



Service failures in times of crisis: An analysis of eWOM emotionality

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ABSTRACT

The COVID-19 pandemic continues to disrupt consumer experiences as well as service operations. Despite the magnitude of this exogenous shock, little is known about the pandemic's impact on consumers. Building on engagement theory, this study examines consumers' emotional responses to service failures on social media. Contributing to the brand equity literature, we test whether electronic word-of-mouth (eWOM) emotionality is contingent on brand strength. To do so, we analyzed 327,205 tweets directed at airline brands over the first 12 months of the pandemic in addition to data from a nonaffected period. The models show that consumers' overall emotionality in tweets was lower during the pandemic than before it. Over the course of the pandemic, levels of joy were lower while levels of sadness and anger were more prominent in tweets directed at weaker brands. Thus, brand strength still acts as a "buffer" if service failures are caused by exogenous shocks.

1. Introduction

As consumers and companies have shifted their activities online due to the COVID-19 pandemic, social media platforms, such as Twitter, have gained importance (Li et al., 2021; Saura, Ribeiro-Soriano, & Saldaña, 2022). Twitter now has an active user base (mDAU) of 229 million people, an increase of 38 % compared to the start of the pandemic (Twitter, 2022). In addition to its impact on well-being and stress levels (Kivi et al., 2021; Lades et al., 2020; Pantano et al., 2021), COVID-19 has also caused many operational and service disruptions that have increased the number of customer inquiries, in some cases, to "unmanageable levels" (Dixon et al., 2020; Mull, 2020). In addition, brands have struggled with reductions in service desk capacities and staff shortages (Sainato, 2022). Consumers often react emotionally to such service failures, i.e., "service performance that falls below the expectation of [...] customers" (Khamitov et al., 2020, p. 520), and they vent their frustrations in the form of electronic word-of-mouth (eWOM) (Berger, 2014; Christodoulides et al., 2021). The emotional state of customers in these nerve-racking and frustrating times adds to the challenges that brands are currently facing (Accenture, 2020). Thus, amplified by the turbulence of the pandemic, social media emerges as one of the most effective tools for listening to customer feedback, monitoring customer sentiment and emotions, and providing customer service (Starita, 2020). Whereas in most cases service failures can be attributed to a specific entity (e.g., the brand, suppliers, individual employees; Folkes, 1984),

disruptions caused by the pandemic are more difficult to attribute to a specific entity. Indeed, the pandemic can be classified as an exogenous shock, i.e., an unpredicted event that transcends past experiences (Amankwah-Amoah et al., 2021).

It remains unclear how service failures caused by an exogenous shock influence consumers' emotional reactions (Ozdemir et al., 2021). As the current health crisis progresses, it also remains to be explored how customer emotions develop over time. Thus, we use an exploratory approach to investigate the impact of this unexpected exogenous shock on consumers' emotions conveyed in eWOM. Furthermore, we explore whether eWOM emotionality differs depending on the strength of the brands that consumers communicate with. To examine these research questions, we analyze the eWOM generated by consumers on Twitter throughout the first year of the pandemic as well as in a control period prior to the pandemic.

We provide an overview of the relevant literature and the contributions of the study in Table 1. The work contributes to the literature in the following four ways.

First, the COVID-19 pandemic has sparked a number of research projects in the context of social media. Such research examined general discussions on social media about COVID-19 (e.g., Perez-Cepeda & Arias-Bolzmann, 2022), health-related messages shared by authorities (e.g., Wang et al., 2021), discussions about health and the pandemic in the general population (e.g., Abd-Alrazaq et al., 2020), the spread of misinformation about COVID-19 (e.g., Apuke & Omar, 2021; Meng

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Table 1
Overview of the relevant literature and the identified research gaps.

Article	Field of Research	Context	Method	Timeline	Duration	Brand-related eWOM	Social Media Data	Emotionality/Sentiment	Brand Strength
The current study	Marketing	Consumers' eWOM directed at brands on social media	Text analysis, Regression-based models	March 1, 2019, to March 31, 2019, and February 1, 2020, to February 1, 2021	13 months	✓	✓	✓	✓
Saura, J. R., Ribeiro-Soriano, D., & Saldaña, P. Z. (2022).	Marketing, Innovation, Human Resource Management, Information Systems	Tweets related to remote working	Latent Dirichlet allocation (LDA) model	April 4, 2021, to August 6, 2021	4 months	×	✓	✓	×
Saura, J. R., Ribeiro-Soriano, D., & Palacios-Marqués, D. (2022).	Operations Management, Innovation Management	Tweets related to operations and innovation management	Latent Dirichlet allocation (LDA) model	April 1, 2021, to June 15, 2021	2.5 months	×	✓	✓	×
Perez-Cepeda, M., & Arias-Bolzmann, L. G. (2022).	Communications, Consumer Culture Theory	General population discussing COVID-19 related topics	Netnography, Lexicon-based model	January 2020 to June 2020	6 months	×	✓	✓	×
Sharma, A., Adhikary, A., & Borah, S. B. (2020).	Marketing, Supply Chain Management	Tweets related to supply chain topics	Thematic analysis, Frequencies Survey, PLS-SEM	January 23, 2020, to May 7, 2020	3.5 months	×	✓	×	×
Al-Omoush, K. S., Otero-Blat, M., & Ribeiro-Soriano, D. (2021).	Innovation Management	Perceived value of crowdsourcing		Cross-sectional	NA	×	×	×	×
Li, S., Wang, Y., Filieri, R., & Zhu, Y. (2022).	Marketing, Tourism	Organizations' COVID-related announcements	Qualitative (fsQCA)	March 1, 2020, to July 31, 2020	5 months	✓	✓	✓	×
Ozuem, W., Ranfagni, S., Willis, M., Rovai, S., & Howell, K. (2021).	Marketing	Customer experiences during the pandemic	Diaries, Qualitative surveys	Not reported	4 weeks	×	×	✓	×
Piccinelli, S., Moro, S., & Rita, P. (2021).	Marketing, Tourism	Comments left on website	Sentiment analysis	January 1, 2020, to April 30, 2020	4 months	×	×	✓	×
Verlegh, P. W., Bernritter, S. F., Gruber, V., Schartman, N., & Sotgiu, F. (2021).	Marketing	Consumers perceptions of control	Longitudinal survey & experiment	March 27, 2020, to October 9, 2020	6 months	×	×	×	×
Xue, J., Chen, J., Hu, R., Chen, C., Zheng, C., Su, Y., & Zhu, T. (2020).	Health	General population discussing COVID-19 health-related issues	Topic modeling, Latent Dirichlet allocation (LDA)	March 7, 2020, to April 21, 2020	1.5 months	×	✓	✓	×
Shanahan, L., Steinhoff, A., Bechtiger, L., Murray, A. L., Nivette, A., Hepp, U., & Eisner, M. (2022).	Health	Young adults' emotional health	Cohort study	Once per year from 2004 to 2020	Multiple waves over 16 years	×	×	✓	×
Jubair, F., Salim, N. A., Al-Karadsheh, O., Hassona, Y., Saifan, R., & Abdel-Majeed, M. (2021).	Information Systems, Health	General population discussing COVID-19 on social media	Sentiment analysis, Text analysis	March 26, 2020, to April 9, 2020	0.5 months	×	✓	✓	×
Abd-Alrazaq, A., Alhuwail, D., Househ, M., Hamdi, M., & Shah, Z. (2020).	Health	General population discussing COVID-19 on social media	Topic modeling, Latent Dirichlet allocation (LDA)	February 2, 2020, to March 15, 2020	1.5 months	×	✓	✓	×
Wang, Y., Zhang, M., Li, S., McLeay, F., & Gupta, S. (2021).	Marketing, Management	Organizations' COVID-related announcements	Manual coding, Experiment	March 1, 2020, to April 30, 2020	2 months	✓	✓	✓	×
Rintyarna, B. S., Kuswanto, H., Sarno, R., Rachmaningsih, E. K., Rachman, F. H., Suharso, W., &	Computer Science, Marketing	Consumers' discussions about service quality of ISPs	Machine learning, (naïve Bayes), Sentiment analysis	February 6, 2021, to February 12, 2021	1 week	✓	✓	×	×

