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WHAT DRIVES VIRALITY OF ONLINE COMPLAINTS? THE CRITICAL ROLES OF CONTENT AND NON-CONTENT FACTORS

by

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ABSTRACT

FACULTY OF SOCIAL SCIENCE

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WHAT DRIVES VIRALITY OF ONLINE COMPLAINTS?
THE CRITICAL ROLES OF CONTENT AND NON-CONTENT FACTORS

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The advent of digital environment has provided ample avenues for consumers to voice their complaints. Meanwhile, it has also removed the restrictions on others' participation in these conversations. Some phenomenal examples including "United Breaks Guitars" on YouTube in 2009 and "United overbook flight 3411" on Twitter after 8 years, United Airlines obviously failed to progress in dealing with online complaints properly. Any online complaint may be substantially discussed, supported, and shared, however, not all of them are. To predict and manage complaints before they become viral is a critical but challenging task for both researchers and managers for several reasons. First, the volume, velocity and variety of user-generated content online are massive, thus, requires tremendous efforts and resources to capture, distinguish, monitor and analyse the complaints and exclude irrelevant information. Second, understanding complaints virality is a challenging task, however, there is no definite strategy or pattern for researcher's and manager's reference. Taking other situational factors into consideration (e.g., the traits of the industry, the equity of the involved brand, and the resource of the organization), investigating online complaints for a specific industry or company tend to be case by case analysis rather than rely on other's experience or existing works. Finally, after analysing the complaints, what response strategy should be adopted is still unclear, which is trickier on public platforms that information is access to broad audience and online firestorm can happen without any warning. To have a comprehensive understanding of complaint virality and aim to propose a more practical method for conducting similar research, this thesis investigated various potential factors for complaint virality from diverse aspects.

A text-mining study was conducted in support of this research. Web scraping was applied to obtain complaints and relevant information from Twitter, followed by natural language processing techniques for data pre-processing, and various big data analysis techniques were adopted and compared to explore all potential factors of complaint virality. Results confirm the importance of the complainer's and the organisation's characteristics as well as the linguistic and psychological attributes of the negative Tweet in predicting complaint virality. The pattern of organisational response and its impact on the virality were also investigated. Finally, the interactive effects of the content attributes and topics were confirmed.

The findings of this study prove that both central and peripheral routes will come into effect when readers react to complaints on social media. The number of follower a complainer has is a predominant factor of complaint virality which is in line with the social network theory. Meanwhile, physical cues of complaints, such as word count and use of attachments, work as obvious signals for readers to assess the complaints. The density of anger is found to trigger reader’s support, confirming the action-stimulating effect of high arousal emotions. Readers are also found more likely to be influenced by expressions with higher social confidence, but they are less likely to support subjective complaints. Furthermore, different complaint topics are found to cause the variance of virality, and the attributes of complaints moderate this relationship. Finally, organisational response is proven to decrease the possibility of complaint virality. More importantly, the tipping point of response effectiveness is found to be three days in this case. These observations provide guidance on how to decide which complaints to respond and when to respond.

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ABBREVIATIONS

ANOVA	Analysis of Variance
CCB	Consumer Complaining Behaviour
ELM	Elaboration Likelihood Model
KMO	Kaiser-Meyer-Olkin
LDA	Latent Dirichlet Allocation
LIWC	Linguistic Inquiry and Word Count
NLP	Natural Language Processing
NLTK	Natural Language Toolkit
POS	Part-of-speech
SD	Standard Deviation
SFR	Service Failure Recovery
UGC	User Generated Content
UK	the United Kingdom
US or USA	the United States
VIF	Variance Inflation Factor
WOM	Word of Mouth

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RESEARCH THESIS: DECLARATION OF AUTHORSHIP

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Title of thesis: What Drives Virality Of Online Complaints? The Critical Roles Of Content And Non-content Factors

I declare that this thesis and the work presented in it are my own and has been generated by me as the result of my own original research.

I confirm that:

1. This work was done wholly or mainly while in candidature for a research degree at this University;
2. Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated;
3. Where I have consulted the published work of others, this is always clearly attributed;
4. Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work;
5. I have acknowledged all main sources of help;
6. Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself;
7. None of this work has been published before submission

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CHAPTER 1 INTRODUCTION

1.1 Overview

This thesis investigates what complainer, organisational and other characteristics drive the virality of complaints on social media. This first chapter presents an overview of this thesis, starting from the research background, which highlights the changes and challenges arising from diverse and evolving complaining behaviours online. Specifically, as the use of social media becomes popular for opinion exchange, complainers are increasingly empowered, which further highlights the need for research in this domain. In addition, this chapter also identifies the research gaps by reviewing the extant marketing literature and understanding marketing practice and proposes a set of research questions. This chapter is structured is as follows. Section 1.2 introduces the research background. Section 1.3 clarifies the research gaps, and Section 1.4 presents the research aim and questions. Finally, Section 1.5 outlines the structure of this thesis.

1.2 Research Background

1.2.1 Consumer Complaining Behaviour

Nowadays, consumers no longer passively rely on the product/service quality signals created and conveyed by the organisation (Kotler and Armstrong, 2012) but actively seek and identify information from various source (Shen and Sengupta, 2018). Shifting from traditional channels, such as newspaper and television, to advanced web technology, the speed and limit of acquiring information have also dramatically changed (Berger and Milkman, 2012). More importantly, as social beings, it is no doubt that people have the desire to connect with others and exchange their attitude rather than just receiving information. The informal opinion exchange process is termed as word-of-mouth (WOM) when the conversation is relevant to some certain products, services and brands (Westbrook, 1987). The rapid development of digital technology and social media in the last decades[1] have facilitated the revolution of communication and information searching methods (Herhausen *et al*., 2023). For instance, the average hours of weekly Internet use per person in the United Kingdom (UK) increased 15 hours from 2005 to 2020 (Statista,

[1] Some social media giants, such as LinkedIn, Meta (former name Facebook) and YouTube were launched in 2003, 2004 and 2005 respectively (LinkedIn Corporation, 2014; Meta, no date; Britannica, 2023).

2022, see Figure 1). The latest data shows that people in the UK spend more than 5 hours on Internet via different devices and 1.56 hours surfing the social media in 2022 (Statista, 2023a; see Figure 2 for distribution).

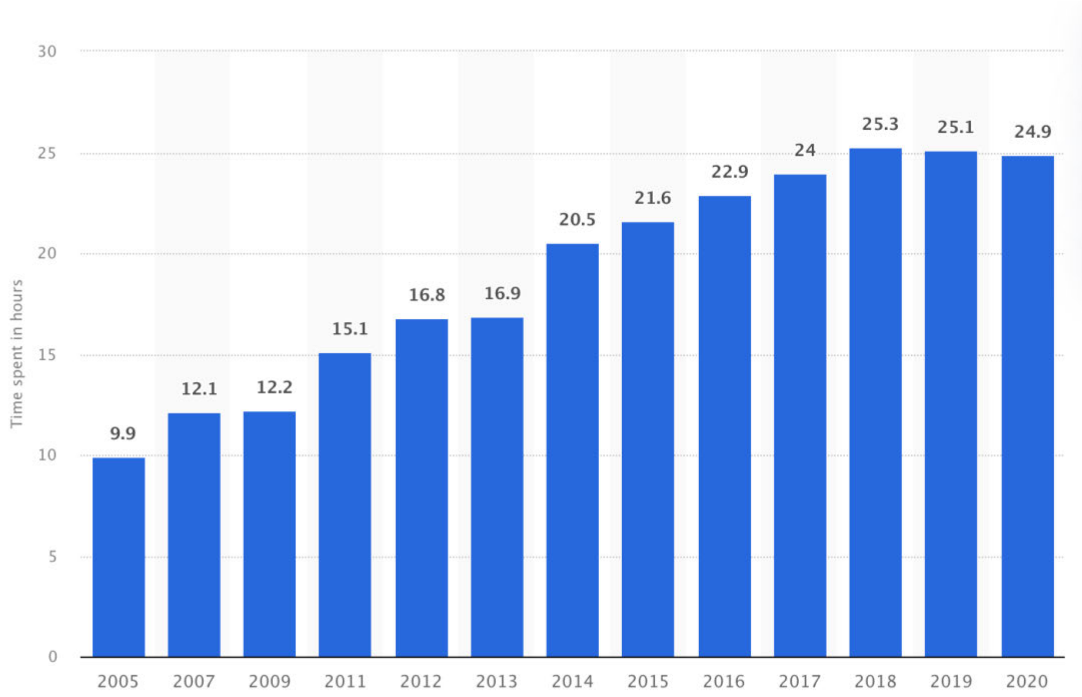

Figure 1 Hours of Internet use per week per person in the United Kingdom from 2005 to 2020

Source: Statista (2022)

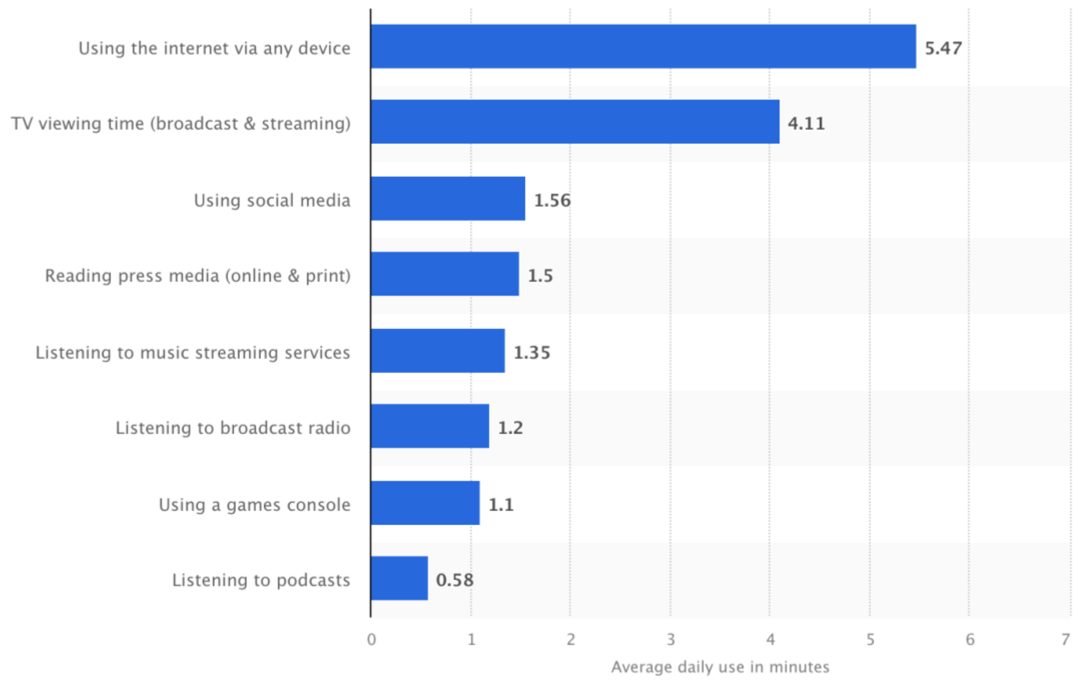

Figure 2 Average daily media use in UK, Quarter 3, 2022

Source: Statista (2023a)

Advances in technology not only enables consumers to contact their family and friends, but also makes contact with other potential consumers accessible without geographical constrains (Jabr and Zheng, 2014). Specifically, online user generated content (UGC) has thoroughly influenced marketing implications, including consumers purchasing process, brand image and reputation and marketing outcomes (Voorhees *et al*., 2006; Ameri *et al*., 2019). This tendency is also significant in consumer complaining behaviour (CCB) as consumers can swiftly access various complaining platforms (Das *et al*., 2022), which to large extent remove the barriers and costs when complaining offline (Dolan *et al*., 2019). Specifically, surveys also found that consumers rely more on digital channels for complaining, which showed an increase from 12% in 2017 to 43% in 2020 (Alcántara, 2022). More importantly, compared with positive comments, negative reviews are regarded as more influential and persuasive (Chen and Lurie, 2013) since consumers who decide to complain in public intent to expose the failure to remind and communicate with other potential consumers (Ward and Ostrom, 2006; Grégoire *et al*., 2018). Around 90% of consumers claimed that they had avoided a product or service provider because of negative reviews (Reviewtrackers, 2018). In addition, more than half of consumers would have expectations towards organisational responses to their complaints on social media but unfortunately received no feedback (Alcántara, 2022) and 97% of observers regarded responses as part of the review (Murphy, 2019).

Furthermore, the online social platforms enable various forms of negative information to spread swiftly, and even virally. A well-known disastrous incident was a Vietnamese American passenger being violently dragged out from an overbooked United Airlines flight (Victor and Stevens, 2017). Other passengers on board uploaded the video of the incident, which turned into a firestorm on social media – viewed 6.8 million times and shared 87,000 times within one day (Chicago Tribune, 2017). United CEO claimed that they would “re-accommodate” the passenger on the next day (United Airlines, 2017), meanwhile, he praised their employee for defending their procedure in their internal email (Rosoff, 2017), which triggered fiercer boycott (Quealy, 2017; Wise, 2017).

1.2.2 Challenges of Complaint Management

The above case, along with many others, raises a simple but important question - how to manage complaints to prevent disastrous situations. Provided with effective recovery solutions, consumers may become satisfied (Augusto de Matos *et al*., 2007). It is also believed that some consumers might be more loyal compared with those who had never come across the failure (Allen *et al*., 2015). On the contrary, the 'double deviation' (i.e., failed recovery situation post initial complaint) would trigger and intensify consumer's negative feelings (Surachartkumtonkun *et al*., 2015), even worse, it would break consumer's trust (Robinson, 1996; Basso and Pizzutti, 2016). However, as the importance of complaint management and failure recovery has attracted sufficient attention, it is still an acid test for all organisations (Morgeson III *et al*., 2020) although many organizations have allocated considerable resources to optimize their strategies (Homburg *et al*., 2010). For instance, the complaint management software market already reached $2.2 billion in 2022, and it is expected that a sustained annual growth of around 11% will be seen from 2023 to 2028 (IMARC Group, 2023). However, there are still a large percentage of complainers who express their disappointment with complaint management (Alcántara, 2022).

This challenge is caused by several factors. First, complaint management strategies are frequently homogeneous, which means that organisations usually provide similar response regardless of consumer's own situation or expectation (Gelbrich and Roschk, 2011). Being an interactive (Tax *et al*., 1998) and dynamic process (Van Vaerenbergh *et al*., 2019), complaint handling requires the consideration of both parties' status and characteristics (Van Vaerenbergh *et al*., 2012). However, previous studies failed to formulate recovery strategies from a comprehensive perspective (Homburg *et al*., 2010). Although some researchers (e.g., Hui and Au, 2001; Schoefer and Diamantopoulos, 2008) investigate the consumer-related determinants of recovery effectiveness, they did not examine how these factors will influence the overall complaining process if certain strategies (i.e., process, outcome or behavioural focused recovery) were adopted (Homburg *et al*., 2010). Another stream of research tend to overemphasize the high-quality of complaint handling but ignore the actual position and attitude of the organisation (see Fornell and Wernerfelt, 1988). For example, given that switching cost for consumers are different in diverse market conditions (e.g., monopoly versus monopsony), the importance of complaint management might be different for organisations in these industries (Evanschitzky et al., 2011).

Second, complaint management has been studied mostly in the offline environment, while research in online scenario is a relatively new domain. However, online complaint handling can be more complex due to the traits of online environment (Balaji *et al*., 2016). For example, the anonymity of the reviewer, the fast speed of information spread, and significant amount of data. More importantly, the open access to online platforms transfers the complaining behaviour from an individual action (offline) into a public conversation, in other words, anyone can observe and get involved. Online interactions are no longer limited to the organisation and the involved 'victim'. Bystanders' judgments of the incident (Chen and Lurie, 2013; Hogreve *et al*., 2019; Surachartkumtonkun *et al*., 2021) and their attitudes towards either side may encourage or dissuade the 'victim' to take further actions (de Campos Ribeiro *et al*., 2018). Meanwhile, organisational response to the complaint will also have impact on bystanders' temporal decision whether they would spread the negative WOM or not (Herhausen *et al*., 2019) as well as bystanders' intention to complain if they come across the failure one day (Wang and Chaudhry, 2018). Thus, studies on online CCB should hold an overall perspective that take into account other stakeholders, meanwhile, the management of online complaints requires outstanding processes compared with offline strategies, such as combining previous offline experience and web-based techniques (Cheung and Thadani, 2012).

