Journal of Retailing and Consumer Services 70 (2023) 103157

Contents lists available at ScienceDirect

Journal of Retailing and Consumer Services

journal homepage: www.elsevier.com/locate/jretconser

# Exploring customer concerns on service quality under the COVID-19 crisis: A social media analytics study from the retail industry

Xinwei Li [a], Mao Xu [a], Wenjuan Zeng [b,*], Ying Kei Tse [a], Hing Kai Chan [c,d]

[a] Cardiff Business School, Cardiff University, Aberconway Building, Colum Drive Cardiff, CF10 3EU, United Kingdom
[b] Essex Business School, University of Essex, The Gateway Building, Southend Campus, Elmer Approach, Southend-on-Sea, SS1 1LW, United Kingdom
[c] Nottingham University Business School China, University of Nottingham Ningbo China, 199 Taikang East Road, Ningbo, 315100, China
[d] Nottingham Ningbo China Beacons of Excellence Research and Innovation Institute, Ningbo, China

A R T I C L E I N F O

*Keywords:*
Text-mining
Crisis management
Supermarket retailers
Social media crisis communication
Service quality

A B S T R A C T

The COVID-19 pandemic has triggered a set of government policies and supermarket regulations, which affects customers' grocery shopping behaviours. However, the specific impact of COVID-19 on retailers at the customer end has not yet been addressed. Using text-mining techniques (i.e., sentiment analysis, topic modelling) and time series analysis, we analyse 161,921 tweets from leading UK supermarkets during the first COVID-19 lockdown. The results show the causes of sentiment change in each time series and how customer perception changes according to supermarkets' response actions. Drawing on the social media crisis communication framework and Situational Crisis Communication theory, this study investigates whether responding to a crisis helps retail managers better understand their customers. The results uncover that customers experiencing certain social media interactions may evaluate attributes differently, resulting in varying levels of customer information collection, and grocery companies could benefit from engaging in social media crisis communication with customers. As new variants of COVID-19 keep appearing, emerging managerial problems put businesses at risk for the next crisis. Based on the results of text-mining analysis of consumer perceptions, this study identifies emerging topics in the UK grocery sector in the context of COVID-19 crisis communication and develop the sub-dimensions of service quality assessment into four categories: physical aspects, reliability, personal interaction, and policies. This study reveals how supermarkets could use social media data to better analyse customer behaviour during a pandemic and sustain competitiveness by upgrading their crisis strategies and service provision. It also sheds light on how future researchers can leverage the power of social media data with multiple text-mining methodologies.

## 1. Introduction

Although consumer behaviour has been described as highly habitual, it becomes much less predictable in ad hoc natural disasters (Sheth, 2020). The COVID-19 pandemic has significantly disrupted both supermarket retailers and consumers worldwide, forcing restrictions on trade to minimise the spread of infection and inducing changes in consumer behaviour (Grimmer, 2022; Guthrie et al., 2021). For example, De Backer et al., 2021 observational study of 38 countries worldwide suggests that self-restraint gives customers more time to shop online and increases their willingness to plan, select and prepare for grocery shopping. Jiao et al. (2022) also find that consumers' confidence in their ability to control their consumption behaviour is significantly affected by the loss of income during COVID-19. The changes in customer consumption behaviours brought about by the pandemic could last for a long time. The failure of supermarkets to adapt quickly enough to these changes and to understand and meet customer needs has resulted in customer inconveniences, such as food scarcity, empty supermarket shelves, and the potential loss of customers due to a poor customer experience.

In light of the catastrophic implications of COVID-19, understanding shifting consumer needs has been a research focus for the retail industry, contributing to improving supermarkets' resilience to adapt to policy and build recovery measures (Kursan Milaković, 2021; McCartney et al.,

* Corresponding author.
*E-mail addresses:* lix154@cardiff.ac.uk (X. Li), xum28@cardiff.ac.uk (M. Xu), wz22123@essex.ac.uk (W. Zeng), tsem1@cardiff.ac.uk (Y.K. Tse), hingkai.chan@nottingham.edu.cn (H.K. Chan).

https://doi.org/10.1016/j.jretconser.2022.103157
Received 7 June 2022; Received in revised form 21 September 2022; Accepted 2 October 2022
Available online 6 October 2022

2021). If retailers want to remain competitive in the market, it is generally essential to provide excellent service to meet customer needs. Especially during a natural crisis, good service quality can increase customer satisfaction and loyalty, ultimately boosting profits (Zhang et al., 2019). Supermarkets' failure to provide the goods and services expected by customers would trigger numerous complaints. It is vital for companies to be aware of customer attitudes and sentiments to increase customer satisfaction. Particularly during the lockdown period, people's life patterns have been considerably changed in response to preventive measures released by the government and organisations to promote health behaviour changes (Abbas et al., 2021). Social media platforms have been increasingly used, and social media has become one of the major channels for people to connect with the outside world, expressing and sharing opinions. This massive quantity of data offers valuable feedback for companies regarding sentiment trends and the reasons behind them (Chang et al., 2022). Companies can better understand their customers and gain marketplace intelligence, new business deals, and partnerships by understanding these messages.

Despite the great value of social media, some companies struggle to use this new source to understand their customers and lack the practical tools to analyse a vast amount of unstructured data (Ramanathan et al., 2017; M. Liu et al., 2021). The major challenges of social media analytics are to utilise data to explore the relevant topics, trends, and events in dynamic communication in social media, as well as to analyse the massive data promptly to respond quickly to changes in customer opinion (Stieglitz et al., 2018a,b). Such changes might be due to various external factors (Ibrahim and Wang, 2019). For instance, in response to the COVID-19 pandemic outbreak, the UK government has implemented several measures to lower the infection rate for individuals, and supermarkets should adopt relevant regulations to comply with these policies. The policy and regulatory changes would impact consumer sentiment and behaviour. Therefore, to accurately analyse the customer perspectives expressed on social media, it is necessary to consider the element of time. Moreover, by conducting a data-driven exploratory analysis with social media data, this study examines the changes in consumer sentiment and concerns over this period and uncovers the reasons for the differences in volume and sentiment of supermarket-related tweets (Kim et al., 2013; Ibrahim and Wang, 2019). Finally, the knowledge will be built to help retail managers make more appropriate future decisions when confronted with emergent circumstances. Hence, the research questions of this study are as follows:

a. What are the primary customer concerns that lead to the changes in volume and sentiment trends of supermarket-related tweets?
b. How do changes in customer opinions correlate with supermarkets' social media response?
c. What are the important insights that managers in the retail industry can obtain from COVID-19 experience to improve their service quality when a crisis happens in the future?

To answer these questions, we employ text-mining techniques to process and analyse 161,921 tweet data. Based on the data from five leading UK supermarkets (Tesco, Sainsbury's, Asda, Morrisons, and Aldi), this study examines the customer comments and posts on the retailers' official Twitter accounts from the start of pre-lockdown until the end of the first lockdown (from March 23, 2020 to April 14, 2020). During the first lockdown period, customers and supermarkets were not adequately prepared for the changes; for example, customers panic purchasing and stockpiling essentials (Prentice et al., 2020); Stores were inconsistent with COVID-19 safety measures. We detect shifts in tweets' volume and sentiment using time series and sentiment analysis. After dividing the sample period into finer time ranges, we apply topic modelling to identify the emerging topics at particular time points. Therefore, the data from that period indicates how customers think and behave under uncertainty.

This study offers several theoretical and managerial contributions to social media crisis management and service quality improvement. First, we demonstrate the role of social media analysis techniques in understanding customers' opinions during and after a pandemic through the situational crisis communication theory (SCCT) lens, which helps us to mine consumers' opinions effectively and develops experience and knowledge from emerging managerial problems. Moreover, our results offer a deeper understanding of customer feedback, business crisis communication, and resource allocation, which benefit different customer groups (e.g., vital workers, vulnerable groups, etc.) in society. Second, by comparing the results of topic modelling in retailers with or without social media response to the UK government's pandemic policy, the study reveals that proactively communicating on social media to show their efforts in addressing the emerging problems, which benefits supermarkets in a number of aspects, such as earlier alert of emerging demand, dynamic observation of demand shifting as well as a more significant amount of available customer data. Third, many studies that analyse social media data focus on a single technique (Ibrahim and Wang, 2019). This study adds the time perspective and uses multiple methods of social media analysis to examine how and why customers' opinions change. This highly effective approach provides a more accurate analysis of social media data (SMD). Last but not least, we further develop the dimensions and sub-dimensions of service quality assessment for text-mining analysis of consumer perceptions and highlight the specific areas that retail managers should focus on during a crisis. The development of service quality assessment enables retail managers to comprehensively consider consumers' real needs and effectively realise the practicality of goods.

The remainder of the paper is organised as follows: section 2 comprises a review of recent crisis management in social media research, crisis communication framework, relevant theory, and service quality. Section 3 outlines the research methodology, while section 4 provides analysis and results. In section 5, we discuss the theoretical and practical implications and limitations of this study.

## 2. Literature review

### 2.1. Crisis management in social media and SCCT

Crisis management is defined as "a systematic attempt by organizational members with external stakeholders to avert crises or to effectively manage those that do occur" (Pearson and Clair, 1998, p.61). It engages with strategy, organisational theory, organisational behaviour, public relations and corporate communication (Bundy et al., 2017). Therefore, the government and industry revenue streams suffer significantly with the emergence of the COVID-19 outbreak (M.T. Liu et al., 2021). Earlier scholars develop a three-phase model to characterise the crisis life cycle: pre-crisis, crisis response, and post-crisis (Coombs, 2007). Information at all stages of a disaster is critical for crisis management. It provides a real-time, precise communication channel for people to cope with uncertainty and generates valuable data for socio-behavioural online participation analysis (Palen and Anderson, 2016). Social media offers a rich data source for professionals and practitioners, which can contribute to the crisis management framework by allowing for monitoring in the early stages of a crisis (Singh et al., 2019), facilitating the flow of valid information (Roshan et al., 2016), offering clues as to why crises occur, and how best to manage them and reduce harm in the future (Jin et al., 2014). Table 1 provides a brief overview of significant literature featuring social media analytics of crises in various settings and focus areas. It can be seen from the table that text-mining techniques have been widely used in analysing multiple crises. To respond to the call of Guthrie et al. (2021) for more research on how online consumer purchasing behaviour evolves during these periods of restriction, we seek to investigate the evolution of top consumers' concerns in the retail business under the COVID-19 crisis. Although retailers have faced challenges related to the pandemic, such as panic-induced stockpiling by customers, there has been little research