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et al., 2021), supply-chain implications (e.g., Sharma et al., 2020), operations management (e.g., Saura, Ribeiro-Soriano, & Palacios-Marqués, 2022) and remote work (e.g., Saura, Ribeiro-Soriano, & Saldaña, 2022). This study contributes to this stream of literature by examining eWOM generated on social media in a consumer-brand engagement context. In particular, we explore the effect of the COVID-19 pandemic on consumers' eWOM in terms of emotionality in brand-directed messages.

Second, building on engagement theory, we aim to extend the literature on eWOM. On the one hand, the study aims to broaden the understanding of eWOM during times of crisis. Prior research has examined eWOM in response to product or service crises (e.g., Grégoire et al., 2015; Hsu & Lawrence, 2016; Khamitov et al., 2020; Schaefers & Schamari, 2016). However, service failures caused by exogenous shocks, such as the pandemic, are different in nature because they are mostly attributed to a "force majeure" (i.e., a circumstance beyond the control of the parties). Such exogenous shocks are not directly attributed to brands, as they cannot prepare for such an event. Thus, the effects of wider economic shocks and health crises, such as the COVID-19 pandemic, on consumer reactions (e.g., in the form of eWOM) remain unclear (Ozuem et al., 2021). This is particularly true for the airline industry, which has been greatly affected by the pandemic (Eurocontrol, 2021), with large numbers of customers reaching out to brands via social media platforms (Piccinelli et al., 2021). On the other hand, we follow the call of Lamberton and Stephen (2016) for more longitudinal social

media research. Thus, this research analyzes consumer eWOM on Twitter during the first year of the COVID-19 crisis (February 1, 2020–February 1, 2021). Overall, the aim is to contribute to the eWOM literature by examining how consumers communicated with brands on social media and how the emotions conveyed in consumers' messages developed during the pandemic.

Third, building on brand equity theory, we examine how eWOM emotionality differs depending on brand strength. Brand equity, which is defined as a consumer's perception of a brand's strength (Aaker, 1991; Hazée et al., 2017), may act as a buffer or safety cushion for the negative impact of negative brand-related events, but it may also amplify these negative effects (e.g., Brady et al., 2008; Hsu & Lawrence, 2016; Khamitov et al., 2020; Liao & Cheng, 2014; Mafael et al., 2022). However, brands may not be directly to blame for service failures caused by the COVID-19 pandemic. Hence, the aim is to expand existing brand equity theory by examining whether a buffer effect exists in cases of exogenous shock-related service failures.

Finally, our research contributes to the understanding of consumers' emotions during the COVID-19 pandemic. While prior research examined the impact of the pandemic on psychological states (e.g., Kivi et al., 2021; Lades et al., 2020), this study examines the emotionality of consumers over time to identify whether the emotions (e.g., sadness, joy) conveyed in consumers' social media messages increased or decreased over time. This approach adds to the understanding of the emotional

Table 1 (continued)

Article	Field of Research	Context	Method	Timeline	Duration	Brand-related eWOM	Social Media Data	Emotionality/Sentiment	Brand Strength
Cahyanto, T. A. (2022).									
Meng, L. M., Li, T., Huang, X., & Li, S. K. (2021).	Information Systems	Spread of rumors during COVID-19	Mixed methods, LDA, Text analysis	November 1, 2020, to February 20, 2021	3 months	×	✓	×	×
Zheng, L., Elhai, J. D., Miao, M., Wang, Y., Wang, Y., & Gan, Y. (2022).	Information Systems, Health	Health-related misinformation	Objective data (Google Trends, Baidu), Surveys	January 27, 2020, to February 29, 2020	1 month	×	×	×	×
Karami, A., Zhu, M., Goldschmidt, B., Boyajieff, H. R., & Najafabadi, M. M. (2021).	Health	Public opinions about vaccines	Machine learning rule-based approach	November 1, 2020, to February 28, 2021	4 months	×	✓	✓	×
Crocamo, C., Viviani, M., Famigliani, L., Bartoli, F., Pasi, G., & Carrà, G. (2021).	Health, Psychology	General population discussing COVID-19 on social media	Sentiment analysis	January 19, 2020, to March 3, 2020	1.5 months	×	✓	✓	×
Bustos, V. P., Comer, C. D., Manstein, S. M., Laikhter, E., Shiah, E., Xun, H.... & Lin, S. J. (2022).	Health	Public opinions about vaccines	Sentiment analysis	March 11, 2020, to May 17, 2021	1 year & 2 months	×	✓	✓	×
Choudrie, J., Patil, S., Kotecha, K., Matta, N., & Pappas, I. (2021).	Information Systems	General population discussing COVID-19 on social media	Deep learning and natural language processing (NLP)	February 1, 2020, to June 30, 2020	5 months	×	✓	✓	×
Wang, Y., Hao, H., & Platt, L. S. (2021).	Information Systems, Health	Crisis communications by governments	Dynamic network analysis	January 1, 2020, to April 27, 2020	4 months	×	✓	×	×
Apuke, O. D., & Omar, B. (2021).	Information Systems, Health	Spread of misinformation during COVID-19	Survey	Cross-sectional	NA	×	×	×	×
Pickles, K., Cvejic, E., Nickel, B., Copp, T., Bonner, C., Leask, J..... & McCaffery, K. J. (2021).	Health	Spread of misinformation during COVID-19	Longitudinal Survey	once per month from April 2020 to June 2020	Multiple waves over 3 months	×	×	×	×
Shahi, G. K., Dirkson, A., & Majchrzak, T. A. (2021).	Information Systems, Health	Spread of misinformation during COVID-19	Content Analysis	January 4, 2020, to July 18, 2020	6.5 months	×	×	✓	×

states of consumers during a time of uncertainty and crisis. For example, one aim of this study is to answer the question of whether a habituation effect occurred. Finally, we attempt to identify implications for decision-makers by describing events that caused consumers' emotional states to deteriorate or ameliorate.

Multiple sets of analyses are presented in this research. First, the emotions (e.g., sadness, fear) contained in Twitter posts (i.e., tweets) directed at brands in March 2020 (the beginning of the pandemic) and March 2019 (before the pandemic) are compared. Then, the trend of emotions conveyed in tweets during the first year of the pandemic (February 2020–February 2021) is analyzed.

