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Recovery of hotels from the crises: evidence from tourists' emotional changes by deep learning sentiment analysis

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ABSTRACT
The hospitality sector is highly susceptible to crises. Understanding guests' emotional reactions and attitudes toward hotels during such times is crucial for developing effective retention strategies and revitalizing the industry. This study examines changes in guest sentiment toward hotel attributes during the overlapping crises of the 2019 Hong Kong protests and the COVID-19 pandemic. Using deep learning methods, specifically the BERT language model, the research analyzed 2,941,710 textual units to track sentiment shifts across pre-crisis, crisis, and post-crisis stages. Results indicate significant sentiment fluctuations affecting various hospitality aspects. This research extends deep learning applications in crisis impact assessment and offers strategic insights for hotel managers to craft marketing strategies throughout a crisis lifecycle.

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Introduction

The recent past has underscored the resilience of the tourism and hospitality industry in weathering crises, both human-made and natural (Duan et al., 2022). The repercussions of these crises ripple through the entire tourism value chain, from destinations to attractions, and involving various intermediaries (such as travel agencies) and service providers (including hotels and restaurants). The profound social, psychological, and economic impacts of such crises in the tourism and hospitality sectors have garnered significant attention (Alegre & Sard, 2015; Samitas et al., 2018). In light of these impacts, there is an increased focus on developing strategies to navigate unforeseen crises by engaging the industry and its stakeholders (Backer & Ritchie, 2017; Cruz-Milan et al., 2016).

Concurrently, another body of research has delved into the strategic responses to crises within specific contexts, examining various crisis types, including terrorist incidents (e.g. the September 11 attacks in 2001), natural calamities (e.g. the Indian Ocean tsunami in 2004), financial downturns (e.g. the global financial crisis in 2008), and epidemics (e.g. the SARS outbreak in 2003). This study contributes to the literature on tourism and hospitality crisis management by critically examining the responses to multiple crises or disasters, thereby extending the discourse on strategic crisis response and preparedness.

Crises have a profound impact not only on the trajectory of tourism and hospitality industries but also on consumer attitudes, needs, and behaviors (Walters et al., 2019). Sigala's (2020) research illustrates that travel during the COVID-19 pandemic has significantly altered visitors' attitudes, risk assessments, intentions, and prospective behaviors. The way visitors perceive crises plays a pivotal role in their decision-making processes, influencing whether they proceed with or cancel their travel plans (Kozak et al., 2007). Such behavioral shifts

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underscore the need for academics and industry professionals to deepen their understanding of visitors' thoughts, perceptions, and needs during crises (Villacé-Molinero et al., 2021).

Cognitive appraisal theory posits that an individual's reaction to events is mediated by their cognitive, emotional, and behavioral responses (Luo & Zhai, 2017). Consequently, the evaluation of an event can elicit a specific emotional reaction, which, in turn, can influence one's behavioral intentions (Frijda et al., 1989). Recognizing the significance of visitor behavior in crisis management, it becomes imperative to assess the emotional responses individuals have to various situations.

The influence of crisis events on human emotions is not uniform but varies with the nature of the event itself. Utz et al. (2013) discovered that different types of crises affect people's emotions distinctly. Breitsohl and Garrod (2016) noted that crises stemming from internal or human-induced factors often result in more significant negative impacts compared to those originating from external factors. Furthermore, Luo & Zhai, 2017 observed that public emotions fluctuate throughout the duration of a crisis. Therefore, comprehending the nuances of visitors' emotional responses as they evolve during various crisis events is crucial. Considering the significance of this subject and the existing research voids, the study poses the following research questions:

(1) What are the emotional responses of consumers to hospitality features in the times of multiple types of crisis events?
(2) Are there any differences in visitors' sentiments to hospitality features in the destination at different stages of the crises? If so, what are these differences?

Hong Kong serves as an exemplary case study due to its exposure to two successive and unprecedented crises since 2019. The Anti-Extradition Law Amendment Bill Movement, commencing in March 2019, significantly challenged the region's social stability and security. This was closely followed by the advent of the COVID-19 pandemic in early 2020, delivering a compounded blow to the city. As a result of the social turmoil, Hong Kong witnessed a decline in tourist arrivals by 14.2%, dropping to around 55.91 million in 2019 (Hong Kong Tourism Board [HKTB], 2020). The onslaught of COVID-19 further exacerbated the decline in tourism, with visitor numbers plummeting to merely 3.57 million in 2020 and a stark 0.09 million in 2021 (HKTB, 2022).

While previous research has often focused on the singular impacts of either the protests or the pandemic on tourist perceptions and intentions (e.g. Girish et al., 2021; Poon & Koay, 2021), this study recognizes the overlap in timelines of these crises and the consequent layered challenges faced by Hong Kong's hospitality industry. The distinction between the two crises – one stemming from public health concerns and the other rooted in social movement – warrants a simultaneous examination of their impacts.

Drawing on the sequential view of the issue-attention cycle theory, this investigation seeks to elucidate consumer responses to multiple types of crises at different stages. A cycle of issue-attention is particularly relevant to the crisis-laden years in Hong Kong. This research is among the first to systematically explore the emotional transitions of visitors in response to various crises over time. It presents a methodological framework for crisis management, geared towards understanding the evolution of tourist emotional responses. Leveraging advanced big data techniques and neural network analyses enhances the precision of sentiment analysis. The findings offer strategic directions for industry practitioners to tailor products and services more effectively by monitoring and addressing the dynamic emotional states of customers (Manosso & Domareski Ruiz, 2021).

Literature review

Tourists' sentiment in times of crises

"Pandemics are not new" (Prayag, 2020, p. 179). The COVID-19 pandemic, while not a novel occurrence in the context of global health challenges, has nonetheless intensified the academic focus on the emotional responses of hotel guests during such a crisis. Das and Tiwari (2021) highlight that consumer travel inclinations, as well as their perceptions and preferences towards the hospitality industry's offerings, are expected to show greater variance in the face of a pandemic. Consequently, there is a pivotal need for the hospitality sector to reassess customer sentiment to ensure the delivery of a reliable, comforting, and reassuring service experience. This re-evaluation is key to fostering customer satisfaction and stimulating the growth of hotel businesses.

