

A BIG-DATA ANALYSIS OF PUBLIC PERCEPTIONS OF SERVICE ROBOTS AMID COVID-19

Yaozhi ZHANG ¹

Department of Business Administration, University of Girona, Spain

ORCID: 0000-0003-0055-6087

ABSTRACT

This research note investigates public perceptions of robotic services in the hospitality and tourism industry in the context of COVID-19. Relevant comments from YouTube videos were crawled and analysed by Natural Language Processing (NLP) techniques including explorative analysis, sentiment analysis, and topic modelling. The results reveal that while there are supporters and opponents toward robotic services during the pandemic, the overall public sentiment is neutral, and confirm that the health factor and a series of social-cultural factors encompassing the employment concern, political influence, and cultural norm should be involved as more significant variables for COVID-Tourism research. Some practical suggestions for robotic services amidst COVID-19 are accordingly put forward.

Article History

Received 23 September 2020

Revised 23 November 2020

Accepted 3 December 2020

Available online 12 Feb. 2021

Keywords

COVID-19

service robot

public perception

hospitality and tourism industry

INTRODUCTION

The impacts of COVID-19 pandemic on the global hospitality and tourism industry are inarguably detrimental and long-lasting, making the health issue become one of the most critical factors for industrial recovery in the foreseeable future. This shift has unprecedentedly led to substantial requirements and needs of hygiene management, social-distancing, and contactless services (Jiang & Wen, 2020). In this context, AI-based robots and pertinent unmanned services have been largely proposed and adopted in different tourism and hospitality sectors (Gretzel et al., 2020; Seyitoğlu & Ivanov, 2020). According to Zeng et al. (2020), the application of service robots amid COVID-19 can be generally classified into six scenarios:

¹ Address correspondence to Yaozhi Zhang, Faculty of Tourism, Department of Business Administration, University of Girona, Spain. E-mail: a810708027@vip.qq.com

hospitals, communities, airports, transportations, recreation, attraction, and scenic areas, and hotels and restaurants.

While the robotic service is not a brand-new realm for hospitality and tourism studies, the COVID-19 crisis may become an essential driving force of changing relevant market profile and industry practice (Gössling et al., 2021; Zenker & Kock, 2020). Recent research agenda specifically focusing on interdisciplinary robotic studies has also been raised by many tourism researchers including Tavakoli et al. (2020), Gretzel et al. (2020), Zeng et al. (2020), and Wen et al. (2020), and it is agreed to be necessary and valuable to study how robotic services can contribute to the tourism restoration. In this process, public perception is undoubtedly a key indicator. Hence, in line with the proposed research agenda and research needs, this study, adopting a big data analysis method, investigates how the public perceives the robotic services in such a special period, the reflections of which would shed light on future academic enquiries and industrial revival.

METHODS

In the big data era, the availability of online reviews, particularly those User Generated Content (UGC) from social media, presents enormous opportunities for capturing and understanding a certain topic more comprehensively. As shown in Figure 1, this study followed the core steps adapted from Knowledge Discovery in Database (KDD) (Tan et al., 2014) comprising data collection, pre-processing, data mining, and interpretation.

In the first step, following the procedure in previous studies (Amatulli et al., 2019; Guo et al., 2017), the English videos and reviews from YouTube were selected as the domain for data collection. Specifically, the word "COVID" or "Coronavirus", combined with "robot" and nine keywords based on robot adoption scenarios claimed by Zeng et al. (2020), namely "hospital", "community", "airport", "transportation", "recreation", "attraction", "scenic", "hotel" and "restaurant", were respectively set as the term searched in the YouTube. To ensure the highest relevance and validity of samples, the eligible comments must be 1) from the objective news report videos; 2) displayed in official channels and 3) directly related to service robots applied in the hospitality and tourism industries. Following the data screening protocol, the results were sorted by relevance and the video contents were carefully checked by the author. Consequently, 3948 reviews from 84 videos, with the counts of "like", "dislike" and "reply", were extracted through the web crawler program as of July 2020.