2. Theoretical background

Next, we provide an overview of the relevant literature and existing theory related to eWOM, service failure and emotionality. Then, we develop and introduce exploratory research questions based on the identified research gaps.

2.1. Customer brand engagement theory

Brands constitute an important part of consumers' lives because they contribute to shaping identities, expressing feelings and emotions, and improving well-being (Escalas & Bettman, 2017). Brands are also perceived as offering order and security to consumers' lives by providing structure and consistency, which contribute to reassuring consumers and restoring a sense of control, particularly in times of crisis (Cutright et al., 2013; Verlegh et al., 2021). Thus, consumers expect brands to meet their needs and demands and to listen through offline channels (such as in-store customer service) and online channels (e.g., complaints voiced on Twitter). According to customer brand engagement theory, engagement refers to any action directed at a brand by a customer that goes beyond forming an attitude toward the brand (Kumar & Pansari, 2016). Such actions include, for example, purchases, referrals, feedback, and even posts on the official social media channels of a brand. Social media therefore constitutes a powerful tool to enhance consumer brand engagement because these media platforms are dynamic, pervasive, and relatively easy for customers to use (Swaminathan et al., 2022).

Social media presence constitutes a crucial factor that brands must consider to enhance their customer-based brand equity (Swaminathan et al., 2022). Thus, together with opportunities to promote their products, brands can use social media channels to build a reputation and increase customers' brand awareness and satisfaction (Swaminathan et al., 2022). As Edosomwan et al. (2011) note, brands that engage in social media activities are perceived as more attractive to customers and tend to perform better than brands that have a poor social media presence. Furthermore, recent estimates of Fortune 500 companies show that these successful firms tend to have at least one social media account (Porteous, 2021). By allowing customers to express themselves, brands can rely on social media as a tool to capture customers' sentiments and feelings conveyed through their eWOM, which can provide them with a constant barometer of dynamics and trends in the marketplace (Li et al., 2021).

2.2. eWOM emotionality

"Any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institutions via the internet" (Hennig-Thurau et al., 2004, p. 39) can be considered a form of eWOM. Consumers often post tweets to share their emotions about an experience (Wakefield & Wakefield, 2018). Indeed, information acquisition and emotional regulation are key functions of WOM (Berger, 2014). In general, given the perceived social risks involved in sharing negative content, users on social media tend to share positively biased content (e.g., Wakefield and Wakefield, 2018). Nevertheless, brand-related eWOM

is often generated in response to negative customer experiences and for the purpose of venting (Christodoulides et al., 2021; Xu et al., 2019). Moreover, emotional discussions on social media generate stronger audience responses than cognitive discussions (Song et al., 2016).

The analysis and understanding of emotions conveyed in large volumes of eWOM messages posted on social media is facilitated by the implementation of machine learning (Chatterjee et al., 2019; Saura, Ribeiro-Soriano, & Palacios-Marqués, 2022; Saura, Ribeiro-Soriano, & Saldaña, 2022). Thus, monitoring consumers' ever-changing sentiments and emotions with the help of social listening tools has become a top priority for researchers and social media marketing managers (Li et al., 2021). In times of crisis, whether caused by internal or external events, monitoring the emotional tone of customers' eWOM on social media has increased in importance (Tim et al., 2017).

2.3. Service failures in times of crisis

Prior research has examined how crises caused by negative marketing events (e.g., brand transgressions, service failures, product harm crises) may drive WOM (Khamitov et al., 2020). In particular, social media platforms are transforming the way brands communicate with dissatisfied customers after a negative event (Grégoire et al., 2015). Social media platforms may help to inform, enable communication, and establish connections during times of crisis (Tim et al., 2017). At the same time, the type of brand (e.g., differences in brand strength) may influence the way consumers interact with brands on social media. Thus, brands are interested in monitoring eWOM because it is visible to other consumers, who in turn may support and engage with negative posts. Attempts to address and satisfy customer complaints in service recovery are of utmost importance in the context of social media (Schaefer & Schamari, 2016). Hsu and Lawrence (2016) show that a high volume and negative valence of eWOM posted in reaction to a product recall crisis can reduce cash flow and firm value. The researchers found that this is particularly true for brands with relatively weak brand equity. In general, stronger brands appear to cope better in times of crisis for a variety of reasons (e.g., consumers' identification with the brand; Einwiller et al., 2006; consumer brand attachment; Ahluwalia et al., 2000; consumers' emotional attachment to the brand; Schmalz & Orth, 2012). However, high levels of equity and strong brand relationships may also amplify negative reactions toward brands (see Khamitov et al., 2020 for a review).

While the effects of crises caused by brands (e.g., service failures) on eWOM have been widely examined, this research builds on this work by examining how an external shock, such as the current COVID-19 pandemic, may affect consumers' eWOM on social media. Moreover, building on longitudinally oriented social media literature (e.g., Hansen et al., 2018; Hewett et al., 2016), this study examines the effects of this long-lasting exogenous shock (i.e., the COVID-19 pandemic) on eWOM. As Lambertson and Stephen (2016, p. 168) note, understanding whether "phenomena change over time" is important in the "fast-paced environment" of social media marketing. Thus, examining how the emotionality of consumers changes over a longer period, such as the pandemic, is important (see Table 1 for a literature review summary of the contributions to the literature).

This study explores three main research questions. First, it examines whether eWOM directed at brands during the COVID-19 pandemic differs in emotionality from the eWOM that was generated prior to the pandemic. Specifically, the aim is to answer the following research question:

RQ1: How did eWOM emotionality change from before the pandemic to during the pandemic period?

Because different stages of the pandemic may entail different levels of customer adaptation to the new situation, the second aim is to explore whether (and how) customer emotions conveyed through eWOM at brands change over time. Hence, by examining a longitudinal set of customer-generated eWOM, the second research question can be

addressed:

RQ2: Does eWOM emotionality change throughout the pandemic?

Finally, this study aims to explore whether the emotions conveyed by customers' eWOM differ depending on the strength of the brand. Specifically, it examines whether the emotionality of the eWOM directed at stronger brands differs from the eWOM directed at weaker brands.

RQ3: Does eWOM emotionality differ depending on brand strength?

In other words, is eWOM directed at stronger brands more positive than eWOM directed at weaker brands?

3. Methodology

The research questions were examined within the context of the airline industry. The airline industry represents a suitable context for this study because (1) it was dramatically affected by the COVID-19 pandemic (Eurocontrol, 2021; Piccinelli et al., 2021), (2) social media is an established communication tool for customers to contact airlines (Golmohammadi et al., 2021; Wolfe, 2018; Xu et al., 2019), (3) most airline customers' travel plans were disrupted by the pandemic, which resulted in a large volume of customer support inquiries (Elliott, 2021), and (4) the airline industry is an established research context for brand-related social media research (e.g., Alantari et al., 2022; Jalali & Papatla, 2019; Vo et al., 2019).