**Table 1**
Summary of representative social media analytics studies of crisis communication.

| Authors | Type of crisis | Research method | Data sources | Underlying theoretical viewpoints | Findings |
|---|---|---|---|---|---|
| Zhao et al. (2018) | The Chipotle *E. coli* crisis | Topic modelling | Twitter | Multiplicity and dynamics of publics' crisis narratives | The analysis identified ten narratives subsumed based on publics' social constructions of their perceived risks and crisis experience. |
| Son et al. (2019) | 2013 Colorado floods | Natural Language Processing, Social Network Analysis, Topic modelling | Twitter | Disaster communication and Media Synchronicity Theory | The influence of Twitter's media capabilities on rapid tweet propagation during disasters may differ based on the communication processes. |
| Abd-Alrazaq et al. (2020) | The COVID-19 | Topic modelling, Sentiment analysis | Twitter | Infoveillance Study | Authors identify 12 topics, which were grouped into four main themes: origin of the virus; its sources; its impact on people, countries, and the economy; and ways of mitigating the risk of infection. |
| Wang et al. (2021) | The COVID-19 | Text-mining techniques, Dynamic network analysis | Twitter | Crisis risk communication | The research identifies inconsistencies and incongruencies on four critical topics and examines spatial disparities, timeliness, and sufficiency across actors and message types in communicating COVID-19. |
| Mirbabaie and Marx (2020) | The Manchester bombing in 2017 | Social network analysis and Content analysis | Twitter | Social media crisis communication | Exerting successive sense-giving becomes more challenging if the collective sense-making has progressed along with the sequence of events. |
| Stieglitz et al. (2019) | The Volkswagen's (VW) emission scandal in 2019 | Social network analysis, Sentiment analysis | Twitter | SCCT and legitimacy | VW's very few tweets were not able to reduce the emotionality and sentiment of the ongoing Twitter discussion; even during quiet phases, the communication remained rather negative. |
| Tse et al. (2018) | The horsemeat scandal – product recall | Text-mining, Machine learning | Facebook | A novel comprehensive data analysis framework alongside a text-mining framework | UK customers have mixed sentiment between both messages toward Tesco regarding the horsemeat scandal. |
| Stieglitz et al. (2018) | The Sydney Lindt Cafe Siege; the Germanwings plane crash; and the Brussels Terror Attacks | Statistical analysis, Sentiment analyses, Social network analysis | Twitter | Social media communication | Authors identify differences in the communication structures of different extreme events. |

into how retailers use SMD for COVID-19 crisis management and communication.

SCCT is the most frequently cited theory in crisis communication studies, and it helps researchers to understand the use of social media for organisational crisis response (Roshan et al., 2016). SCCT is usually used to select the appropriate strategies to minimise the crisis reputational threats. According to Coombs (2007), the strategies are divided into primary crisis response strategies (i.e., denial, diminish, and rebuilding) and secondary crisis response strategies (bolstering). Denial strategies indicate that the organisation is not responsible for the occurrence of the crisis. Diminishing strategies seek to reduce the attribution of control over the crisis or the negative impact of the crisis. Rebuilding strategies aim to improve the organisation's reputation by compensating and apologising. Bolstering strategies attempt to establish a favourable connection between the organisation and stakeholders (Roshan et al., 2016). In general, the SCCT suggests that organisations need to provide and adjust appropriate information before selecting a crisis response strategy. This process is accomplished by determining the crisis type and crisis type cluster and then checking whether the organisation has had a negative reputation or similar crisis history in the past (Coombs, 2007). Thus, drawing from crisis response strategies developed by the SCCT, we first identify the grocery companies that engage in social media communication with customers. Then we annotate what social media crisis response strategies are used by each grocery company.

### 2.2. Service quality

Numerous researchers and practitioners have developed service quality concepts across different fields, such as banking (Pakurár et al., 2019), retailing (Yang et al., 2021), and tourism (Yu et al., 2021). Parasuraman et al. (1985, p.42) define service quality as results perceived from "a comparison of consumer expectations with actual service performance." Service quality can be understood as customers' evaluation of corporate service and how companies meet customers' expectations and provide satisfaction (Pakurár et al., 2019). Service quality has been acknowledged as a determinant factor for customer satisfaction and loyalty (Shi et al., 2014), leading to company profitability (Prentice et al., 2019). A growing body of retailing literature also investigates the implication of service quality on legitimacy on behavioural intention (Yang et al., 2021).

To measure service quality, different scholars and researchers have brought up a variety of perspectives in the earlier discussion of the literature. Scholars have developed various models for assessing service quality; for instance, Parasuraman et al. (1988) introduce SERVQUAL to measure service quality across five dimensions: reliability, responsiveness, assurance, empathy, and tangible. Despite its widespread use, academics have criticised the model for failing to select the service quality aspects relevant to specific industries effectively. As a result, new context-specific models have been created to capture better the service quality dimensions of other industries (Nunkoo et al., 2020). This study follows the model proposed by Dabholkar et al. (1996) since it has been applied in many settings to understand consumer satisfaction and perceptions in different retail areas (Brandtner et al., 2021). The model incorporates five categorical dimensions in service quality, including physical aspects, reliability, personal interaction, problem-solving, and policy measure. Furthermore, Brandtner et al. (2021) improve this model by adding more sub-dimensions to the initial categories. To the best of our knowledge, extant research has not fully explored the service quality perceived by customers. Due to the adverse impacts that COVID-19 has caused globally, there have been significant changes in retailer and consumer behaviour. There still is a lack of studies that address the unique service quality assessment that the COVID-19 crisis has brought to the retail industry.

## 3. Methodology

### 3.1. Overview of the research process

Fig. 1 provides an overview of the research process. We start with the data collection, which is followed by pre-processing the data and converting unstructured textual data to a structured format. Next, we conduct sentiment analysis and time-series analysis to identify the changes in customers' sentiments. Lastly, we extract evolving topics from the text by applying topic modelling and time-series analysis.

### 3.2. Data collection and pre-processing

The timeline under observation is linked to the UK government announcements before and during the first lockdown (see Fig. 2). Since the COVID-19 outbreak is an unpredictable challenge to humanity, the UK government's response to the crisis has drawn national and world attention. Meanwhile, the UK government's decision to gradually advance the control of COVID-19 and determine the large-scale lockdown with complete restrictions on mobility is also an unprecedented response to the crisis, called the timed intervention policy (TIP). TIP is also considered a demand-management policy (Bin et al., 2020), including phased social distancing and lockdown measures based on the virus conditions within the community. The primary purpose of such policy is to minimise the negative impacts of the pandemic so that there are adequate facilities and resources to treat infected patients in the healthcare system (Prentice et al., 2020). In this process, the adaptation of the public and organisations greatly depended on the guidance and regulations of the UK government. The timing of implementing the TIP is essential and can lead to various consequences (Bin et al., 2020). Therefore, we focus on retail supermarkets, an industry inseparable from the public; it is interesting to capture consumers' perceptions of supermarket service quality and changes during the first lockdown time window. Specifically, the UK government Coronavirus Action Plan (contain, delay, research and mitigate) was launched on March 3, 2020, while further restrictive social distancing measures were announced before the lockdown. After announcing a 3-week lockdown (on March 23, 2020), the estimated first revaluation date was April 14, 2020. Hence, to comprehensively analyse customers' opinions about grocery shopping before and during the first lockdown, we capture the data from March 23, 2020 to April 14, 2020.

Twitter is a powerful platform providing real-time updates. Compared with other platforms like Facebook for relationships and LinkedIn for building professional identity, Twitter focuses more on debate and conversations. Hence, we capture tweets mentioning any of the five leading UK grocery companies. Tesco, Sainsbury's, Morrison, Asda, and Aldi account for 74% of UK grocery sales (Kantar-World-Panel, 2021). They are considered influential on social media as they are active on Twitter and have large numbers of followers. We employ ExportComments tool to extract 161,921 tweets using the search

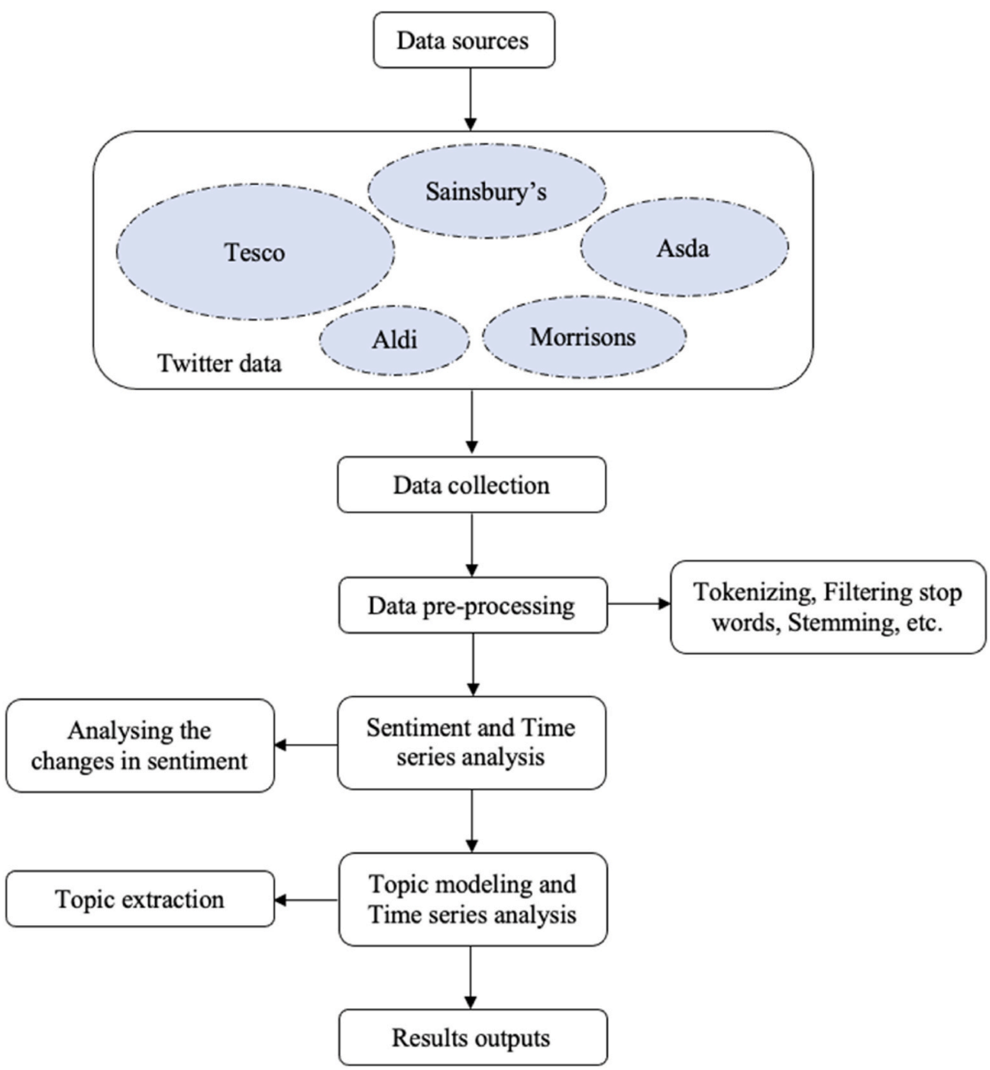



**Fig. 1.** The research processes.

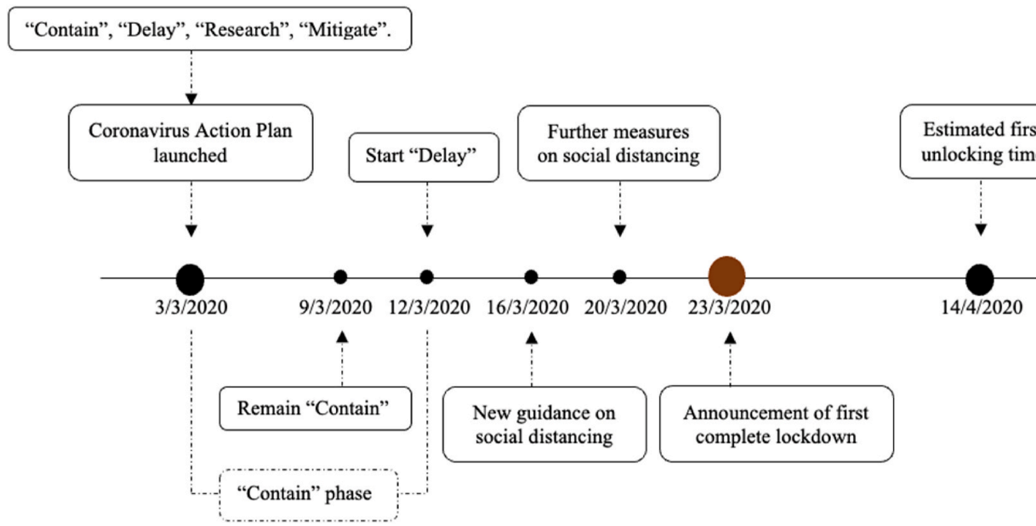



**Fig. 2.** Timeline of UK government announcements around first official lockdown.
Source: GOV.UK (https://www.gov.uk/coronavirus).