To this end, researchers such as Mehta et al. (2023) have employed sentiment analysis techniques to dissect guest perceptions and preferences in the context of hospitality and tourism facilities and services. In an era where hygiene and safety are of paramount concern, as underscored by Das and Tiwari (2021), it is crucial to understand how priorities have shifted. Notably, much of the existing literature has concentrated on singular temporal segments – usually during the crisis itself – without juxtaposing sentiments across different stages of the event's progression (Hu et al., 2021; Mehta et al., 2023). An exception is the work by Hu et al. (2021), which illuminates the sentiment evolution between the "within-crisis" and "post-crisis recovery" phases of the COVID-19 epidemic. Their findings suggest a marked shift in guest priorities, focusing heavily on hygiene, service quality, and staff responsiveness during the crisis, with a reversion to standard preferences such as facilities and breakfast quality in the aftermath.

The exploration of emotional dynamics within the field of tourism, often referred to as the "emotional turn," has become increasingly prevalent, indicating a shift in focus towards understanding the affective experiences of tourists (Picard & Robinson, 2012).

Emotions are inherently dynamic, characterized by continuous evolution, fluctuations, synchronization, lingering, merging, and spillover across time (Kuppens & Verduyn, 2017). Although the dynamic nature of emotions has primarily been studied within individuals (Krone et al., 2018), emotional contagion theory suggests that emotions often originate and intensify in interpersonal contexts, potentially escalating from individual to group-based emotions on social media (Bringmann et al., 2018; Hatfield et al., 1993). Moreover, social media serves as a potent tool for tracking the ebb and flow of people's emotions over time (Chung & Zeng, 2020).

Despite its growing popularity, research specifically addressing emotional changes related to crisis events remains scarce (Breitsohl & Garrod, 2016). Much of the existing scholarship has focused on emotional responses during the pre-crisis and crisis phases, often overlooking the post-crisis period when emotions begin to stabilize (Rivera, 2020). An illustrative study in this area is by Luo & Zhai, 2017, who explored the Occupy Central incident in Hong Kong and observed escalating negative sentiment on Sina Weibo as the situation intensified. More recently, Hao et al. (2024) highlighted the dynamic and interpersonal nature of emotions on social media in response to the pandemic over time. Their research suggests that social media not only facilitates emotional expression but also plays a constructive role in disaster risk reduction and management, acting as an emotional coping mechanism for individuals affected by disasters.

Sentiment analysis has seen diverse methodological applications within the hotel and tourism industry, yet critiques by Mehraliyev et al. (2022) point to the underutilization of "big data" in terms of its scope and scale. This suggests that much of the existing research has not fully exploited the advantages offered by big data analytics in hospitality and tourism studies (Li et al., 2018). The methods and tools for sentiment analysis have seen both traditional approaches and innovative strides as interest in the area grows (as indicated in Table 1).

Advancements in computer science and big data have propelled the evolution of research instruments, enhancing the ability to garner comprehensive and persuasive insights. Nevertheless, the application of deep learning algorithms, which have revolutionized various domains of natural language processing with their data-driven, end-to-end training processes, remains relatively rare in this field (LeCun et al., 2015; Mehraliyev et al., 2022). Deep learning models can perform without the need for extensive pre-annotation of data and have shown superior results in many language processing tasks (Xu et al., 2019).

Despite these capabilities, there is a noted gap in research employing deep learning models to investigate the shift in customer emotions within crisis-affected destinations (Nadeau et al., 2022). The current study aims to bridge this gap, becoming one of the pioneers in comparing emotional transitions based on tourists' accommodation experiences during different stages of multiple crises by implementing an advanced deep learning model. This approach not only advances academic research in crisis management but also offers actionable insights for the hospitality industry in managing customer emotions effectively throughout the various phases of a crisis.

The issue-attention cycle and the stages of Hong Kong crises

The Anti-Extradition Law Amendment Bill Movement, commonly referred to as the 2019 protests, was indeed a significant event that deeply impacted Hong Kong, a city renowned for its status as a global financial hub and a popular tourist destination. These protests emerged from the widespread public

Table 1. Partial research on sentiment analysis regarding hotels and tourism.

Author (year)	Research Topic	Data Source	Analysis Algorithm/Instrument
Bjorkelind et al.	Opinion mining on online travel agencies	984,962 reviews posted on TripAdvisor and Booking.com	SentiWordNet and machine learning
Vu et al. (2015)	Consumer behavior of inbound travelers	29,443 photos from Flickr	Density clustering *P*-DBSCAN, Markov Chain
Duan et al. (2016)	Hotel service quality and performance	70,103 comments of hotels in the Washington, D.C.	Naïve Bayes (NB)
Luo & Zhai, 2017	Communication of emotions on social media regarding Occupy Central	440 posts from Weibo in Chinese mainland	ROST Emotion Analysis Tool
Micu et al. (2017)	Restaurant consumers' reviews on social media	22,369 reviews on Yelp.com of restaurants in two American cities	Natural Language Toolkit (NLTK) and Textblob
Hao et al. (2020)	Hong Kong residents' attitudes toward Mainland Chinese Tourists	72,755 Chinese news articles	Support Vector Machine (SVM)
Albayrak et al. (2021)	Competitiveness of two theme parks in Hong Kong	13,398 reviews on the TripAdvisor website	Valence Aware Dictionary for Sentiment Reasoning (VADER)
Hao et al. (2021)	Chinese mainland visitors' perception of Hong Kong	52,950 travel microblogs from Weibo in Chinese mainland	Convolutional Neural Network (CNN) model
Jiang et al. (2021)	Online destination image of Hong Kong	72,284 review posts on three online tourism platforms in Chinese mainland	Deep learning models in Baidu AI platform
Paolanti et al. (2021)	Destination management in tourism	12,762 Italian and English tweets by tourists to Cilento, Italy	Deep Neural Network (DNN)

outcry against a proposed bill that would have allowed extradition to mainland China. The ramifications of the protests were extensive, permeating various aspects of Hong Kong's social fabric and economic vitality. The tourism and hospitality sectors, which are key components of the city's economy, faced particular challenges. Mainland Chinese tourists, who represent a substantial proportion of the tourist influx into Hong Kong, drastically reduced their visits due to the escalating tensions and uncertainties brought about by the protests. This decline from 4.8 million to 2.8 million mainland visitors, as reported for August 2019 compared to the previous year, marked a significant downturn for the industry (The Economist, 2019).