Twitter is widely used by airline customers to communicate with brands and generate eWOM (Piccinelli et al., 2021; Vo et al., 2019). A total of 44.3 % of UK-based internet users were active on Twitter in January 2021 (Kemp, 2021). Thus, in line with prior brand-related social media research (e.g., Borah et al., 2020; Golmohammadi et al., 2021; Lee, 2021; Rust et al., 2021), Twitter was used as a data source for this study (Boegershausen et al., 2022). Approximately 327,205 tweets were extracted that matched the search criteria (described in detail below) using the social listening tool Pulsar TRAC (<https://www.pulsarplatform.com>). Pulsar TRAC is linked to the Twitter application programming interface (API) and enables researchers to scrape tweets that match specific search criteria in a bulk approach. Furthermore, Pulsar TRAC is integrated with IBM's Watson Tone Analyzer API, a machine learning algorithm that facilitates the analysis of emotions contained in tweets. To ensure a high level of data quality, a set of sample criteria was applied to the search before scraping the data from Twitter.

First, the sample was restricted to tweets in the English language sent by users who indicated the United Kingdom, a country severely affected by the pandemic (Office for National Statistics, 2021), as the location on their Twitter profiles. On the one hand, focusing on tweets posted in the English language ensured the highest possible reliability when applying automated text analysis tools. Most machine learning-based text analysis tools, such as the IBM Watson Tone Analyzer, are primarily trained in the English language and thus are more powerful in this linguistic context. Previous work has identified IBM Watson as a successful tool for understanding consumer habits using its artificial intelligence platform (Latinovic & Chatterjee, 2022). The authors acknowledge that IBM Watson can also be used in the context of Twitter messages to understand the behavior, habits, and preferences of Twitter users as well as their repliers.

On the other hand, restricting the sample to UK-based consumers ensured that the respondents were more homogeneous. Considering that airlines have an international customer base and given the global scale of the pandemic, focusing on one group of consumers reduced the number of factors that could explain their emotional states. For example, UK-based airline consumers were primarily affected by the travel restrictions imposed by UK regulators.

Second, to examine the impact of COVID-19 on consumers' emotions conveyed by their eWOM, we scraped tweets posted during the period from February 1, 2020, to February 1, 2021. This period covers the first outbreak of COVID-19 in the United Kingdom (spring 2020), the relaxation of the initial restrictions (summer 2020), the second spike of COVID-19 cases (fall 2020), the restrictions during the holiday season of

2020–2021, and the beginning of the third British lockdown. To compare the emotions contained in tweets during this COVID-19-affected period with those during an unaffected period, we also scraped all historical tweets posted in March 2019. Specifically, the March 2019 sample included 17,141 tweets, while the February 2020–February 2021 sample included 310,064 tweets, totaling 327,205 tweets.

Third, the tweets of four leading airlines in the United Kingdom were scraped by the number of passengers (UK Civil Aviation Authority, 2022). Specifically, tweets directed at British Airways (i.e., tweets that included the @British_Airways handle), Virgin Atlantic (i.e., tweets that included the @VirginAtlantic handle), EasyJet (i.e., tweets that included the @easyJet handle), and Jet2 (i.e., tweets that included the @jet2-tweets handle) were collected. This choice of airlines was twofold: 1) it allowed for a large and representative cross-section of the UK airline customer base, with British Airways and Virgin Atlantic focusing on long-haul and business customers in the higher-price segments and EasyJet and Jet2 focusing on short-haul and leisure travelers in the lower-price segments, and 2) it allowed for the inclusion of airline brands that were stronger (i.e., British Airways and Virgin Atlantic) and weaker (i.e., EasyJet and Jet2). According to Skytrax World Airline rankings (World Airline Awards, 2021), in 2019, British Airlines and Virgin Atlantic were ranked 19th and 21st in the world ranking of airlines, respectively, and EasyJet and Jet2 were ranked 37th and 95th, respectively. This ranking is in line with the separate product ratings for each of the airlines: Virgin Atlantic (7/7), British Airways (6/7), EasyJet (2.5/5), and Jet2 (2/5) (Airlineratings, 2021).

In total, the search criteria scraped 127,491 tweets that included the @British_Airways handle, 115,459 tweets that included the @easyJet handle, 38,305 tweets that included the @VirginAtlantic handle, and 45,950 tweets that included the @jet2tweets handle. Tweets that were directed at more than one of these airlines were excluded.

Finally, the sample did not include any retweets because a retweet is a copied tweet shared with other users. Therefore, retweets contain the same content as original tweets, often with the additional identifier "RT." Thus, the inclusion of retweets in the sample could lead to an overreporting of certain emotions contained in the retweeted tweets.

To analyze the emotions conveyed in the scraped tweets, the widely used Tone Analyzer API was employed, which is part of the cognitive computing system IBM Watson (Dessi et al., 2019). The Tone Analyzer API computes emotional tone scores and is particularly suitable to analyze short texts and social media engagement such as tweets because it is designed to "analyze emotions and tones in what people write online, like tweets and reviews" (IBM, 2021). The tool uses a well-trained machine learning algorithm that builds on existing language and emotion models, such as *n*-gram, lexical, and support vector machine models (Berger et al., 2020; Bhuiyan, 2017). Moreover, the Tone Analyzer API adds features such as emoji and slang detection (Agrawal & An, 2012; Gundecha, 2016; Li et al., 2009; Wang & Pal, 2015). Thus, the tool's "bottom-up" approach is more reliable and accurate in detecting emotions than its merely lexical (or "top-down") counterparts, such as Language Inquiry and Word Count (Humphreys & Wang, 2018; Kübler et al., 2020). The dataset only included tweets for which Tone Analyzer detected emotions in the content.

4. Data analysis

The dataset contained 327,205 tweets directed at leading UK airline brands. The data included daily tweets between March 1, 2019, and March 31, 2019, as well as daily tweets between February 1, 2020, and February 1, 2021.

Multiple approaches were used to examine the research questions. First, an analysis of tweets in March 2019 (before the pandemic) with those in March 2020 (during the pandemic) was used to compare the emotionality of consumers between those periods. Second, the emotionality scores were compared over time (February 2020 –

February 2021) at the brand level. Third, the emotionality of tweets during different stages of the pandemic was compared, e.g., during the second lockdown in November 2020.

4.1. Comparing emotions in tweets between 2019 (before the Pandemic) and 2020 (during the Pandemic)

To facilitate the comparison between 2019 and 2020, the dataset was restricted to tweets posted in March 2019 and March 2020 for two reasons. First, the start of the pandemic on the European continent can be roughly traced to the beginning of March 2020 (World Health Organization, 2021). Second, the pre-COVID-19 control period in 2019 was restricted to March. In addition, there are systematic differences between tweets generated in 2019 and 2020. Tweets in 2020 received significantly more retweets ($M_{2020} = 0.10$, $M_{2019} = 0.02$; $F(1, 79402) = 289.53$, $p < .001$). Conversely, tweets in 2019 generated significantly more impressions ($M_{2020} = 274.40$, $M_{2019} = 717.01$; $F(1, 79402) = 81.67$, $p < .001$). Furthermore, in 2019, users who tweeted had a higher number of followers ($M_{2020} = 2688.49$, $M_{2019} = 6522.62$; $F(1, 79402) = 63.21$, $p < .001$), their tweets received more likes ($M_{2020} = 1.32$, $M_{2019} = 4.67$; $F(1, 79402) = 108.68$, $p < .001$), and they had a higher number of friends ($M_{2020} = 1435.73$, $M_{2019} = 852.98$; $F(1, 79402) = 343.65$, $p < .001$). Finally, the number of tweets in March 2020 was substantially higher than that in March 2019 ($N_{2020} = 62262$, $N_{2019} = 17141$).

