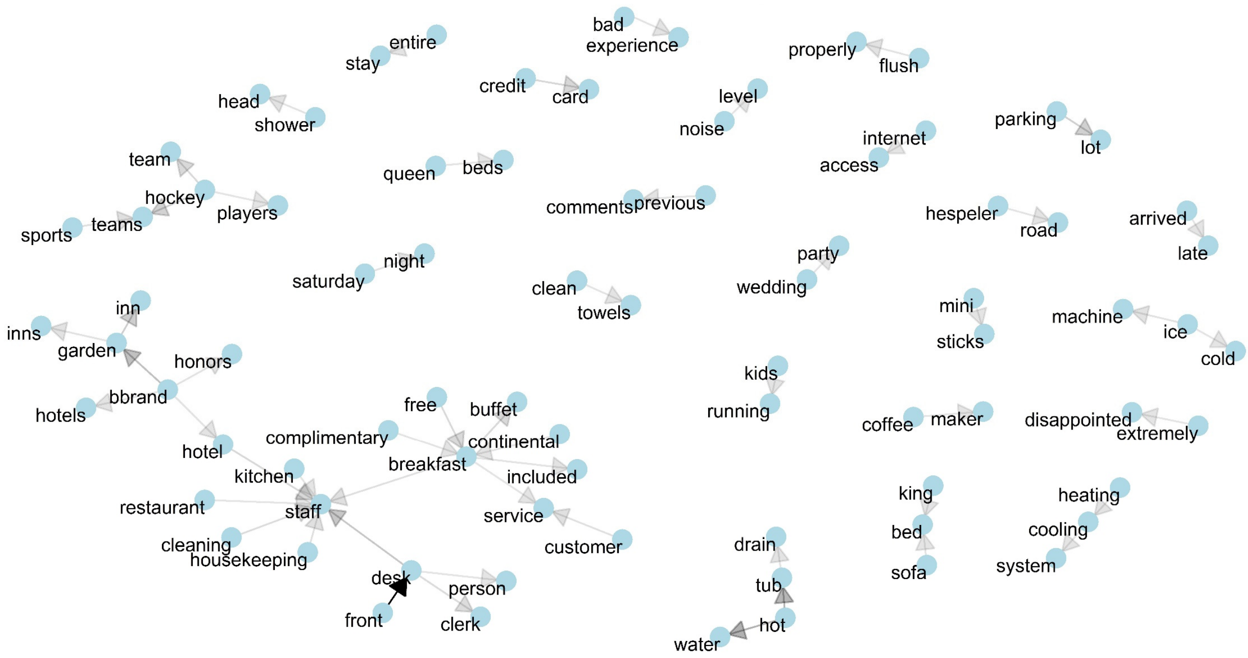

Figure 4. Common bigrams in the dataset, with some polishing.

4.5. TF–IDF Analysis

Besides term frequency, as shown previously, another approach to investigate the importance of different terms is IDF. By combining the term frequency and inverse document frequency, a specific term TF–IDF is calculated to determine whether words are distinguished in one document within a set of documents [75–77]. The advantage of TF–IDF is that it puts less weight on more commonly used terms and more weight on less frequently used words [62].

The following TF–IDF results indicate the differences in critical words between groups (i.e., the relative importance of specific words). A higher TF–IDF value shows a bigger difference, whereas lower values indicate that words occur equally between groups. As displayed in Figure 5, more words appeared in the female group, showing that the focus of females may be wider than that of males, and more detailed issues may cause an unpleasant experience. Additionally, food-related words appeared more frequently for females, including words such as "salad", "pancakes", (mini) "sticks", "ketchup", "tray", "salt", and "soup", suggesting that a delightful dining experience is more important to females. Not surprisingly, males have a higher TF–IDF on "beer." Furthermore, males focus more on the functionality aspect of hotel facilities, with words such as "center", "laundry", "connected", "speed", "leaked", "silverware", and "thermostat", as well as experiences, with words such as "badly", "functional", and "experiences".