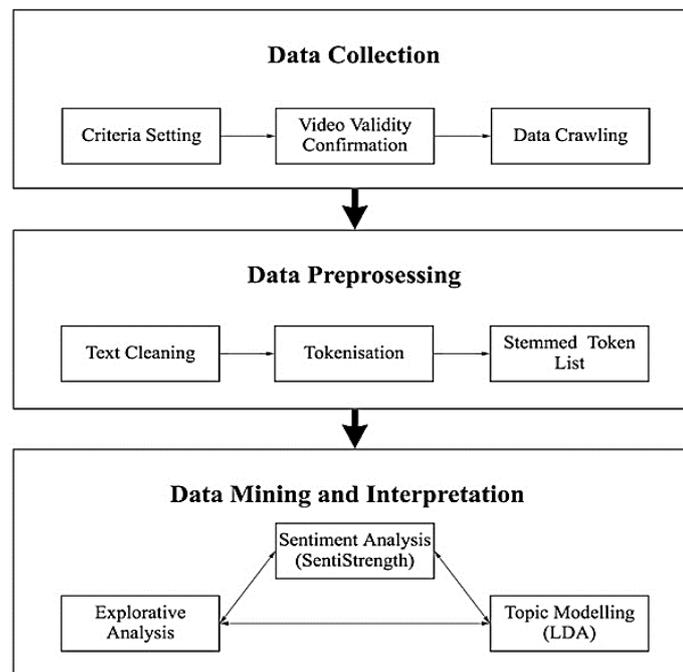


Figure 1. *Research framework*

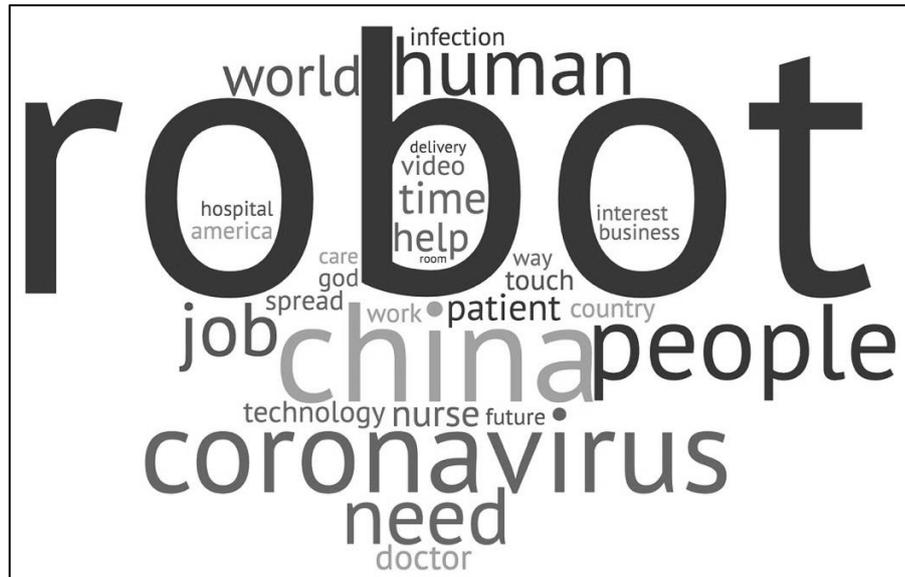
The data pre-processing was performed by Python 3.7 with the Natural Language Toolkit (NLTK) package. Suppose the original downloaded review data set $R_0 = (r_1, r_2, \dots, r_{3948})$. First, this study discarded all non-English texts and all replies to original comments. After that, 1852 reviews were finally confirmed as the dataset $R_1 = (r_1, r_2, \dots, r_{1852})$. Next, all r in R_1 were joined together as one string, and the texts in the string were transformed into lowercase, followed by removing all numbers, URLs, punctuations, and symbols within the string to formulate the cleaned dataset. Then, the cleaned dataset was loaded into the NLTK tokenizer algorithm where the texts were broken into tokens. After that, with NLTK Part-of-Speech Tagging (POST), each token was tagged with their part of speech such as noun, adjective, verb, etc. These tokens were later inputted into the NLTK Word Net Lemmatizer to transform all tokens into their stem or root forms. Finally, nonsensical stop words were removed from the tokens to form the new stemmed token list dataset R_2 , and accordingly, a noun list R_3 derived from R_2 was also prepared.