4.1.1. Results

To investigate the differences between tweets from 2019 and 2020, a series of fractional regressions were run using the different emotion scores extracted from each tweet's content as dependent variables. Fractional regression models are appropriate to estimate these effects because the main dependent variables are the different emotions communicated in each tweet. The text analysis tool provides fractions between 0 and 1 that describe the presence of verbal cues for the different emotions in each tweet. In this case, treating the data as continuous leads to biased estimators (Murteira & Ramalho, 2016; Ramalho et al., 2011) because the predicted values of the dependent variable are not restricted to the unit interval (i.e., $0 \leq y \leq 1$). In fractional regression models, the effects are interpreted as standardized probit coefficients that can be more easily interpreted as average marginal effects, denoting the percentage change in the dependent variable for a 1 % change in the covariates (Papke & Wooldridge, 2008). In other words, changes in the proportion of different emotions present in tweets were observed. Since the overall emotionality score is the sum of all emotions contained in tweets, it does not range between 0 and 1. Therefore, a linear regression model with heteroskedasticity-robust standard errors was run (Long & Ervin, 2000).

The dependent variables were the five distinct emotions (i.e., sadness, joy, fear, disgust, and anger) as well as the overall emotionality score extracted from the content of each tweet. To explore differences across years and brands, two dummy variables (Year: 1 if 2020, 0 if 2019; Brand: 1 if strong brand (British Airways, Virgin Airlines) and 0 if weak brand (EasyJet, Jet2)) were included. A given tweet's number of retweets and number of likes as well as the user's number of friends and number of followers were included as control variables to adjust for the remaining differences between tweets. Initial inspection of the proportions for the different emotions revealed an overall pattern of increasing proportion for each of the emotions. Importantly, while tweets contained similar proportions of fear, disgust, and anger, a higher proportion of joy was observed in 2019 and a higher proportion of sadness was seen in 2020. Overall emotionality based on the sum of all distinct emotions showed that emotionality was slightly lower in 2020

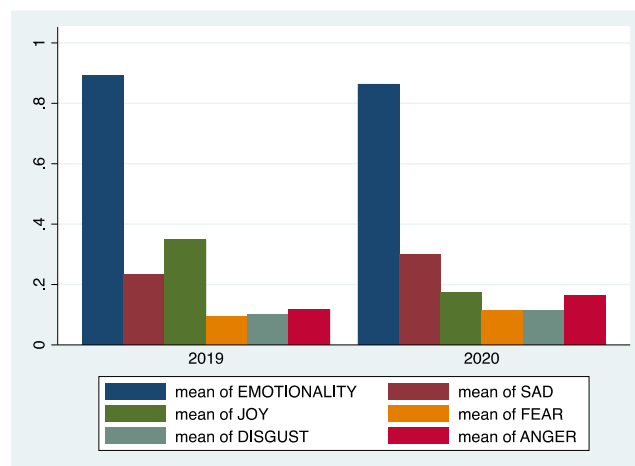


Fig. 1. Proportion of emotions pre- vs post- COVID (March 2019 vs March 2020).

(see Fig. 1).

The results from the fractional regression models corroborate this model-free evidence and mirror recent findings that emotional tweeting behavior has changed as a result of the pandemic.¹ First, for all negative emotions (i.e., sadness, fear, anger, and disgust), the results show that these emotions were proportionally more present in tweets from March 2020 than from March 2019 and that these differences in proportions were significant. Second, tweets from March 2019 featured proportionally more joy than tweets from March 2020.

4.2. Comparing emotions in tweets across brands and time

To compare differences in the emotionality of tweets over time, a Tobit panel model for all fractional dependent variables (i.e., for all emotions) and the emotionality score was run. The upper limits were defined to capture the censored nature of the data (Amore & Murtinu, 2021).

Models from the Tobit family are appropriate to estimate effects on dependent variables that are censored at the lower and upper limits (here, 0 and 1) (Amemiya, 1984; Greene, 2004). The dataset was structured as panel data at the monthly level. Observations covered a period of one year, from February 2020 to February 2021. Daily data were collapsed to monthly means, retaining the brand identifier. The number of followers, the number of likes, and the number of friends were included as covariates to capture potential confounds in the data that might bias the estimates of interest. The focal independent variable was the dummy variable denoting brand strength (1 = strong brand, 0 = weak brand). An interaction term was included between the brand dummy and the year to capture potential changes in the brand effect over time. Finally, a one-month lag of each emotion was included to remedy autocorrelation and capture monthly carry-over effects. A main effect-only model (Model 1) and the full model (Model 2) were run, including the interaction term between brand strength and year as well as all covariates.

5. Results

Evaluating the results from the main effects model first, overall, tweets directed at strong brands were more emotional than tweets directed at weak brands ($p < .05$). Furthermore, the results show that the

¹ Because the analytical focus is on the differences across emotions between years, coefficient estimates for the covariates were not included in the results. The extended results including all estimates are available on request.

emotional tone of tweets changed over time depending on brand strength. Specifically, tweets directed at strong brands contained a significantly lower proportion of sadness relative to weak brands ($p < .005$). Moreover, a significant negative interaction effect ($p < .05$) was found between yearly changes and brand strength on sadness. These results are independent of carry-over effects from the previous month's tweets ($p = .59$) and are not determined by a time trend. In addition, tweets directed at strong brands contained significantly more joy ($p < .05$). However, no significant interaction between yearly changes and brand strength emerged. Thus, the higher proportion of joy in tweets directed at strong brands was not dependent on yearly changes. Tweets directed at strong brands contained significantly more fear in 2021 compared to tweets directed at weak brands ($p < .05$). Finally, tweets directed at strong brands contained significantly higher proportions of disgust ($p < .005$) independent of yearly changes. Table 2 summarizes the model estimates.

To identify potential monthly trends, Model 2 was re-estimated using the monthly time series dummy. A significant carry-over effect was observed for emotionality such that the emotional tone in the previous month had a negative lagged effect on the emotionality of tweets in the subsequent month ($p < .05$). This suggests that once users have vented their emotions in a tweet, their tweets are less likely to be equally emotional the next month. In support of this notion, further inspection of the specific emotions revealed significant lagged negative effects for sadness, joy, fear, and anger (all $ps < 0.005$). No significant lagged effect

Table 2
Emotions in Tweets Across Brands and Time.