The cessation of the 2019 protests coincided with the emergence of COVID-19 in early 2020. Hong Kong detected its first case on January 23, 2020, prompting the government to implement stringent cross-border traffic controls with mainland China. Measures included flight reductions, the halting of railway services, and a suspension in issuing new visas to mainland Chinese citizens (The Government of Hong Kong Special Administrative Region Press Releases [GovHK Press Releases], 2022). On 25 March 2020, these restrictions intensified, with the government barring all non-resident air travelers from entering Hong Kong and imposing a mandatory 14-day quarantine on arrivals from the Chinese Mainland, Macau, and Taiwan (GovHK Press Releases, 2022). Consequently, tourism suffered a dramatic decline, with visitor numbers plummeting to just 3.57 and 0.09 million in 2020 and 2021, respectively (Hong Kong Tourism Board [HKTB], 2022). Hotel occupancy rates hit a nadir in February 2020; despite intermittent recoveries, they did not exceed 60% by year's end. Although 2021 saw a marginal improvement in occupancy rates, they remained more than 20% lower than pre-protest levels of 2018 and 2019 (HKTB, 2020).

The "issue-attention cycle" serves as a theoretical framework for delineating the stages of public interest during a crisis (Shih et al., 2008; Villacé-Molinero et al., 2021). Downs' seminal work in 1972 probed the cyclicality of media and public reactions to issues, observing an arc where an issue "suddenly leaps into prominence, remains there for a short time, and then – though still largely unresolved – gradually fades from the center of public attention" (Downs, 1972, p. 38). This five-stage model has proven versatile, applicable to a spectrum of events from terrorist acts (Hall, 2002) to disease outbreaks (Shih et al., 2008), and stands as a pivotal concept in understanding public attention's fluctuations in times of crisis (Hall, 2002). While there is extensive research on various crises, studies examining the intricate intersection of social and health crises are scant. Specifically, the five stages of the issue-attention cycle encapsulate the unfolding of Hong Kong's crises:

(a) Pre-problem stage: Here, public awareness of the issue is minimal, with understanding largely confined to experts or special interest groups. This stage parallels the period before the 2019 protests and the pre-COVID-19 situation in

Hong Kong, with resident and local security concerns understood mostly by governmental and political specialists. In a similar vein, when Wuhan first reported the outbreak in December 2019, awareness outside the city remained relatively muted.

(b) Alarmed discovery and euphoric enthusiasm: The public begins to recognize and express concern for the issue, yet maintains a hopeful outlook on resolving it through decisive action. This phase aligns with the initial spread of news regarding the intense protests and consequent travel advisories. The burgeoning spread of the virus also elevated public alarm, prompting travel restrictions across 217 destinations by May 2020 (UNWTO, 2020).

(c) Realization of the cost of significant progress: Acknowledgement dawns that addressing the problem entails substantial financial, social, and security sacrifices from consumers and industry stakeholders alike. The tourism and hospitality sector in Hong Kong has tallied its losses due to both the protests and the pandemic (Chan et al., 2021) and has started to devise recovery strategies (Zhang et al., 2021).

(d) Gradual decline of intense public interest: Public engagement with the issue starts to wane. The protests, which erupted in June 2019, persisted until February 2020. The advent of COVID-19 shifted public focus to the health crisis from mid to late January 2020. By May 2021, with no new local cases confirmed, the Hong Kong government announced a series of moderated preventative measures (Xinhua, 2021).

(e) Post-problem stage: This final stage emerges when the issue is either resolved or overshadowed by new concerns.

This study examines the progression of both the 2019 protests and the COVID-19 pandemic. The pre-problem phase spanned the period before May 2019, with subsequent stages (b) and (c) unfolding from June 2019 through May 2021. During this period, hotel occupancy rates exhibited an upward trend, ascending from 64% in June 2021 to a peak of 72% in December 2021 since the initial 2020 outbreak (HKTB, 2022). However, the advent of the Omicron variant post-Christmas 2021 precipitated a fifth wave of infections in January 2022 (GovHK Press Releases, 2022). Consequently, the interval from June 2021 to December 2021 corresponds with a phase of diminishing public interest, marked by decreased risk perception and a revival in travel inclinations (Villacé-Molinero et al., 2021). The impact of COVID-19 on the tourism and hospitality sector is anticipated to be enduring (Zhang et al., 2022).

Methodology

Data collection

Prior research has often limited its focus to visitors from specific countries or regions, such as mainland China (Hao et al., 2021), or to customer reviews from singular data sources like TripAdvisor, resulting in a uniformity of source material and language (Mehraliyev et al., 2022). In contrast, the current study broadens the scope to encompass the entire spectrum of inbound visitors, avoiding an exclusive emphasis on select target markets. The data were sourced from both TripAdvisor and Qunar.com. TripAdvisor, a dominant online platform for travel reviews, boasted a contribution of over a billion reviews and opinions by 2021 (TripAdvisor, 2022), offering digital services in accommodations, reservations, and experiential discovery. Qunar.com, second to Ctrip as a distribution channel for hotel and tourism in China in 2019 (Analysys, 2020), has emerged as a burgeoning brand with nearly 600 million users to date. It offers extensive services, including accommodations, ticketing, and itinerary planning. In 2021, Qunar.com achieved industry-leading user engagement, evidenced by its rank at the top in terms of monthly active users and aggregate monthly usage time, indicative of its preeminent user stickiness and loyalty (iResearch, 2021).

While this study does not specifically segment sentiment by tourist type, it recognizes that shifts in the proportions of mainland Chinese and international tourists over time could influence aggregate sentiment dynamics. Changes in demographic composition might impact overall trends, even if the sentiments within specific groups remain stable. For instance, if international tourists, who may have different preferences or cultural expressions of satisfaction, made up a larger portion of the reviews during certain periods, their sentiment tendencies could significantly affect the overall sentiment trends.