format: (#brand name) lang:en until: [end date] since: [start date]. Then, we perform data pre-processing, transforming textual data into a more digestible format that machine learning algorithms can understand. First, we remove URL links within the tweets, next, all the data are nominated to text. This is followed by tokenisation to break down the text into a sequence of discretising words. Then, we transform all the text to lowercase. Afterward, we filter out stop words (e.g., is, and, if) and reduce words to their stem using the "Porter stemmer" (e.g., delivery to deliveri, shopping to shop). Finally, we exclude noise and data redundancy to obtain a clean dataset.

### 3.3. Sentiment analysis

Natural language processing in the study of machine learning enables researchers to analyse, manipulate and potentially generate human language. This study uses text-mining techniques (e.g., sentiment analysis, topic modelling) to automatically identify and classify patterns from a large number of data sets and generate insights from an unstructured text corpus. Sentiment analysis is commonly used in investigating linguistic features in terms of sentiment. This technique can help researchers detect sentiment polarity from textual data, thereby helping researchers to elucidate the relationship between the formation of public opinions and events, such as predicting the daily changes in the closing values of the Dow Jones Industrial Average (Bollen et al., 2011), analysing the brand image and brand positioning (Alzate et al., 2022), helping companies identify customer sentiment regarding their retail services (Wu and Chang, 2020). However, research that merely describes customer sentiment cannot offer sufficient explanation for the drivers behind those changes. When researching the impact of social events on sentiment, a dynamic observation alongside a timeline of the event's development can offer a more profound understanding (Ibrahim and Wang, 2019). Thus, we combine time-series analysis with sentiment analysis to show how customers' sentiments alter regarding grocery shopping during the UK's lockdown period.

This study applies SentiStrength, a lexicon-based sentiment strength detection software that uses non-lexical linguistic information and rules. Previous tests show that SentiStrength is robust in the sentiment analysis of social web contexts (Thelwall et al., 2012). It scores text with a 5-point scale for both positive and negative sentiment: [no positive emotion or energy] 1, 2, 3, 4, 5 [very strong positive emotion]; [no negative emotion] −1, 2, −3, −4, −5 [very strong negative emotion] (Thelwall et al., 2012). Each text is assigned two scores (positive and negative), and the emotional valence of tweets is calculated by the overall polarity (polarity = positive + negative). Hence, we obtain the final polarity with an 11-point scale ranging from −5 (negative) to 5 (positive). Texts with a score of "0" are labelled as neutral.

### 3.4. Time-series analysis

Continuous data collection across time allows time-series analysis, which is significant in exploring a set of longitudinal data. This study employs the time-series concept to divide the research period into shorter time intervals using the captured daily tweets. Time-series analysis is usually combined with sentiment analysis (Thelwall et al., 2012) to investigate sentiment changes. As above, sentiment analysis of tweets can provide different sentiment strengths. This study refers to Lansdall-Welfare et al. (2012) and Kulkarni et al. (2015) to perform a series of analyses, including the frequency method and the difference in mean. We aim to understand customer sentiment strengths and identify their changes in the time series. Furthermore, we use the significant sentiment change points to support dividing the data at critical time points, thus laying the foundation to extract emerging topics in the topic modelling analysis.

### 3.5. Topic modelling

Before extracting topics, we classify the grocery companies into two groups based on companies' COVID-19-related announcements and posts availability during the first lockdown on social media. Next, we follow the crisis response strategies proposed by Coombs (2007) and annotate groceries with the crisis communication strategies based on their posts. Then we obtain two groups: those who provide a social media response (i.e., Tesco, Sainsbury's, Asda) and who do not offer a social media response (i.e., Morrisons and Aldi) to the UK government's pandemic policy. This is followed by dividing the comments into two groups (No response: 5460 comments, response: 157028 comments) and applying topic modelling to extract topics. In spite of fewer customer comments extracted for the no response company, those comments are valuable for this study as we use specific search terms (i.e., #company name) and limit the time window to the first lockdown period. Therefore, we can compare topic modelling results in retailers with or without social media response to the UK government's pandemic policy.

For grocery companies that provide a social media response, the annotation result shows that grocery companies use the same combination of crisis response strategies during the first lockdown, namely diminish, rebuild, and bolstering crisis response strategies. We define diminish as companies claiming they still have control of the product shortage situation. Rebuild refers to grocery compensating consumers by providing priority slots, particular shopping hours, and bolstering stands for grocery companies to broadcast what effort they have made to ease the crisis.

This study adopts the Latent Dirichlet Allocation (LDA) topic modelling to extract meaningful topics from the tweet corpora to evaluate customers' concerns and attitudes regarding UK grocery shopping during the pandemic crisis. LDA topic modelling is a flexible and efficient unsupervised machine learning approach to extracting topics from textual documents. It tackles the limitations of opaque vector representations of topics and documents and incorporates the generative process of documents with Dirichlet distribution (Blei and Lafferty, 2009). This technique has been widely applied to social media data to mine customers' opinions by automatically identifying word patterns from document collections (e.g., Kim, 2022; Verkijika and Neneh, 2021; Nilashi et al., 2022). In this study, it would be impossible to identify critical change points in customers' mindsets if we regarded the collected data as one dataset. To address this concern, we divide the timeline into five phases after identifying several essential time points using sentiment and time-series analysis. Then, we adopt topic modelling to detect underlying thematic information. Therefore, this research can provide a dynamic observation of customers' sentiment changes over the lockdown period and their reasons.

Next, for the selection of topic number (k), topic coherence scores are used to evaluate the degree of semantic similarity between high-scoring words in the topic (Stevens et al., 2012). By plotting the scores, the peak of the curve shows us which value of k is the optimal coherence value for this model. This is followed by labelling the dimensions of customer comments with topics (Luo et al., 2012), using a three-stage process to optimise objectivity. Firstly, three investigators label the detected topics independently with the pre-defined labelling criteria, starting with the words and topics with the heaviest weight, indicating a higher frequency in the corpora. Secondly, we validate each topic by discussion and data retrieval. Thirdly, we merge the topics which discuss the same issues and remove useless topics which do not specifically focus on customers' responses to groceries (e.g., advertisements). This process determines the final topics in each tweet corpora, ranked according to the overall topic weight. Full details of topic labelling are available from the authors on request.

## 4. Results and discussion

We begin by identifying trends in tweet volume, sentiment from the daily tweet volume, the frequency distribution of the overall tweets, and the daily volume of positive and negative tweets. Then we adopt a series of event detection analyses to figure out the shifts in volume and sentiment to identify the dates of significant changes. We examine negative sentiment further because it accords well with the critical events in our study period. This is followed by topic modelling analysis to uncover the underlying reasons causing the negative customer experience.

### 4.1. Trends in tweet volume and sentiment

During the pre-lockdown and lockdown period, supermarkets implemented a series of measures in response to government policy on COVID-19 prevention and control. As shown in Fig. 3, government policy and supermarket regulations arouse intense discussion on social media. We observed a spike, with 161,921 tweets, on 19 March, when most UK supermarkets introduced limits to shopping hours with early closures for restocking. Coincidentally, 19 March is also the day after many supermarkets began limiting shoppers to a maximum of three of any of the same grocery items and only two products in high demand. Given that fear, anxiety, and a sense of isolation tend to trigger stockpiling and panic buying, these measures might have heightened such negative emotions. Meanwhile, the inability to stock up on daily necessities leads to many complaints through social media.

SentiStrength estimates the strength of positive, negative, and neutral sentiment in collected customer tweets. The sentiment score ranges from −5, which denotes extremely negative, to 5, extremely positive. This automatic sentiment analysis is suited to analyse Twitter text sentiment because it can decompose the grammatical structure of texts that are grammatically incomplete or incorrect (Thelwall et al., 2012). Fig. 4 shows the frequency distribution and the distribution line of each score. The frequency of neutral sentiment remains highest, while negative sentiment has a slightly higher proportion than positive sentiment. This suggests that neutral tweets dominate the whole dataset, and the number of negative tweets is roughly more than positive tweets.

We narrow our focus to the volume of positive and negative tweets during our study period. Fig. 5 exhibits the daily normalised number of positive and negative tweets. Volume tendencies for both positive and negative tweets are consistent with the overall volume trend shown in Fig. 4, and tweets expressing positive and negative sentiment spike at different times. In detail, both positive and negative sentiments peak on 19 March, when supermarkets receive the most tweets; however, negative comments outnumber positive comments, which indicates that the new regulations cause inconvenience and disappointment among customers. Subsequent peaks are highly correlated with government announcements and the associated supermarket regulations. The volume of tweets in later peaks decreases gradually. It might be due to the continuous improvement of supermarket services. However, negative tweets continue to outnumber positive tweets. The consistent standard deviation (σ) trendline throughout the period displays that our data is concentrated and not spread out, while the fluctuating mean shows the intense reaction of customers during this period.

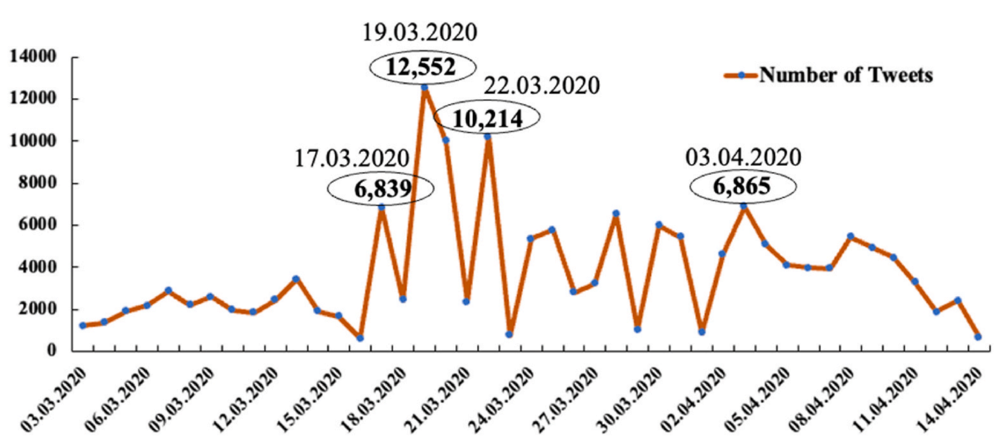



**Fig. 3.** Twitter searching trends of the UK Top 5 supermarkets (Note: The value in the circle is the number of tweets on the corresponding date).