Emotion	Coefficient	SE	z value	p value	Log-likelihood
Sadness					
Year	-0.01	0.04	-0.02	0.93	71.86
Brand	0.04	0.03	2.05	0.04	
Number of Followers	0.00	0.00	1.50	0.63	
Number of Likes	-0.00	0.01	-0.07	0.94	
Number of Friends	-0.00	0.00	-0.46	0.64	
Joy					
Year	0.01	0.01	0.39	0.69	83.02
Brand	0.03	0.02	1.83	0.06	
Number of Followers	0.00	0.00	0.75	0.45	
Number of Likes	0.01	0.00	1.94	0.05	
Number of Friends	0.00	0.00	2.65	0.01	
Fear					
Year	-0.01	0.01	-0.87	< 0.001	142.33
Brand	0.01	0.01	1.73	0.08	
Number of Followers	0.00	0.00	2.88	0.01	
Number of Likes	-0.00	0.00	-1.97	0.05	
Number of Friends	-0.00	0.00	-0.52	0.60	
Disgust					
Year	-0.01	0.01	-0.64	0.53	134.71
Brand	0.01	0.01	0.98	0.34	
Number of Followers	0.00	0.00	1.25	0.21	
Number of Likes	0.00	0.00	2.51	0.01	
Number of Friends	-0.00	0.00	-0.96	0.34	
Anger					
Year	-0.01	0.02	-0.37	0.71	111.18
Brand	0.01	0.01	0.59	0.55	
Number of Followers	-0.00	0.00	-0.14	0.88	
Number of Likes	0.00	0.00	0.90	0.37	
Number of Friends	-0.00	0.00	-0.77	0.44	
Emotionality Score					
Year	-0.02	0.07	-0.37	0.77	37.09
Brand	0.08	0.04	2.16	0.03	
Number of Followers	0.00	0.00	1.79	0.07	
Number of Likes	0.01	0.01	1.22	0.22	
Number of Friends	0.00	0.00	0.35	0.73	

Notes. Estimation based on N = 57 observations. Year (1 = 2021, 0 = 2020) and brand (1 = strong brand, 0 = weak brand) are dummy variables.

emerged for disgust.

Specifically, there was a significant negative effect of brand strength on the proportion of sadness such that tweets directed at strong brands contained lower proportions of sadness ($p < .005$). This effect was also determined by a significant time trend, such that relative to weak brands, the effect increased between February and May 2021 (all $ps < 0.05$). Furthermore, tweets directed at strong brands contained a lower proportion of fear, even though this effect was only marginally significant ($p = .05$). The interaction between the monthly dummy and brand strength revealed that tweets directed at strong brands contained significantly higher proportions of fear only in February 2020 and January and February 2021 (all $ps < 0.05$).² All these effects are relative to the previous month. A similar pattern emerges for anger: tweets directed at strong brands contained lower proportions of anger ($p = .05$), especially in May and June 2021 (all $ps < 0.05$). For joy, a significant effect of brand strength was observed such that tweets directed at strong brands contained significantly more joy than tweets directed at weak brands ($p < .05$). However, this effect was not determined by monthly changes.

5.1. Comparing emotionality in tweets across different COVID stages and across brands

The temporal periods in the dataset were coded to represent the major events during the lockdown in the United Kingdom. Specifically, the temporal periods were coded as follows: 1) first lockdown of COVID-19 (March 20, 2020 – July 4, 2020), 2) first relaxation of measures (July 4, 2020 – November 4, 2020), 3) second lockdown of COVID-19 (November 5, 2020 – December 2, 2020), 4) second relaxation of measures (December 2, 2020 – January 5, 2021), and 5) third lockdown of COVID-19 (January 6, 2021 – February 1, 2021). The period before March 2020 was coded as zero to represent the control group. It was specified as the baseline condition in the following analyses to allow for comparison of the emotionality of users in each of the post-COVID-19 periods with the pre-COVID-19 period.

Following the coding process, emotionality was first regressed using a linear regression with robust errors on the temporal periods, specifying pre-COVID-19 as the baseline condition and controlling for brand strength, number of retweets, number of likes, number of friends, and number of followers, using robust errors in the estimation. The analyses were repeated with sadness, joy, and anger. As shown graphically in

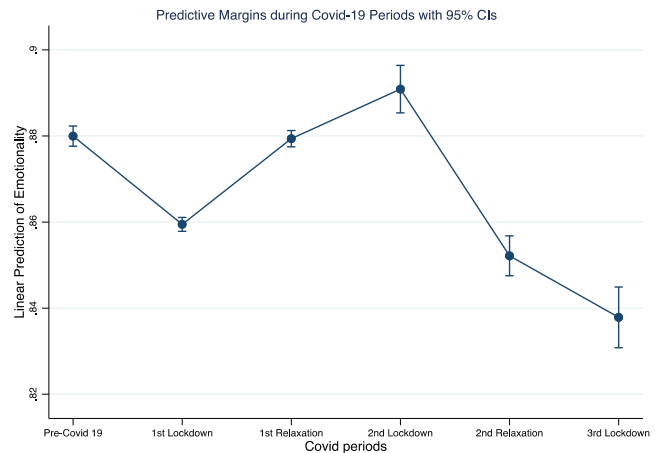


Fig. 2. Fluctuations in emotionality during the COVID-19 period.

² All effects are relative to the previous month.

Fig. 2, the results suggest that emotionality decreased in the first lockdown period compared to the pre-COVID-19 period ($b = -0.02$, $SE = 0.001$, $p < .001$). Surprisingly, emotionality increased in the second lockdown period compared to the pre-COVID-19 period ($b = 0.01$, $SE = 0.003$, $p = .002$), and it decreased again in the third lockdown period ($b = -0.04$, $SE = 0.004$, $p < .001$). Regarding the relaxation of measurements and restrictions following each lockdown period, the results suggest that emotionality marginally decreased in the first relaxation of the measurement period compared to pre-COVID-19 ($b = -0.002$, $SE = 0.001$, $p = .086$), and it significantly decreased in the second relaxation of measurements compared to pre-COVID-19 ($b = -0.03$, $SE = 0.003$, $p < .001$).

Following the main effect analyses, predictions about the relationship between emotionality and the interaction of brand strength and the different COVID-19 periods were tested. Emotionality was regressed in temporal periods, specifying pre-COVID-19 as the baseline condition, and brand strength (on the interaction term between the categorical temporal variable and brand strength) while controlling for the number of retweets, number of likes, number of friends, and number of followers using robust errors in the estimation.

The results of the interaction test suggest a positive interaction between the first lockdown period (vs pre-COVID-19 period) and high (vs low) brand strength ($b = 0.04$, $SE = 0.003$, $p < .001$) on emotionality, which was replicated in the second lockdown period for high brand strength ($b = 0.03$, $SE = 0.007$, $p < .001$) but not in the third lockdown period ($p = .510$). Moreover, emotionality increased in the first relaxation of measurements (vs pre-COVID-19 period) for high (vs low) brand strength ($b = 0.049$, $SE = 0.003$, $p < .001$), but this was not replicated for the interaction term between the second relaxation of measurements (vs pre-COVID-19) and high (vs low) brand strength ($p = .676$). For further details on each specific emotion, please refer to Table 3 and Fig. 3.

Overall, sadness and anger were higher for weaker brands, although stronger brands suffered from steeper increases in these negative emotions. Similarly, joy and emotionality were higher for stronger brands, providing support for the notion that a buffer effect of brand strength exists if an exogenous shock, such as the COVID-19 crisis, occurs.

6. Discussion and conclusion

This study explores the impact of an unforeseen exogenous shock (e.g., the COVID-19 crisis) on consumers' emotionality conveyed through eWOM. To address this research question, we examined the crisis from two perspectives. First, we compared tweets directed at four airline brands before (i.e., March 2019) and during (i.e., March 2020) the crisis. We found that while overall emotionality decreased, the tone of the tweets shifted from being predominantly joyful before the pandemic to mostly sad during the pandemic.

