An Exploratory Study of Consumers' Travel-Related Concerns About COVID-19

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Abstract. This study explores consumers' travel-related concerns about the COVID-19 pandemic via YouTube comments. Drawing on the risk perception theory and adopting a Markov Chain approach, this study demonstrates the topics that consumers discussed and empirically illustrates perceived risk in the tourism and hospitality industry via sentiment analysis across four sectors: recreation and entertainment, accommodation, transportation, and food and beverages. Results indicate discussion regarding travel-related videos is not only limited to travel-related topics but also includes a broad perspective of social, political, and historical topics. For instance, hotels have a new function as quarantine facilities with effective disease control procedures and social responsibility for public health. Additionally, health, performance, financial, social, and psychological risks are identified. Whereas the presence of travelers is typically regarded as positive, travelers during the crisis are regarded as “irresponsible” and “selfish” individuals who spread the virus and endanger public health. This shift of perception calls for both the industry and academia at large to educate people about the importance of disease control and rebuild travelers' image and reputation. Recommendations to reduce the perceived risk in each sector are also provided.

Keywords: Risk perception · Sentiment analysis · Markov chain · YouTube comments · User-generated content

1 Introduction

Even though the outbreak of Covid-19 imposed extraordinary uncertainty and crisis in the hospitality and tourism industry, the World Tourism Organization (UNWTO) has announced to switch the direction towards reopening and restarting tourism [1]. Because the pandemic-related restrictions are gradually lifted and COVID-19 vaccination doses have been widely administered in U.S. [2], people are heading back to restaurants and travel destinations [3]. Based on the report released by [4], the level of the seated customers in restaurants has reached the pre-pandemic levels in the U.S.

Following the devastating impact and forthcoming recovery in the hospitality and tourism industry, numerous studies are calling for theoretically driven, and systematic research about how customers perceived travel-related activities and correspondingly perceived risk and concerns [1–4], so that the hospitality and destination managers can develop the coping strategy to reduce the perceived risk and recover the whole industry [5].

However, the majority of current studies about perceived risk are conducted in designed questionnaires [5–7], which constrained the capability that consumers can freely speak out their perceived risk. In fact, it calls for an exploratory study related to COVID-19 in tourism and hospitality, instead of fully grounded in the existing literature [5]. Considering the outbreak of Covid-19 pandemic created an unprecedentedly social and economic environment, people are likely to have unpredictable behaviors and feelings, which makes the validity of existing knowledge under the new normal much more challenging and questionable [6].

Given the identified research gap, this study explored the consumers' travel-related concerns about the crisis of the Covid-19 pandemic. Drawing on the risk perception theory, this study adopted the Markov Chain text mining method to identify the topics discussed by consumers and empirically illustrated the perceived risks in the overall tourism and hospitality industry and four sectors respectively. Results show that when consumers are watching travel-related and Covid-19 related videos, what they are discussing is not constrained in travel-related topics, but include a broad perspective of social, political, and historical topics. Noticeably, hotels are assigned a new function, the quarantine facilities, which require hotel businesses to develop effective disease control procedures and shoulder more social responsibility for public health. Additionally, health risk, performance risk, financial risk, social risk and psychological risk are all identified. Different from the previous that travelers are regarded as positive image, travelers during the crisis are regarded as “irresponsible” and “selfish” who spread the virus and danger the public health. It calls for both the industry and the academia to educate the importance of disease control and rebuild travelers' image and reputation. Practically, this study can benefit policymakers and managers to understand customers' beliefs and behaviors under the crisis as well as consumers' expectations towards the post-pandemic, which is crucial for designing and operating actionable policies and coping strategies.

2 Literature Review

2.1 Risk Perception

Perceived risk refers to the potential future loss that may happen if a particular decision has been made [8]. People perceive risk since the uncertainty may potentially trigger negative outcomes. Perceived risk has been widely recognized as the critical factor that have an effect on consumers' decision-making and behavior [8–10]. There are a variety of perceived risks that have been identified in destination marketing [11], food delivery [12], and service industry [13]. Performance risk refers to the expectation may not be satisfied after the service is delivered [14–16]. Financial risk refers to the potential financial loss that the service has to be replaced, fixed or compensated [17, 18]. Psychological risk refers to the psychological discomfort (e.g., regret, worry) caused by the service experience [11, 19]. Social risk is linked to the probability of a customer's buying behavior that can influence another customer's opinion and perception [20–22]. Health risk reflects the situation that the consumption of the service can trigger an unprecedented hazard to the customer's health [15, 23].