Third, the other challenge of complaint management is the number of complaints, which is now surging given that consumers are more empowered (Weitzl and Einwiller, 2020) and familiar with the complaining channels (Miquel-Romero *et al*., 2020). For example, complaints against airlines and travel agencies presented to the Department of Transportation in the United States increased 568.4% from 2019 to 2020, reaching more than 100 thousand in 2020 (Schmidt, 2021). Consumers turn to public, especially online platforms if they fail to hear from the organisation through public complaining channels (Istanbulluoglu *et al*., 2017). They expect to receive satisfying recovery since they believe the nature of the publicity and high speed of spread can place the organisation under pressure (Van Noort and Willemsen, 2012). Meanwhile, the ease of the interaction and use of the channels require less efforts to complain (consumers no longer need to travel to the shop or make dozens of phone calls and keep waiting), which also contribute to the massive number of complaints. However, for organisations, how to legitimize the great number of complaints and decide whether and how to reply is both a time-consuming and difficult task. Thus, studies on large-scale of CCB data may need to automate the process of identifying the key components of complaints and proposing corresponding recovery strategy.

Finally, the response speed is related to consumer's satisfaction with recovery outcome (Taylor, 1994), some studies have proven that prompt responses may not always be beneficial (Van Vaerenbergh *et al*., 2019) and there is no linear relationship between consumer expectation and organisational response time (Hogreve *et al*., 2017). Thus, the interactions between timing and other aspects of complaint handling (Zhou *et al*., 2014) should be included when discussing response timing issues to verify the contradictory findings by previous studies. Meanwhile, it is impossible for organisations to respond to all complaints simultaneously, which lead to a prioritization challenge for organisations identifying which complaints to deal with at the appropriate time. Thus, how to prioritise the complaints remains a major challenge especially when the volume of complaint is substantial in online environment. Against this backdrop, the author believes that a study on the online CCB is timely and warranted.

1.3 Research Gaps

This thesis focuses on the virality of online CCB, and the research gap presented here examines the unexplored dimensions of extant studies. The primary shortcoming with some previous studies is that the boundary between online CCB and general eWOM and the different characteristics of online CCB and general complaints are not always clarified (Liu *et al*., 2019; Gruen *et al*., 2006; Zhang *et al*., 2010). For example, research on video game industry finds that number of online reviews has positive impact on the purchase intention of experienced players and can also stimulate the sales of unpopular games (Zhu and Zhang, 2010). Another study on box office (Liu, 2006), investigates the mutual effect between eWOM and sales. Specifically, the number of eWOM is found have positive impact on both concurrent movies sales but also on the non-concurrent films although the impact is not long-lasting. In return, similar effects are also observed by investigating the impact of sales on eWOM volume (Duan *et al*., 2008). Besides, the other stream of studies show interest in motivations of participating in eWOM and draws to the conclusion that desire for communication, monetary incentives, self-enhancement and showing concerns for others are main reasons (Hennig-Thurau *et al*., 2004). While another study illustrates that desire to help others is more critical compared with seeking for monetary benefits (Yoo *et al*., 2013). However, a common deficiency of these studies on online UGC is failing to distinguish the valence of contents. Specifically, a large proportion of online UGC studies tend to use the eWOM as the synonym for positive eWOM (Liu *et al*., 2019; Gruen *et al*., 2006; Zhang *et al*., 2010). It is worth mentioning that motivation and purpose of posting and sharing positive and negative information are diverse. For instance, consumers are found more likely to share negative WOM with those who have higher interpersonal closeness with them because the distance trigger the motivation to protect others; while communication between people with lower interpersonal closeness tend to stimulate the self-enhancement intention, thus, positive information are more frequently shared with closer people (Dubois *et al*., 2016). More importantly, apart from the general reasons of posting and sharing eWOM (e.g., consumers post/share positive reviews for recommendation and post/share negative comments to warn other consumers), consumer online revenge, as a very specific purpose, cannot be categorized into any of these mentioned motives. Specifically, consumers want to express their anger and punish the organisation by posting and sharing negative eWOM (Grégoire *et al*., 2010). Therefore, it is essential for researchers to distinguish the valence of eWOM (Tan *et al*., 2021).

Although some researchers realise the necessity to differentiate the valence of online UGC, studies tend to show interest in specific outcome of online CCB (Allard *et al*., 2020). Attitude and behavioural intention towards the brand/product/service are the most widely investigated. In general, most of the studies prove that negative online WOM will lead to negative attitude towards the organisation/brand (e.g., Ho-Dac *et al*., 2013) and decrease the expectation of the brand (Nath *et al*., 2018). Subsequently, reducing the probability to purchase from the organisation/brand (Barhorst *et al*., 2020). Meanwhile, since the authenticity of online UGC is difficult to confirmed, the existence of unfair reviews is common in online scenarios. Recent studies also highlight that the intention to purchase, to donate and to write positive reviews will increase to show consumer's empathy if the negative eWOM is regarded as unfair or suspicious (Allard *et al*., 2020; Reimer and Benkenstein, 2016). Some researchers investigated moderators including but not limited to sunk cost of prior information search (Golmohammadi *et al*., 2020), types of failure (Hansen *et* *al*., 2018) and organisational response (Surachartkumtonkun *et al*., 2021). The other stream of research examined consumers' behavioural intentions directly towards the complaint itself, i.e., whether other consumers will support the negative eWOM and the underlying reasons. The influence of online complaints from this aspect are usually the perceived persuasiveness, helpfulness (Zhang *et al*., 2010) and participation including like, comment and spread (Huang and Ha, 2020; Relling *et al*., 2016). Specifically, the complaints which can address the injustice in transaction are more likely to receive support (Chen and Lurie, 2013). Meanwhile, researchers find that consumers spread negative WOM for social information sharing and helping others, and the underlying psychological factors are social comparison and self-affirmation (Alexandrov *et al*., 2013; Ruvio *et al*., 2020). Some individual factors are also analysed to clarify the boundary conditions. Self-esteem no doubt plays a critical role, and specifically transmitting negative WOM is out of self-enhancement purpose and this phenomenon is more widely seen among those who have lower self-esteem (De Angelis *et al*., 2012). Furthermore, according to the social learning theory (Bandura and Walter, 1977), individuals will also learn from others' behaviours. Thus, consumers may also be encouraged to participate in negative eWOM when they seeing others doing so and received satisfying responses from the organisation (Hogreve *et al*., 2019).

It is worth mentioning that the research on other's reaction towards online complaints is not only restricted to the individual level (i.e., whether and why other consumers will support the negative eWOM), and researchers now picking up the trend to investigate the aggregation effects because of the unignorable fact that social media now provide the breeding ground for content virality (Herhausen *et al*., 2023). Unlike the studies on individual attitudes which are mostly use self-reported intentions, studies on content virality are interested in cumulation of likes, shares, and comments (Tellis *et al*., 2019). In general, one stream of research focuses on non UGC contents, such as news articles (Berger and Milkman, 2012) and advertisement (Akpinar and Berger, 2017; Tellis *et al*., 2019). On the other hand, the research on online UGC is further categorised into brand/product/service relevant (e.g., Herhausen *et al*., 2023) and irrelevant (e.g., Tan *et al*., 2014) contents.[2] Research on the virality of negative UGC has gradually attracted researchers' attention because it has become a threat to the brands/organisations,

[2] The topic of interest is online complaint virality, thus, further discussion will mainly focus on the brand/product/service relevant studies.

however, it is also challenging. For data scraping, accessibility to platforms such as social media and review websites are different because of the diverse regulations and limitations, and the returned raw data is mostly unstructured which requires tremendous pre-preparation work. Meanwhile, the open access of online channels allows various parties to involve in the conversation, in other words, complainers, bystanders, the focal brand, other organisations can all participate in the discussion, which makes content analysis more difficult and effort-consuming. Therefore, extant studies on content virality tend to focus on only limited dimensions of attributes overcome the difficulties. Table 1 summarises some recent studies on content virality.

Table 1 Review of extant content virality studies

Studies	Data source	Dependent variables	Independent variables	Key findings	Gaps	Contribution of this research
Berger and Milkman (2012)	New York Times articles	Virality (highly shared via email)	Valence of the article, evoked emotions (awe, anger, anxiety, and sadness); Control: usefulness, interestingness, unexpectedness of the content, position of the article on New York Times, level/density of advertisement of the article	In general, positive contents are more likely to go viral. Furthermore, virality is found caused by high level of physiological arousal, emotions such as awe, anger, and anxiety are proven to be strong predictors.	- Information sharing via email is rather different from posting on social media as email is a point-to-point communication while social media allows everyone to have access to the contents. Therefore, the subsequent interactions are not captured. - In line with the previous point, the purpose of sharing the news article via email is different from posting on public platforms. - Linguistic characteristics of the contents are not included in this study. - This is a general study of content virality, in other words, not relevant to specific product/service.	Given that the purpose and reason for spreading positive and negative information are different, this specific research on the virality pattern of negative contents is warranted. Furthermore, this research also generalises the findings in a more public environment, social media, to which everyone can have access. Finally, this research also confirms the critical role of linguistic characteristics when studying the contents.
Tan *et al.* (2014)	Tweets	Popularity of social media contents (number of retweets)	Wording difference, time of tweets with similar ideas by same author, informativeness: word count, use of mentions (@) and hashtags (#), explicit requests (i.e., request readers to retweet), using headlines or not, positive or negative sentiment; Control: author and topic	The informativeness of content is a positive predictor of content virality. Meanwhile, if the author explicit the expectation in reader's sharing, it will increase the popularity of the Tweets. The impact of content sentiment is not found in this study.	- This study is conducted by comparing paired Tweets (Tweets with similar meanings posted by one author), however, the findings cannot be generalised to other online contents studies since the author not controllable. Use online CCB for example, both repeated complainers and new complainers are mixed together and the differences between complainers cannot be ignored.	This research investigates the contents in a comprehensive perspective, in other words, the research goes beyond the characteristics of the content and includes other external factors, such as the traits of the author and the participation of the organisation. Furthermore, this study further confirms the importance of high

						arousal negative affect in terms of content virality.
Li and Xie (2020)	Product relevant Tweets and Instagram posts	Engagement (number of likes and shares on Twitter; likes on Instagram)	Present versus absence of image, characteristics of images: quality, source of image, colourfulness, human face with emotional expression; characteristics of contents: sentiment, topic, psychological constructs, behavioural motivation (self-enhancement versus information sharing); linguistic variables: word count, use of emojis, mentions and hashtags; fit between content and image	Use of images have significantly positive impact on consumer's social media engagement. The quality and resolution of images have consistent positive impact on both platforms. While the impact of colourfulness is determined by the product type. Furthermore, using human face and high fit between image and text are found trigger more engagement only on Twitter.	- Both UGC and organisation generated contents are included, however, readers have different perception in this regard, which is not distinguished in this study. - Contents with different valence are not separated, i.e., whether the content is positive, or negative is unclear. - This study mainly focuses on image rather than the content. For example, the impacts of different topics are not compared. - Number of replies, also being a significant engagement parameter, is not included in this study.	This thesis specifically focuses on negative UGC, which has been proved have different pattern and purpose of spreading compared with positive contents. Meanwhile, this research also integrates diverse characteristics of different parties involved in the conversation.
Herhausen *et al.* (2019)	Contents in Facebook brand communities	Virality (sum of likes, comments, and shares)	Intensity of emotional arouse: anxiety, anger, disgusting and sad; frequency of communication within the community; similarity of linguistic style between the complainer and the community; organisational response (if present): intensity of empathy and explanation; Control: size of brand community, average number of likes and comments of each customer post and average number of organisational	Arousal emotions, complainer's tie strength and linguistic style fit with the community all found increases the possibility of online firestorm. From the organisation's perspective, no response will increase the possibility of online firestorm. Apology and switching platform are effective ways to prevent the virality at the early stage of complaint management; however,	- Facebook community is a very special and to some extent close channel for CCB. Simply put, only those who has joined the community can have access to the content and join the conversation. Brand communities are mostly the group for brand supporters, which might lead to more bias and advocacy when there are negative comments compared with more open platforms that everyone can have access. Meanwhile, the community is organized and managed by organisation, the impact of	Based on the findings of this Herhausen et al. (2019) paper, this thesis first generalise some of the extant findings in a more public environment that everyone (either brand advocators or detractors) can participate in this conversation. Furthermore, this thesis proves that both linguistic and psychological attributes of complaints have great importance, meanwhile, meanwhile, the topic of complaint is also

			respond to each consumer’s post, average tie strength, variance of linguistic style match, number of other posts at the same time, average word count of each sentence and complexity of words, complainer’s previous complaints, time of organisational response	when the complaints start to receive more supports, these methods can backfire and may worsen the situation.	organisational manipulation cannot be ignored. - This study focuses more on the sentiment but ignore the impact of topics. - Some other variables, such as the characteristics of complainer and linguistic traits of complaints are not investigated.	found lead to variety levels of virality.

It is not difficult to find that some extant research on the virality of WOM still implicitly assume the eWOM to be positive or investigate mix results of eWOM with different valence. Research on complaint virality specifically is relatively scarce (Herhausen *et al*., 2023). In addition, studies tend to investigate one or several of the following groups of characteristics: complaint, complainer, (involved) organisation and organisational response. Specifically, the attributes of complaints and organisational response are composed with both linguistic/structural variables, for instance, word count, use of attachments and readability (Heimbach and Hinz, 2016; Visentin *et al*., 2021) and psychological variables, such as sentiment and authenticity (e.g., Herhausen *et al*., 2023); meanwhile, characteristics of the complainer and organisation look at some statistical variables, for example, number of followers and number of negative comments posted/received (e.g., Relling *et al*., 2016; Wang *et al*., 2019). Furthermore, some studies also show interest in the topics of content (e.g., Wang *et al*., 2019). However, most of the studies only focuses on limited aspects meanwhile control or ignore the impacts of other variables (e.g., highlight the influence of sentiment but not taking the topic of complaint into consideration; tend to weaken the impact of linguistic style; focus only on the content itself and ignore the power of social network). Here are some real examples from the exploratory study of online complaint virality. Figure 3 lists some screenshots of complaints and the numbers of author followers (when data was collected) are labelled.

Figure 3 Screenshots of sample complaints on Twitter (with number of author's followers attached)

The first complaint received a vast number of likes, replies and retweets, which can be regarded as viral complaint. However, it is difficult to decide whether it is because of the number of followers (the third complainer has more followers and reported the similar service failure – theft) or the topic of complaint (the number of followers of final complainer is almost 100 times of the first complainer while complain about different failure – poor service quality, which is more common and maybe more likely to trigger other's empathy). Although previous studies already provide rather insightful findings, the mentioned question still cannot be answered. It is still unclear whether the topic of complaint or how the topic is described is more critical in complaint virality or maybe they have the same weight? Furthermore, studies tend to ignore the impact of the complainer's network because the default assumption is that posts by more influential people are more likely to go viral, however, the mentioned examples prove this is not (always) the case. Thus, also raise an unanswered question is it wise to exclude the influence of these situational factors which are actually having impacts in reality. Thus, this thesis will conduct a comprehensive study on the virality of complaints on social media to fill these research gaps.

1.4 Research Aims and Questions

Against the research background and based on the identified research gaps, the main research question of this thesis is as follows:

- *What characteristics of complaint contents will increase the possibility of virality?*
- *Whether the virality of complaint is influenced by non-content factors?*
- *Whether organisational response to complaints will hinder the complaint virality?*
- Additionally, this thesis also aims to explore *what are the factors that will influence the organisational response to the complaint?*

To answer the above research questions, web scraping was conducted to obtain complaints and relevant information from social media, natural language processing techniques were applied for data pre-processing and various big data analysis techniques helped to provide comprehensive marketing insights considering all potential factors of diverse aspects attached with CCB.

1.5 Thesis Structure and Summary

This thesis consists of eight chapters, which are structured as follows. The first chapter introduces the research background, research gaps and presents the research questions and objectives. Chapter 2 reviews the extant literature on CCB and complaint management. Specifically, the literature review starts from introducing the evolving CCB definition and typology, then look at the whole process of CCB including the factors and the underlying mechanism. Subsequently, online complaining as a specific type of CCB is further explained and specifically, the focus of this study - online complaint virality is discussed. Finally, the definition of complaint management as well as the strategies and impacts are explored. Following the introduction of extant literature, Chapter 3 is devoted to the hypotheses development and explains the theories concerned with the hypotheses. Furthermore, a research framework is proposed. The research methodology is presented in Chapter 4, including the research philosophy, approach, and design. Detailed research process is demonstrated in Chapter 5, that starts with the introduction of research context, followed by data collection, pre-processing and variable measurement procedures. Chapter 6 demonstrates the exploratory analyses with the help of different models and the performance is compared to find more reliable and robust techniques. Considering the complexity of the data structure, further analysis are conducted in Chapter 7 to test the remaining hypotheses and finalise the interactive effects of attributes. Finally, Chapter 8 summarises the findings and clarifies the contribution of this thesis from theoretical, managerial and methodological aspects. Meanwhile, limitations of this research are evaluated and avenues for future research are suggested.