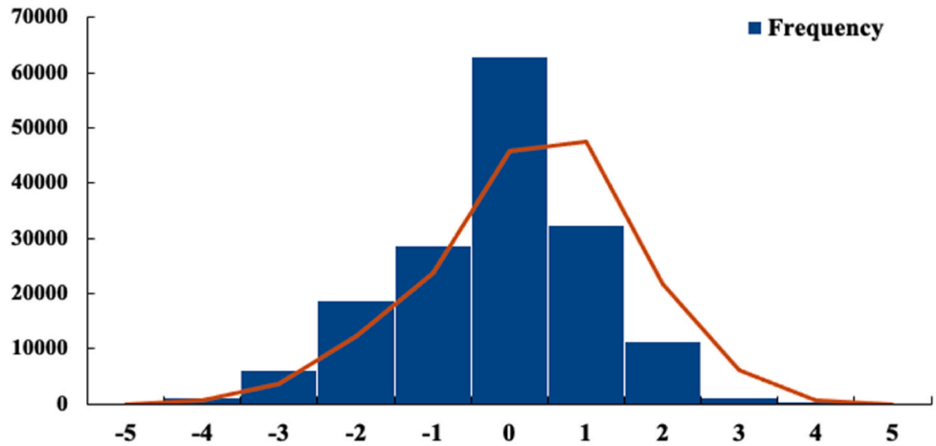



**Fig. 4.** Frequency distribution of the overall tweets.

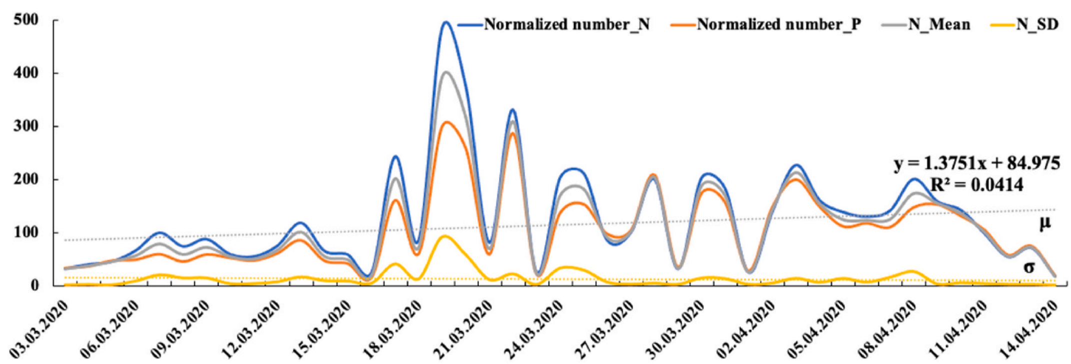



**Fig. 5.** Volume of positive and negative tweets.

Fig. 6 reveals the evolution of the daily average sentiment polarity further to understand the sentiment trend in the time series. It shows that negative sentiment scores gradually decrease while positive sentiments increase. This indicates that while customers expressed concern or dissatisfaction with the supermarket's actions early in the crisis, they gradually acknowledged the retailer's efforts to deal with the pandemic over time. Several significant spikes can be detected in the graph. For the negative sentiment in Fig. 6(a), 15 March, 30 March, and 8 April show the lowest emotional scores, whilst for positive sentiment in Fig. 6(b), 14 March, 21 March, and 28 March present the highest scores. The graphs also show that the average score range for negative sentiment is more significant than that for positive sentiment, suggesting that customer negative tweets may have become more extreme.

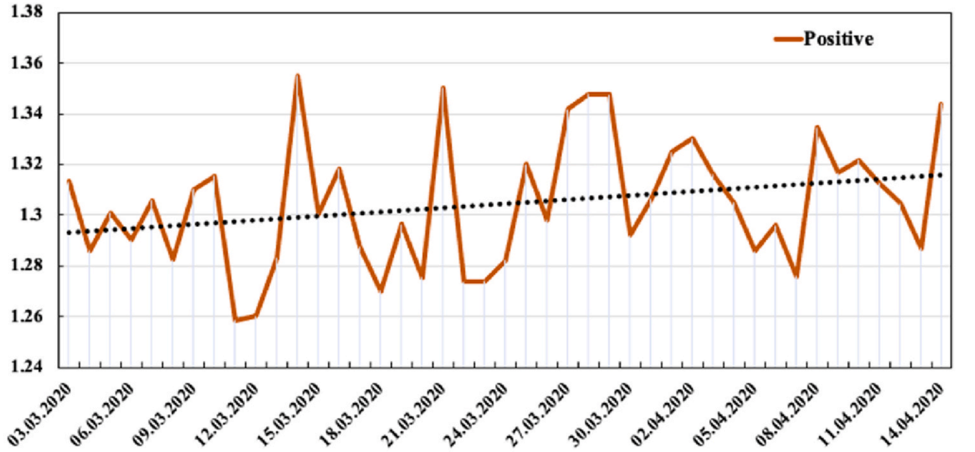
### 4.2. Event detection

Lansdall-Welfare et al. (2012) argue that significant events can be detected from the sentiment time series. In social media research, the detected events lead to changes in the number of SMD discussing related topics at a specific time (Chen et al., 2018). In this study, we use event detection analysis to explore shifts in sentiment and capture the times at which these changes occur. As discussed in 3.4, we employ two approaches to detect the time points in the time series: the frequency method and the difference in mean.

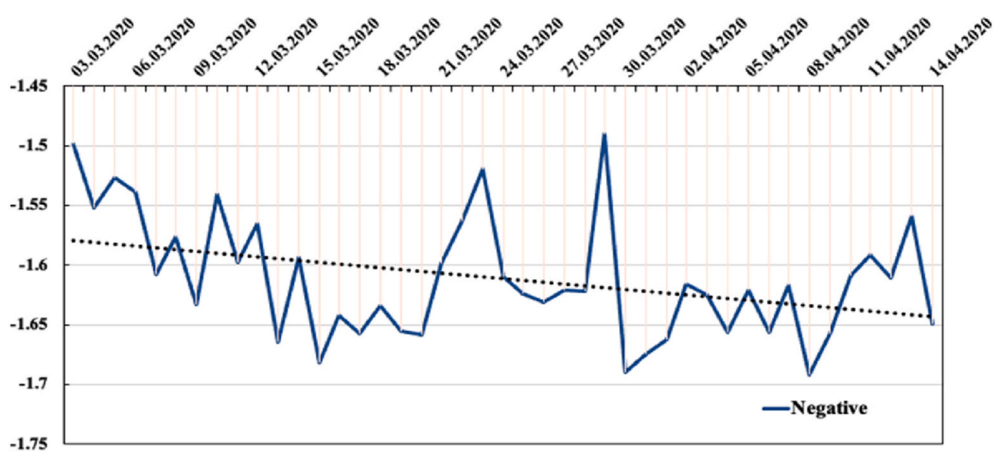
#### 4.2.1. The frequency method

Kulkarni et al. (2015) indicate that tracking frequency change is the most direct way to detect a sequence of events. Fig. 7 shows the results of sentiment changes deploying the frequency method. Fig. 7(a) displays the time series of positive sentiment frequency. We track positive emotions over time to capture the critical time points before and after the changes. Compared to Fig. 7(b) and (c), the time intervals in this figure are relatively scattered (shown as orange dashed lines). Since these dates do not coincide closely with previously defined events, they have no apparent significance. From this perspective, the frequency changes of positive sentiment may not be the most appropriate choice for subsequent analysis.

Fig. 7(b) displays the time intervals detected under negative tweet sentiment. This figure captures some key dates, including 5, 6, 24, and 26 March, at which the frequency of negative emotions changes most significantly. These changes are likely to stem from several critical measures introduced by the UK government. For example, 3 March saw the launch of the Coronavirus Action Plan, which set out how the UK would take all necessary and reasonable steps to tackle the outbreak; on 23 March, British Prime Minister Boris Johnson announced the first UK complete lockdown (GOV.UK, 2020). Compared to Fig. 7(a), the time series of negative sentiment frequency accords well with critical events over the study period. Fig. 7(c) presents the total sentiment frequency, both positive and negative. The main changes occurred on 5, 6, 16, and 17 March, and 14 April. 5 March, 6 March, and 14 April align with pre-defined key events. On 16 March, the UK government announced drastic action to deal with the epidemic, such as recommending that people work from home, stop non-essential contact with others, and stop unnecessary travel. Consequently, 16 March and 17 March are also critical dates. However, the significance reflected by these two dates is notably less than for 24 March and 26 March in Fig. 7(b). Overall, some critical time points tracked by the frequency changes of negative sentiment in Fig. 7(b) are closer to the events on the timeline we previously defined. The key events include the launch of the COVID-19 Action Plan and the first official lockdown announcement.




a)




b)

**Fig. 6.** Trend of (a) positive sentiment polarity and (b) negative sentiment polarity.

#### 4.2.2. *The difference in mean*

To verify and confirm the negative sentiment analysis results, we track the peaks in the negative sentiment time series by establishing the mean difference, including the most negative or positive spikes. The spikes indicate the days that show the most significant shifts during the period, leading to the most significant impacts in the following days. Following Lansdall-Welfare et al. (2012)'s method, we calculate the mean difference by measuring the absolute difference between the daily averages (Mean difference = $\mu1 - \mu2$). This measure is used to identify apparent changes in the mean of sentiment valence and detect significant events.

As shown in Fig. 8, there is a fluctuating curve representing the changes in mean difference for each day. We can observe significant peaks in negative sentiment between 9 March and 10 March and between 12 March and 13 March, related to the "Contain" and "Delay" phases of the COVID-19 Action Plan. A similar peak occurs between 23 March and 24 March, when the UK enters its first lockdown. There are two prominent spikes around 29 March in the time series. Motivated by concern that such a short time interval might impair the effectiveness of the overall data analysis and that the interpretation of one day's dataset would be inadequate in the later topic modelling, we selected the more significant spike on 30 March. This time point falls about one week after the announcement of the first official lockdown. Event detection analysis helps us identify the key time points that fit our time series. Maintaining a focus on the peaks indicating abrupt changes in customers' negative sentiment, in the later analysis, we use topic modelling to identify the topics of most concern to customers and to determine the reasons for the changes.