In the current study, the examination of emotional shifts in visitors amidst successive crisis events necessitated a temporal categorization of online reviews into distinct periods. These periods were demarcated as follows:

(a) Pre-crisis stage (January 2018 – May 2019), considered the baseline prior to any significant disruptions;
(b) and (c) Crisis stages (June 2019 – May 2021), representing the height of the crises;
(c) and (e) Recovery stage (June 2021 – December 2021), denoting the phase of recuperation.

A targeted search using the term "Hong Kong" yielded a corpus of 531,728 online hotel reviews dated from 1 January 2018 to 31 December 2021. These reviews were extracted via a Python-based web crawler. The information retrieved encompassed user IDs, types of travelers, check-in dates, and the full text of reviews. To ensure the accuracy of the data extraction process, a subset of 500 reviews was randomly selected and meticulously verified against sentence segmentation rules. The subsequent parsing of the reviews employed punctuation marks – commas (","), periods ("."), Chinese full stops ("。"), semicolons (";"), and spaces (" ") – as delimiters for tokenization. This process yielded a comprehensive dataset of 2,941,710 tokens for analysis. Figure 1 presents the established methodological framework.

Data analysis

Figure 2 displays a word cloud map of 79 hotel feature terms, revealing patterns through textual transformation into vectors via Word2Vec for subsequent analysis (Wu et al., 2017). We employed the K-means algorithm to classify nodes by sentiment intensity into clusters, determining an optimal K-value of 7 for maximal clustering efficacy (Riaz et al., 2019). These clusters were categorized as Cleanliness, Environment, Facility, Food and Beverage (F&B), Location, Staff, and Value, as detailed in Table 2. The study incorporated Chinese Word Vectors from Li et al. (2018), which offers a comprehensive array of word vectors across various Chinese domains, aligning with our data's linguistic scope. Additionally, we utilized the authoritative dataset by Prof. Songbo Tan (IEEE DataPort, n.d.) – a benchmark for hotel reviews containing 3,000 entries each of positive and negative feedback, each distinctly annotated.

We trained three models on this dataset to identify the most effective one. The SVM model, traditionally favored for classification tasks, was juxtaposed with BiLSTM and BERT – both deep learning derivatives. SVM (Support Vector Machine) works as a supervised machine learning algorithm used for classification tasks. It works by finding the optimal hyperplane that separates data points into predefined classes while maximizing the margin between them. BiLSTM (Bidirectional Long Short-Term Memory) is a type of recurrent neural network that can capture dependencies in sequential data by processing input in both forward and backward directions. BERT (Bidirectional Encoder Representations from Transformers) is a

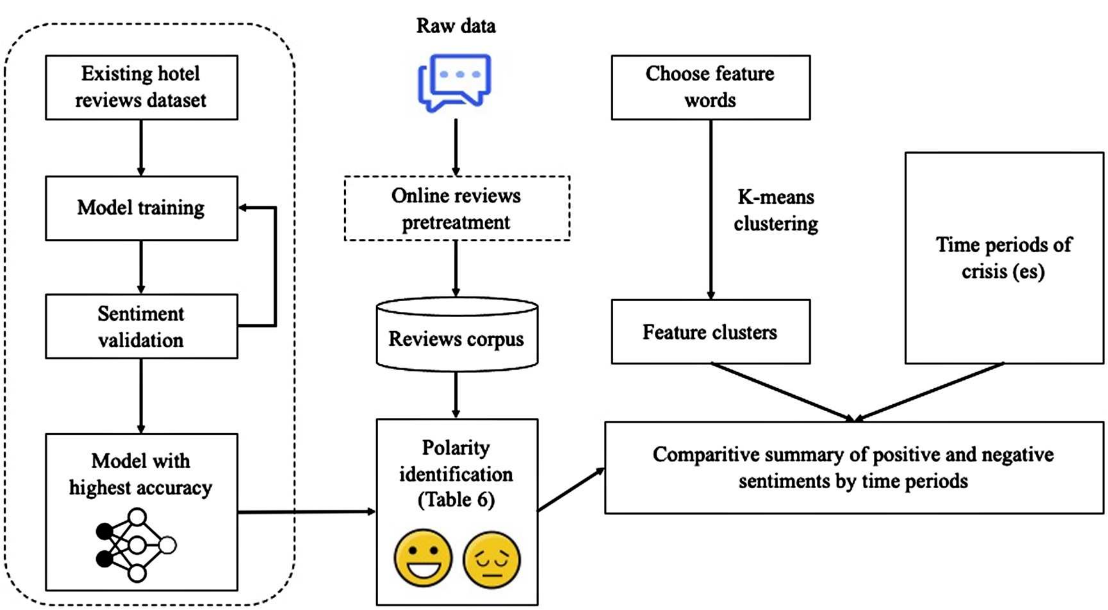

Figure 1. Methodological framework of the study.

Figure 2. Word cloud map of high-frequency words.

Table 2. Hotel feature word classification based on K-means clustering.

Cleanliness	Environment	Facility	F&B	Location	Staff	Value
Clean	Appearance	Bed	Bar	Airport	Attitude	Charge
Dirt	High level	Comfortable	Breakfast	Area	Check-in	Discount
Disinfection	Horizon	Design	Buffet	Close	Employee	Expensive
Hygiene	Night view	Device	Food	Convenient	Friendly	Free
Pandemic prevention	Privacy	Drink	Choice	Downstairs	Front desk	Price
Tidy	Scenery	Fitness center	Coffee	MTR station	Housekeeper	Room rate
	Sea view	Jacuzzi	Dinner	Nearby	Kind	Value for money
	Smell	Maintenance	Lunch	Opposite	Polite	Worth
	Space	Mini bar	Quality	Outside	Professional	
	Upgrade	Refrigerator	Type	Transportation	Reception	
	View	Soundproofing		Shopping	Service	
		Style		Surrounding	Waiter	
		Washroom		Walk		

pre-trained transformer-based model that leverages bidirectional context by jointly considering the words before and after a target word in a sentence.