CHAPTER 2 LITERATURE REVIEW

2.1 Introduction

This chapter reviews the literature of the consumer complaining behaviour (CCB) and complaint management to provide a comprehensive understanding of these steams of research. The first part of this chapter introduces the evolving definition and typology of CCB, followed by the explanation of CCB process and factors which are found drive CCB. The subsequent section discusses the characteristics, reasons, and impacts of online CCB. Specifically, the cumulative outcome, complaint virality, is explained and highlighted. Finally, from the organisational standpoint, CCB response/management is defined, and the strategies are described.

2.2 Consumer Complaining Behaviour: Definition and Typology

Although the investigation of consumer complaining behaviour (CCB) can be traced back to the early 1970s, it has attracted sufficient attention from researchers since the Firestone failure in 1978 emphasized the importance of assessing consumer satisfaction and the potential crisis along with CCB (Jacoby and Jaccard, 1981).[3] Unlike the previous consumers who were reluctant to take efforts to complain (Bateson and Hoffman, 1999), nowadays, consumers are to some extent familiar with CCB in practical as they engage in regular consumption activities on daily basis, and the level of their satisfaction or dissatisfaction (CS/D) is determined by the comparison between their expectations and actual experience (Oliver, 1997). When experiencing dissatisfaction, they may express their negative emotions in various ways (Richins, 1983). However, with the change and the development of consumer-organisation relationship and complaining channels, the definition and typology of CCB are evolving over the decades.

2.2.1 Definition of CCB

In the seminal research, Hirschman (1970) points out two types of negative responses by dissatisfied consumers. The first is to ‘exit’, involving active company/brand rejection, while, the ‘voice’, on the contrary, indicating the

[3] In 1978, the National Highway Traffic Safety Administration released overwhelming number of complaints about the Firestone steel-belted radial tires. Complainers were reported to claim for refunds, which further led to a large amount of economic loss for the organisation (The New York Times, 1978).

expression of dissatisfaction. Voice complaint, initially used as synonym for CCB, is regarded as the action taken by an individual to convey negative information regarding a product or service to a manufacturing/marketing company or a third-party organisation (Jacoby and Jaccard 1981). Since dissatisfaction is frequently an antecedent of CCB (Singh, 1988; Singh and Wilkes, 1996; Tronvoll, 2012), it is also defined an action (Mowen, 1993) or a set of actions (Rogers *et al*., 1992) triggered by perceived unsatisfying purchase experience.

The standpoints of the earlier literature highlight the outcome of economic exchange; however, the consumer-organisation relationship becomes diverse and complex (Wolter *et al*., 2022) and consumers are gradually empowered by variety of information-sharing channels (Vilpponen *et al*., 2006; Berger and Milkman, 2012). Thus, CCB is also interpreted as a more active and effective coping strategy to dissatisfying experience (Stephens and Gwinner, 1998) since it can to some extent reflect one's mastery over the situation (Duhachek, 2005). Furthermore, since service-dominant (S-D) logic becoming predominant because products are utilized resources (Vargo and Lusch, 2004), CCB is regarded as a dynamic process in which negative accidents may constantly happen if the service experience is below the consumer's acceptance, moreover, the time span of complaining is not limited to the transaction stage (Tronvoll, 2012). Building on the earlier work, this thesis operationalizes CCB as *a complete set of successive or simultaneous non-behavioural and behavioural actions by the complainer to an unsatisfactory consumption experience*.

Based on the evolving theoretical meaning, more attention has also focused on the classification of dissatisfied consumers' response style (Nasir, 2004). The exploration in CCB typology is both necessary and critical since apart from direct complaining to organisations, other consumer behaviours are seldom investigated although they are overwhelming in both volumes and forms (Richins, 1987; Istanbulluoglu *et al*., 2017). A better understanding of CCB types can benefit organisation by clarifying the purpose of complaining, accessibility of the complaints, and potential witnesses, which further helps them take proper actions (Stephens and Gwinner, 1998; Istanbulluoglu *et al*., 2017). The following paragraph will introduce different typology of CCB and explain some of the influential taxonomy in more detail, furthermore, their strengths and weaknesses will be discussed as well.

2.2.2 Typology of CCB

The general CCB definitions incorporate both non-behavioural (e.g., exit quietly) and behavioural activities (e.g., spread negative word-of-mouth) (Singh, 1988), and the options are usually triggered by diverse antecedents and determined by the different receiver and the channel of the complaint (Istanbulluoglu *et al*., 2017). Building on this notion, Hirschman's (1970) foundational framework divides CCB into exit, voice, and loyalty, and lays the foundation of the CCB typology study development. Based on this common rule, the hierarchical dichotomy (Day and Landon, 1977) distinguishes dissatisfied consumers' reactions into 'take no action' and 'take action', and whether the actions are taken in public or privately. While trichotomy model (direct voice to the organisation, negative WOM and complain to third parties) proposed by Singh (1988) only focuses on the consumers who take actions. Singh and Pandya (1991) further summarize the previous models to include both actions in different scenario and exit choice, and upcoming studies also investigate potential outcomes and impacts of these actions (e.g., Davidow and Peter, 1997). However, given that these typologies of CCB are proposed several decades ago, Istanbulluoglu *et al*. (2017) introduce an integrated taxonomy which aim to clarify the boundaries between different actions and including the new complaining channels.

2.2.2.1 Exit, voice, and loyalty

Hirschman (1970) proposes that consumer's exit choice benefits from the competition within the industry, and the direct harm to the organisation is the revenue loss. Meanwhile, it may also work as the starting point of management improvement since massive amount of consumer churn will threat the sustainability of the business. However, Hirschman also highlight the ideal mechanism of consumer exit - the organisation has consumers with both sensibility and inertness, who would urge the organisation to take actions and who would accept time lag respectively.

Voice is defined as expressing consumer's negative feedback to the organisation's management team or other authorities by various types of actions or in public settings. Unlike the exit consumers who avoid more interactions with the organisation, consumers who voice out the problem to "articulate the interest" (Almond and Powell, 1966) and maybe seek for resolutions as well (Day *et al*., 1981; Thøgersen *et al*., 2009). For organisations, discontented consumer's voice is a reminder for them to remedy the problem before the volume is accumulated. Similar to the exit option, organisations expect to be given some time to make changes after consumers raise the problems. Unlike the exit option will have single outcome, Hirschman suggests that voice is constructive for the organisation since it is a “complement” and “alternative” to exit. However, consumer’s voice can get troubling if it turns into aggressive expressions or purposeful protest, rather than helping the organisation to improve their performance (Istanbulluoglu *et al*., 2017).

Given that the level of competition in different industries and organisations’ attitudes to remedy can be diverse, consumer’s choice between exit and voice is situational. Thus, Hirschman (1970) also clarifies the conditions of choice and relationship between choices. If the feasibility to exit is low (i.e., consumer has no alternative choice in the industry), voice, although works as the forced option, empowers consumers with discourse to oversight and alarm the organisation. On the other hand, if there are alternative choices in the industry, consumer will evaluate the effectiveness of voice and speak out, and they will finally turn to the exit option if the outcome of voice is disappointing.

As mentioned, consumer’s comparison between the difficulty of exit and the effectiveness of voice will decide their choice. Apart from the intensity of industrial competition, consumer’s judgement is also influenced by the attachment with the organisation, which is also called consumer loyalty. Specifically, higher loyalty will hinder the intention to exit because of the higher psychological barrier to exit (Jones *et al.*, 2000), meanwhile, voice represents the effort to affect the organisation, which will reinforce the attachment in turn. Loyal consumers, according to Hirschman (1970), are less likely to abandon the organisation, and may keep silence. However, they may have the expectation that the organisation will improve the performance either spontaneously or after other consumers’ reminding. Since voice is determined by the evaluation of recovery effectiveness, it is more difficult compared with exit, thus, loyalty works as the balance mechanism because it increases the cost to exit.

Being one of the fundamental CCB typology, Hirschman’s (1970) model (see Figure 4) clarifies consumer’s intention after dissatisfying experience with the help of elastic of overall demand, and its use is broadened to corporate management (Farrell, 1983), political system (Dowding *et al*., 2000), and social affairs as well (Pfaff and Kim, 2003). One significant implication of Hirschman’s model is it takes the exit option into account, which has only been mentioned in literature of business competition but lacks detailed explanation of how it is precisely conducted (Hirschman, 1970). The propose of this model laid the foundation for CCB typology since it incorporates various behaviours which are well studied in the following CCB studies, such as personal boycotting (Day *et al*., 1981) and switching patronage (Day and Landon, 1977). It is also worth mentioning that 'exit' is a choice if consumers fail to force the organisational improvement, they have to turn to the other competitors. Thus, from the macro perspective, Hirschman reveals consumer's exit is a zero-sum game within the industry. Furthermore, the interpretation of separate components (i.e., exit, voice, and loyalty) not only demonstrates economic environment's impact on consumer's choice (Morgeson III *et al*., 2020), but also explains the dynamic switches among these options.

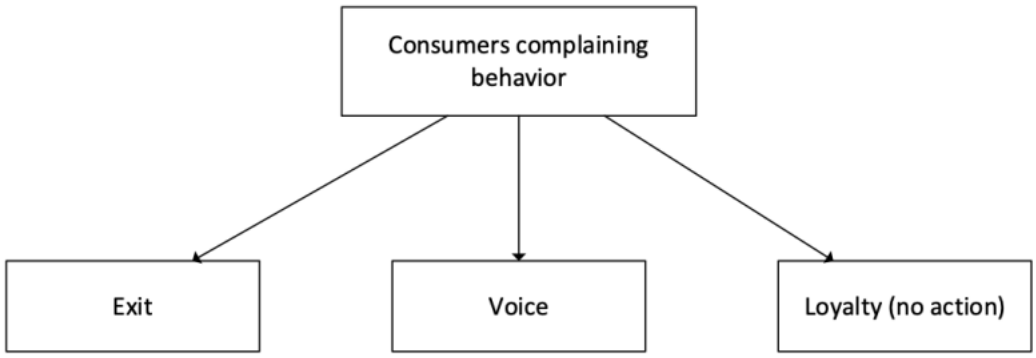

Figure 4 Exit, Voice, and Loyalty
Source: Hirschman (1970)

However, as an exploratory study, Hirschman's (1970) model has its own limitations. First, since the discussion is based on the "quality elasticity of demand", in other words, consumer's dissatisfaction happens because of increasing price and decreasing product quality. However, given the complex reasons for the price and quality change (e.g., overall inflation, product innovation, upstream and downstream influences, industry-wide increase, and decline, etc.), the level of consumer satisfaction is not always caused by obvious and direct changes in price and quality. Furthermore, the other issue with this macro model is consumer's impact as a single person. Hirschman claims that organisations may not take consumer loss so seriously and they will remedy the problem until the overall consumer impact reach the intermediate level, in other words, only the cumulated consumer power will warn the organisation and they will notice the CCB. However, as many real examples and research outcomes have proven the potential harm of a single case (i.e., musician Dave Carroll's guitar broken by baggage handlers of United Airlines [4]), it is understandable that nowadays organisations may deal with single case carefully rather than leave them disseminating and cumulating to certain level and deal with them together (Felix *et al*., 2017). Second, the precondition of the model is consumer's unconsciousness of other consumer's attitude or uninfluenced by others, in other words, only the organisation-relevant characteristics (e.g., competition, price and quality, attachment, attitude of management team, etc.) will decide their choice. However, it is now widely agreed that consumers choice (exit, voice, or loyalty) is unavoidably influenced by others' opinions (Schaefers and Schamari, 2016) or by comparing with others (Alexandrov *et al*., 2013), meanwhile, their choices may also be visible to and have impact on others (Chen *et al*., 2020). Lastly, Hirschman (1970) proposes that consumers give up their right to voice if they exit, meanwhile, only if the consumers decide to keep the interaction with the organisation, voice will get on the stage. Also, loyal consumers will keep silence and stay with the organisation. However, consumers may keep complaining about revenge although they decide never to go back to the organisation, they may also abandon the organisation because they are disappointed many times although they used to be loyal, and loyal consumers may also voice out for the organisation's good. In general, Hirschman's (1970) model is undoubtedly one of the founding explorations in CCB study, it has some shortcomings from today's perspective.

2.2.2.2 Hierarchical dichotomy

Another frequently used model proposed by Day and Landon (1977) divides consumer's choice into hierarchies, which first distinguish whether consumers take actions or not. Non action means no obvious actions (also called "non-behavioural" by Singh, 1988) after dissatisfying experience. It is worth clarifying that consumers in this condition will not change their transaction behaviour or complain, however, unlike the "loyal" consumers who have expectation in the organisation, this non-action seems to be a passive choice. While "loyalty" in Hirschman's model is one of the conditions in the dynamics between exit and voice, rather than a type of complaining behaviour.

[4] Musician Dave Carroll's guitar was broken by baggage handlers of United Airlines and his voice were not taken serious by the company, until his music video 'United Breaks Guitars' for complaining went viral online (Ismagilova *et al*., 2017). Inspired by Dave Carroll, more consumers tried to share their previous dissatisfied experience with United Airlines subsequently (BBC, 2009).

On the other hand, behavioural actions, usually refers to dissatisfaction expression, can be further classified according to their exposures, i.e., in public or privately. According to Day and Landon (1977), whether consumers will make the complaint public or not is to large extent depend on their input. In other words, if the price of the product is higher, the purchasing process is more complex and with higher involvement, consumers would expect their complaints to be heard by others (Blodgett *et al*., 1993).

Specifically, Day and Landon (1977) further divide public actions by their channels (seeking redress from the organisation, taking legal actions, and complaining to third parties), and private actions according to the involved target (personal boycott behaviours and warning those in one's own social circle, see Figure 5). The purpose and reason of public complaining can be diverse. Redress seeking from the organisation including both/either monetary (e.g., refund, discount, coupon, etc.) and non-monetary (e.g., explanation, apology, promise, etc.) requests, which are the direct costs the organisation needs to compensate (Albrecht *et al*., 2019). Sometimes, redress may not be necessary for some consumers as they just want to vent their negative emotions and reduce their anxiety (Nyer, 1997) to balance their psychological state (Hogreve *et al*., 2017). Besides, consumers will contribute to organisations by complaining, since they believe their advice can help the organisation to realize and focus on their shortcomings and make improvements (Blodgett *et al*., 1997). However, some consumers may look for support or solution via in-direct channels, for example, legal agencies, media, NGOs, consumer protection organisations (Dunn and Dahl, 2012), these actions are more likely to be taken if the outcome of direct complaining is not satisfying (Joireman *et al*., 2013) or some ethical or social problems involved (Grappi *et al*., 2013).

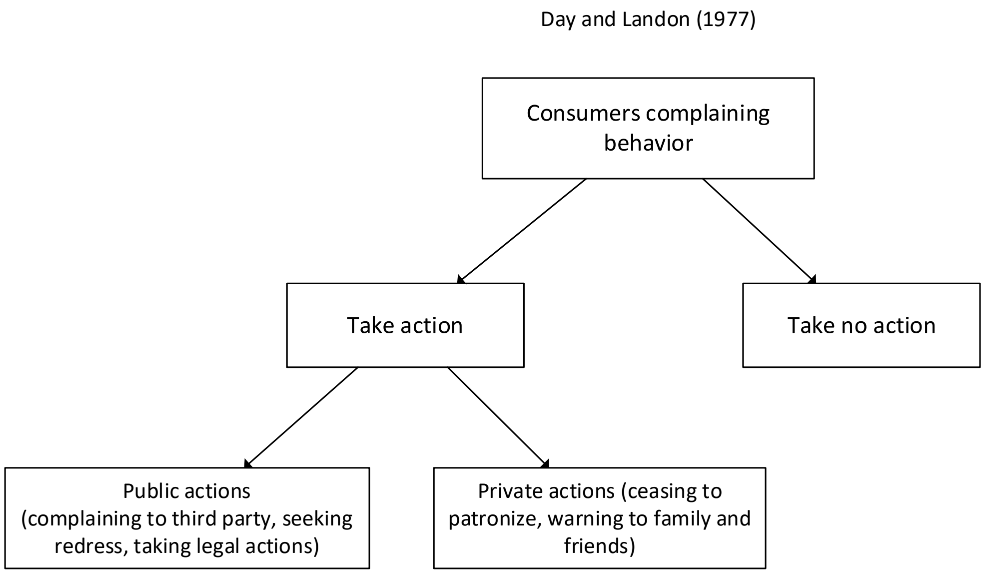

Figure 5 Hierarchical dichotomy

Individual's boycott action is similar to "exit" in Hirschman's model and sharing the negative experience with one's family members and friends is also termed "negative word-of-mouth (NWOM)" (Richins, 1984). The possibility of individual's own resistance or quitting is not predictable, and its impact is difficult to measure to some extent. Thus, understanding and maintaining these silent consumers can always be a tricky task (Stephens and Gwinner, 1998). Consumers may spread NWOM for altruistic purposes. Consumers are willing to help others sometimes (Hennig-Thurau *et al*., 2004), i.e., they wish to prevent others from unwise purchasing behaviours (Sundaram *et al*., 1998). Product/service relevant information sharing is rather common among one's social network, and NWOM are more likely to be shared and spread among the close ones (Richins, 1987; Hart *et al*., 1990; Zhang *et al*., 2014). Its influence is considerable as the closeness between the communicators can indirectly change the purchasing behaviours after the NWOM is spread (East *et al*., 2008). Social practice is also a critical reason since consumers can obtain support or resolutions from sharing their encounters with others (Dolan *et al*., 2019).