### 4.3. *Robustness check of sentiment analysis result*

To verify the reliability and accuracy of the sentiment analysis model, two additional sentiment analysis tools called Bing and AFINN sentiment lexicon is used for comparison. Bing is a labelled list of sentiment lexicon which can cope with misspellings and morphological variations and specifically focuses on detecting emotional orientation and customer reviews (Hartmann et al., 2019). AFINN lexicon is dedicated to mining microblog texts and emphasis on acronyms (e.g., "LOL"), which also offer the same score range as SentiStrength (Nielsen, 2011). These two sentiment lexicons can support our social media

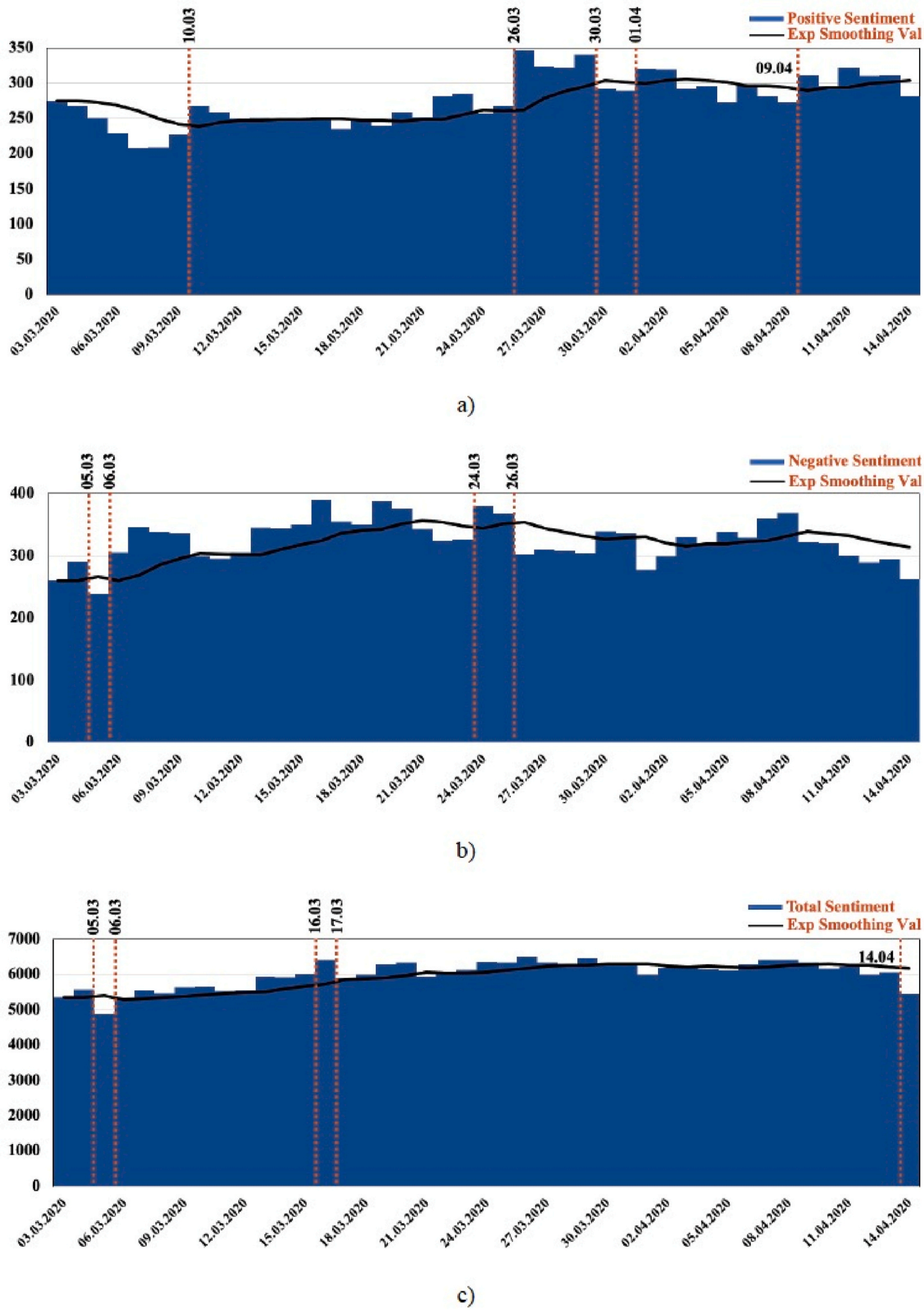



**Fig. 7.** Daily frequency of (a) positive sentiment, (b) negative sentiment, (c) positive and negative sentiment.

analytical research, which both have demonstrated effectiveness in social media business research (e.g., Airani and Karande, 2022). Thus, we benchmark the result of three SA tools, as suggested by Berger et al. (2020), to improve the accuracy and robustness of the SA process. As the main focus of this study is the negative comments for identifying the critical time point, Table 2 shows the proportion of the negative sentiment classes of each day's tweets using SentiStrength, Bing, and AFINN. Overall, the performances of the three lexicons are similar in classifying the negative comments, which indicates a reliable result from the SentiStrength tool.

### 4.4. *Evolving topics over time*

As shown in Figs. 9 and 10, the key topics appear in the topic dynamic diagrams. In both graphs, five phases are divided by the time series, listed in descending order of topic weighting. Fig. 9 displays the customers' concerns about supermarkets' social media response related to COVID-19. Coincidentally, all three supermarkets use the same combinations of SCCT crisis response strategies, including denial, diminishing, rebuilding, and bolstering crisis response strategies. Therefore, the diagram also displays how customers' concerns evolved

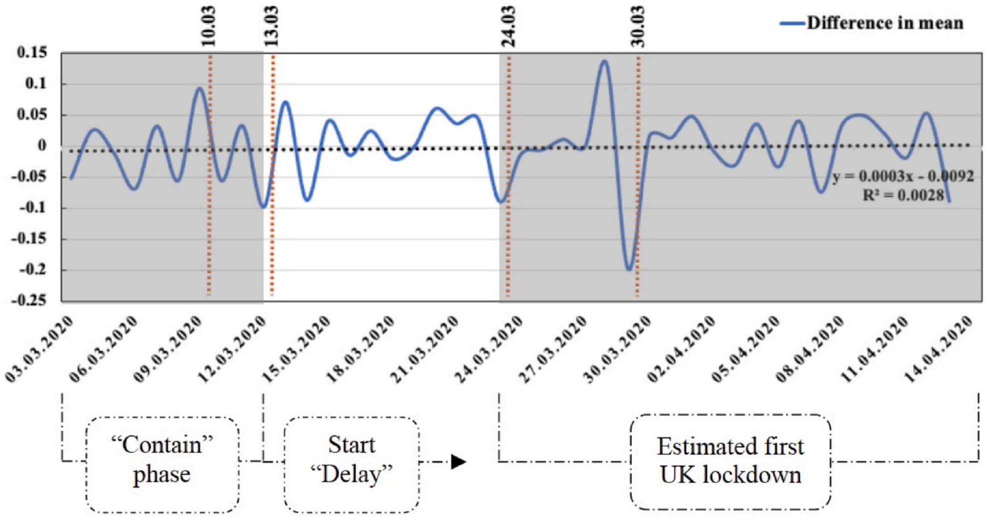



**Fig. 8.** The comparison of the UK government announcement timeline and difference in mean of negative sentiment.

**Table 2**
The result of negative sentiment classification.

| Date | Tool | | | Date | Tool | | |
|---|---|---|---|---|---|---|---|
| | SentiStrength | Bing | Afinn | | SentiStrength | Bing | Afinn |
| 3.3 | 26% | 26% | 28% | 3.25 | 37% | 33% | 35% |
| 3.4 | 29% | 27% | 30% | 3.26 | 30% | 27% | 30% |
| 3.5 | 24% | 22% | 26% | 3.27 | 31% | 29% | 32% |
| 3.6 | 31% | 30% | 34% | 3.28 | 31% | 28% | 30% |
| 3.7 | 35% | 34% | 39% | 3.29 | 31% | 29% | 31% |
| 3.8 | 34% | 33% | 38% | 3.30 | 34% | 32% | 33% |
| 3.9 | 34% | 31% | 35% | 3.31 | 34% | 31% | 32% |
| 3.10 | 30% | 29% | 33% | 4.1 | 28% | 28% | 27% |
| 3.11 | 30% | 30% | 34% | 4.2 | 30% | 27% | 30% |
| 3.12 | 30% | 29% | 36% | 4.3 | 33% | 32% | 32% |
| 3.13 | 36% | 34% | 40% | 4.4 | 32% | 30% | 32% |
| 3.14 | 34% | 33% | 37% | 4.5 | 34% | 30% | 31% |
| 3.15 | 35% | 32% | 36% | 4.6 | 33% | 31% | 32% |
| 3.16 | 39% | 34% | 38% | 4.7 | 36% | 33% | 33% |
| 3.17 | 36% | 32% | 39% | 4.8 | 37% | 33% | 34% |
| 3.18 | 35% | 32% | 36% | 4.9 | 32% | 29% | 31% |
| 3.19 | 39% | 34% | 38% | 4.10 | 32% | 29% | 31% |
| 3.20 | 37% | 32% | 37% | 4.11 | 30% | 28% | 29% |
| 3.21 | 34% | 29% | 32% | 4.12 | 29% | 27% | 29% |
| 3.22 | 32% | 28% | 32% | 4.13 | 29% | 29% | 29% |
| 3.23 | 33% | 23% | 28% | 4.14 | 26% | 35% | 32% |
| 3.24 | 38% | 36% | 36% | | | | |

when retail companies employed SCCT crisis response strategies in social media posts. Food and essential supplies attract the most attention in the first two phases, and interest in this subject begins to wane in the third stage. The latter three stages are mainly concerned with vulnerable and elderly shoppers. We notice that people's attention shifts to minority protection once the store items are ensured. Meanwhile, delivery is a significant worry in the first four phases of topic modelling, reflecting the importance of grocery delivery services in times of crisis. Additional subjects are depicted in this figure, which will be explained in different dimensions later.

Fig. 10 presents the customer concerns about supermarkets that do not post anything regarding COVID-19. The figure shows that panic buying is the subject of most care in the first three phases. The topics of most significant concern in the following stages are delivery and support of vulnerable and elderly shoppers. Simultaneously, food, vital supplies, and a shopping experience are mentioned several times in the figure. However, there is a significant decrease in the number of topics compared to the prior figure.