As a result, BERT demonstrated superior performance, achieving an accuracy of 89%. Additionally, BERT exhibited higher precision, improved recall, and a balanced F1-Score, as detailed in Table 3. This indicates that BERT more effectively minimizes false positives, enhancing the accuracy and reliability of sentiment classifications. With its heightened sensitivity, BERT captures a greater proportion of true sentiments, reducing the risk of overlooking critical information. By achieving a robust balance between precision and recall, BERT offers well-rounded performance, making it particularly adept at handling the complex emotional nuances present in hotel reviews. A robustness check by comparing sentiment outputs from the BiLSTM and BERT models was also performed. The Pearson correlation coefficient between these two methods stood at 0.88, indicating strong alignment in sentiment trends across various hotel attributes and time periods. While BERT demonstrated slightly higher accuracy (89% compared to 87%) and superior capability in capturing nuanced language patterns, the BiLSTM results also supported the main findings, thus validating the robustness of the results.

Table 3. Accuracy comparison of three models.

Models	SVM	BiLSTM	BERT
Accuracy	84%	87%	89%
Precision	82%	85%	90%
Recall	77%	83%	89%
F1-Score	79%	84%	89%

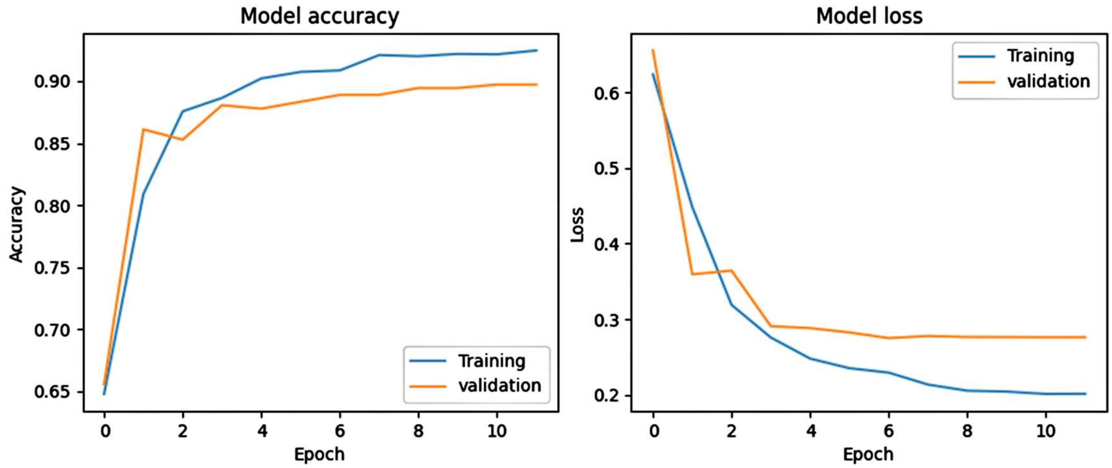

Figure 3. BERT Model accuracy and loss in training and validation.

Figure 3 graphically presents BERT's performance metrics during training and validation phases. To assure the model's robustness, trained on Prof. Tan's dataset, for our dataset, we undertook a manual verification of 100 randomly chosen entries, labeled multiple times. The model exhibited consistent accuracy, maintaining a range of 80-82%.

To ascertain the sentiment polarity of each token, they were scored on a scale from 0 to +1, reflecting their likelihood of embodying positive or negative sentiment. Scores were represented as a pair: (negative sentiment likelihood, positive sentiment likelihood). Tokens with a negative sentiment likelihood exceeding 0.50 were classified as "negative"; conversely, tokens with a positive sentiment likelihood above 0.50 were classified as "positive." Neutral sentiment was excluded due to its inherent ambiguity and the nascent state of its analytical frameworks (Duan et al., 2016). The tokens were then segregated into three temporal categories: pre-crisis, crisis, and recovery periods. Within these temporal bands, the frequency and proportion of positive and negative sentiments for each category were collated to facilitate comparative analysis across the different phases.

Results

Table 4 displays the distribution of traveler types during the study periods. Prior to the crises, the predominant traveler categories were families (32.4%), classified as "other" (15.7%), and friends (15.4%). Amid the crises, the groups "other" (23.6%), families (22.1%), and couples (19.1%) were most frequent. In the recovery phase, the proportions shifted, with couples (39.3%), families (18.7%), and solo travelers (14.6%) leading. Notably, there was a marked increase in the proportion of couples traveling, surging from 12.4% to 39.3%, equating to a 26.9 percentage point rise. Conversely, the representation of family and business travelers demonstrated a declining trend, with family travelers decreasing from 32.4% to 18.7% – a 13.7% drop, and business travelers decreasing from 14.0% to 5.6%, an 8.4% decline. These trends underscore that traveler types, which vary in their needs and preferences, exhibit distinct behaviors

Table 4. Descriptive statistics of the collected online reviews.

		Pre-crises		Within-crises		Recovery	
		No.	%	No.	%	No.	%
Total tokens		1173709	48.5%	983369	40.6%	262499	10.8%
Breakdown of tokens by tourist type	Business	164455	14.0%	132833	13.5%	14613	5.6%
	Couples	145188	12.4%	187520	19.1%	103093	39.3%
	Family	380396	32.4%	217232	22.1%	49020	18.7%
	Friends	180490	15.4%	99460	10.1%	31406	12.0%
	Solo	119237	10.2%	113983	11.6%	38363	14.6%
	Others	183943	15.7%	232341	23.6%	26004	9.9%

and intentions that correspond to their specific characteristics (Wang et al., 2023). While this current study does not explicitly analyze sentiment dynamics segmented by tourist types, it is important to recognize that variations in the composition of domestic and international tourists may have influenced the overall sentiment. For example, if international tourists generally express more positive sentiments, an increase in their proportion during certain periods could skew the aggregate sentiment upwards, even if the sentiments within each individual group remain constant.

The sentiment polarity of each token was systematically assessed, as Table 5 delineates. Accompanying each token, the dataset provided an index, the commenter's check-in time, and a sentiment score, which facilitated the determination of the token's overall polarity. The shifts in the volume and proportion of positive and negative reviews across various dimensions are encapsulated in Tables 6 and 7. There was a notable decrease in the number of tokens across most dimensions from the pre-crisis to within-crisis and recovery stages, with the exception of Facility and Food & Beverage (F&B), which exhibited a marginal increase from the first to the second period.