Although this CCB taxonomy is widely accepted by researchers (e.g., Bearden and Teel, 1983), a number of weaknesses have been highlighted. For instance, the criteria and regulation of classification seems neither consistent nor scientific as limited empirical studies can support this model (Singh, 1988) and with the diversification of CCB channels, this categorisation is far from enough for today's business environment (Istanbulluoglu *et al*., 2017). The other doubtful point lies in the condition under which public or private actions will be taken. Although Day and

Landon (1977) claim that consumers tend to make complaints public if their input is high (either finical or psychological), however, in a later study by Day and Ash (1979), they find that consumer's intention to complain about durable products in public decreases, which contradicts the model. On the other hand, using consumer's effort/input to predict CCB fails to figure out the individual differences in terms of complaining propensity although the failure is similar (Thøgersen *et al.*, 2009).

2.2.2.3 Trichotomy

Based on the evaluation and summary of the existing typology, Singh (1998) further proposed a new CCB classification with the help of empirical studies. To incorporate the characteristics of failures in different scenarios and various levels of dissatisfaction they might trigger (Best and Andreasen, 1977), Singh collected and analysed data from four different industries (i.e., medical care, grocery shops, auto repair stations and banking), and tested them in previous CCB models. Besides, both recalled experience and future intention data were collected to minimise the inaccuracy caused by vague memory. However, findings show that none of the proposed typologies can effectively explain the observations. In line with the outcomes, Singh summarised the trichotomy (see Figure 6) which classify CCB into voice (e.g., directly complain to the organisation and no-action), private (e.g., spreading WOM and personal boycotting) and third-party CCB (e.g., taking legal actions, reporting to consumer agencies, contacting media).

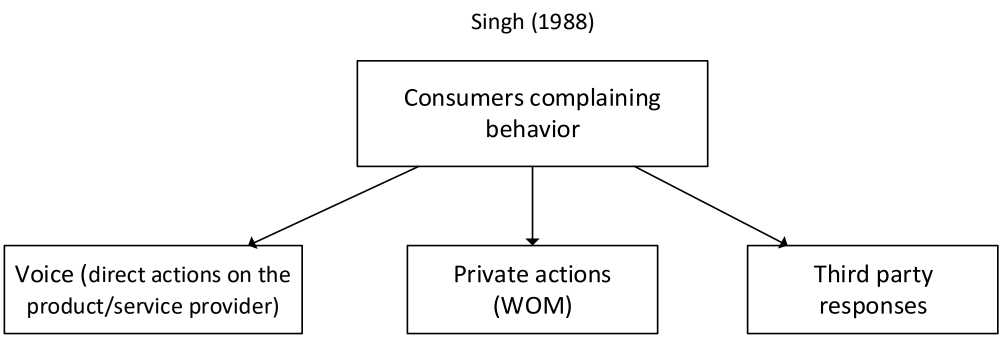

Figure 6 Trichotomy

In this model, the regulation of classification is who is the CCB receiver. Voice CCB are conveyed to those who are directly engaged in the failure, but not in the complainer's close network, while private actions target at those who are in the complainer's direct social circle but not directly involved in the encounter, and finally, third-party complaining involves those who neither have direct connection with the complainer nor participate in the failure (see Table 2).

Table 2 Dimensions of complaint receiver

		Engaged in the failure	
		Yes	No
	Yes	-	WOM
In close network	No	Voice	Third party complain

Singh's trichotomy no doubt improves previous models statistically. However, the scopes and boundaries of the types seem ambiguous and dated because it focuses on the target of CCB rather than the behaviour itself (Maute and Forrester, 1993). For example, Singh classifies no-action ("forget about the incident and do nothing") into the voice category because it represents consumer's attitude toward the seller (who is involved but not in consumer's network). However, it is obvious that the meaning of no-action contradicts the definition of "voice". Furthermore, personal boycotting or stop patronaging as well as NWOM are classified as private actions in Singh's model. However, he claims that the receivers of private actions are those not related to the failure, which seems problematic as complainer him/herself is the victim or to some extent engaged in the failure most of the time. Besides, the coverage and spread of NWOM is controversial now given the evolving in communication channels. The target of WOM tacitly refers to family members and friends, however, how information is transferred is not specified which causes further ambiguities. Traditional NWOM are spread via face-to-face conversation within one's immediate network, while nowadays, consumers can convey negative comments to their family or friends via online social media, which informs/warms their social network meanwhile available to those who have access to these channels (Van Noort and Willemsen, 2012). Thus, the accessibility to these information enables the function of public complaining, i.e., although the complainer is not deliberately complaining to the third-party, the outcome may turn into viral spread online.

2.2.2.4 Integrated taxonomy

After realizing the gap between the extant typology and the fast development in CCB reality, Istanbulluoglu *et al*. (2017) introduce the integrated model which distinguish the audience and behavioural differences. This model first divides the actions according to the complaint's visibility to the organisation, thus, the third-party and the organisation being audiences are classified together; the invisible to organisation group includes the situation when there is no audience and if the audiences are within one's own network and extended social circles. The no audience situation is further divided into inertia and exit. Inertia, as its meaning, refers to the consumers who neither take any actions nor continue to patronage although they are dissatisfied. As the contrary views on whether non-actional consumers are loyal or not (e.g., Hirschman claim that loyal consumers will not voice their dissatisfying while Umashankar *et al*. (2017) find the connection between complaining and loyalty), the inertia group only highlights the non-action trait rather than signifying whether this is because of loyalty or consumer's patience. Besides, from the organisation's perspective, as Istanbulluoglu *et al.* (2017) suggest, organisations have no clue of the reason of consumer's inertia. Exit is regarded as the termination of the purchasing from the organisation, however, the differences between inertia and exit consumers is the later ones are unwilling to voice their dissatisfying to the organisation because they decide to give it up, i.e., not give the organisation a second chance. The risk of exit has already been emphasized by scholars and marketers (Day *et al*., 1981) since it is not only related to consumer churn but also deprive the chance to identify and remedy the problem from the organisation (Orsingher *et al*., 2022).

The other condition in which complaint is invisible to the organisation is when the receivers of complaints are only limited to the complainer's direct network (e.g., family and friends) and the extended social network (e.g., acquaintances online and offline). Complainer's potential actions include exit, negative WOM and exit with negative WOM. The complainer's immediate family and friends may notice the complainer's abandon the organisation although they are not told purposefully. Furthermore, complainers may spread negative WOM in their direct and extended network by leaving the organisation. To sum up, complainer's exit happens both without and with audience, in other words, consumers can silently quit the relationship or privately boycott, meanwhile, some consumers can notify others within their immediate or extended network.

On the other hand, complainers may also voice their complaints and the visibility to the organisation is their target. A common way is directly connecting the organisation to express dissatisfaction, including face-to-face communication, phone call, email, register on official websites and forum, and via social media account. If these above channels are unavailable or complainers are not satisfied with the recovery outcome, they may turn to third-party for assistance. Third parties might inform, monitor, or even sanction the organisation depending on their traits and rights. While consumers take these public actions, they may also clarify their intention to exit or even boycott the organisation simultaneously (see Figure 7 for the whole model).

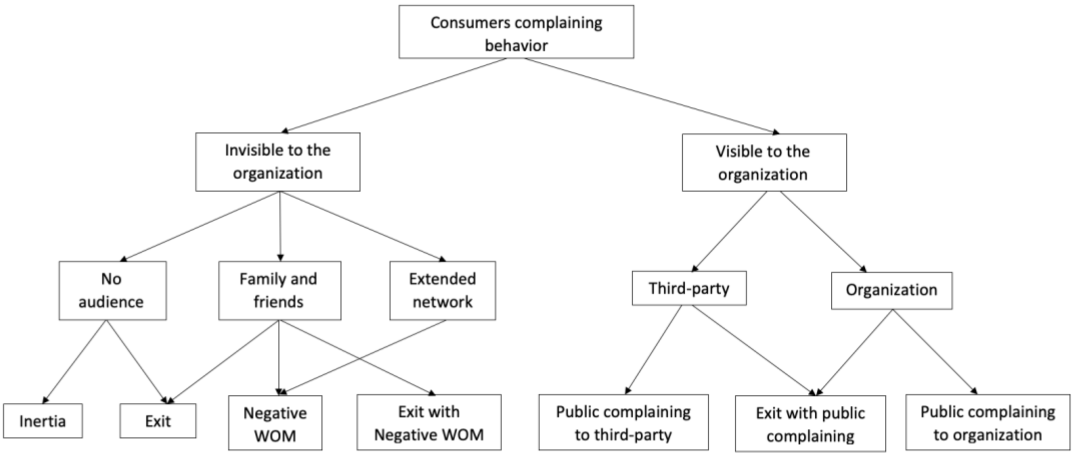

Figure 7 Integrated taxonomy

2.2.2.5 Summary of the models

Hirschman (1970) “Exit, voice, and loyalty” theory works as the foundational and seminal exploration of CCB classification. Based on this, Day and Landon (1977) propose the multi-level model according to whether the consumer takes obvious action and whether the action takes place in public or privately. These two models are both deductive studies to define and explain consumers options after they encounter dissatisfying experiences. Later, Singh (1988) conducted confirmatory factor analysis to induce a new model which classifies CCB into voice, private action and third-party complaint based on the involvement and connection of the complaining target. Istanbulluoglu *et al*. (2017) doubt the use of complaining channel in previous models since they argue that method is not an important variable of CCB definition. Instead, they emphasize the visibility to the organisation and the potential actions of complainers, which they believe is more critical from the organisation’s perspective. However, the rationale for this classification is unclear since several of the proposed actions are lack of theoretical or empirical support. Meanwhile, although they claim this typology integrates the new CCBs, conflicts between the criteria and reality are obvious. For example, online complaining with friends according to the model is classified as “negative WOM”, which is the sub-group of “invisible to organisation”, however, if the complaint is spread virally online, the extended social network, third parties, and organisations may all have access to it.

By reviewing the previous models, an integrated structure of CCB is proposed to clarify the relationships and differences between different complaining behaviour. It is widely accepted that consumers would decide to take actions or not after negative experience (e.g., Blodgett *et al*., 1993; Stephens and Gwinner, 1998; Evanschitzky *et al*., 2011). Those who take actions can be divided into exit action (no longer have transaction with the product/service supplier, and personal boycott without telling others) and voice (express the dissatisfaction). In order to avoid potential ambiguities caused by target-focusing, the behaviour itself is still the core classification criteria. Thus, the integrated model continues to distinguish complaining behaviours according to their channels, in other words, whether the complaint takes place in public or private (Day and Landon, 1977). Specifically, private actions refer to the complaint only conveyed in complainer’s social circle (private NWOM) while public actions may reach those who are external to the complainer’s close network. Based on this sorting method, public complaining includes direct complaints to the organisation, complaints to a third-party or take legal action, and public NWOM (Boote, 1998). See Figure 8 for the integrated model applied in this study, in which the final options are in bold: “no action”, “exit”, “private action (private NWOM)”, “direct complain to organisation”, “third-party complain”, and “public NWOM)”.

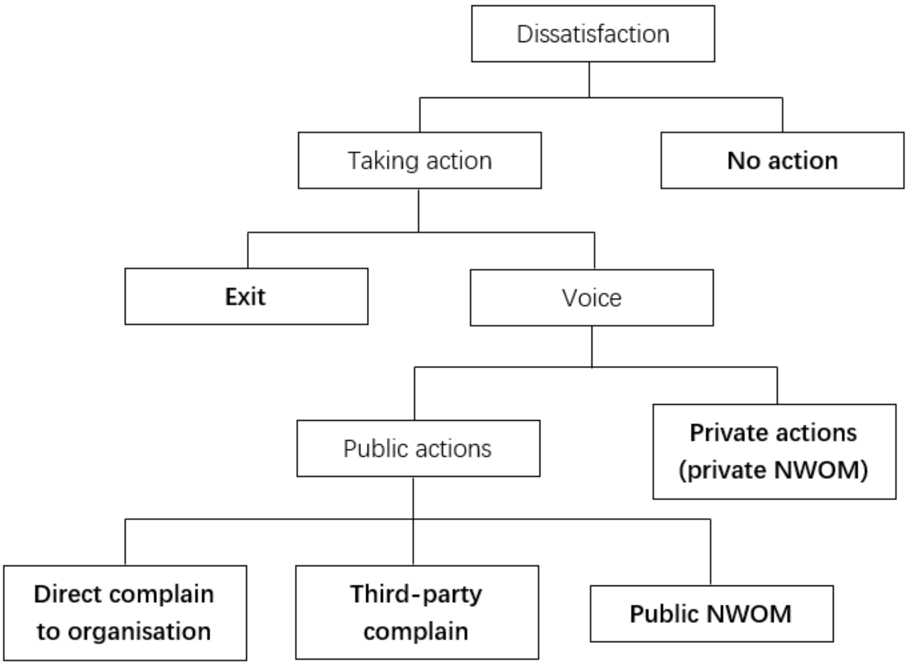

Figure 8 Integrated CCB taxonomy in this study

2.3 Process of CCB

Being a mature stream of research, CCB has been studied through a variety of theoretical lenses that aim to answer the question 'why and how consumers complain' (Alexandrov *et al*., 2013). This section will answer this question by synthesizing the factors lead to CCB and the whole process of CCB. The findings of systematic review (Ben *et al*., 2023) and empirical studies (e.g., Bearden and Teel, 1983; Homburg *et al*., 2010) on CCB all suggest understanding CCB process by clarifying the antecedents, underlying mechanisms, and other factors.

2.3.1 Antecedents of CCB

In general, the prominent factors lead to CCB including level of dissatisfaction, negative emotions, and individual socio-demographics.

2.3.1.1 Level of dissatisfaction

Although the impact of dissatisfaction can only explain part of CCB variances (Bearden and Teel, 1983), it is already well-recognized to be a fundamental factor of CCB (e.g., Kähr *et al*., 2016; Maxham and Netemeyer, 2002; Singh, 1988; Szymanski and Henard, 2001). Specifically, researchers propose that CCB works as the function of dissatisfaction and other factors further trigger or hinder the actual actions (Day, 1984; Miquel-Romero *et al*., 2020). In general, satisfied consumers seldom take negative actions while dissatisfied consumers tend to participant in CCB (Augusto de Matos *et al*., 2009; Tronvoll, 2012). Early literature on satisfaction regard it as a bipolar construct, i.e., satisfaction versus dissatisfaction (Day, 1980; Mittal *et al*., 1999). However, researchers doubt this rough idea which only looks at the opposite poles of a spectrum by dividing consumers into absolutely satisfied and absolutely dissatisfied. Thus, they further enrich the literature on (dis)satisfaction by investigating its level, i.e., see it as a measurable variable (Prakash, 1991; Sinha, 1993), and this notion is also reflected in CCB. Specifically, type and density of subsequent actions have been proven determined by the level of dissatisfaction (Singh and Pandya, 1991; Thøgersen *et al*., 2009). For example, higher level of dissatisfaction is found more likely to trigger complaining to third parties (Hogarth *et al*., 2001), switching to other suppliers, voice complaints (Zeelenberg and Pieters, 2004), and complainers tend to spread negative WOM to more people and even encourage them to boycott the organisation (Johnston, 1998). It is worth highlighting that dissatisfaction is the mental reaction towards the gap between one's expectation and actual encounter (Oliver, 1997), in other words, the evaluation of this gap is personal and subjective and influenced by some other internal and external factors (Stephens and Gwinner, 1998; Thøgersen *et al*., 2009; Tojib and Khajehzadeh, 2014), which will be further discussed in following sections.