When comparing the topics shown in the two figures, whether the retail companies post information relating to COVID-19, the subjects that consumers are concerned about the most in the research period are similar, such as panic buying, delivery, and vulnerable and elderly shoppers. More topics, however, can be gathered when supermarkets integrate COVID-19-related information into their social media posts. Despite their modest relevance, these topics can more fully convey people's concerns in various aspects. This can be explained by the fact that the supermarket has taken the initiative and efforts to bring up activities taken by the organisations in response to COVID-19, which also provides a channel for customers to share their ideas under the posts, so considerably promoting contact between the retail companies and their consumers (Rensburg et al., 2017). As a result, proactive discussions about the crisis can increase the diversity of collected customer information. Furthermore, when supermarkets publish information related to COVID-19, key topics such as deliveries, food and essentials supplies, and vulnerable and elderly shoppers come up earlier than not mentioning the crisis. This implies that proactively responding to the crisis can help retail companies more quickly and acutely perceive important concerns of the customer. It is worth mentioning that posting

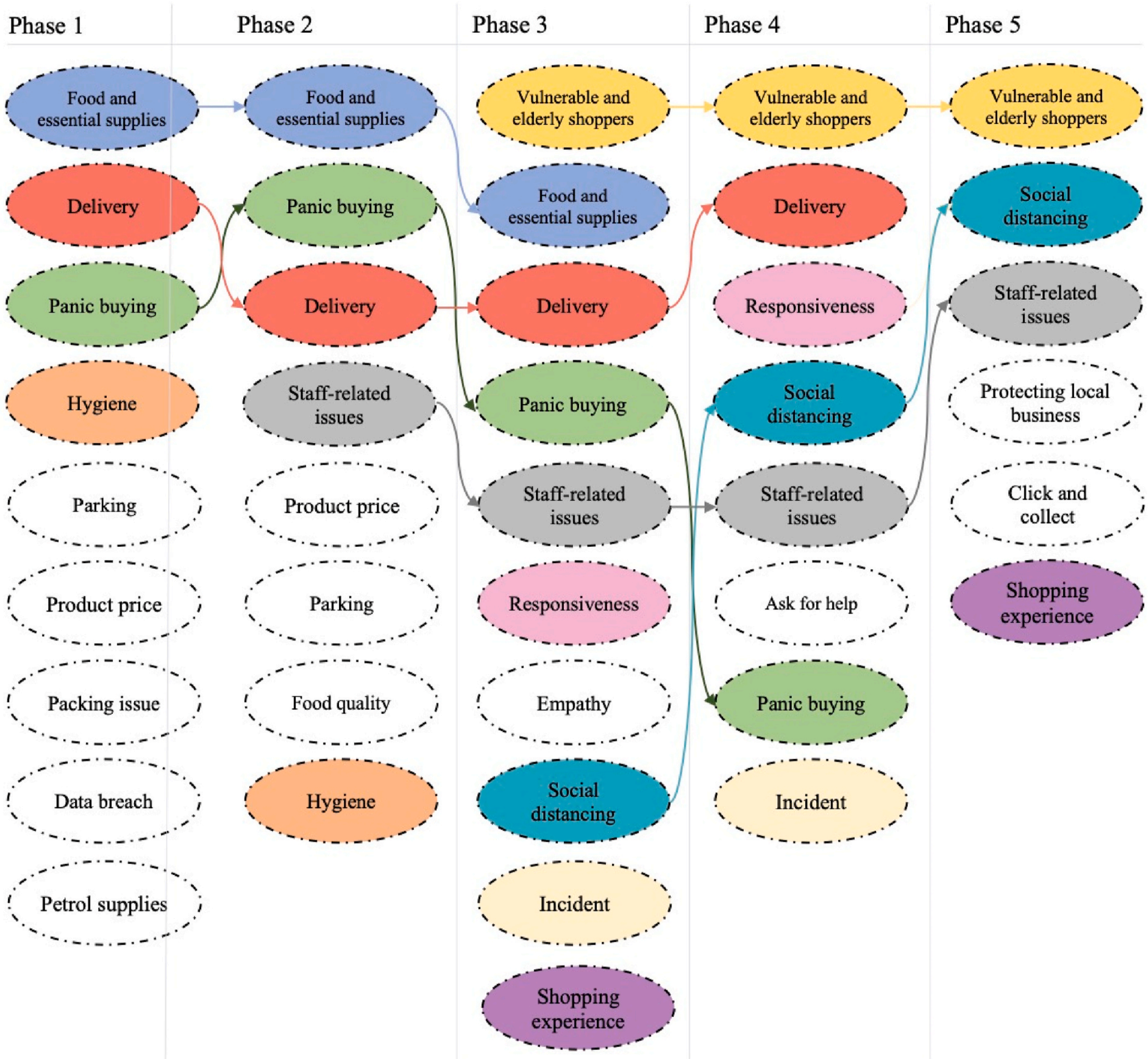



**Fig. 9.** Topic dynamics of supermarkets (i.e., Tesco, Sainsbury's, Asda) with social media response relating to COVID-19.

crisis-related information in social media communication not only brings positive consumer feedback but also raises worries and negative comments. If organisations can promptly identify these concerns and opinions and make appropriate improvements, the user experience may be considerably enhanced.

### *4.5. Service quality dimensions and associated customers' concerns*

Notwithstanding the classification of service quality assessment discussed in previous literature, limited research has used social media data during COVID-19 to develop a new sub-dimension. Since the earlier studies used text-mining-based analysis of consumer perceptions to determine the sub-dimension, in our research, we treat the topics as sub-dimension and match them with four dimensions (Brandtner et al., 2021). By doing so, this study provides more precise and comprehensive sub-dimensions in the scenarios of pandemics (see Table 3).

(1) Physical aspects include the convenience provided to customers by the arrangement of the physical facilities (Dabholkar et al., 1996). Consumers' shopping experience has changed dramatically due to the changes in physical facilities, and difficulty in parking is a concern that causes negative experiences during the crisis. Additionally, customer comments regarding "Incidents" are prompted by two cases, one of a man arrested on suspicion of attempted murder, dangerous driving, and assaulting a police officer at an Exeter Sainsbury's superstore on 12 March, and the other of a group of men smashing the doors of a south London Sainsbury's after raiding the store for alcohol on 18 March. Although there is no evidence that these incidents are related to COVID-19, they raise people's concerns about shopping in physical stores. Safety concerns begin to draw more attention after several incidents, focusing on fear of accidents and staff contracting the disease due to a lack of hygiene products. This supports Calvo-Porral and Lévy-Mangin (2019)'s argument regarding the importance of security and safety in the shopping area for customers' willingness to visit. Even though incidents and crises are mostly unpredictable and uncontrollable, supermarkets are encouraged to provide a safe and comfortable place for customers to shop.

(2) Reliability can be understood as "the combination of keeping promises" and "doing it right" (Dabholkar et al., 1996). Since this study focuses exclusively on negative comments, the subjects in this category reflect the actions resulting from failing to meet commitments and not completing them correctly. Specifically,

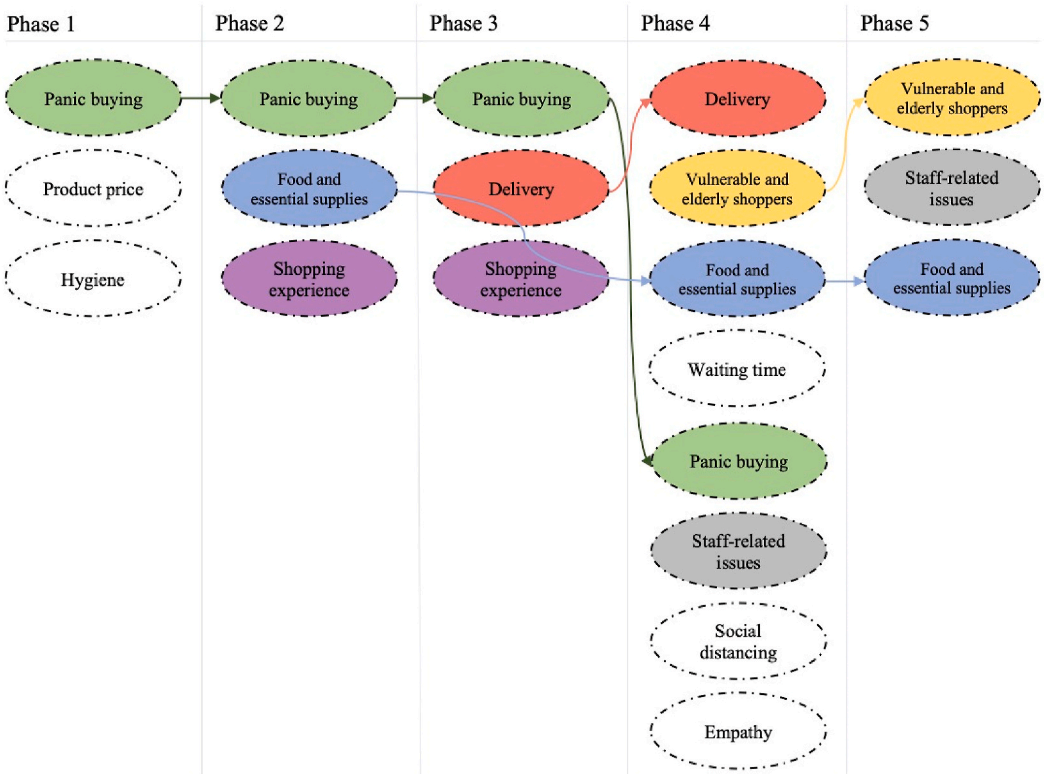



**Fig. 10.** Topic dynamics of supermarkets (i.e., Morrisons, Aldi) with non-social media response relating to COVID-19.

**Table 3**
Dimension and sub-dimension of customers' service concerns.

| Dimension | Sub-Dimension |
|---|---|
| Physical aspects | Shopping experience |
| | Incident |
| | Parking |
| Reliability | Food and essential supplies |
| | Panic buying |
| | Delivery |
| | Hygiene |
| | Data breach |
| | Petrol supplies |
| | Food quality |
| | Ask for help |
| Personal interaction | Responsiveness |
| | Staff-related issues |
| Policies | Vulnerable shopping priority |
| | Click and collect |
| | Social distancing |
| | Waiting time |
| | Product price |

Note: Empathy, protecting local business are not included in this table since they are invoked to individuals, and not related to service quality improvement.

"food and essential supplies" emerges as a particular customer concern in each phase. For example, customers comment on the lack of "hygiene products", "toilet rolls", and "pasta", indicating heavy demand for essentials in the early period. We suggest they can enhance their essential product stock management and shift their attention from product diversity-oriented to essential product continual supply-oriented under crisis conditions. Moreover, it is recommended that retail companies establish tighter cooperation with their suppliers and develop more flexible procurement strategies. The lack of food and essential supplies also leads to panic buying in many regions. Panic buying is induced by the fear of not having essentials, while rumour on social media is also considered one of its drivers (Finch et al., 2016). Therefore, we recommend companies combat false information and rumour by actively communicating with customers online and offline. Further, supermarkets can take early action by introducing this measure to address stockpiling and bulk buying due to the effectiveness of limiting customer purchases. Moreover, the dramatic increase in demand for deliveries created difficulties for supermarkets, and slot availability became a severe problem. It is suggested that supermarkets expand their delivery teams and reserve special delivery slots for vulnerable groups, making delivery arrangements more flexible for different customers.

(3) Personal interaction relates to how the employee treats the customer. "Responsiveness" refers to how quickly and well an organisation provides timely feedback or solves customer problems. Current relationship theories regard perceived responsiveness as the vital aspect of a satisfying relationship (Lemay et al., 2007) and a practical method to yield better feedback and accelerate improvement in service quality. Low ratings for responsiveness reflect poor service quality and further reduce customer satisfaction. According to Maisel and Gable (2009), who understand responsiveness from a psychological perspective, individuals who feel sad and anxious on a given day usually report that their partners are less responsive. This might explain why customers are more eager to receive supermarket feedback on their needs during the pandemic. Consequently, supermarkets should strengthen interaction and timely customer response under the circumstances. Besides, "Staff-related issues" include staff behaviour and supermarkets' treatment of their employees. Concerns regarding employees' behaviour focus mainly on failure to maintain social distancing. A possible reason is that supermarkets recruited many new employees who might not have received adequate training before starting work. Therefore, we

suggest that supermarkets strengthen staff protection systems and give timely training to improve service quality.