Perceived risk from COVID-19 is very critical since it has severely negative impacts on revisit intention for hotels [24]. However, most of the studies are supported by primary data [5–7], which constrained the capability that consumers can freely speak out their perceived risk [25]. This study adopted the User-Generated Content, specifically, YouTube comments, to explore consumers' travel-related concerns in the inductive way.

2.2 User-Generated Content

User Generated Content (UGC) is regarded as the creative work that is published on accessible and public platforms and usually has no direct linkage to commercial profits or monetary interests [26]. Customers are more likely influenced by the UGC with negative valence [27]. Novelty, reliability, understandability, and interestingness embedded in UGC would influence consumers' selection of destination [28]. Since Covid-19 is the first pandemic most of us faced, the repercussions for the travelers are not researched before. This study aims to explore the risk perception of travelers via YouTube comments, classify the risks based on different tourism sectors, and understand the sentiment of these comments. YouTube comments were selected since this platform features genuine debates on controversial issues and has been regarded as a significant public space for engaging in debate and exchanging opinions [29]. For many less active social users are the observers, their attitudes and intentions may be influenced by being exposed to YouTube comments [30], highlighting the significance of exploring them as a textual corpus of study.

3 Method

3.1 Sample

This study employed YouTube Comments as the sample. First, we designed a list of keywords that includes both Covid-19 related words and tourism and hospitality related words. Next, we scraped the YouTube videos whose titles include any of the keyword. Finally, we exported the comments below each of the video and compiled all the comments as the sample of this study. The data sample includes 521 YouTube videos and 9,727 unique comments. The data were collected on October 5, 2020. At that time, the videos that include the keywords were relatively limited. Since the perception from consumers is the research objective in this study, the producers and origins of the videos were not collected.

3.2 Contribution of Sentiment Words

Sentiment analysis was used to not only understand the opinions and attitudes delivered in the comments, but also capture which words with emotional and opinion information are critical in the text. Considering the exploratory nature of this study, we didn't assess the sentiment scores in traditional way but explore the most significant sentiment words according to the frequency of the word.

3.3 Popular Bigrams

We further examined the relationship between words by Markov Chain. Markov Chain, the common model in text mining, was selected as the approach for visualization [31]. Markov chain theory refers to the adjacent characters sequences are employed to generate the probabilities transition matrices. In the linguistic field, Markov Chain has been widely used in identifying malicious attack [32], predicting the geo-location of Twitter users [33], evaluating digital document authentication [34]. In fact, Markov Chain have been used in tourism literature to forecast tourist arrivals [35] or model the spatial and temporal movement of tourists [36] but rarely used for text analysis [37]. This study innovatively used Markov Chain to visualize the topics that consumers discussed about the travel-related concerns. Markov chain in this study is used to identify the words are more likely to follow others immediately or to co-occur within the same document. Specifically, we tokenized the text into pairs of two consecutive sequence of words to explore how often word A is followed by word. This process is called “bigrams” [38].

3.4 Sector of Hospitality and Tourism

In order to capture the dynamics of each sector underlying the hospitality and tourism industry, we categorized the YouTube Videos in the sample into five groups based on the sector of hospitality and tourism industry, including accommodation, food and beverage, entertainment and recreation, transportation, and others [39–41]. Tables 1 and 2 demonstrate the process of classifying the YouTube Videos.

Table 1. Keywords for classifying videos based on four sectors.

Sector	Keywords
Recreation and entertainment	Travel, tour, beach casino, park, Las Vegas, Florida, Disney, holiday, wedding, Halloween, gym, vacation
Accommodation	Hotel, motel, Airbnb
Transportation	Airplane, airport, flight, fly, train, bus, car
Food and beverages	Restaurant, bar, food, dining

Table 2. Descriptive information about the sample.