A triangulation structure was set in the data mining step. The explorative analysis set out to discern the key words emerging from the reviews, by producing a Word Cloud involving thirty most frequently mentioned noun-words based on dataset R_3 and by presenting the top five comments with the highest number of agreements (computed by the number of “likes” minus “dislikes”) and replies. The sentiment analysis was

carried out by SentiStrength, a widely-used opinion mining tool in academia (Abdelhamied, 2011), to investigate the general public's attitudes. In detail, each *r* in R1 went through the SentiStrength algorithm and produced a scale between -4 (extremely negative) to 4 (extremely positive), and then the mean value and weighted mean value influenced by the number of agreements were calculated. Lastly, the Latent Dirichlet Allocation (LDA) topic modelling technique, an unsupervised learning algorithm based on the probabilistic generation model, was applied through the Gensim python library. This step comprised several attempts to respectively import data sets R1, R2, R3 to try different combinations of the number of topics and the number of words contained in topics, so as to obtain the most sense-making solution. The findings are shown and interpreted in the following.

FINDINGS

According to the Word Cloud (Figure 2), though the words "robot" and "coronavirus" were within the expectation, it was unexpected that the second most frequent word was "China". Two deductions were thereby made: first, service robots were widely used in China during the pandemic; second, there existed some general discussions such as critiques, compliments, political disputes about China that had nothing to do with robots. The first deduction was somehow proved by Table 1 that three out of five most arguable comments were directly related to the service robot adoption in China while the latter one needed to be further confirmed. Other than that, another noticeable word set was "patient", "doctor", "nurse", "care" and "hospital", revealing that the comments were much concentrated on the healthcare scenarios, which could be inferred that the current booming emergence of service robots was essential for health reasons. In addition, the words "job" and "work" were also evident in the diagram, implicating that people might be awfully concerned with the job opportunities deprived by the service robots. Lastly, as can be seen from Table 2, the comments that appeared to show the worries and downsides of service robots received the most agreements. Nonetheless, to verify whether the general public had negative attitudes towards service robots, the results of sentiment analysis have to be referred to.

Figure 2. *Word Cloud*Table 1. *Top five comments with most replies*

Comments	Number of replies
"China actually is a very technological advance country."	41
"Imagine if it happened in my country, more than 800 million would have been infected while believing a cow dung has a cure over it"	28
"Please keep your social distance...this is your first warning..."	27
"What don't kill CHINA will only make China stronger"	26
"the start of something new. In 5 years, robots will be everywhere in China, you can bet on it."	25

Table 2. *Top five comments with most agreements*

Comments	Number of agreements
"Scientists: 'technology will soon lead to the end of the world'"	788
"Please keep your social distance...this is your first warning..."	764
"Robots: find cure"	540
"Everyone's gangsta until the robots start taking over..."	358
"This is too much like the start of a Black Mirror world"	332

Interestingly, as shown in the bar chart of sentiment value distribution (Figure 3), the results manifested a mean sentiment value of 0.05 with an approximately normal distribution pattern. For the weighted mean considering the influence of the agreement level, the score remained at 0.14, which is even a little higher than the unweighted mean. Thus, the sentiment analysis results did not support the negative attitude

assumption, and it can be further concluded that even though the negative comments were eye-catching and there were extreme supporters and opponents, the mainstream of people actually holds a neutral attitude when watching the videos pertaining to service robots.