(4) Policies capture service quality aspects directly influenced by store policy. With the gradual implementation of lockdown policies, several store policies are implemented accordingly to reduce infection. Nevertheless, it also leads to customer compliance. For instance, social distancing rules make it difficult for elderly or disabled people to receive assistance from family and friends. Although grocery companies update their shopping rules to adapt to the evolving crisis, concerns are not fully solved, for example, tweets like "what age do you consider to be elderly" or "can I ask what proof you require from the vulnerable group please" can be found, receiving the responses from Tesco said, "rely on common decency of the public respect". Besides, "Click and collect" have significant weight (Milioti et al., 2020) as customers complain about the availability of this service. These comments reveal that supermarkets should strengthen in-store management and provide staff with safety awareness training while also improving flexibility to offer more click-and-collect slots or assign more staff to that service. Moreover, there are challenges to implementing the shopping rule: "my elderly parents went at 9 a.m. this morning only to find the store packed with people of all ages including children", which indicates a lack of clear definition for "priority groups". The continuous discussion of these topics shows that customers' concerns are still not entirely resolved, suggesting an urgent need to develop a better online and offline shopping mechanism for priority groups.

## 5. Conclusions

The COVID-19 pandemic and lockdown have significantly impacted people's daily lives. Faced with less predictable consumption behaviour, supermarkets struggle to understand their customers' needs. This study integrates social media analysis to examine the significant changes in customers' sentiments and concerns towards supermarkets in an emerging situation. Besides, drawing on SCCT, the use of response strategies generally would impact customers' sentiment and experience with the companies. Therefore, text-mining techniques are then applied to two groups (i.e., social media response and non-social media response to crisis) to assess the difference in unobserved customer information. The results uncover various social media interaction levels during the crisis have different service attributes. The findings show that customers who engage in particular types of social media interactions may assess qualities differently, resulting in various degrees of customer data collecting for businesses. Additionally, this study develops the sub-dimensions of service quality assessment according to the results of text-mining-based analysis of consumer perceptions; the insights would know the specific factors that retail managers should focus on, particularly during a crisis. In general, the analytics of SMD reveals critical crisis management attributes to help supermarkets design better strategies in emerging circumstances.

### 5.1. Theoretical implications

This finding has several critical theoretical implications for the literature. First, this study provides a more profound knowledge of customers' opinions regarding supermarket services and insights into what customers honestly think during a crisis. Unlike most studies focusing on social media and using only a single strategy, this study obtains more robust and generalisable research findings by applying multiple text-mining tools to analyse several datasets. Adopting these approaches embraces the advantages of offering a dynamics observation on social media data, which also largely avoids the weakness of the single text-mining technique and single dataset analysis. Specifically, this study adopts text-mining techniques along with time-series analysis to present a dynamic evolution process of SMD and reveal the causes of sentiment change in each time series to analyse a large number of customer opinions expressed on Twitter and understand the changes in customer opinions. In other words, this study effectively associates sentiment, topic, and time to examine the change in SMD more accurately (Ibrahim and Wang, 2019). It facilitates SMD as a core resource that allows companies to understand customers' concerns and design timely business strategies to improve their service and deal with issues during a crisis.

Second, drawing on SCCT, separate topic modelling is applied to uncover how customer opinions differ between supermarkets that have social media responses to COVID-19 and those that do not. The results demonstrate that different levels of social media interaction during a crisis could have different service attributes. Those retail companies that interact with customers proactively tend to use the same types of crisis communication strategies (Rensburg et al., 2017), thus answering the second research question regarding the correlation between the changes in customer opinion and supermarkets' social media response. Customers may value qualities differently due to social media interaction, leading to varying degrees of consumer information generation. Since the era of information is a significant part of the corporate response and influences the strategies used, this study highlights the importance of proactive interaction in social media communication and the use of crisis response to generate information during a crisis (Ramanathan et al., 2017).

Third, this study extends the existing literature by associating text-mining analysis with service quality literature and uses the results of topic modelling to determine the new sub-dimension of service quality assessment under the category of physical aspects, reliability, personal interaction, and policy capture aspects. Text-mining approaches allow retail managers to gain important insights to improve service quality. This is consistent with Lee et al. (2021) that user-generated content such as online reviews, which usually include personal narratives of experience about a particular product or service, provides more insights than customer likes and dislikes. Furthermore, service quality evaluation needs to evolve according to changing circumstances, as the customer experience is a complex system that changes with the environment (Nilashi et al., 2022). This requires that retail managers supporting decisions to solve customer problems have a flexible understanding of the changing sub-dimensions of service quality. As a result, this study adds to the body of knowledge on service quality by providing strategic options for retailers in crises and constructively demonstrating how SMD analysis can collaborate with service quality assessment to assist supermarkets in understanding consumer concerns in the retailing context.

### 5.2. Managerial implications

This study provides several practical implications and bridges the gap between technical and managerial perspectives. Since implementing new regulations and policies could significantly influence customers' shopping behaviour and experience, retail managers should be aware of the dynamic change in customers' sentiments and focuses (Islam et al., 2021). We also suggest that topics identified from the topic modelling with high frequency and high weighting, and new emerging topics, should be prioritised by grocery retailers. While the frequency of topics in the time series indicates their importance across different phases, the weight represents their importance at a particular time. Understanding the data collected from tweets in this period can help to prompt appropriate responses to these emerging topics. By employing current SMD in a methodical and effective manner, companies could recognise abnormal shifts in consumer sentiment and enhance their grasp of customer requirements.

By merging contemporary social media analytic methodologies into crisis management, our study is of actual use to organisations. When a crisis develops, some businesses may keep silent to decrease controversy and resources spent on customer communication. However, we argue that leveraging social media for crisis communication might help gather more information from customers and swiftly uncover management faults. Retail companies that use social media to communicate during a crisis, for example, understand customers' concerns more accurately, and there is an early notice of customers' demands during the crisis. This study also explains the strategies that supermarket retailers should consider when a crisis occurs and how it helps supermarkets receive faster and more detailed information that they should prioritise and monitor than supermarkets that do not respond to social media. Furthermore, when new strains of COVID-19 emerge, certain nations and places are suffering the second or third wave of the pandemic; merchants may still benefit from this research in terms of better understanding consumers' developing concerns and thereby enhancing service quality.

Furthermore, retail managers place a premium on creating social media ties with customers, giving them a better knowledge of improving the service quality. With the aid of two text-mining techniques, time series analysis together with the theoretical lens of service quality assessment framework, we provide actionable guidance on how retail companies can better prepare and respond to the crisis in four dimensions (i.e., physical aspects, reliability, personal interaction, and policies), for example, establishing tighter cooperation with their suppliers and develop more flexible procurement strategies, combating false information and rumour by actively communicating with customers online and offline, strengthening instore management and provide staff with safety awareness training, while also improving flexibility to offer more click-and-collect slots or assign more staff to that service. Hence, retail managers can benefit from our results as they can better understand which areas are more relevant and urgent during the pandemic than in regular times through crisis communication on social media. The essence of retailing service is two-way value creation through active customer connection, engagement, and interaction. Only by fully communicating and understanding with customers can companies truly meet the needs of customers (Brandtner et al., 2021).

### *5.3. Limitations and recommendations for further research*

This study has several limitations that open avenues for future research. First, it looks only at the views of customers who are used to sharing their opinions on social media. In contrast, customers' views seldom use social media are excluded. Future research could achieve a more accurate representation of the population by examining other groups of customers by using survey or interview methods. Secondly, this research only focuses on the retail industry in the UK, which may limit the generalisability of the research. The latter studies could further investigate this field in other countries and target a larger population. Thirdly, we suggest that future research can use different methods or techniques to further analyse the SMD, for example, topic network analysis to examine the relationships among the topics and categories derived from topic modelling or predictive analytics to forecast customers' behaviour. Finally, due in part to the fact that the target supermarkets posting COVID-19 information on social media use the same combination of SCCT crisis response strategies, the study does not examine the effectiveness of individual or other combinations of strategies, which will be valuable for future studies.

## Declaration of competing interest

None.

## Data availability

The data that has been used is confidential.

## References


Abbas, J., Wang, D., Su, Z., Ziapour, A., 2021. The role of social media in the advent of COVID-19 pandemic: crisis management, mental health challenges and implications. Risk Manag. Healthc. Pol. 14, 1917–1932.

Abd-Alrazaq, A., Alhuwail, D., Househ, M., Hamdi, M., Shah, Z., 2020. Top concerns of tweeters during the COVID-19 pandemic: infoveillance study. J. Med. Internet Res. 22 (4), 19016.

Airani, R., Karande, K., 2022. How social media effects shape sentiments along the twitter journey? A Bayesian network approach. J. Bus. Res. 142, 988–997.

Alzate, M., Arce-Urriza, M., Cebollada, J., 2022. Mining the text of online consumer reviews to analyze brand image and brand positioning. J. Retailing Consum. Serv. 67, 102989.

Berger, J., Humphreys, A., Ludwig, S., Moe, W.W., Netzer, O., Schweidel, D.A., 2020. Uniting the tribes: using text for marketing insight. J. Market. 84 (1), 1–25.

Bin, M., Cheung, P., Crisostomi, E., Ferraro, P., Myant, C., Parisini, T., Shorten, R., 2020. On Fast Multi-Shot Epidemic Interventions for Post Lock-Down Mitigation: Implications for Simple Covid-19 Models, p. 1125 arXiv preprint arXiv:2003.09930.

Blei, D.M., Lafferty, J.D., 2009. Topic models. In: Text-mining. Chapman and Hall/CRC, pp. 101–124.

Bollen, J., Mao, H., Zeng, X., 2011. Twitter mood predicts the stock market. J. Comput. Sci. 2 (1), 1–8.

Brandtner, P., Darbanian, F., Falatouri, T., Udokwu, C., 2021. Impact of COVID-19 on the customer end of retail supply chains: a big data analysis of consumer satisfaction. Sustainability 13 (3), 1464.

Bundy, J., Pfarrer, M.D., Short, C.E., Coombs, W.T., 2017. Crises and crisis management: integration, interpretation, and research development. J. Manag. 43 (6), 1661–1692.

Calvo-Porral, C., Lévy-Mangin, J.-P., 2019. Profiling shopping mall customers during hard times. J. Retailing Consum. Serv. 48, 238–246.

Chang, W.Y., Xian, X., Liu, M., Zhao, X., 2022. Health communication through positive and solidarity messages amid the COVID-19 pandemic: automated content analysis of Facebook uses. Int. J. Environ. Res. Publ. Health 19 (10), 6159.

Chen, X., Wang, S., Tang, Y., Hao, T., 2018. A bibliometric analysis of event detection in social media. Online Inf. Rev. 43 (1), 29–52.

Coombs, W.T., 2007. Protecting organization reputations during a crisis: the development and application of situational crisis communication theory. Corp. Reput. Rev. 10 (3), 163–176.

Dabholkar, P.A., Thorpe, D.I., Rentz, J.O., 1996. A measure of service quality for retail stores: scale development and validation. J. Acad. Market. Sci. 24 (1), 3–16.