2.3.1.2 Negative emotions

Dissatisfying experience is always accompanied with negative emotions (Sánchez-García and Currás-Pérez, 2011) because emotions are easily aroused during the interaction (e.g., anger and embarrassing) and after consumer recall the failure experience (e.g., disappointed and regret, Levine, 1996). Negative emotions instigate behaviours, both online and offline (Verhagen *et al*., 2013; Wetzer *et al*., 2007). According to the idea of functional approaches to emotions (Lerner and Keltner, 2000), individuals would be triggered by emotions and swiftly react (physically, psychologically, and behaviourally) to encounters (Frijda, 1986). Research on emotion's motivational function also hold the same opinion (Zeelenberg and Pieters, 2006). Furthermore, researchers have emphasized the importance to distinguish specific types of negative emotions when studying subsequent reactions (Bougie *et al*., 2003; Nyer, 1997). Thus, various types of emotions, such as anger (Joireman *et al*. 2013), befooled (Kasnakoglu *et al*., 2016), and disgust (Grappi *et al*., 2013), are proven as strong predictors of CCB variances. Basically, extremely outward emotions, such as anger, are usually because of external blame and lead to fierce actions including revenge (Crolic *et al*., 2022; Joireman *et al*., 2013). On the contrary, restraining, and mild emotions, sadness for example, are associated with deliberative reasoning, reduced physiological activity, and behavioural expression, and are less likely to trigger complaining actions (Crolic *et al*., 2022). Specifically, consumers feeling regret tend to spread negative WOM to warn others (Lee and Wu, 2015; Wetzer *et al*., 2007).

2.3.1.3 Individual socio-demographics

Demographic characteristics have been investigated to support their impacts on CCB (Boote, 1998), including gender (Manickas and Shea, 1997; McColl-Kennedy *et al*., 2003), age (Day and Landon, 1977; Heung and Lam, 2003; Grougiou and Pettigrew, 2009), the education level (Heung and Lam, 2003; Ngai *et al*., 2007), among others. However, some researchers claim that only limited dimensions of demographics can be used to predict potential CCB (Bolfing, 1989). Furthermore, the earlier studies usually investigate them solely and the findings are rather controversial. Initially, some researcher tried to draw a picture of typical active complainer - the middle-aged parents with higher educational level and income are more likely to take actions (Moyer, 1984), however, others hold different opinions. For example, males are believed to prefer face-to-face complaining (Manickas and Shea, 1997) because they are eager to figure out the explanation of the failure (Huang *et al*., 1996); consumers who are younger and have higher income tend to be experienced complainer (Grønhaug and Zaltman, 1981); public CCB are found more common among the older consumers and those with lower level of education (Ngai *et al*., 2007); Specifically, although the impact of demographic has been studied a lot, whether it is a strong factor is worth considering since there is still no consistent findings and some researchers find these background characteristics have lower predictive value by comparing them with other factors (Lilleker *et al*., 1969; Thøgersen *et al*., 2009; Blodgett *et al*., 2018). Thus, recent studies are encouraged to explore demographics along with other situational characteristics (Kasnakoglu *et al*., 2016). For example, male tend to complain when the front-line staff serve them with negative attitudes (Mattila *et al*., 2003); females are afraid of image-impairment when they share negative WOM with those who are distanced, but they have less concerns when this conversation takes place within the acquaintances (Zhang *et al*., 2014); female consumers with higher income prefer writing detailed complaints to provide solutions (Kasnakoglu *et al*., 2016).

As mentioned, demographics can explain limited amount of CCB differences, thus, researchers also take socio-psychological traits into consideration. For example, self-esteem, as a critical aspect of self-concept, always attract attention from researchers to explore individual's emotional states and predict potential subsequent actions (Orth and Robins, 2014). Individuals with low self-esteem tend to participate in activities which they believe can enhance their self-concept compared with those have higher self-esteem (Shrauger, 1975). For instance, consumers with lower self-esteem are found more likely to spread negative WOM, however, they are reluctant to post negative WOM by themselves (De Angelis *et al*., 2012) because sharing their own negative experience will decrease their self-concept but highlighting others' helps them feel superior (Tesser, 1988). Similarly, consumers with arrogance (Ruvio *et al*., 2020) and high intention to help others (Alexandrov *et al*., 2013) also increase the possibility to participate in negative WOM because for self-affirmation and enhancement purpose. Contrarily, CCB can be hindered because of some psychological reasons. For example, those who have higher levels of empathy (Pera *et al*., 2019) and fear of organisational revenge are less likely to take actions (Grégoire *et al*., 2010). Furthermore, individual's evaluation of CCB realizability can also have impact, thus, consumer's perception of their own power (Sembada *et al*., 2016) and their familiarity of complaining channels (Miquel-Romero *et al*., 2020) might hinder or encourage their behaviours.

2.3.2 Underlying Mechanisms

Although the differences between various reactions to dissatisfying experience reflects individual's own cognition (Joireman *et al*., 2015), studies still find similar psychological routines followed by consumers after encounter with failures (e.g., Grégoire *et al*., 2010; Sembada *et al*., 2016). In general, consumers start from assessing the failure and the failure attribution; then, the outcome may trigger their negative emotions and they would try to take the internal and external situations into consideration, to figure out an appropriate strategy for coping. However, these intentions may not always turn into actual actions since consumers may undergo several evaluations of the situation. It is worth mentioning that these processes vary under different conditions, and one may go through some or all stages. Meanwhile, these evaluations may happen simultaneously, asynchronously, or repeatedly. This CCB process is complex in nature, and the CCB mechanism has been studied through several main theoretical lenses according to the findings of the review (Ben *et al*., 2023), which will be further explained in the following sections.

2.3.2.1 Cognitive appraisal

Cognitive appraisal theory (Lazarus and Folkman, 1984) is one of the most commonly used and primary theories for CCB interpretation (Bagozzi *et al*., 1999), which describes the process of evaluating whether the encounter is relevant to one's well-being (Folkman *et al*., 1986). Specifically, the appraisal is composed with two main stages: assessment of the dissatisfying experience (primary appraisal) and the evaluation of the coping strategies (secondary appraisal) for welfare restoration (Kähr *et al*. 2016), subsequently, consequent actions might be taken (Watson and Spence, 2007; Joireman *et al*., 2015). During the primary appraisal stage, the perceived incongruence may trigger negative emotions if the failure is more self-relevant (Crolic *et al*., 2022). For secondary appraisal, the evaluation of threat-coping strategy highlights the consistence between situation and action (Folkman and Moskowitz 2004). For example, if the consumer power is high, it helps to decrease the perceived harm, thus, will be less likely to lead to fierce actions (Sembada *et al*., 2016). Besides, the likelihood of organisational response has positive impact on the intention to complain (Evanschitzky *et al*., 2011). It is worth mentioning that the behavioural response varies because it is the outcome of a comprehensive process during which the factors of the primary and secondary appraisals may come into effect synchronously and interactively (Lazarus, 1991; Gyung Kim *et al*., 2010); moreover, each of the appraisal stages is influenced by diverse factors (Stephens and Gwinner, 1998). For instance, specific failure types (e.g., ethical violation of the organisation: Surachartkumtonkun *et al.*, 2013; organisational betrayal: Kähr *et al*. 2016) are regarded as significant threats.

In general, the evaluation criteria can be further classified into three dimensions, namely outcome, fairness, and agency appraisal (Watson and Spence, 2007). Outcome appraisal, just as its literal meaning, is the appraisal of the well-being relevant outcomes and it will further trigger individual's emotion (Babin and Harris, 2016). Being a post-transaction action (Day, 1980), CCB is mainly result-focused (Tronvoll, 2012). Therefore, the assessment of outcome and the efficacy of CCB can influence the CCB intention to some extent (Stephens and Gwinner, 1998; Chebat *et al*., 2005). However, negative perception of outcome fails to fully explain behaviours since specific emotions and actions may also be caused by other appraisals (Watson and Spence, 2007). Fairness appraisal assessing the level of justice of the experience and the perceived equity is found influencing level of (dis)satisfaction (Voorhees and Brady, 2005) and corresponding actions (Augusto de Matos *et al*., 2009; Blodgett *et al*., 1995). Although fairness is emphasized in evaluating the complaint management outcome (Tax *et al*., 1998; Smith *et al*., 1999), researchers highlight the relationship between perceived fairness plays a critical role throughout the whole CCB process after analysing the similarity of the context within the stages (Voorhees and Brady, 2005). In other words, consumers would take part in CCB to restore justice because of the evaluation of imbalance (Oliver, 1997; Kwon and Jang, 2012). Furthermore, determining who is responsible for the failure is regarded as the agency appraisal (Watson and Spence, 2007). Specifically, when the failure is attributed to the company, negative emotions are more likely to be aroused (Bitner *et al*., 1990; Maxham and Netemeyer, 2002) and they would take actions because they expect the resolution by organisation (Esmark Jones *et al*., 2018; Folkes, 1984). Conversely, consumers who attribute the failure to themselves tend to take self-accusation as a coping strategy and they would be less likely to complain (Stephens and Gwinner, 1998).

2.3.2.2 Failure attribution

In many cases, appraisals lead to attribution of failure, and thus attribution theory is widely employed in CCB literature. Attribution theory is defined as the causal interpretation process with the help of gathered information (Fiske and Taylor, 1991). The attribution of failure is a critical factor which impacts appraisal outcomes, as it triggers emotions and even behavioural responses (Grégoire *et al*., 2010). At the pre-CCB stage, when consumers are exposed to a negative situation or outcome, they would ascertain the failure severity and cause (Joireman *et al*., 2013). The major characteristics of attributions, namely locus, stability, and controllability, provide consumers with a more elaborate basis to infer who is responsible for the failure. In line with the agency appraisal, the locus of attribution distinguishes who is responsible for the failure (Maxham and Netemeyer, 2002). Although the attribution of blame can be either external or internal (Dunn and Dahl, 2012; Philp and Ashworth, 2020), bias can have a strong impact on this perception process as consumers tend to impute failures to the organisation rather than blame themselves (Manrai and Gardner, 1991; Gooding and Kinicki, 1995; Weiner, 2000). It is worth underlining that the locus of attribution can vary from person to person or in different situations. For example, individuals who have lower power would tend to blame themselves and restrain the complaining intention out of self-esteem (Harvey *et al*., 2014; Min *et al*., 2019). Interestingly, some consumers are found blaming themselves to avoid being judged negatively by others for complaining (Sorensen and Strahle, 1990).

Situational stability and controllability are two widely examined aspects in CCB research (Van Vaerenbergh *et al*., 2014; Voorhees *et al*., 2017) because consumers frequently react according to their evaluation of whether the failure is temporary or permanent (Kaltcheva *et al*., 2013) and whether failure can be prevented in advance (Folkes, 1984; Weiner, 2000). Given that the problem is assessed to be stable, consumers may not only avoid repatronage but also warn others because they reasonably deduce that the organisation is accountable for the failure based on the stable attribution of constant problems (Weiner, 2000; Maxham and Netemeyer, 2002; Van Vaerenbergh *et al*., 2014; Sugathan *et al*., 2017); meanwhile, if the situation is believed to be controllable, consumers' negative emotions will be triggered because they expect the problem to be prevented in advance (Blodgett *et al*., 1995; Smith and Bolton, 1998; Van Vaerenbergh *et al*., 2014) and more seriously, they may even react more punitively (Grégoire and Fisher, 2008). Furthermore, higher complaining intention, possibility to engage into negative WOM and desire to seek redress (Blodgett *et al*., 1995) are frequently found when the situation is either stable or controllable (Folkes *et al*., 1987; Hess, 2008; Van Vaerenbergh *et al*., 2014).

2.3.2.3 Justice dimensions

As mentioned in previous section, the evaluation of justice plays a critical role in consumer's psychological process after the dissatisfactory experience because of the perceived unfairness (McColl-Kennedy *et al*., 2011), meanwhile, the type and density of the CCB is determined by the degree of injustice (Grégoire *et al*., 2018). Both justice theory and equity theory lenses have been frequently used in investigating CCB (Allard *et al*., 2020; Grégoire *et al*., 2010) through fairness principle. Justice theory and its three dimensions, namely, distributive, procedural and interactional (Adams, 1965), together work as a widely adopted framework to consistently explain the reasons of CCB (Van Vaerenbergh *et al*., 2018) as well as the satisfaction with CCB management in the case of conflicts and failures (Colquitt *et al*., 2001; Smith *et al*., 1999).

Distributive justice derives from the distribution of costs and benefits (Deustsch, 1985), and it refers to the consumer's perception of the level of justice of service encounter outcome in CCB literature (Voorhees and Brady, 2005). Procedural justice is defined as the equity of the decision-making process, including but not limited to the ethical measurement, reducing biases, information accuracy, and consistency between individuals (Barrett-Howard and Tyler, 1986). In CCB studies, procedural justice assess how fair organisational procedures and policies are conducted (Voorhees and Brady, 2005). Interactional justice is defined as the fairness of interpersonal behaviours during the outcome and procedures accomplishment (Gilliland, 1993) and it refers to the extent to which the consumer is treated equally when interacting with the organisation (Davidow, 2003). Specifically, the violation in different justice dimensions is found to lead to diverse reactions since consumer's perception of harm is caused by different types of injustice (Griffis *et al*., 2012). For example, interactional injustice caused by unequal treatment will trigger revenge on employees (McColl-Kennedy *et al*., 2011) while procedural injustice is more likely to encourage opportunistic claims since consumers want to express their discontent with the policies (Wirtz and McColl-Kennedy, 2010).

However, unlike justice theory which covers multiple dimensions, equity theory specifically emphasizes the balance between input and outcome. For example, consumers' confidence in future transactions with the organisation will decrease because of the gap between their psychological input and the outcome of the exchange (Tan *et al*., 2021). Equity theory is also regarded as the construct of consumer revenge (Grégoire *et al*., 2010) since it emphasizes the ultimate purpose of revenge is to restore the equity which aims to offset the failed transaction with the organisation (Kähr *et al*., 2016).

2.3.3 Other Factors Drive CCB

Apart from the common psychological process mentioned, Hofstede's (1980) dimensions of culture are frequently employed to explain the cross-national culture differences in CCB (Ngai *et al*., 2007; Richins, 1983; Yuksel *et al*., 2006). During the cognitive appraisal, culture differences would lead to various evaluations and reactions (Matsumoto, 2006), and trigger different CCB actions (Liu and McClure, 2001; Surachartkumtonkun *et al*., 2013). For example, consumers from feminine cultural background tend to show more care and empathy, and they are reluctant to complain in case of hurting the employees (Yuksel *et al*., 2006). Besides, consumers from a more individualistic and larger power distance culture background tend to express their emotions more strongly (Baker *et al*., 2013). While consumers from collectivist countries find it difficult to voice complaints to the organisation (Yuksel *et al*., 2006) because they are afraid of losing face (Liu and McClure, 2001), meanwhile, they would prefer to share the dissatisfying experience with those who are in their social network (Huang *et al*., 1996). Interestingly, collectivistic consumers are found more likely to complain when the failure makes them embarrassed (Wan, 2013).

From a situational perspective, CCB may be influenced by consumer's previous relationship with the organisation (Ward and Dahl, 2017), for example, the level of commitment (Kaltcheva *et al.*, 2013) and frequency of transactions (Wirtz and McColl-Kennedy, 2010). In summary, relationship strength and affective commitment between the consumer and the organisation may have buffering effects when the faults are slight (Ganesan *et al*., 2010). However, CCB is more likely to be triggered if the relationship is reciprocal or is endowed with strong self-relevance. Reciprocity-targeted consumers are more eager to restore justice (Kaltcheva *et al*., 2013) and consumers may feel serious harm to their self-concepts when failure happens if they strongly connect the brand with their self-images (Johnson *et al*., 2011; Khalifa and Shukla, 2021). Furthermore, in repeated transactions, compared with one-off purchases, consumers are less likely to engage in opportunistic CCB (Wirtz and McColl-Kennedy, 2010).

2.4 Online CCB

2.4.1 Overview

The proposed typologies of CCB mainly focus on the receivers and applied channels, and with the popularity of Internet use, online complaining as a public action, is now becoming an unneglectable CCB channel for both consumers and organisations. Online complaining is regarded as the interactive form of dissatisfaction expression via online channels (Mattila and Wirtz, 2004). It is worth mentioning that the definition of online CCB only emphasizes the channel rather than distinguishing receivers since anyone can be the receiver of the online complaints, and this trait of online CCB will be further discussed in section 2.3.2 in more detail. Furthermore, with more complex functions of online complaining, the boundary between CCB types is vague (Lee and Cude, 2012). Thus, in line with the mentioned definition and characteristics, online CCB, negative eWOM and negative reviews are used as synonyms in this study.

In general, online WOM (or eWOM) is defined as any positive, neutral, or negative comments made by any consumers (actual or potential) about products/services/organisations/brands through online platforms which are accessible to mass audiences (Hennig-Thurau *et al*., 2004). However, extant studies on eWOM focus more on solely positive eWOM (e.g., Jeong and Jang, 2011) or are implicitly regarded as positive (e.g., Grewal and Stephen, 2019), or has not distinguished between positive and negative comments (Duan *et al*., 2008). This calls for researchers to have a better understanding of the specific aspect of eWOM – negative eWOM (or online CCB), meanwhile, to re-examine whether some extant findings are still valid if different valences of eWOM are separated. Thus, in this study, negative eWOM are distinguished from the reviews with other valences but regarded as a type of online complaining. The following sections will explore online CCB in depth, including the characteristics, reasons, and outcomes of online CCB. Finally, a specific phenomenon of online CCB, online firestorm will be introduced.