Sector	Number of Video	Percentage	Number of Comments	Percentage
Recreation and entertainment	186	35.70%	3630	37.32%
Accommodation	78	14.97%	1157	11.89%
Transportation	39	7.49%	1024	10.53%
Food and beverage	36	6.91%	603	6.20%
Others	182	34.93%	3313	34.06%
Total	521		9727	

4 Results and Discussion

4.1 Sentiment Contribution

There are 2,441 unique sentiment words identified in the dataset, including 1,656 negative words and 785 positive words. Table 1 demonstrates the top 20 Words that contribute to negative and positive sentiment. The results in Table 3 demonstrate three types of risk, including health risk as the direct outcomes of the Covid-19 (“die”, “infect”, “sick”, “symptom”, “outbreak”, “cold”, “kill”), the psychological risk as the cognitive perception of Covid-19 (“bad”, “risk”, “fear”, “hard”, “scare”, “lost”, “sad”) and social risk as the skeptical behavior towards the related information (“lie”, “fake”, “stupid”, “wrong”, “blame”). As anticipated, health risk is the most salient risk, which is consistent with current study that there is significant interaction between perception of coronavirus pandemic and perceived health risk besides non-pharmaceutical intervention [42].

Table 3. Top 20 words contributing to negative and positive sentiment.

Negative sentiment	Positive sentiment
Virus, die, bad, infect, risk, sick, symptom, lie, fear, fake, stupid, hard, scare, lost, outbreak, wrong, sad, cold, kill, blame	Safe, love, protect, clean, free, healthy, nice, healthy, nice, glad, happy, cure, support, enjoy, trust, beautiful, top, freedom, amazing, bless, fine, luck

Table 3 illustrates the top 20 positive words that contributed most. Consumers are very concerned about the disease protocol issues in the travel process, including “safe”, “protect”, “clean”, “healthy”, “cure”, “support”, and “trust”. At the same time, consumers still anticipate the travel experience with “love”, “nice”, “glad”, “happy”, “enjoy”, “beautiful”, “amazing”, “fine”. It indicates consumers concerned about the performance risk and are very likely to expect both high level of precautions and positive travel experience at the time same, which presents a significant challenge for practitioners to satisfy consumers’ expectations.

Figure 1 demonstrates the most popular bigram that occurred more than 10 times, which reflects the consumers’ travel-related concerns from a comprehensive point of view. The largest cluster of the bigrams is represented by “covid-19”, which includes the testing and spreading process as well as the negative consequences of Covid-19. “People” represents the second cluster, which focuses on the self-protection activities, including mask wearing and staying home. Next came the cluster called “quarantine”, which demonstrated the 14-day requirement endorsed by CDC. Noticeably, “hotel industry”, “hospitality”, “airlines” and “restaurant” are closely related to this cluster, indicating our industry, especially hotels, are assigned new function as the quarantine facilities during the pandemic. Another representative cluster is “travel”, which strongly tied with “travel ban” and “travel restrictions”. The topic related to politics cannot be ignored, including nations and government (e.g., “china”, “uk”) and political figures (e.g., “trump”, “prime minster”, “johnson boris”). Consumers can also consult

historical event to understand this pandemic, including “spanish flu”, “1984”. Media plays an important role to introduce the practice of social distancing, but the credibility of the media is questioned as “fake news”. Additionally, medical experts and organization are regarded as the authority to provide relevant information, including “fauci”, “morris”, “john”, “richard” as the medical professionals and “nih”, “nlm”, “ncbi” as the medical organizations and departments.

Fig. 1. Common bigrams showing those that occurred more than 10 times.

Table 4 summarizes the positive words and negative words in each sector separately. In order to explore consumers' idiosyncratic concerns towards four sectors of tourism and hospitality industry respectively, we excluded the words that have already included in Table 3. First, the Recreation and Entertainment Sector includes "selfish", "crowded", "nervous", "hoax", "ignorant", "correct", "peace", "ready", "worth", "fun". Different from normal time that travelers are regarded as people with positive personality, such as adventurous, empathetic and curious, travelers during the pandemic are perceived as "selfish", "hoax", "ignorant", which reflect the social risk that an individual's traveling behaviors will influence another people's opinion. In terms of the performance, people are concerned the travel destination is "crowded" and whether the disease control procedures are "correct" or "ready" to let people enjoy the travel experience with "peace" and "fun". Additionally, people are concerned about the psychological risk as "nervous" and financial risk as "worth".

Table 4. Sentiment words in each sector.