De Backer, C., Teunissen, L., Cuykx, I., Decorte, P., Pabian, S., Gerritsen, S., Matthys, C., Al Sabbah, H., Van Royen, K., Corona Cooking Survey Study Group, 2021. An evaluation of the COVID-19 pandemic and perceived social distancing policies in relation to planning, selecting, and preparing healthy meals: an observational study in 38 countries worldwide. Front. Nutr. 7, 621726.

Finch, K.C., Snook, K.R., Duke, C.H., Fu, K.-W., Tse, Z.T.H., Adhikari, A., Fung, I.C.-H., 2016. Public health implications of social media use during natural disasters, environmental disasters, and other environmental concerns. Nat. Hazards 83 (1), 729–760.

GOV.UK, 2020. Prime Minister's Statement on Coronavirus (COVID-19), 23 March 2020. GOV, UK. Retrieved 5 February 2022. https://www.gov.uk/government/speeches/pm-address-to-the-nation-on-coronavirus-23-march-2020.

Grimmer, L., 2022. Lessons from the COVID19 pandemic: the case of retail and consumer service firms. J. Retailing Consum. Serv. 68, 103012.

Guthrie, C., Fosso-Wamba, S., Arnaud, J.B., 2021. Online consumer resilience during a pandemic: an exploratory study of e-commerce behavior before, during and after a COVID-19 lockdown. J. Retailing Consum. Serv. 61, 102570.

Hartmann, J., Huppertz, J., Schamp, C., Heitmann, M., 2019. Comparing automated text classification methods. Int. J. Res. Market. 36 (1), 20–38.

Ibrahim, N.F., Wang, X., 2019. Decoding the sentiment dynamics of online retailing customers: time series analysis of social media. Comput. Hum. Behav. 96, 32–45.

Islam, T., Pitafi, A.H., Arya, V., Wang, Y., Akhtar, N., Mubarik, S., Xiaobei, L., 2021. Panic buying in the COVID-19 pandemic: a multi-country examination. J. Retailing Consum. Serv. 59, 102357.

Jiao, W., Liu, M.T., Schulz, P.J., Chang, A., 2022. Impacts of self-efficacy on food and dietary choices during the first COVID-19 lockdown in China. Foods 11 (17), 2668.

Jin, Y., Liu, B.F., Austin, L.L., 2014. Examining the role of social media in effective crisis management: the effects of crisis origin, information form, and source on publics' crisis responses. Commun. Res. 41 (1), 74–94.

Kantar-World-Panel, 2021. Grocery market share UK, 5 February 2022. https://www.kantarworldpanel.com/en/grocery-market-share/great-britain. (Accessed 5 February 2022).

Kim, S.Y., 2022. The impact of customer-generated evaluation information on sales in online platform-based markets. J. Retailing Consum. Serv. 68, 103016.

Kim, H.G., Lee, S., Kyeong, S., 2013. Discovering hot topics using Twitter streaming data social topic detection and geographic clustering. In: 2013 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining. ASONAM 2013, pp. 1215–1220.

Kulkarni, V., Al-Rfou, R., Perozzi, B., Skiena, S., 2015. Statistically significant detection of linguistic change. In: Proceedings of the 24th International Conference on World Wide Web, pp. 625–635.

Kursan Milaković, I., 2021. Exploring consumer resilience during COVID-19: demographics, consumer optimism, innovativeness and online buying. Econ. Bus. Rev. 23 (4), 260–272.

Lansdall-Welfare, T., Lampos, V., Cristianini, N., 2012. Effects of the recession on public mood in the UK. In: Proceedings of the 21st International Conference on World Wide Web, pp. 1221–1226.

Lee, C.K.H., Tse, Y.K., Ho, G.T.S., Chung, S.H., 2021. Uncovering insights from healthcare archives to improve operations: an association analysis for cervical cancer screening. Technol. Forecast. Soc. Change 162, 120375.

Lemay Jr., E.P., Clark, M.S., Feeney, B.C., 2007. Projection of responsiveness to needs and the construction of satisfying communal relationships. J. Pers. Soc. Psychol. 92 (5), 834.

Liu, M., Wang, S., McCartney, G., Wong, I.A., 2021. Taking a break is for accomplishing a longer journey: hospitality industry in Macao under COVID-19 pandemic. Int. J. Contemp. Hospit. Manag. 33 (4), 1249–1275.

Liu, M.T., Xue, J., Liu, Y., 2021. The mechanism leads to successful clickbait promotion in WeChat social media platforms. Asia Pac. J. Market. Logist. 33 (9), 1952–1973.

Luo, J., Ba, S., Zhang, H., 2012. The effectiveness of online shopping characteristics and well-designed websites on satisfaction. MIS Q. 1131–1144.

Maisel, N.C., Gable, S.L., 2009. The paradox of received social support: the importance of responsiveness. Psychol. Sci. 20 (8), 928–932.

McCartney, G., Pinto, J., Liu, M., 2021. City resilience and recovery from COVID-19: the case of Macao. Cities 112, 103130.

Milioti, C., Pramatari, K., Kelepouri, I., 2020. Modelling consumers' acceptance for the click and collect service. J. Retailing Consum. Serv. 56, 102149.

Mirbabaie, M., Marx, J., 2020. 'Breaking'news: uncovering sense-breaking patterns in social media crisis communication during the 2017 Manchester bombing. Behav. Inf. Technol. 39 (3), 252–266.

Nielsen, F.Å., 2011. A new ANEW: evaluation of a word list for sentiment analysis in microblogs. In: Proceedings of the ESWC2011 Workshop on 'making Sense of Microposts': Big Things Come in Small Packages, pp. 1–6.

Nilashi, M., Abumalloh, R.A., Minaei-Bidgoli, B., Zogaan, W.A., Alhargan, A., Mohd, S., Azhar, S.N.F.S., Asadi, S., Samad, S., 2022. Revealing travellers' satisfaction during COVID-19 outbreak: moderating role of service quality. J. Retailing Consum. Serv. 64, 102783.

Nunkoo, R., Teeroovengadum, V., Ringle, C.M., Sunnassee, V., 2020. Service quality and customer satisfaction: the moderating effects of hotel star rating. Int. J. Hospit. Manag. 91, 102414.

Pakurár, M., Haddad, H., Nagy, J., Popp, J., Oláh, J., 2019. The service quality dimensions that affect customer satisfaction in the Jordanian banking sector. Sustainability 11 (4), 1113.

Palen, L., Anderson, K.M., 2016. Crisis informatics—new data for extraordinary times. Science 353 (6296), 224–225.

Parasuraman, A., Zeithaml, V.A., Berry, L.L., 1985. A conceptual model of service quality and its implications for future research. J. Market. 49 (4), 41–50.

Parasuraman, A., Zeithaml, V.A., Berry, L.L., 1988. SERVQUAL: a multiple-item scale for measuring consumer perceptions of service quality. J. Retailing 64 (1), 12–40.

Pearson, C.M., Clair, J.A., 1998. Reframing crisis management. Acad. Manag. Rev. 23 (1), 59–76.

Prentice, C., Wang, X., Loureiro, S.M.C., 2019. The influence of brand experience and service quality on customer engagement. J. Retailing Consum. Serv. 50, 50–59.

Prentice, C., Chen, J., Stantic, B., 2020. Timed intervention in COVID-19 and panic buying. J. Retailing Consum. Serv. 57, 102203.

Ramanathan, U., Subramanian, N., Parrott, G., 2017. Role of social media in retail network operations and marketing to enhance customer satisfaction. Int. J. Oper. Prod. Manag. 37 (1), 105–123.

Rensburg, A., Conradie, D., Dondolo, H., 2017. The use of the situational crisis communication theory to study crisis response strategies at a university of technology. Communitas 22, 62–74.

Roshan, M., Warren, M., Carr, R., 2016. Understanding the use of social media by organisations for crisis communication. Comput. Hum. Behav. 63, 350–361.

Sheth, J., 2020. Impact of Covid-19 on consumer behavior: will the old habits return or die? J. Bus. Res. 117, 280–283.

Shi, Y., Prentice, C., He, W., 2014. Linking service quality, customer satisfaction and loyalty in casinos, does membership matter? Int. J. Hospit. Manag. 40, 81–91.

Singh, J.P., Dwivedi, Y.K., Rana, N.P., Kumar, A., Kapoor, K.K., 2019. Event classification and location prediction from tweets during disasters. Ann. Oper. Res. 283 (1), 737–757.

Son, J., Lee, H.K., Jin, S., Lee, J., 2019. Content features of tweets for effective communication during disasters: a media synchronicity theory perspective. Int. J. Inf. Manag. 45, 56–68.

Stevens, K., Kegelmeyer, P., Andrzejewski, D., Buttler, D., 2012. Exploring topic coherence over many models and many topics. In: Proceedings of the 2012 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning, pp. 952–961.

Stieglitz, S., Bunker, D., Mirbabaie, M., Ehnis, C., 2018a. Sense-making in social media during extreme events. J. Contingencies Crisis Manag. 26 (1), 4–15.

Stieglitz, S., Mirbabaie, M., Ross, B., Neuberger, C., 2018b. Social media analytics-Challenges in topic discovery, data collection, and data preparation. Int. J. Inf. Manag. 39, 156–168.

Stieglitz, S., Mirbabaie, M., Kroll, T., Marx, J., 2019. Silence" as a strategy during a corporate crisis–the case of Volkswagen's "Dieselgate. Internet Res. 29 (4), 921–939.

Thelwall, M., Buckley, K., Paltoglou, G., 2012. Sentiment strength detection for the social web. J. Am. Soc. Inf. Sci. Technol. 63 (1), 163–173.

Tse, Y.K., Loh, H., Ding, J., Zhang, M., 2018. An investigation of social media data during a product recall scandal. Enterprise Inf. Syst. 12 (6), 733–751.

Verkijika, S.F., Neneh, B.N., 2021. Standing up for or against: a text-mining study on the recommendation of mobile payment apps. J. Retailing Consum. Serv. 63, 102743.

Wang, Y., Hao, H., Platt, L.S., 2021. Examining risk and crisis communications of government agencies and stakeholders during early-stages of COVID-19 on Twitter. Comput. Hum. Behav. 114, 106568.

Wu, J.J., Chang, S.T., 2020. Exploring customer sentiment regarding online retail services: a topic-based approach. J. Retailing Consum. Serv. 55, 102145.

Yang, K., Kim, J., Min, J., Hernandez-Calderon, A., 2021. Effects of retailers' service quality and legitimacy on behavioral intention: the role of emotions during COVID-19. Serv. Ind. J. 41 (1–2), 84–106.

Yu, M., Li, Z., Yu, Z., He, J., Zhou, J., 2021. Communication related health crisis on social media: a case of COVID-19 outbreak. Curr. Issues Tourism 24 (19), 2699–2705.

Zhang, M., He, X., Qin, F., Fu, W., He, Z., 2019. Service quality measurement for omni-channel retail: scale development and validation. Total Qual. Manag. Bus. Excel. 30 (Suppl. 1), S210–S226.

Zhao, X., Zhan, M., Jie, C., 2018. Examining multiplicity and dynamics of publics' crisis narratives with large-scale Twitter data. Publ. Relat. Rev. 44 (4), 619–632.