Although the Facility and Location dimensions witnessed some fluctuation in numbers and percentages, they did not display a markedly consistent trend. In the initial stage, the highest proportion of positive sentiments was found in Environment, shifting to Location in the subsequent stages. The Value dimension recorded the lowest percentage of positive sentiments before and during the crisis, which transitioned to Cleanliness in the recovery phase. The evolving proportion of positive sentiments across the seven dimensions throughout the three stages is graphically represented in Figure 4, using a line chart to illustrate the dynamic shifts.

In the analysis of negative sentiments, the data revealed that Location garnered the highest number of negative tokens during the pre-crisis and crisis periods, shifting to Staff in the recovery phase. Conversely, Food and Beverage (F&B) recorded the fewest negative tokens in the initial two periods, and Value in the final period. Negative sentiment percentages demonstrated an inverse trend to that of positive sentiments. Notably, the fluctuations for Cleanliness and Environment were particularly marked: Cleanliness experienced an increase from 43% pre-crisis to 57% during recovery, and Environment went from 29% to 43%. The variations for Facility and Location were less pronounced. In terms of proportion, Value dominated negative commentary during the pre-crisis and crisis periods, while Cleanliness ascended during the recovery. Initially, Environment had the lowest share of negative comments, but in the subsequent periods, Location assumed this position. Figure 5 illustrates these shifts, depicting the dynamic changes in the percentages of negative

Table 5. Sample results of sentiment polarity identification.

Index	User check-in time	Comment token	Score (negative possibility, positive possibility)	Sentiment polarity
731366	January 2018	" … also, kind to provide us with more bottled water and juice and paper towels."	(0.015, 0.985)	Positive
973397	October 2019	"Good value for money."	(0.350, 0.650)	Positive
1207468	October 2020	"The environment is comfortable and quiet."	(0.004, 0.996)	Positive
1270408	October 2021	"Apart from the long queues to check in, … "	(0.910, 0.090)	Negative
2366198	June 2019	"Transportation is very, very inconvenient."	(0.965, 0.035)	Negative
2854575	February 2020	"The outdoor swimming pool was with beautiful views."	(0.003, 0.997)	Positive

Table 6. Number and percentage of positive sentiments in tokens by three time periods.

	Pre-crises		Within-crises		Recovery	
	Total	Percentage	Total	Percentage	Total	Percentage
Cleanliness	31340	57%	21329	48%	5036	43%
Environment	68130	71%	41571	64%	9319	57%
Facility	26458	60%	29889	58%	11831	60%
F&B	14057	54%	15334	56%	5732	58%
Location	165209	66%	96751	68%	18746	65%
Staff	62500	65%	59031	62%	19720	62%
Value	21844	37%	13904	37%	3712	49%

Table 7. Number and percentage of negative sentiments in tokens by three time periods.

	Pre-crises		Within-crises		Recovery	
	Total	Percentage	Total	Percentage	Total	Percentage
Cleanliness	24069	43%	22872	52%	6633	57%
Environment	28013	29%	23664	36%	7170	43%
Facility	17544	40%	21365	42%	7793	40%
F&B	12065	46%	12208	44%	4091	42%
Location	83688	34%	45422	32%	9906	36%
Staff	34246	35%	36627	38%	12169	38%
Value	37509	63%	24057	63%	3905	51%

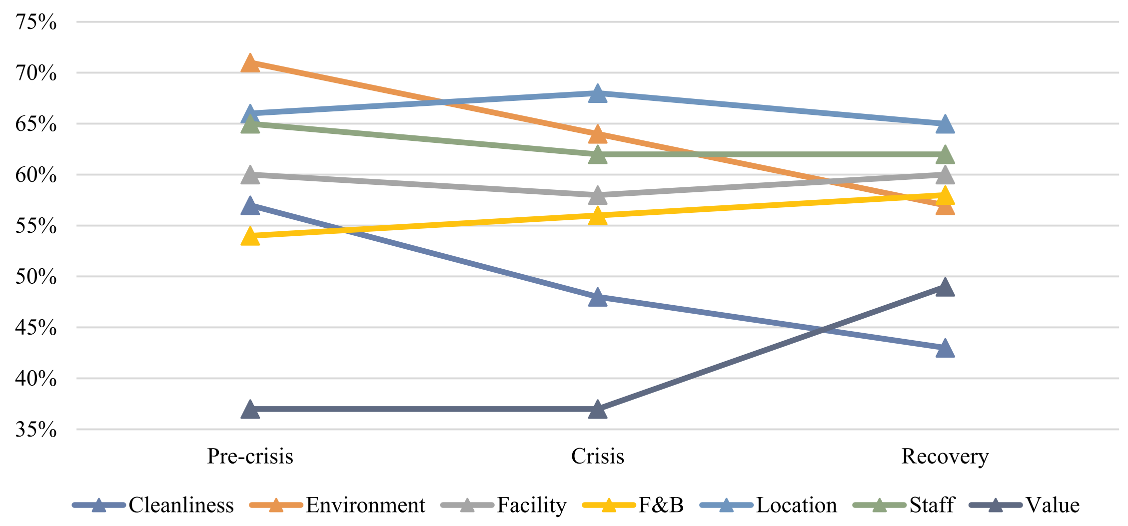

Figure 4. Percentage change trend of positive sentiments in three time periods.