Regarding the differences between business and leisure travelers, the leisure group contains more words (see details in Figure 6). In other words, they have broader focuses because leisure travelers are usually with family, friends, and other companions. Compared to business travelers, who might travel alone most of the time, it is much more difficult to satisfy the needs of all the leisure travelers in one group. Also, the risk of service failure increases when the number of leisure travelers increases.

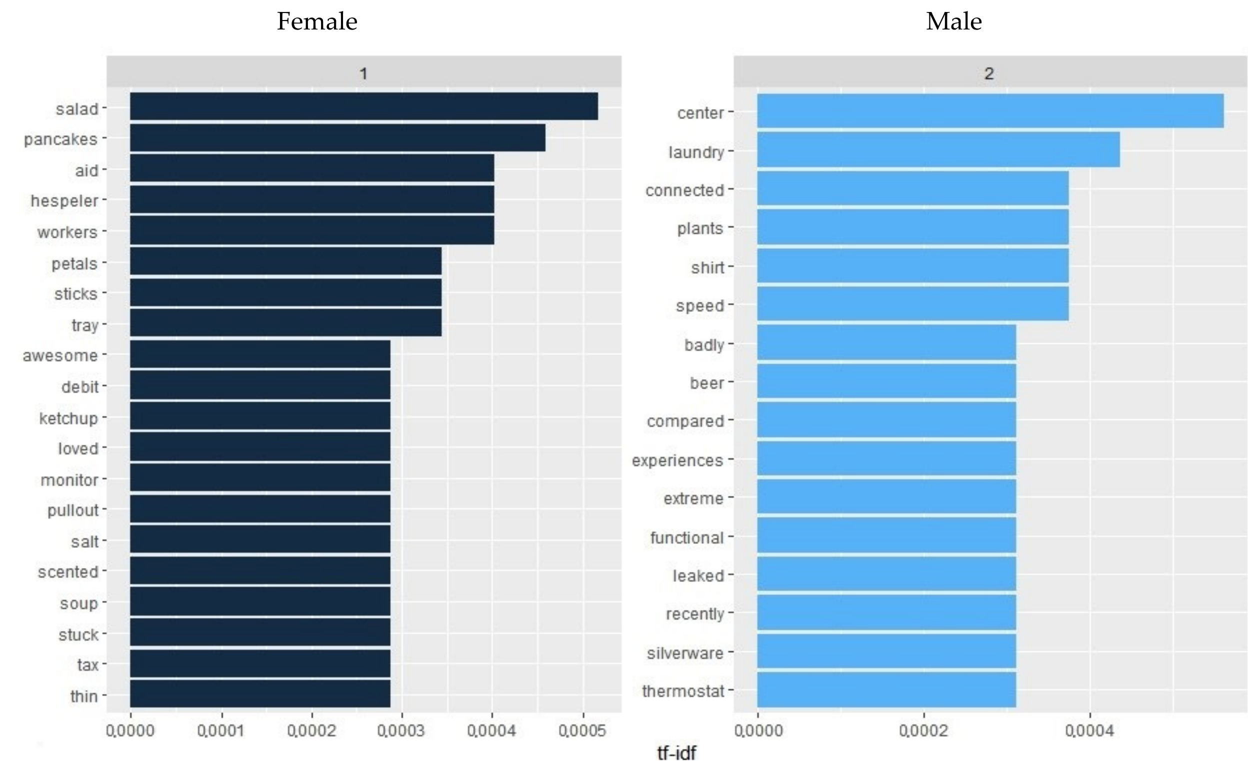

Figure 5. The highest ranked TF-IDF words: females vs. males.