Sector	Negative	Positive
Recreation and entertainment	Selfish, crowded, nervous, hoax, ignorant	Fun, worth, ready, peace, correct
Accommodation	Expensive, cheap, disgusting, collapse, recession	Smart, fair, refund, approve, affordable
Transportation	Useless, selfish, cheap, expensive, contagious	Brave, comfortable, ease, accurate, appreciated
Food and beverage	Idiots, carp, panic, irresponsible, destroy	Effective, fast, backbone, benefits, fresh

Next, Accommodation Sector includes “expensive”, “cheap”, “disgusting”, “recession”, “collapse”, “affordable”, “refund”, “approve”, “fair”, “smart”. Financial risk is the most salient risk in this sector. People are worried about the price (e.g., “expensive”, “cheap”, “affordable”) and also the change or cancel of the booking can be “refunded” successfully. At the same time, people are worried about the cleanness of the accommodation (e.g., “disgusting”) as the performance risk. Interestingly, people are aware the loss and challenge that the accommodation sector are facing right now and worried about the overall social and economic condition as “collapse” and “recession”. We recommend hotel companies and Airbnb need to clarify the coronavirus related changes, in terms of cancellation policies and price policies on booking websites to reduce perceived financial risk. It is also necessary to circulate positive industry news to boost the overall confidence. For example, SoftBank’s is investing \$1.7 billion in Yanolja, the company that provides AI-powered hotel software and contactless services for guests. The endorsement of SoftBank represents a wave of travel-related optimism [43].

In the Transportation Sector, people as usual are concerned about the punctuality (e.g., “accurate”) and on-board experience (e.g., “ease” and “comfortable”) as the performance risk. Consistent with the accommodation sector, people are concerned about the financial risk (“cheap” and “expensive”) and social risk (e.g., “selfish”). Noticeably, consumers are concerned the health risk considering the virus can spread in the close environment with the interaction with people (e.g., “contagious”). We recommend airlines companies should highlight the coronavirus change and cancellation policies on booking websites to decrease perceived financial risk. It is also critical to strictly follow the CDC guidelines and demonstrate the efforts on social media platforms.

Last, in the Food and Beverages Sector, social risk is the most salient risk since drinking in bars and similar activities are regarded as “idiots”, “crap” and “irresponsible”. While people feel “panic” as the psychological risk, they still anticipate the food and beverage service can be “fresh”, “fast”, “effective”, which can reflect the performance risk. We strongly recommend restaurants and bars strictly follow the CDC guidelines, including preparing adequate supplies (masks, soap, hand sanitizer and disinfectant wipes) and maintaining healthy environment by cleaning and disinfecting regularly [44]. Additionally, social media can be used to communicate how restaurants

and bars strictly implement the strategies, considering social media is an critical tool in crisis communication and crisis management plan [45]. We suggest restaurants and bars can reduce customers perceived social risk and psychological risk by demonstrating the process of executing the relevant protocols on various social media platforms.

5 Discussion and Conclusion

Drawing on the risk perception theory, this study explored the travel-related concerns about the outbreak of Covid-19 by automated text analysis. It is the first study which employed YouTube comments as the sample to conduct tourism research. Sentiment analysis of the overall tourism and hospitality industry indicates that the health risk is most concerned by consumers, showing that people are highly aware of their health in terms of the general travel activities. By drawing the most popular bigrams by Markov Chain, this study found that when consumers are watching travel-related videos, what they are discussing is not constrained in travel-related topics, but include a broad perspective of social, political, and historical topics. At the same time, this study explored consumers' idiosyncratic concerns towards four sectors of the tourism and hospitality industry and provides practical recommendation to reduce the perceived risk.

Despite its contribution, this study has some limitations. First, this study focused on the UGC in English language. Considering the Covid-19 is a global crisis and is devastating the worldwide industry, Asian customers may perceive travel risks drastically different from American and European customers [46], which is calling for future research to explore this topic in different language settings (e.g., Chinese, Spanish and Korean etc.). Also, policymakers need to consider different approaches for dealing with the pandemic among different regions [47]. Second, this study adopted YouTube comments as the sample, but the comments are highly associated with the specific videos [48]. Future research can explore UGC from other social media platforms in order to understand a comprehensive picture of the travel-related concerns. Third, this is an exploratory study focusing on the descriptive findings. Future studies can empirically conduct relational analysis, for example, particular risks or concerns are related to demographic variables.

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