Second, we examined the way the emotionality of eWOM changed over time throughout the pandemic. For this purpose, we reviewed tweets directed at airline brands in the period from February 1, 2020, to February 1, 2021. The results of the interaction tests between the specific COVID-19 periods – as opposed to before COVID-19 – and brand strength suggest that sadness, fear, disgust, and anger in the 1st and 2nd lockdowns and the 1st and 2nd relaxation of restrictions (vs the pre-COVID-19 period) interacted positively and significantly with brand strength. This means that for strong (vs weak) brands, sadness, fear, disgust, and anger were higher during the 1st and 2nd lockdowns and the 1st and 2nd relaxation of restrictions than during the pre-COVID-19 period. In line with this, the scores for joy for strong (vs weak) brands were lower during the 1st and 2nd lockdowns and the 1st and 2nd relaxation of restrictions compared to the pre-COVID-19 period.

6.1. Theoretical contributions

The findings build on the extant literature in multiple ways. First, following the tradition of using large datasets consisting of Twitter data

Table 3
Emotions during the COVID-19 periods and across brands.

VARIABLES	Emotionality	Sadness	Joy	Anger
1st Lockdown (vs Pre-COVID-19)	-0.0426*** (0.00210)	0.0187*** (0.00418)	-0.112*** (0.00593)	0.0395*** (0.00415)
1st Relaxation (vs Pre-COVID-19)	-0.0254*** (0.00223)	0.00835* (0.00445)	-0.0324*** (0.00627)	0.00253 (0.00444)
2nd Lockdown (vs Pre-COVID-19)	-0.00667 (0.00554)	-0.0631*** (0.0119)	0.224*** (0.0164)	-0.0790*** (0.0128)
2nd Relaxation (vs Pre-COVID-19)	-0.0232*** (0.00437)	-0.0882*** (0.00846)	0.176*** (0.0121)	-0.103*** (0.00882)
3rd Lockdown (vs Pre-COVID-19)	-0.0328*** (0.00677)	-0.00643 (0.0141)	0.0867*** (0.0187)	-0.0426*** (0.0135)
Brand Strength (High vs Low)	-0.0124*** (0.00239)	-0.0879*** (0.00499)	0.140*** (0.00703)	-0.0297*** (0.00491)
1st Lockdown (vs Pre-COVID-19) * Brand Strength (High vs Low)	0.0434*** (0.00290)	0.0150** (0.00600)	0.0408*** (0.00845)	-0.000660 (0.00587)
1st Relaxation (vs Pre-COVID-19) * Brand Strength (High vs Low)	0.0491*** (0.00307)	0.0268*** (0.00643)	0.0186** (0.00893)	0.0252*** (0.00633)
2nd Lockdown (vs Pre-COVID-19) * Brand Strength (High vs Low)	0.0336*** (0.00666)	0.0671*** (0.0146)	-0.125*** (0.0198)	0.0424*** (0.0154)
2nd Relaxation (vs Pre-COVID-19) * Brand Strength (High vs Low)	-0.00228 (0.00547)	0.0669*** (0.0113)	-0.0919*** (0.0157)	0.0107 (0.0114)
3rd Lockdown (vs Pre-COVID-19) * Brand Strength (High vs Low)	-0.00538 (0.00817)	-0.0338** (0.0172)	-0.0536** (0.0227)	-0.0260 (0.0167)
Number of Retweets	0.0102*** (0.00188)	0.0321*** (0.00431)	0.00469 (0.00379)	-0.00241 (0.00252)
Number of Likes	0.000392*** (4.23e-05)	-0.000658*** (7.22e-05)	0.00135*** (0.000115)	-5.24e-05 (4.84e-05)
Number of Friends	2.31e-07 (1.65e-07)	-5.23e-06*** (5.90e-07)	9.94e-06*** (7.88e-07)	-6.32e-06*** (9.15e-07)
Number of Followers	-1.20e-07*** (2.69e-08)	-1.88e-07*** (5.83e-08)	4.79e-09 (3.22e-08)	-1.58e-07*** (5.71e-08)
Constant	0.885*** (0.00177)	-0.492*** (0.00361)	-0.896*** (0.00510)	-1.012*** (0.00364)
Observations	310,064	310,064	310,064	310,064
R-squared	0.006			

Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

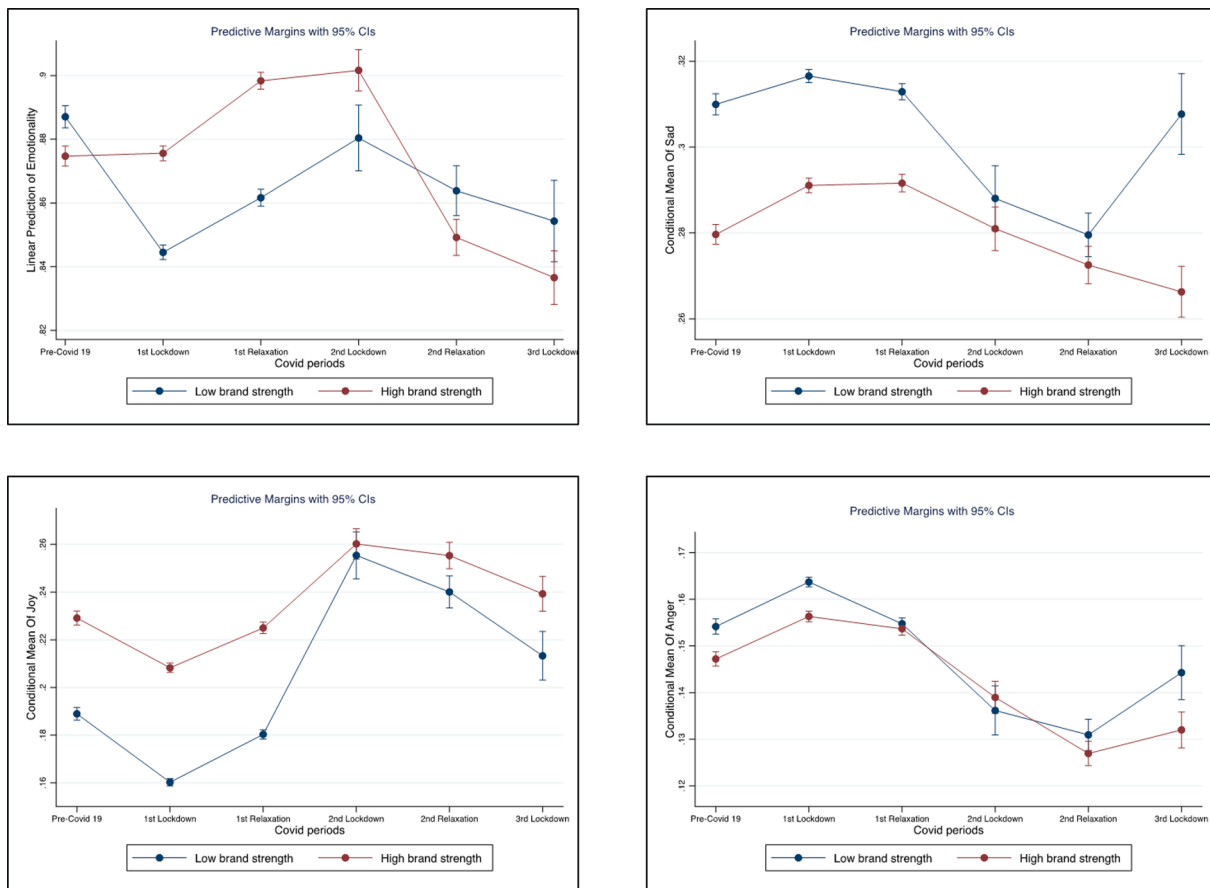


Fig. 3. Fluctuations of emotionality, sadness, joy, & anger during COVID-19 periods across brands.