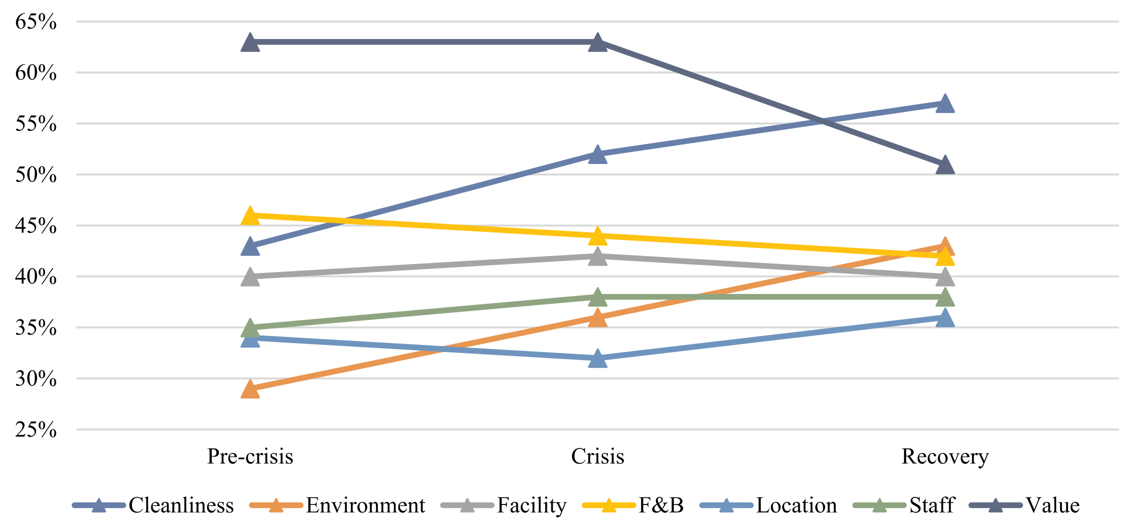

Figure 5. Percentage change trend of negative sentiments in three time periods.

sentiments across the seven dimensions using a line chart.

Discussion and conclusion

Conclusions

Through the application of the advanced deep learning technique BERT, this study aims to illuminate shifts in consumer sentiment polarity towards various hotel attributes throughout the pre-crisis, mid-crisis, and recovery stages, with a focus on the Hong Kong context. The persistent threat of outbreaks in tourism, exemplified by the global COVID-19 pandemic, has compelled a reevaluation of travel practices. However, the challenges and risks in tourism stem not only from natural disasters but also from human-induced risks like political conflicts. Our research explores the impact of multiple complex disasters on the dynamic emotional responses of consumers.

The findings of this study confirm that customers' emotional responses to hospitality dimensions have evolved throughout the successive pandemic crises. It illustrates how the cyclical nature of public attention influences emotional shifts over time. Changes in emotions are a natural progression, aligning with the stages of the issue-attention cycle. This cycle is shaped by the public's awareness of the severity of crises, risk perceptions that influence travel decision-making processes, and attitudes towards destinations, which are predominantly informed by media portrayals. Shih et al. (2008) illustrate how different stages of media attention reflect varied narrative focuses, and these patterns shift with the evolution of a crisis.

During the initial stage of the pandemic, many individuals are often unaware of the risks, typically underestimating their personal susceptibility compared to others (Wise et al., 2020). Our results also indicate that tourists exhibit relatively optimistic sentiments about the assessed dimensions at the crisis's onset, showing more positive emotions. According to cognitive appraisal theory, an individual's response to events is mediated by their cognitive, emotional, and behavioral reactions (Song & Lu, 2024). The combined impact of the COVID-19 pandemic and political protests on hotels has led to diverse emotional evaluations from customers, subsequently influencing their travel decision-making behavior. This aligns with findings by Matiza (2022), which demonstrate the significant role of perceived health risks in shaping tourist behavior post-COVID-19, particularly in the initial stages of the decision-making process, where perceived risks associated with COVID-19 are likely to affect tourists' decisions before traveling to a specific destination.

In the "alarmed discovery" and "realization" stages of the cycle, the research indicates noticeable shifts in guest sentiment, particularly an increase in negative comments regarding cleanliness. This aspect became significantly more relevant during the COVID-19 pandemic than during the 2019 protests, aligning with findings by Mehta et al. (2023). The heightened focus on hygienic standards in hotels, driven by perceived infection risks, encompasses guest expectations for stringent sanitation, social distancing, and thorough staff training (Chan et al., 2021; Gursoy & Chi, 2020). However, guest reviews suggest that these expectations are not being fully met, leading to dissatisfaction with the health and safety measures implemented. This trend indicates that various media channels have gradually heightened public awareness of the crisis's severity (Shih et al., 2008). Additionally, psychological research underscores the significant role of emotional contagion in crisis communication (Kramer et al., 2014; Zhai et al., 2019), with digital communication environments intensifying this phenomenon (Kolliakou et al., 2020).

Regarding the Environment, which encompasses room aesthetics and amenities, there is a heightened demand for comfort and reassurance during crises, reflecting a gap between expectations and experiences (Mehta et al., 2023). Furthermore, an uptick in negative feedback about Staff indicates a decline in service satisfaction. Consistent with previous studies (Li et al., 2013), quality guest service remains paramount. The present study also suggests that guest disillusionment may be heightened during the pandemic (Yang & Wong, 2021), underscoring the crucial role of empathetic and personalized service in these challenging times (Kuo, 2007).

Conversely, the F&B and Value dimensions saw an increase in positive sentiments. This could be attributed to Hong Kong hotels' innovative efforts in F&B to enhance guest experience and provide value through special promotions and discounts (Hao et al., 2021). The success of such strategies is evident in guests' positive responses, particularly towards value-added services.

Lastly, the study's findings on Location indicate a consistent valuation by guests of the hotel's accessibility and proximity to points of interest. Even amidst crises, the importance of location remains largely unaffected, echoing Li et al.'s (2013) conclusions about its significance across different hotel tiers.

Theoretical implications

Most existing research has analyzed the impact of crises on tourism and hospitality from broader macro or meso-level perspectives (Hu et al., 2021). However, this study offers a granular, micro-level view by examining the evolution of travelers' emotions, thus addressing the impact of crises through a novel lens. By segmenting the crisis into pre-crisis, within-crisis, and recovery phases, the study provides nuanced insights into the shifting emotional landscapes of tourists in relation to hospitality attributes. Prior literature acknowledges the variances in consumer sentiments toward hotel services during crises (Breitsohl & Garrod, 2016). Nonetheless, there remains a gap in understanding how these emotions evolve over time. This study not only confirms the influence of major crisis events on travelers' emotions but also expands current knowledge by mapping the dynamic progression of these emotional responses across a multi-year period, rather than a static snapshot.