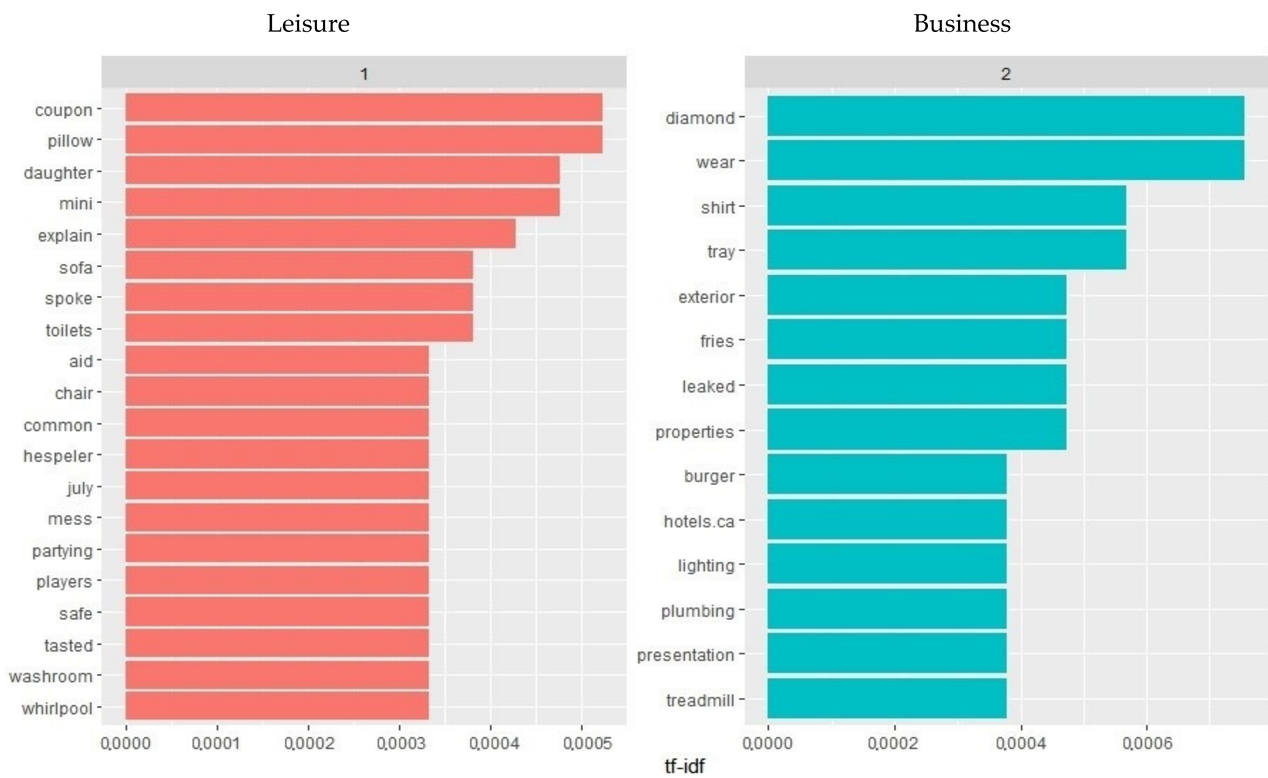

Figure 6. The highest ranked TF-IDF words: leisure vs. business travelers.

Specifically, leisure travelers have the highest complaints about the use of "coupons" because they are more price-sensitive and are more likely to have issues with coupons. Leisure travelers put a higher emphasis on their room experiences, which can be associated with words like "pillow", "sofa", "toilets", "chair", and "washroom." Another focus can be linked to their family members, like "daughter", and also safety and security issues (e.g., "aid", "safe"). On the contrary, the needs of business travelers are fewer, but not simpler. The word "diamond" is a service experience guaranteed by the brand, which might be the business traveler's main reason for staying at a particular hotel and the main reason for an unsatisfied experience. They are looking for a better experience related to business activity, which can be indicated in words like "wear", "skirt", "presentation", and "treadmill." Another aspect is connected to the functionality of the hotel facilities and the room, indicated by words like "exterior", "leaked", "lighting", and "plumbing".