2.4.2 Traits of Online CCB

2.4.2.1 Low input

From the perspective of economists, cost may always be considered before taking actions, which including both time and effort input (Grønhaug and Gilly, 1991). To complain or not is evaluated by comparing the combination of economic loss and complaining cost (Kolodinsky, 1995) with the benefit from the complaining (Day, 1984; Voorhees *et al*., 2006). According to the outcome and fairness appraisal, if the consumers perceive the complaining requires more efforts, the less likely they would regard the outcome to be equal (Lu *et al*., 2018; Wen and Chi, 2013), which no doubt will to some extent hinder their actions. In the past, the majority of silent consumers choose to save their time and efforts even though they experience a feeling of dissatisfaction (Cho *et al.*, 2002; Stephens and Gwinner, 1998) because traditional complaining process requires more input such as commute, waiting time and phone charges. Thus, consumers may only take actions when the price of the failed product/service is high when there were only traditional complaining methods (Gilly and Gelb, 1982; Kolodinsky, 1993; Voorhees *et al*., 2006; Thøgersen *et al*., 2009), specifically, contacting third-party is less frequent because of the higher complexity and cost (Yuksel *et al*., 2006). However, these costs are no longer exist when complaining online, which can make complaining process more convenient and stimulate CCB through online platforms (Berry *et al*., 2002).

2.4.2.2 Accessibility to everyone

One of the phenomenal changes brought by online CCB channels is the high accessibility to everyone. Traditional CCB is mostly ‘one-to-one’ or ‘one-to-some’ (spread of negative WOM to relatives and friends) communication. However, the advances in Internet use and communications technology enable complainers to conduct ‘one-to-many’ conversations (Balaji *et al*., 2016). Audience wise, the receivers including but not limited to the complainer’s own network, previous, current, and potential consumers of the involved brand/organisation, organisations and their other stakeholders, third parties such as NGOs, media, policy makers, etc. This mass-audience trait of online CCB makes complaints public thanks to its specific channel which is attainable to anyone who has access to Internet (Grégoire *et al*., 2009), meanwhile, the information asymmetries between different parties are massively lessened (Litvin *et al*., 2008). It is also worth noting here that the conversation is interactive and open to both complainers and audiences (Carl, 2006; Allard *et al*., 2020). For example, after the complainer posting a negative review online, organisation can respond to the complaint, meanwhile, other consumers may decide to support or blame the complainer or organisation based on their own experience by having direct communication with both sides. It is widely agreed that the ease of use is related to the likelihood of applying the technology, simply put, if the difficulty of using a technology is low, people are more willing to accept it (Venkatesh, 2000). Various types of online platforms (e.g., social media, general complaining forum, government platform, and corporate hate websites) provide complainers with high convenience and flexibility when sharing their dissatisfying experience online (Holloway and Betty, 2003)[5]. With one click, consumers can swiftly post and share their attitude towards an organisation or a brand on the Internet (Van Noort and Willemsen, 2012).

2.4.2.3 Anonymity

Every coin has two sides. Although complaints can be regarded as the chance for organisations to remedy the failure (von Janda *et al*., 2021), they might also threaten

[5] It is rather common that users will share information across platforms and sometimes it will lead to diverse outcomes. For example, an airline passenger’s complaint about British Airways flight delay was initially posted on “British Airways Complaints Advice” Facebook page, which is public community has 29.3k members when this thesis written. After that, it was shared by other users on FlyerTalk (an airline forum) titled “unbelievable Facebook Post”. However, it did not get viral before another user came across the FlyerTalk post and shared it on Twitter, which was viewed more than 56,000 times in a short period (Clark, 2023).

the business in some circumstances. Compared with offline complaining, online CCB are more likely to cause harm to organisations partly because of the anonymity characteristics (Van Noort and Willemsen, 2012). Fear of retaliation (Pera *et al*., 2019; Teubner and Hawlitschek, 2018) and ruin self-competence/self-reputation (Ert and Fleischer, 2019; Mussweiler *et al*., 2000) can hinder CCB to some extent, however, these concerns are eliminated in the online channels. More importantly, consumers may behave differently when in public versus when they regard their identities are unknown (Ratner and Khan, 2002). The anonymity provides consumers considerable freedom to publish their comments (Matthews *et al*., 2009) without being evaluated (Verhagen *et al.*, 2013), therefore, negative comments are rife online (Melián-González *et al*., 2013; Woong *et al*., 2011). Furthermore, anonymity will not only determine whether consumers will complain or not, but also related to what and how they complain (Dyussembayeva *et al*., 2020). Although it is widely agreed that perceived anonymity works as the protection for individuals, diverse opinions are proposed, such as individuals will act more honestly (Joinson, 2001), more personalized (Ratner and Khan, 2002), more aggressively (Rehm *et al*., 1987) or even opportunistically (Ehrhart and Naumann, 2004). Specifically, although consumers are found to be franker when sharing experience online (Suler, 2004), they also tend to exaggerate negative sentiments (Gelb and Suresh, 2002) and express caustically (Dunn and Dahl, 2012). Considering the significant influence of high-arousal negative emotions (Heath *et al*., 2001), organisations usually regard online CCB as a thorny problem (Ward and Ostrom, 2006) and it will take more efforts for them to evaluate the credibility of reviews and the failure situation than verified consumers which are easy to recognize in offline scenarios (González Bosch and Tamayo Enríquez, 2005). Meanwhile, observer's attitude is also affected by this trait since anonymity can decrease the reliability and objectivity of the information (Qian and Scott, 2007), thus, they need to evaluate the justice of complaint and organisational response (Allard *et al*., 2020; Johnen and Schnittka, 2019), which might not be necessary when they are familiar with the complainers in the offline environment.

2.4.3 Reasons of Online CCB

2.4.3.1 Negative emotion venting

Consumers post and share negative comments for diverse reasons. According to the cognitive dissonance theory proposed by Festinger (1957), psychological imbalance or tension can be caused by the inconsistency between one's cognition and environment. Then, various types of negative emotions might be triggered because of the dissonance status (Hennig-Thurau *et al*., 2004). Negative emotions, such as anger (Strizhakova *et al.*, 2012; Grappi *et al*., 2013; Joireman *et al*., 2013), contempt (Grappi *et al*., 2013), disgust (Grappi *et al*., 2013), offended and befooled (Kasnakoglu *et al*., 2016), etc. have been proven to be strong predictors of CCB. The mentioned intensive emotions work as the immediate reaction strategy against failure or threat (Bodenhausen *et al*., 1994). Once these emotions are aroused, one would attempt to reduce the dissonance by adjusting the inconsistent cognition or environment (Bawa and Kansal, 2008). It is believed that emotion sharing can help reduce dissonance psychologically (Berger, 2014), thus, emotion venting is no doubt a common purpose for negative WOM in public (López-López *et al*., 2014; Kähr *et al*., 2016). More importantly, compared with face-to-face complaining, radical emotions and biased expressions are found more frequently in online environment (Dunn and Dahl, 2012; Gelb and Suresh, 2002), which also proves that complainers may use online channels as an 'emotional dumpster'. Interestingly, although it is widely believed that complaining in social environment can to some extent release and relieve negative feelings (Nyer and Gopinath, 2005), and suppressing may lead to further discomfort and dissatisfaction (Kowalski, 1996). However, whether complainer's level of dissatisfaction is decreased (Nyer and Gopinath, 2005) or enhanced afterwards is still controversial (López-López *et al*., 2014).

2.4.3.2 Support seeking

Not all complainers post negative WOM for emotion expression. Some complainers post negative comments online to get support, either psychological or physically, which is rather common if double deviation, i.e., without or failed recovery, happens (Grégoire *et al*., 2010). Although some researchers claim that consumers are less likely to conduct negative WOM in public (Nyer and Gopinath, 2005), however, CCB in public sometimes works as the final coping strategy after the failed direct complaining (Singh and Wilkes, 1996) or dissatisfying recovery (Anderson, 1998). After product or service failure, consumers usually have the expectation that the organisation will fix the problem (McColl-Kennedy and Sparks, 2003). However, if they realize the difficulty of getting the problem solved offline, they might turn to online platforms for solutions (Dolan *et al*., 2019), from the organisation or third-party institutions by reminding and pressing on the organisation with the help of mass media or invite third-party's interference (Weitzl and Hutzinger, 2017). Thus, these public actions not only reflect consumer's attitude towards the failure, but also regarding their satisfaction with the recovery (Singh, 1989). Meanwhile, support is not limited to failure recovery or monetary compensation, and psychological feedback is also critical for some consumers. Sharing complaints online is sometimes for accomplishing self-affirmation (Alexandrov *et al*., 2013). It is worth highlighting that unlike the self-enhancement purpose of positive WOM, according to self-affirmation theory, affirmation is needed as a self-protection mechanism (Sherman and Cohen, 2006) when the consumer's worth and integrity is threatened (Gilbert *et al*., 1998). Meanwhile, the negative WOM in these occasions are mainly attribution switching. In other words, the complainer would blame the product/service or external factors to make information receivers believe the failure is not their own responsibilities, and probably receive comfort from the audiences (Asugman, 1998).

2.4.3.3 Economic incentives

It is undeniable that economic incentives can be strong motivations to post online negative WOM for some consumers even if they are satisfied with the organisation, or they are not even actual consumers (Jacoby and Jaccard, 1981). The visibility of complainer's personal information can to large extent influence this purpose (Proserpio *et al.*, 2021). As channels allow anonymous complaining, social platforms are more likely to be the places where opportunistic complaining takes place (Surachartkumtonkun *et al*., 2021) mainly for monetary benefits (Wirtz and McColl-Kennedy, 2010). Rational choice theory proposes that people make decisions after they rationally evaluate the input/output ratio (Gary, 1978). Therefore, if consumers assume that they can get larger benefits than the risk of illegitimate complaining online, they are more likely to take this risk. These behaviours are found more common in service industries because service failures are relatively subjective assessments and rather difficult to prove (Tsarenko and Strizhakova, 2013), thus, makes it easier for these opportunists to exaggerate and lie about the failure and ask for more compensation (Ro and Wong, 2011) or claim fake premises (Fullerton and Punj, 2004). Thus, illegitimate CCB is attracting researchers to investigate the psychological mechanisms (e.g., Wirtz and McColl-Kennedy, 2010) and typology (Huang *et al*., 2014), meanwhile, data scientists also propose more refined and robust detection methods to distinguish the unreliable complaints (Budhi *et al*., 2021).

2.4.3.4 Social engagement

Some complainers send negative WOM for social engagement, in other words, to connect others. Instead of seeking solution or comfort, these complainers share their experience or knowledge to help or warn others (Hennig-Thurau *et al*., 2004). This phenomenon is rather common among those consumers who regard themselves as altruistic or have higher social responsibility (Sundaram *et al*., 1998). According to the self-perception theory, one's own attitudes and perceptions are formed by the summary of observing his/her own behaviours (Bem, 1967). In marketing, this theory demonstrates how persuasiveness is increased by consistent image, in other words, once one claims a self-image, he/she will be more likely to take relevant actions to make the image more reliable (Brown *et al*., 2007). Thus, those who assume themselves to be altruistic or social contributors are willing to post or share negative WOM to warn others against the organisation/brand (Hennig-Thurau *et al*., 2004). More importantly, if the complainers receive positive feedback, e.g., others praise their behaviour, increase interpersonal bonding, others benefit from their warning, etc., they may reinforce this behaviour, i.e., keep posting negative WOM to fit their image (Swaminathan *et al*., 2007).

2.4.3.5 Revenge seeking

There is also a group of consumers complaining online to target the organisation. Unlike those with directly contact organisations to help them improve (Verhagen *et al*., 2013), those who choose the public channels to voice their dissatisfactions because they have the intention to expose the issue and warn the organisation (Ward and Ostrom, 2006). Meanwhile, rather than helping or warning other consumers, they purposefully do so to hurt and punish the involved organisation/brand (Weitzl and Einwiller, 2020). Consumers who are ignored (Tripp and Grégoire, 2011), feel betrayed (Grégoire and Fisher, 2008), and feel harmed (Bechwati and Morrin, 2003) tend to take revenge against the organisation. Loyal or repeated consumers become a rather tricky group in these cases. On the one hand, their previous experience with the organisation remains full of grateful feelings in their mind and they may want to continue the stable relationship with the organisation if the failure can get fixed (Migacz *et al*., 2018). On the other hand, because of the prior connection, consumers tend to have higher expectations and trust in the organisation. Once the failure happens, the sense of unevenness and inconsistence will trigger stronger feelings of disappointment and betrayal because they used to have more confidence in the organisation (Herr *et al*., 1991) and this expectation disconfirmation will cause high level of dissonance (Yi and La, 2004). The higher the level of perceived harm, the stronger the intention to get revenge (Sembada *et al*., 2016).

2.4.3.6 Socio-demographics and behavioural factors

Finally, CCB is also found related to some demographic and behavioural variables (Casidy *et al*., 2021; Han *et al*., 1995). Although there is limited research in online environment, some studies still draw conclusions on that front. For example, older consumers are more willing to take public actions while higher educational level seems hinder the intention to complain via social channels (Ngai e*t al.*, 2007). Channels of shopping are also to some extent determine the complaining channel (Miquel-Romero *et al*., 2020) and familiarity with the channels will increase the intention to complain online (Dijkmans *et al*., 2015).

2.4.4 Impact of Online CCB

It is agreed that the impacts of negative online CCBs are more profound compared with traditional negative word-of-mouth since the exchange of negative content is no longer restricted to one's own interpersonal connections but extended to the world with the help of various online platforms (Ward and Ostrom, 2006).

It is widely believed that negative comments will decrease consumer's expectation toward the product/service (Babić Rosario *et al.*, 2016; Minnema *et al*., 2016), and largely inhibit the purchase intention (Wang *et al*., 2015) and organisation's profitability (Karaman, 2021) if the amount is large enough. More importantly, if extremely positive and negative comments both exist, readers will suffer from information overload which will greatly lower the perceived quality of the review, and further add difficulties to decision making (Lutz *et al*., 2022). Meanwhile, this high level of uncertainty will make those who have bought the product/service doubt about their choice (Khare *et al*., 2011; He and Bond, 2015), further reduce the post-purchase satisfaction (Rust *et al*., 1999) and the intention to recommend (Barhorst *et al*., 2020), and probably increase the product returns (Minnema *et al*., 2016).

Interestingly, some factors are found hindering the negative content further spreading or even benefiting the organisation/brand to some extent. Bystanders may not always believe what they see. Thus, if they realize the negative WOM in public is unfair, their feeling of empathy towards the organisation will be stimulated by the evaluation of equality, which further lead to supporting behaviours like higher purchasing intentions, higher rating, and more donations, etc. (Allard *et al*., 2020)[6]. Bystanders also have mutual impacts among themselves, in other words, their attitudes are influenced by others' reactions. For example, if they realize the negative WOM is not agreed or transmitted by the majority (or confronted by many), they may shift the blame to the complainer or find the excuse for the organisation (Laczniak *et al*., 2001). Defensive actions (e.g., higher purchasing intentions) are also found among those who believe themselves to have strong connection with the target organisation/brand out of the self-identification protecting purpose (Wilson *et al*., 2017). Meanwhile, similar buffering effects are found in brands with stronger equity because from the perspective of signalling theory, high brand value works as a predominate signal when evaluating the performance of the brand (Ho-Dac *et al*., 2013). Apart from the impact of online CCB on individual level, the aggregation effect, namely virality of individual's participation in online CCB has attracted researchers' interest and will be introduced separately in the following section.

2.4.5 Virality of Online CCB

The word virality (in marketing) is closely related to the term "viral marketing", which used to refer to the free Hotmail service spread by referrers[7] (Kaikati and Kaikati, 2004). Gradually, it has captured the communications about the product/service in one's own network (Bampo *et al*., 2008), thus, it is also used as the synonym for "word-of-mouth (WOM) marketing" (Baker *et al*., 2016; Kozinets *et al*., 2010) or the Internet version of WOM marketing (Kotler and Armstrong, 2020: 502). Besides, viral/WOM marketing can be classified as "endogenous" and "exogenous" according to the initiators (Godes and Mayzlin, 2009). The former form is conducted by (organisations) recruiting consumers to share their "authentic" experience in online

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[6] Supporting behaviors can be diverse, and sometimes bystanders share and comment on the negative WOM to against the complainer. Use the same example in note 5, the British Airways passenger complained about the flight delay because one passenger suddenly allegedly died, and staff performed CPR to save the dying passenger. The complainer was dissatisfied with the airline because "the flight services were halted" and no meals or drinks were served which made them "very tired, frustrated and hungry" and they asked for compensation from British Airways. After this Facebook post was reposted on Twitter, tremendous number of bystanders participate in this conversation. Instead of supporting the initial complainer, bystanders either show their empathy toward the staff (e.g., "Those poor crew.", "How is this BA's fault in any way?") or blame/attack the complainer (e.g., "Some people are unbelievably selfish.", "I certainly hope the writer of the complaint has carefully planned where and when his/her death will occur in order not to upset others.").