Additionally, this research contributes to the tourism and hospitality literature by applying the issue-attention cycle framework to examine the progression of consumer perceptions and sentiments through different stages of crisis development. Previous studies predominantly analyzed public attitudes from a cognitive standpoint. This study, however, presents evidence that consumer emotional engagement also follows a systematic, cyclical pattern, thereby extending the discussion to include emotional attentiveness.

Our study reveals that in scenarios involving multiple overlapping crises, the traditional linear progression of the issue-attention cycle is disrupted. For instance, during our analysis, the emergence of a secondary crisis, such as a natural disaster coinciding with a pandemic, reignited public attention, resulting in a "double peak" in sentiment dynamics. This overlap extended the "alarmed discovery" phase and amplified emotional responses, particularly negative ones. These findings indicate that the conventional issue-attention cycle model requires modification to accommodate such disruptions effectively. The insights gained from this study contribute to refining the issue-attention cycle framework by underscoring its adaptability to complex, real-world crises.

This paper also innovates in crisis management research by juxtaposing human-induced and health-related crises and assessing their combined effects on consumer emotions. The integration of diverse crisis contexts offers a novel approach that could influence future crisis management research trajectories.

Methodologically, this study stands out by utilizing big data to analyze consumer sentiments towards hotel features, fulfilling the promise of truly large-scale data analysis – as argued by Mehraliyev et al. (2022) regarding previous research's limited scale. By harnessing nearly three million tokens for analysis, this study substantiates the application of big data in sentiment analysis within the hospitality context.

Furthermore, by leveraging BERT – a state-of-the-art pre-trained language model in natural language processing (NLP) – this research surpasses traditional lexicon-based and machine learning methods in sentiment analysis (Mostafa, 2020). The deep learning approach, with its neural network capabilities, significantly enhances the precision of the analytical outcomes. The established framework (Figure 1) presents a replicable and broadly applicable methodology for future studies on crisis management direction in the tourism sector.

Managerial implications

This study provides significant insights into the shifts in customer sentiment towards hotel attributes across the stages preceding, during, and post-crisis. Drawing from boundary spanning theory, Mehta et al. (2023) suggested that crises pose challenges and opportunities for hotel management, necessitating alignment of internal practices with external environmental trends. The primary managerial implication of this research is the ability for hotel managers to discern operational strengths and weaknesses through customer emotional feedback, thereby informing strategic improvements to bolster post-crisis satisfaction (Olsen, 1996).

First, in light of the pandemic's impact on satisfaction regarding hygiene, hotels must implement and visibly communicate enhanced sanitation measures to reassure and satisfy guests. Regarding negative feedback about environmental aspects, managers should investigate whether staff inattentiveness or miscommunication during booking contributes to the dissatisfaction – bridging the gap between guest expectations and reality (Parasuraman et al., 1988).

During the crisis recovery phase, guest commendations for value in terms of cost increased. However, with the gradual improvement of the situation, an upward adjustment in occupancy and rates is expected. It is crucial for hoteliers to employ pricing strategies that delicately balance rate hikes with customer contentment. Furthermore, the prominence of location in guest feedback underscores the necessity for managers to promote hotel accessibility and ensure service staff clarity in directions to destinations.

The enduring significance of human-centric service in conveying hospitality, ensuring quality, and providing psychological comfort remains paramount, even in post-crisis recovery (Rivera, 2020). Hotels must invigorate staff empathy and commitment to exceed guest expectations (Padma & Ahn, 2020). Fostering a culture of value co-creation between guests and hotels is essential to support the industry's rebound (González-Mansilla et al., 2019).

As travel resumes post-COVID-19, the industry must anticipate, rather than react to, potential crises (Wiebers & Feigin, 2020). A proactive understanding of consumer emotional shifts across different stages of a crisis will enable the tourism sector to tailor strategies that preemptively address consumer needs and effectively manage future crises.

Limitations and future research

This study acknowledges certain limitations. Firstly, although our approach circumvents the challenge identified by Duan et al. (2016) of distinguishing between sentiments of varying directions in a single sentence, it still struggles with sentences that express conflicting emotions (e.g. "The room was clean but the facilities were very outdated"). Future studies should investigate more sophisticated methods for assigning appropriate emotional polarities to such mixed sentiment sentences within the relevant dimensions. The decision to exclude neutral sentiments and mixed-emotion sentences, while methodologically driven and scoped within the limits of our study, may diminish the granularity of our analysis. Future research should consider methodologies that can more effectively capture these complexities. For example, the integration of sentiment analysis models designed to handle mixed emotions, such as multi-label classification frameworks, could enhance the detection of nuanced sentiments. Furthermore, we recommend that future studies employ methodologies that can separate the effects of changes in demographic composition from those of sentiment dynamics. This could involve using statistical models or sentiment segmentation approaches to precisely assess the impact of each factor on overall sentiment trends.

Secondly, we relied on data from the widely-used platform TripAdvisor, which has been a foundation for numerous scholarly investigations. However, the veracity of the reviews on this platform is not entirely assured (Kirilenko et al., 2018). Researchers in the future might consider extracting data from a broader spectrum of review platforms for a more robust data set or validating TripAdvisor findings against those from alternative sources to enhance the reliability of the insights. Additionally, reviews from specific platforms may exhibit biases related to distinct user demographics, platform-specific cultures, and review behaviors. To enhance the robustness and representativeness of the findings, future research should incorporate data from a broader range of platforms, such as Ctrip, Yelp, and social media platforms like Weibo or Twitter.

Lastly, the civil unrest in 2019 and the COVID-19 pandemic present a distinctive case study to explore tourist emotional reactions to different crisis types in Hong Kong. Although Hong Kong presents a unique case with overlapping social and health crises, the scope of this study limits its applicability to broader global contexts. Future research should consider adapting the methodological framework to various regions or types of crises to enhance its generalizability. In addition, at the time of finalizing this paper, COVID-19-related travel restrictions have largely been lifted globally. It would be beneficial for subsequent research to undertake a longitudinal analysis in a post-pandemic context to better understand the impact of complex crises on consumer sentiment across a complete crisis cycle.

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