5. Discussion and Conclusions

Service failure and negative guest experiences are common situations; however, it is challenging for hotels to effectively recover from them. Despite efforts to understand diverse types of incidents in the customer's journey, service-failure experiences among diverse groups remain underexplored in the hotel industry. By text-mining 1224 actual hotel reviews (73,622 words of textual content), this study examined guests' service-failure experiences during their stays at a branded hotel. Specifically, the study helps to understand the key themes of why the same service fails among diverse groups by focusing on group differences, such as gender and purpose of the stay. In addition, we employed sentiment analysis in order to compare the relative importance of different service attributes among service-failure reviews. The study's findings support the proposed group differences concerning experiential and functional hotel services [28].

Methodologically, we present an example of extracting meaningful insights from unstructured text data using text mining and the NLP approach. Such textual data are commonly found in the real world but cannot be analyzed using traditional quantitative and qualitative techniques. This study shows that text mining can be effectively applied to analyze extensive textual information and to generate insights for decision making in management practices.

Significant differences in service-failure experiences were identified between female and male guests, as well as between leisure and business travelers. Women were more sensitive to affective feelings during a hotel stay, whereas men were more concerned with the experience of facilities/amenities. Leisure travelers demonstrated greater price sensitivity and were more likely to have issues with amenities and meals, such as breakfast service and the swimming pool. In contrast, business travelers were more concerned about business-related issues and the hotel's functionality, such as Internet speed and air conditioning. These results suggest that more diverse strategies must be implemented when providing service and recovering from service failures and be differentiated according to type of traveler.

Our findings confirm that regardless of gender and travel motives, guests want a comfortable, warm, clean, quiet, and safe place to rest, with commonly mentioned issues across groups including cold, smell, and noise. Therefore, the first practical implication for hoteliers is that these common and tangible issues should be avoided through renovation and refurbishment. In addition, it is imperative to ensure that hotel service is perceived as worth the cost, especially when offering physical elements to guests. For instance, sleep quality can be improved by purchasing high-quality pillows and mattresses and providing regular maintenance and cleaning, which highly resonate with the brand standard. In addition, hotels can offer support to help guests reduce any possible sleep disturbances with interventions such as yoga class recommendations and eye masks with earplugs.

Regarding noise control, hotels need to ensure that all of the facilities work noiselessly, significantly reducing the noise caused by the HVAC, refrigerators, toilets, and bathroom sinks. Furthermore, soundproof walls can be installed between hotel rooms. In addition, room-assignment techniques can be implemented to alleviate noise; for instance, guests on a romantic trip should be placed on different floors than group guests who are part of a larger social gathering. Employees need to be more assertive when introducing the lobby and pool rules intended to curb uncivil guest behaviors.

Another imperative is to acknowledge group differences and to provide differentiated service based on customer type. For example, when dealing with female guests, it is important to make sure employee training programs are more focused on showing empathy, being positive, and showing respect, as suggested by the word "rude" in our results. For leisure travelers, it is essential to ensure that the conditions of using coupons are fully explained and that more realistic expectations are communicated in advance. Finally, to develop a structural relationship with business travelers, hotels can emphasize in-room technology amenities, such as high-speed Internet and universal power outlets, in marketing materials, as well as other membership-related benefits.

Several study limitations can be identified. Notably, the human involvement in finding a dictionary and interpreting text-mining results can lead to subjectivity issues, which is one of the critical limitations of text mining [78]. Additionally, although text-mining techniques allow for context-enhanced searches, the technical limitations of these tools may lead to missing values and inaccurate results [54]. Future studies should further validate our results through the use of an expert panel or comparison with the literature. Moreover, despite our success in identifying different perceptions of service failures according to gender and travel-motive groups, more variables must be considered when analyzing these incidents. Future research should explore the effects of more variables on the cause of service failures, for example, age, culture, and experience.

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