[7] Hotmail's viral marketing campaign was a hit as it attracted more than 20,000 new subscribers in one month after this product was first launched in July 1996. The number soared to 1 million in January 1997 thanks to an email with the message "Get your private, free e-mail from Hotmail" sent by the referrers from the recipient's own network.

social settings after use the focal product/service, which might reach potential consumers and innovators (Kaikati and Kaikati, 2004). Meanwhile, the latter one highlights the voluntary and autonomy of the sender (Riedl and Konstan, 2002), i.e., the conversation is initiated and continued naturally by consumers (Godes and Mayzlin, 2009). However, no matter who strikes up or supports the “experience sharing”, the influence of viral/WOM marketing is dramatic, especially in online environment (Berger and Milkman, 2012). These online UGCs have thoroughly influenced marketing implications, including consumers purchasing process, brand image, reputation, and marketing outcomes (Ameri *et al*., 2019). The feasibility is based on the construct that content shared by users, rather than organisations, are more likely to be exposed to new consumers (Gong *et al*., 2017). More importantly, potential consumers are less resistant when the information is shared by opinion leaders in their own network rather than how marketers claimed (Kozinets *et al*., 2010), because the persuasiveness of message relies heavily on the attribution of information source (Eagly *et al*., 1978). Therefore, receivers believe that organic information sharing is more trustworthy because they would assume that the senders are independent from the organisation, and they spread the information out of their sincere intentions (Wilson and Sherrell, 1993).

The definition of virality is unstandardized and not properly formulated (Goel *et al*., 2016). One stream of definitions derived from diffusion studies (e.g., Iyengar *et al*., 2011), which regard virality as the automatic and geometric content sharing process within the network (Golan and Zaidner, 2008; Van der Lans *et al*., 2010). The level of virality is interpreted as the probability and willingness of information spreading (Hansen *et al*., 2011) or cumulation of information adoption (Fichman, 1992) and influence (Garg *et al*., 2011). Based on the emphasis on reach and behavioural responses, some researchers enlarge the scope of virality to the phenomenon among consumers who take actions include but not limited to comment, like or dislike, raising further conversations (Tucker, 2011; Alhabash and McAlister, 2015). However, the other stream of research tends to interpret virality by the dimensions, mainly volume and velocity. Specifically, some researchers emphasize the swift transmitting within short period (Tellis *et al*., 2019), while some others tend to ignore the amount or frequency of access but consider virality as one of the features of the content which are widely shared (Heimbach *et al*., 2015). Given that there is no confirmed virality definition, in this thesis, the virality is regarded as: *the massive volume of all potential audiences’ active behaviours* (like/dislike, share, comment, discuss, etc.) *triggered by the organic or spontaneous content posted by others within or beyond their network*. It is worth mentioning that the range of WOM/post initiators is not limited to the direct social networks, because one can have access to others post via searching keywords, relevant organisation, and person, or from the conversations following the initial comments. Meanwhile, the limit on timing is weakened in this definition since characteristics are the focal aspect in this research and cumulative impacts are investigated to minimize the limitations caused by the regulations and restrictions of social platform data scraping (see detailed explanation in Chapter 5).

Consumers nowadays are more empowered with the help of the shift into relationship marketing era and tremendous growth in Internet use. Thus, they have accessibility to share their experience, either positive or negative via any convenient approach (Shen and Sengupta, 2018). Meanwhile, they can interact with other consumers on various platforms (Raval, 2020) without geographical limitations (Berger and Milkman, 2012; Jabr and Zheng, 2014). Unfortunately, for most of the organisations, negative “endogenous” WOM marketing (Herr *et al*., 1991; Chen and Lurie, 2013) and negative eWOM (Park and Lee, 2009) are perceived more influential (Baumeister *et al.*, 2001) and more likely to go viral compared with positive ones (Godes and Mayzlin, 2004). One of the explanations is the differences in attribution of positive and negative comments. Specifically, the positive information is regarded as one’s subjective reflection, while the negative feedback is based on the actual product/service experience (Chen and Lurie, 2013). This phenomenon can be explained by negativity bias, which refers to the tendency that human would encode negative information into more attracting and influential memories (Rozin and Royzman, 2001), thus, they are more likely be transmitted because of the vividness in their perception and memory (Herr *et al*., 1991). Meanwhile, according to psychologists, sensitivity to negative events is inherent in human genes, which helps us to predict and cope with external threats promptly (Baumeister *et al*., 2001). Prospect theory can also help to explain this phenomenon. People feel more frustrated when they experience loss than the happiness they can get from gain (Kahneman and Tversky, 1979). Therefore, it is reasonable that negative WOM are more influential for consumer’s acceptance and further actions (Mizerski, 1982), such as spreading them to help others (Herhausen *et al*., 2019).

To sum up, the virality of negative comments on social media will be the target of this research for the following reasons. First, unlike exogenous WOM initiated and manipulated by organisations, consumer launched WOMs are more difficult to predict and control, which require attention to the potential factors lead to virality. Besides, the popularity of social media enables (e)WOM to spread without regional restrictions. Content sharing via these channels, no matter positively or negatively, will trigger more profoundly and dramatically outcomes which are uncommon in offline settings or in relatively close environments (e.g., brand forums). Further, the impact of negative WOM may hurt the reputation of organisation more seriously compared with the favorable image presented by carefully designed and conducted positive WOM marketing campaign because of the intrinsic negativity bias. Thus, investigating the virality of negative eWOM for a better understanding of the strong predictors constitute significant academic and managerial priority (Herhausen *et al*., 2019). On the other hand, the involved organisation/brand, being a key party in the CCB process, may also play a critical role as catalyst or inhibitor of complaint virality (such as the United Airlines case mentioned in Chapter 1). In the following section, complaint management and failure recovery literature are reviewed to introduce the development of this marketing practice and to explain why complaint management is of great importance to complainers, bystanders and organisation's own well-being.

2.5 CCB Response/Management: Definition and Strategy

2.5.1 Definition of CCB Response/management

Complaint response and/or management, on the other hand, refers to the strategies applied to address consumers' complaints. In this study, complaint response/management and Service Failure Recovery (SFR) as used as synonyms to include diverse types of failures (i.e., product/service failure as well as ethical/social violations) and all the situations whether consumers raise the complaint or not. Earlier definitions of SFR were proposed from the perspective of economic exchange, as the organisation's effort to offset the consumers' loss by offering them some forms of resolution (Hess *et al*., 2003; Smith *et al*., 1999). From the outcome-oriented perspective, SFR is an attempt to regain consumers' faith after the dissatisfying service experience (Basso and Pizzutti, 2016). The SFR definitions have substantial overlaps with the process of complaint management although there are slight differences in: a) whether the consumer voiced their complaint or not; and b) whether the failure is service- or product-specific. Therefore, some researchers also propose that failure recovery is the organisation's action to cope with the consumer's complaint because of the service/product failure (Holloway and Beatty, 2003). This study incorporates both the economic exchange and outcome-orientation aspects with regards to studying complaint management. This is of particular importance because in today's digital marketplace, many times, consumers do not officially raise a face-to-face complaint. However, they may inform the company of their views via social media by sharing their experiences or commenting on others' experiences. In those cases, also, complaint management becomes an important process for organisations to maintain their standards and reputation.

2.5.2 Response Strategy

Organisations are believed to survive in society with the help of taking socially expected actions (Guthrie and Parker, 1989). Based on this, legitimacy theory proposes that organisations can legitimize their actions through disclosure reactions to environmental factors (Hogner, 1982), especially when they are facing negative situations (Elsbach, 2003). The management of legitimacy can be realized through the communication between organisations and their stakeholders (Elsbach, 1994). Meanwhile, a thorough understanding of what appropriate responses are and how to conduct various coping techniques can help legitimacy maintenance (Suchman, 1995). To be more specific, organisation's evaluation of the threat will trigger its intent to take action or not (Perks *et al*., 2013). Therefore, on the basis of proper legitimacy management principle, concrete organisational responses to CCB can be subdivided into multiple general strategies to analyze the impacts on consumers (Basso and Pizzutti 2016; Davidow, 2003; von Janda *et al*., 2021), namely no response, defensive response, and accommodative response[8].

[8] Organisations may adopt one or multiple strategies at a time or simultaneously. For example, a customer complained on Facebook Canterbury Residents' group about the 15 inch pizza they ordered from Westgate Pizza turned out to be 13 inch. And they called the catering staff liars because they denied the problem and insisted this is 15 inch pizza because the box say so. The Facebook post then went viral and some audiences commented: "If I bought 15lb of anything I would not expect 13 lb or if I bought something that is advertised as 100miles an hour , I would not like too find out it only some 75mph" and "Sounds a piffling complaint but represents almost 25% less pizza." Seeing the virality of the complaint, the pizza shop explained that they initially made the 15 inch pizza, however, pizza will shrink when it is cooked. They also highlighted that they have already apologized, invited the customer to see their pan sizes, and offered the refund which the customer also took (which can be regarded as accommodative responses). They defended that they always trying to satisfy their customers and they have never received complaints like this (Brooks, 2022; Wright, 2022).

No-response is regarded as the equivocal attitude toward failure (Raju *et al*., 2021). Defensive responses (Marcus and Goodman, 1991) refer to responsibility-shirking behaviours, such as shifting the blame, denying the failure, or even attacking the complainer (Wilson *et al*., 2017)[9]. Accommodative strategies usually involve remedy actions which indicate the organisation admit their responsibility (Johnen and Schnittka, 2019) directly or indirectly. Overall, most of the extant studies draw the conclusion that accommodative responses are most effective in terms of improving complainers' satisfaction (Béal and Grégoire 2022; Chang *et al*., 2015; Sameeni *et al*., 2022; Weitzl and Hutzinger, 2017). For example, active listening and showing empathy to the complainer can increase complainer's gratitude to the organsation especially when the initial complaint was expressed with high level of negative arousal on public channels (Herhausen et al., 2023). However, in the conditions wherein clarification is expected, defensive replies might be necessary (Weitzl and Einwiller 2020). Meanwhile, defensive reactions are more effective in terms of consumer's purchase intention in hedonic contexts compared with utilitarian scenarios (Johnen and Schnittka, 2019). It is believed that accommodative responses contribute to the mitigation of negative WOM for the consumers who have lower desire for revenge (Weitzl and Einwiller, 2020), however, for those who have high retribution tendencies as well as high loyalty, there is no huge difference in no defensive, accommodative and no response.

Finally, researchers suggest organisations avoid no response strategy (Herhausen *et al*., 2019) since consumers have no clue to infer organisation's concern for them (Sparks *et al*., 2016). However, opposing research proposes that no response may not always do harm to the organisation since replying to complaints in specific social scenarios, they even find potential harm to the firm value when organisations reply to criticisms on specific social platforms, such as Twitter, since they might cause complaint publicization problem (Golmohammadi *et al*. 2021). However, it is worth highlighting that failure recovery usually requires considerable resources (Homburg

[9] On many occasions, attacking consumers tend to trigger disastrous outcomes, especially on public channels. For example, a customer called Freeman complained on her Facebook about the decoration of the rainbow cake was different from the cake maker's (Kylie Kakes Dessert Bar & Café) advertisement and she thought she has been overcharged given the ugly looking of the cake. The complaint itself initially did not receive much attention. However, the owner of the dessert bar attacked the customer on TikTok, calling her "the worst client", which then went viral with more than 5 million views in a short period. The owner's behaviour obviously irritated the client, and she fought back by posting a TikTok video with the picture of the ugly cake and screenshots of their conversation. As Freeman said the owner "wants to be TikTok famous", however, it turned out that audience showed their empathy toward the client instead (Tolentino, 2023).

et al., 2010), which might be rather limited or challenging for the organisation (Harrison-Walker 2019). In fact, organisations use a variety of systems in replying to complaints as simultaneous, homogeneous, and appropriate response might not be realistic on most occasions.

It is also worth mentioning that organisational reactions are also determined by various non-consumers factors, such as stakeholders' visibility, potential impacts (Branco and Rodrigues, 2006), and the size of the organisation (Patten, 1991). Moreover, Lindblom (1994) proposes that organisations can legitimize their actions by informing stakeholders their intent to improve, attracting stakeholders' attention with the help of positive activities, and changing stakeholders' perceptions and expectations. In sum, when organisations propose and implement their response strategies, not only the consumers' perceptions but also the organisations' own status should be taken into account.

2.5.3 Responder

Apart from whether and how to respond to the complaints, who to respond is attracting increasing attention in recent years. Although the default responders in previous studies are involved organisations, with more diverse product/service and failure types, it is necessary to categorize the different actors responding to complaints (Crolic *et al*., 2022; Weber and Hsu 2020). Esmark Jones *et al*. (2018) fail to find significant differences between direct organisational response and reply from employee. In other words, although organisations may have definite complaint response guidelines, employees who carry out the response may still use diverse processes leading to different outcomes. To be specific, employees alter their attentiveness or strategy according to consumer's expressed anger (Glikson *et al*., 2019), status and the service climate of the organisation (Jerger and Wirtz, 2017). On the other hand, employee's own traits, such as appearance, may have different impact although same actions are taken (Li *et al*., 2022). Since consumer's attributes are uncontrollable, it is critical to promote the internal recovery management system for the service-oriented mindset of employees. Active knowledge sourcing and practice in recovery behaviours (Van der Heijden *et al*., 2013) benefits the effect of response as well as the integrated system itself (Smith *et al*., 2010), which requires both mechanistic guidelines and organic support from other internal entities (Yilmaz *et al*., 2016).

In addition to parties involved, the latest research also explores the efforts by other organisations, and particular attention is paid to external or affiliated support (Allen *et al*. 2015). For example, Weber and Hsu (2020) draw the conclusion that recovery from external and unaffiliated organisations is perceived more effective, and it is followed by external affiliated company and internal recovery. However, in an online environment, Gunarathne *et al*. (2017) find that consumers tend to have negative feelings if they are handed over to other departments. Furthermore, since co-creating is believed to contribute to the connection between consumers and organisations, there is also a trend in investigating the conditions and process of consumer's participation in recovery with the organisation (Dong *et al.* 2016; Hazée *et al*., 2017; Roggeveen *et al*. (2012) or to solve the failure of self-service technologies before they communicate with employees (e.g., Zhu *et al*. 2013). For example, co-creating is found to have a positive impact on consumer's post-recovery assessment in serious service delay situations (Roggeveen *et al*., 2012; Hazée *et al*., 2017). In addition, webcare (online response) from both organisations and bystanders are found helpful in improving the consumer-brand relationship (Weitzl and Hutzinger, 2017).

2.6 Summary

Extant complaint management/SFR studies generally explore the above mentioned two aspects, i.e., who to respond and how to respond to complaints. Although some recent studies show the importance of integrating the characteristics of complaint and complainer when designing complaint handling strategies (Homburg *et al*., 2010), most of these studies focus on offline complaints (e.g., Marinova *et al*., 2018; Surachartkumtonkun *et al*., 2013). More importantly, the studies on complaint management tend to examine the outcome at the individual's level, i.e., how will the complainer or bystander perceive the response, but ignore the cumulative power of complainer/bystander as a whole group. Although some recent studies cover multiple aspects including organisation's efforts, traits of complaints and bystander's reactions, such as Herhausen *et al*. (2019), they tend to highlight limited attributes rather than take a comprehensive examination that involves interaction of multiple factors as occurring in real-life situations. Without such comprehensive examination, the generalisation of these outcomes can be doubtful as complaint virality can be influenced by complex and diverse triggers in reality. Therefore, this research aims to explore a significant proportion of potential factors which might lead to complaint virality.

CHAPTER 3 HYPOTHESES DEVELOPMENT

3.1 Introduction

As the outcome of endogenous content sharing might become viral and uncontrollable, researchers are interested in whether it is a random phenomenon (Cashmore, 2009) or it is possible to figure out the factors that might cause virality in public. Researchers still argue about whether the content of review is the only factor that readers pay attention to. Those who regard non-content information as heuristic clues (Grewal and Stephen, 2019; Shah and Daniel, 2008) propose that these additional cues only come into effect when consumers have to evaluate competing information (e.g., comparing reviews).