to analyze people’s emotions (Boegershausen et al., 2022), a dataset of 327,205 tweets was utilized to examine the effects of the COVID-19 pandemic on consumers’ emotions. While a growing body of literature uses social media data to analyze phenomena related to COVID-19 (e.g., Abd-Alrazaq et al., 2020; Meng et al., 2021; Saura, Ribeiro-Soriano, & Palacios-Marqués, 2022; Wang et al., 2021), to the best of our knowledge, no such research has focused on consumer emotionality. Thus, previous research is extended by examining how the COVID-19 crisis influences consumers’ eWOM emotionality. Ozuem et al. (2021) stressed the need for further research to understand consumers’ reactions to service failure and recovery strategies during COVID-19. This research shows that the crisis affected the way consumers reached out to brands as well as how eWOM evolved over time.

Second, the findings extend existing eWOM theory by showing how an unforeseen and long-lasting exogenous shock, such as the COVID-19 crisis, affects consumers’ eWOM. This study therefore answers Lambertson and Stephen’s (2016) call for more longitudinal social media datasets. This research builds on the extant eWOM literature by demonstrating that consumers adapted to the pandemic in a relatively short period. The findings add to existing research by lending support to the notion that consumers adapted to the situation, and consequent service failures due to renewed travel restrictions did not generate the same level of eWOM emotionality as when the pandemic hit in March 2020.

Third, our findings build on prior work related to brand equity theory and brand-level differences in reaction to service failures (e.g., Aaker, 1991; Hazée et al., 2017; Hsu & Lawrence, 2016; Khamitov et al., 2020). Specifically, we found that weaker brands suffered more from negative eWOM than stronger brands throughout the course of the pandemic. Thus, brand strength may act as a safety cushion for negative brand-related eWOM in cases of service failures that are not attributed to

brands. In other words, the research contributes to the literature by demonstrating that the brand buffer effect still exists even if a service failure is caused by an exogenous shock.

Finally, the findings add to the understanding of emotions throughout the COVID-19 crisis (e.g., Kivi et al., 2021; Lades et al., 2020) by showing changes in consumers’ emotionality over time. Specifically, consumers adapted relatively quickly to the new situation, and the levels of negative emotion conveyed in their tweets decreased over time. Moreover, consumers’ emotionality appeared to gradually decrease throughout the first year of the pandemic.

6.2. Managerial implications

While this paper provides a series of theoretical contributions, the findings are also important to marketing managers. Overall, the findings provide some indications of what managers should expect in situations of crisis exogenous to the brand. The study found that brands that operate in an industry that is affected by a crisis will be subject to consumer anger and sadness. In this case, COVID-19 service disruptions were studied, but the findings should be applicable to any similar shock, such as other health emergencies, natural disasters, or even political crises such as conflicts and wars.

The findings provide important insights into how companies can react to situations of exogenous crisis depending on the stage of the crisis and, especially, the strength of their brand in the market. Both stronger and weaker brands received negative reactions at the onset of the pandemic, signaling that the unexpectedness of the crisis did not seem to particularly influence consumers’ reactions. However, stronger brands managed to survive consumers’ negative sentiments better under an exogenous shock, while weaker brands suffered more from consumers’ negative reactions. This effect suggests that while companies cannot

control the extent of exogenous shocks, they can work on brand strength perceptions and can emphasize this aspect of their branding, especially in times of crisis. Building these capabilities in advance allows marketing practitioners to prepare emergency plans and to address consumers' negative sentiment through communication campaigns, promotions, and other service recovery strategies.

Thus, managers of weaker brands should pay particular attention to building dynamic capabilities to manage crises, such as investing in customer service to strengthen their image and aspiring for a softer recovery when the brand is experiencing trouble. Similarly, managers of stronger brands may capitalize on their image by designing specific communications to reassure customers at the onset of a crisis. Because consumers do not seem to react negatively when brands attribute a crisis to *force majeure* and external factors, stronger brands can develop better responses by highlighting the resources they can invest to mitigate disruptions, ultimately leading to a more positive evaluation of the brand.

6.3. Limitations and Future research directions

Our research describes how the COVID-19 pandemic affected consumers' emotionality in eWOM over time and offers several potential avenues to further examine factors, mechanisms, and outcomes that we could not include in our investigation. First, while we investigated the context of airline brands as the key setting for our inquiry, future studies might compare different sectors. Service disruptions can occur in all sectors of the economy, and each affects consumers' emotionality in different ways. A postponement of a long-awaited trip may elicit a stronger emotional response than, for example, not finding a favorite brand on a supermarket shelf. Future research could expand our inquiry by comparing these different settings and identifying common factors as well as their peculiarities.

Second, to minimize the potential influence of confounding factors on our results, our study focused on UK-based consumers only. This allowed us to be more detailed in our analysis and to have a homogeneous subset of respondents who shared commonalities. Moreover, this focus on one country ensured that the patterns observed in the data were not dependent on cultural and policy differences (e.g., travel restrictions). Future research might examine whether different cultural contexts, especially those defined by higher levels of power distance or uncertainty avoidance, have a significant impact on consumers' emotional well-being.

Finally, while Twitter is one of the most commonly used tools for customers to reach out to airlines (e.g., Piccinelli et al., 2021), future research may also examine whether eWOM emotionality on Twitter differs from other social media platforms. Users on these platforms are diverse in their behaviors and demographic characteristics. Our data limit inferences about the influence of these characteristics on emotionality in tweets. Future research could address this limitation, thereby adding further depth to our findings and providing more nuanced insights into individual differences in social media behavior.

Conflict of Interest.

The authors confirm they have no conflict of interest to declare. Authors also confirm that this article adheres to the ethical guidelines specified in the APA Code of Conduct as well as the authors' national ethics guidelines. The authors confirm that the article submitted, to the knowledge of all authors, has not been published elsewhere previously and is not under consideration for publication elsewhere. This submission is approved by all authors and by the responsible authorities where the authors carried out the work. If accepted for publication, this article will not be published elsewhere including electronically in the same form, in English, or in any other language, without the written consent of the copyright-holder.

CRedit authorship contribution statement

Maximilian H.E.E. Gerrath: Supervision, Formal analysis, Data curation, Conceptualization, Methodology, Writing - original draft, Writing - review & editing. **Alexander Mafael:** Methodology, Formal analysis, Data curation, Conceptualization, Visualization, Writing - original draft, Writing - review & editing. **Aulona Ulqinaku:** Visualization, Validation, Project administration, Methodology, Data curation, Conceptualization, Formal analysis, Writing - original draft, Writing - review & editing. **Alessandro Biraglia:** Conceptualization, Formal analysis, Methodology, Writing - original draft, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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