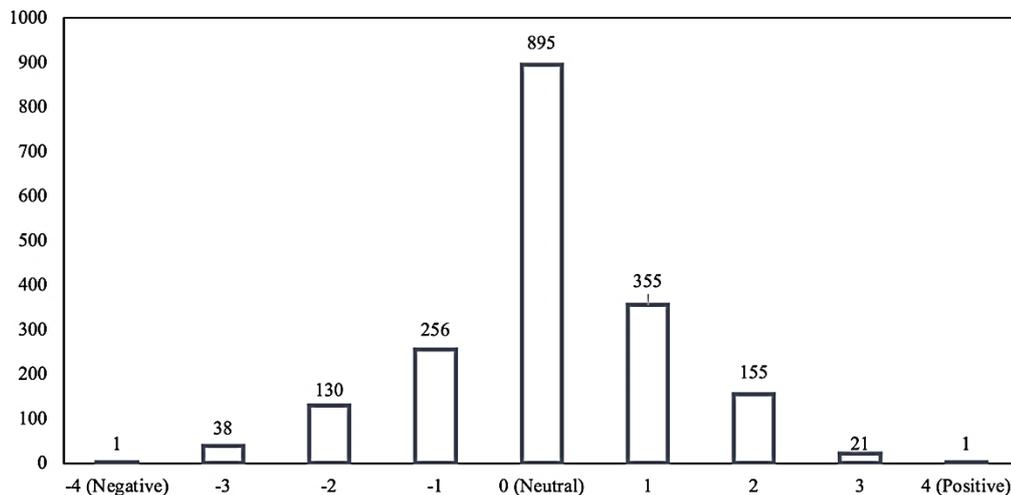


Figure 3. *Sentiment analysis results*

As to the LDA results, the most sense-making outcome was by using dataset R2 with four three-word topics: topic 1 = 0.015*"robot" + 0.007*"China" + 0.006*"make", topic 2 = 0.034*"robot" + 0.010*"China" + 0.009*"coronavirus", topic 3 = 0.023*"robot" + 0.009*"people" + 0.009*"help", topic 4 = '0.012*"robot" + 0.008*"coronavirus" + 0.006*"job". Instead of naming for the four topics as LDA analysis usually does, this study tried to interpret their latent meanings by relating them to the above discussion. For the first two topics, the words "robot" and "China" were respectively correlated with "make" and "coronavirus". This can be used to infer that the reasons for the emergence of "China" in the comments were due to both its large-scale robot manufacturing and other non-robotic discussions regarding the virus. Therefore, it can be reasonably said that robotic services would go beyond the technological realm and be politically, socially, and culturally interpreted, especially considering the contemporary complicated socio-political environments in the world. The third topic ("robot", "people", "help") denotes the positive facets of the service robots and helps explain why there was a certain quantity of robotic service supporters. Conversely, the fourth topic validates employment as a potentially predominant negative concern for the massive robot implementation in the service industry.

CONCLUSION

Theoretically, previous studies have revealed numerous factors affecting the adoption of service robots in the hospitality and tourism industry, such as the cost, novelty, usefulness, ease of use, etc. on the supply side as well as various demo- and psycho-graphic factors including the income, educational level, attitude to technology, etc. on the demand side (Ivanov et al., 2019; Ivanov et al., 2018; Kuo et al., 2017; Lu et al., 2019; Yu, 2020). Nevertheless, none of them has mentioned the health factor. As a matter of fact, recent COVID-related studies have already started to focus on the perceived trust and risk reduction functions provided by service robots (Shin & Kang, 2020; Wan et al., 2020). Therefore, consistent with Jiang and Wen (2020), the health factor should be included as a more significant push and pull factor in future hospitality and tourism research related to robotic services. Meanwhile, in line with Sigala (2020), this study also calls for paying attention to how a series of societal factors play a role in technological application in the current- and post-pandemic worlds, such as the trade-off between technology adoption and job deprivation, the influence of political discourse and orientation, the new social norms of social-distancing and so forth. This research note would further elicit such arguable and critical research questions as whether a person who worries about AI or does not wear a face mask would support service robots, whether an anti-China regime would import those robots made in China, and whether the social-cultural background allows service robots to be widely employed. All these questions must be investigated from country to country, culture to culture, and person to person basis.

Practically, due to the public's neutral sentiment towards service robots and the reality that there is a sizable group of supporters, a niche market for service robots does exist. In the meantime, the health guarantee provided by robotic services further promotes the level between service providers and customers, which would speed up the progress of service robots' adoption. Therefore, this research note confirms the argument made by Zeng et al. (2020) that the COVID-19 provides a precious window period for the popularization of robotic services. On their basis, we would further suggest that robots that can facilitate sanitation management during the service process, such as item delivery, auto-registration, information provision, and disinfection would have a comparatively broader prospect, and practitioners should pay more attention to these opportunities.

In conclusion, this research note attempts to initiate the discussion of service robots in the context of COVID-19 by providing insights based on

public perceptions. To formulate a more up-to-date and in-depth understanding, it is recommended that future empirical studies in the form of survey and interview should be conducted by considering more factors related to COVID-19, focusing on customers from different social, political, cultural backgrounds, and looking into specific segmented service robot category and application scenarios.

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