However, according to the information system studies which investigate the key factors of information quality, some variables, such as reliability, objectivity, and understandability (Bailey and Pearson, 1983; Mahmood and Medewitz, 1985; Negash *et al.*, 2003) are highlighted when analysing the information. Literature analysis on the theoretical perspectives of eWOM finds that dual-process theory is most frequently used in explaining the information processing of the eWOM (Cheung and Thadani, 2012). Specifically, adopting elaboration likelihood model (Cheung *et al.*, 2008) and heuristic-systematic model (Gupta and Harris, 2010; Zhang and Watts, 2008), among others. The elaboration likelihood model (ELM) proposes that stimuli processing can go through the central route when individuals consider and evaluate the actual value of the information or undergo the peripheral route which is a simple reaction to the environmental stimuli without checking the merit of the presented information (Petty and Cacioppo, 1986). Similarly, heuristic-systematic model also claims that information processing involves either systematic investigating the reliability and content of the information or relying on the effortless cognition as the short cut (Chaiken, 1980). More studies are looking at the intercorrelation between the routines and believe that attitudes are influenced by both central and peripheral cues (Petty *et al.*, 1997). Meanwhile, criticisms on elaboration likelihood model argue that previous studies are conducted based on the notion that information recipients are not capable of processing cues simultaneously (Stiff, 1986). Researchers then confirm that the possibility of dual-routine processing cannot be dismissed, and the so-called “central” factors can be influenced by peripheral cues significantly (Petty *et al.*, 1987). Further research also proves the interaction (Coulter and Punj, 2004; MacKenzie *et al*., 1986) and the joint effect of the routines (Lord *et al*., 1995). Thus, the boundary between core and peripheral routes may be ambiguous and they may together come into effect when readers appraise the complaints especially when they are exposed to rich information context, such as social media (Barhorst *et al*., 2020). Furthermore, from the perspective of consumer inference theory (Kardes *et al*., 2004), consumers' judgments are usually made based on the limited information and knowledge. In online scenarios, the level of information incompleteness is higher than face to face situations, thus, consumers' evaluations rely more on the limited information which are attainable. Therefore, this research opines that both central and peripheral process have critical impact on the evaluation of the complaints.

In fact and in practice, more and more empirical studies (e.g., Pan and Zhang, 2011; Reimer and Benkenstein, 2016) find that characteristics of content, source and other external factors are critical to the influence of negative eWOM. However, since existing studies only focus on limited aspects of complaints and there is no unified conclusion which are the main factors that lead to virality, it is necessary and timely to conduct a comprehensive analysis of all potential factors. The current research will fill this gap based on the assumption that the possibility of virality is determined by different parties' engagement, namely, the complaint and the complainer, the involved organisation and its reaction, and the bystander's participation. Meanwhile, various characteristics of each party will be taken into account.

3.2 Characteristics of Complaint

When studying the online CCB, content of the complaint is no doubt a widely discussed topic (Grewal and Stephen, 2019). Extant research show that the virality of content posted on social platforms are found to some extent caused by factors which can be classified into linguistic and psychological influences.

3.2.1 Linguistic Influences

3.2.1.1 Length of text

Length of text, usually demonstrated by the word count of the text, is found related to the perceived helpfulness of UGCs since they may include more detailed explanations or information of the product/service or the organisation/brand (Mudambi and Schuff, 2010; Pan and Zhang, 2011), which provides as a short cut for consumers to evaluate the performance of the organisation (Salehan and Kim, 2016). It is also believed that longer text tend to contain more and vivid sentiment signals than shorter paragraphs (Hartmann et al., 2023). According to the signalling theory (Spence, 2002), the length of the UGC works as the signal for readers to infer the reviewer's effort in writing the content. Therefore, texts with more words are regarded to have higher persuasiveness and helpfulness (Mudambi and Schuff, 2010; Salehan and Kim, 2016; Zhang *et al*., 2010). Specifically, longer contents, on the other hand, are more eye-catching (Salehan and Kim, 2016), thus, are more likely to be seen and may have a higher probability to be shared. Researchers also find that information processer's confidence in the information (termed as "illusion of validity") will be to large extent boosted when the length of presented information is increased (Tversky and Kahneman, 1974), meanwhile, they also tend to engage and support the information as more cognitive resources are devoted in processing the information (Petty and Cacioppo, 1984). Therefore, the hypothesis is proposed:

Hypothesis 1: The length of online complaints will have positive impact on the virality.

3.2.1.2 Readability

Readability of text refers to the difficulty of reading and understanding (Zakaluk and Samuels, 1988; Smith and Taffler, 1992). In line with cognitive fit theory (Korfiatis *et al*., 2012), the perceived helpfulness of the information is influenced by its readability as the understandable content is easier to fit the reader's information processing system according. Cognitive fit theory proposes that the effectiveness of problem solving is highest when the problem and all aspects of solution are aligned (Vessey and Galletta, 1991). In other words, if the readability of the content is good, it can align with the reader's cognitive level, which will attract more people's attention and interest (Korfiatis *et al*., 2012) and will increase the probability of adopting and recommending the information is largely improved as well (Srivastava and Kalro, 2019). Specifically, when exposed to massive information, consumers tend to follow the easier cognitive path for information processing (Mackiewicz and Yeats, 2014), thus, information conveyed in a more readable form is more likely to be understood (Cai et al., 2023). The processing fluency theory also suggests the similar psychological mechanism. Processing fluency theory demonstrates the convenient process of information-processing and decision-making (Alter and Oppenheimer, 2009). Specifically, processing fluency theory proposes that the information is more effectively recognized, processed, and memorized when it is presented in a readable form (Liza et al., 2019). When reading online complaints, the fluency of information extraction is important when analysing the contents (Winkielman *et al*., 2013) because it will influence the perceived trustworthiness of the complaints (Unkelbach, 2006); thus, higher readability is more likely to fit more readers' understanding, thus, further increases the probability of virality. Therefore, this research proposes that:

> Hypothesis 2: Higher readability of the online complaints will have positive impact on the virality.

3.2.1.3 Use of attachment

How to express views is now regarded as important as what to express on social media if the author wants to increase others' engagement (Li and Xie, 2020). Along with usefulness, vividness, and interactivity are regarded as critical content characteristics (Peters *et al*., 2013). Social media now allows various types of content, which is not limited to text, but also enables users to add emoji in text and attach multimedia content. Studies on advertising effectiveness already proven that the presence of images can easily catch attention regardless its content, size and format (Bruce et al., 2017; Pieters and Wedel, 2004). On social media, users are always facing information overload problem, and information has to compete for user's attention. Thus, a post with images or other visual contents can be eye-catching and outstanding among the posts with no visual stimuli (Li and Xie, 2020; Song et al., 2021). More importantly, the use of visual cues helps to increase the perceived extra effort of the author and this effect is more profound if the text and image matches well (Li and Xie, 2020). Last but not the least, pictures/videos work as the prove of the experience (Boley et al., 2013), thus, complaints with relevant pictures/videos tend to be more reliable as they provide supplementary evidence of the incident. Therefore, it is worth investing whether the use of attachment (can be images, videos, and other visual stimuli) can have impact on other's intention to like, share and reply to the complaint.

> Hypothesis 3: Adding attachments to online complaints will have positive impact on virality.

3.2.2 Psychological Influences

3.2.2.1 Polarity

The polarity of the text refers to whether the direction is positive or negative (Salehan and Kim, 2016), sometimes may also include neutral according to the applied polarity classifier. Literature on the polarity is rather controversial, in other words, researchers have opposite ideas of whether positive or negative comments are more persuasive and more likely to be shared. From the self-image maintenance perspective, to post or share positive information may also improve one's self-image (De Angelis *et al*., 2012; Philp and Ashworth, 2020). Since purchasing behaviours are sometimes choices after one's own deliberation (Putsis Jr and Srinivasan, 1994), and level of satisfaction/dissatisfaction to some extent demonstrates the pre-purchase assessment is wise or not (Philp and Ashworth, 2020). Therefore, sometimes dissatisfied consumers tend to participate in positive WOM, especially in public, because they are reluctant to admit their wrong choice (De Angelis *et al*., 2012). Thus, it seems who is the audience is also a critical factor. Specifically, the number of audiences can influence the valence of expressions to some extent. Negative comments are usually avoided if the communication happen on social platforms (Gonzales and Hancock, 2011) or when the number of information receiver is large. Meanwhile good images are presented by positive speech in these occasions (Barasch and Berger, 2014) for impression management (Goffman, 1959). Similar phenomenon is found among the information bearers that those who share negative information are less favourable (Bell, 1978), therefore, negative comments are less posted and shared (Forest and Wood, 2012).

Meanwhile, the closeness between sender and receiver is also a critical factor for what contents to share and the findings from this perspective have some opposite opinions to the considerations of audience number. When communicating with those who are in the closer relationship, self-enhancing is the main purpose, therefore, relative positive information is preferred; while, as the interpersonal connection getting weaker, spreading negative messages are more common for protecting others (Dubois *et al*., 2016) in case they undergo the same experience (Hennig-Thurau *et al*., 2004). Interestingly, warning others can decrease the interpersonal distance, which to some extent strengthen their social bonds (Wetzer *et al*., 2007). However, the speed and range of the information transmitting is also determined by the audience (Dubois *et al*., 2016). Information sharing with distant audiences or strangers can reach a wider range of social networks geometrically, therefore, it will become more influential (Burt, 1992). In sum, sharing negative information with those out of one's own network have higher probability to be exposed to considerable number of audiences. Furthermore, it is also found that participation in positive or negative WOM may be contingent on whether the experience is relevant to one's own experience or others', i.e., who is involved. Consumers are found more willing to claim they have pleasant experience with their own purchasing, however, tend to talk about others' dissatisfying experience for self-enhancement purpose (De Angelis *et al*., 2012). With all these diverse ideas regarding, whether positive or negative contents are more likely to go viral becomes inconsistent.

Finally, comments which have negative polarity, either extremely, moderately, or slightly negative, can lead to diverse impacts. The existence of extremity effects has been proven by psychologists that extreme behaviours tend to receive more attention and being more influential compare with moderate actions, because they are believed to be more diagnostic (e.g., Fiske, 1980; Skowronski and Carlston, 1989; Qiu *et al*., 2012). Specifically, the impact of extreme negativity may be more salient when most of the contexts are positive. According to the adaptation level theory (Helson, 1964) and the neutral point works as the reference of judgment, however, this point is subjective and affectable. Thus, the "neutral" point will shift to relatively positive side if one is exposed to more positive information, and the negative information will be evaluated as more negative. More importantly, the extremely negative effects may become more eye-catching since they offer a significant contrast with the majority's perceptions (Asch, 1951). The credibility of information is found heavily amplified by the extremity no matter the source is reliable or not (Fishbein and Ajzen, 1975). Marketing researchers also notice this phenomenon and have conducted some exploratory studies by investigating the extreme ratings. Extreme ratings, either positive or negative, are perceived more informative and helpful in catering (Park and Nicolau, 2015) and online retailing (Forman *et al*., 2008). Thus, this research proposes that:

> Hypothesis 4: The tone polarity of online complaints will have positive impact on the virality.

3.2.2.2 Subjectivity

In language use, subjectivity is regarded as to what extent the language user can express his/her idea in a subjective way (Benveniste, 1971), and higher level of subjectivity is closely related to affective reactions (Anand *et al*., 1988). Thus, many computer science scholars highlight the importance of distinguishing facts and subjective information when conducting natural language processing (Cho *et al*., 2014; Deng *et al*., 2017; Giatsoglou *et al*., 2017), and it is widely believed that objective information tends to have higher persuasiveness (Petty and Cacioppo, 1984). However, from the extant literature, it is obvious that although general natural language processing may conduct sentiment polarity and subjectivity analysis as a pair, it has not attracted sufficient attention from marketing researchers' when studying online CCB.

When complaining about an organisation, the complainers tend to describe the dissatisfying experience or express their negative perceptions enormously (Sparks *et al*., 2016), thus, they may unavoidably use subjective words and expressions to some degree (Zhao *et al*., 2019). It is worth highlighting that the polarity and subjectivity together reflect the complainer's sentiment, specifically, polarity refers to the degree and type of emotion while subjectivity shows how the emotions are demonstrated by the complainer's texts (Geetha *et al*., 2017). Unfortunately, although most of the online CCB/negative WOM studies have found how polarity can affect reader's emotion, attitude, and behaviour, the associated subjectivity is always ignored.

The impact of content subjectivity on virality can be explained by congruity theory, which is frequently adopted to demonstrate why some statements are more/less persuasive and potentially the following attitudinal formation and change (Tannenbaum, 1967). According to congruity theory, one would alter his/her evaluation to the direction of which the congruence with extant reference is higher (Osgood and Tannenbaum, 1955), in other words, one is more willing to react positively when the received information is more consistent with his/her own believes or expectations. This phenomenon is also regarded as the coping mechanism to overcome the negative feeling of cognitive dissonance (Festinger, 1964).

When bystanders browsing the complaints, it is quite common for them to evaluate to what extent the communication is out of personal reasons or situational reasons (Folkes, 1988). Generally, readers would assume the one who posted the comments without any proactive animosity towards the organisation, and they frequently expect these negative WOM are unbiased and rational comments based on true experience (Chen and Lurie, 2013) rather than personal emotional venting or revenge. Thus, when they come across the complaints with extreme subjectivity, it causes the inconsistency with their initial perception and expectation. Therefore, it is reasonable that they may not support these highly subjective complaints because they would doubt whether the complainer described the failures authentically or exaggeratedly, and whether the blame is reasonable, or it is out of the complainer's own egoistic purpose. In line with the attitudinal tendency proposed by congruity theory, they would avoid the behaviours which may support these complaints, in other words, they may disagree with these complaints and necessarily will not share or like these negative comments. Therefore, purposed here:

> Hypothesis 5: Subjectivity level of the online complaint will have negative impact on virality.

3.2.2.3 Analyticity

Online complaints, as one type of text, have some basic linguistic characteristics, for example, use of functional words (Pennebaker *et al*., 2003). These linguistic traits also reflect the underlying cognitive process (Nisbett *et al*., 2001). Analytical thinking embedded in the text is frequently helped with providing explanations, stating formal arguments, and demonstrating knowledge (Bevan *et al*., 2015). Thinking patterns are found closely related to the cultural dimensions, for example, the level of individualism (Zhang *et al*., 2021). Researchers find that people from high individualism cultural background think more analytically (Kitayama *et al*., 2003; Talhelm *et al*., 2014; Kumar *et al*., 2022). The results have been tested and confirmed by comparing European and American countries with East Asian countries (Zhang *et al*., 2021). Therefore, it seems plausible to assume that analytic contents may be easier to understand for readers from high individualism culture according to the cognitive fit theory (Korfiatis *et al*., 2012), because high similarity in writing style and thinking can make the information processing more convenient. Therefore, this study proposes:

Hypothesis 6: Analytical online complaints will be more likely to go viral.

3.2.2.4 Clout and authenticity

Clout in text refers to the confidence, social hierarchy, leadership, certainty, and expertise expressed (Pennebaker *et al*., 2015), and it is widely examined in analysing the expertise and tone of the text (Brauer *et al*., 2022). The prosperous network flow relies heavily on more equal information sharing and less hierarchical interpersonal connections (Himelboim *et al*., 2017). This can be explained by the small world theory that interconnected individuals group as clusters, and these clusters further aggregate into the human society (Milgram, 1967). It is worth highlighting that level of hierarchy and expertise will hinder the information flow within the network (Himelboim *et al*., 2017; Wang *et al*., 2010), thus, higher level of clout may decrease the fluency of information spread via the interpersonal connections. Furthermore, showing too much confidence can to some extent hinder other's intention to join the conversation (Moore *et al*., 2021), and similar results have been proven in interactions in online forums (Pilny *et al*., 2019).

On the other hand, consumers tend to believe in other consumers' feedback rather than organisations' advertising because they perceive these WOMs are more authentic (Allard *et al*., 2020). Meanwhile, the level of authenticity is one of the criteria to evaluate the value of information (Cheung *et al*., 2009; Barhorst *et al*., 2020) since authenticity in social communication is no longer limited to how real the expression is, but determined by whether unnecessary social inhibitory words and phrases are used (Markowitz *et al*., 2023).[10] Similar to the effect of the author's over-confidence, social inhibitions can also restrain others to participate in the conversation whereas authentic conversation are usually more inviting.
Thus, it is proposed that:

Hypothesis 7: Clout of the online complaint will have negative impact on virality.
Hypothesis 8: Authenticity of the online complaint will have positive impact on virality.

[10] High authenticity means low social inhibitions.

3.2.2.5 Affect

Affect of text represents how emotional the text is (Melumad *et al*., 2019; Hovy *et al*., 2021), and writing emotional comments is rather common (Rocklage and Russell, 2020) because they regard the emotional texts will be more persuasive (Rocklage *et al*., 2018). Meanwhile, emotion is one of the critical dimensions of stimuli (Osgood, 1962), which might trigger further actions, such as sharing emotional reviews (Berger, 2014). Indeed, influencing others is one of the key social functions of emotions when expressed in interpersonal connections (Keltner and Haidt, 1999).

In terms of the types of emotions, it is generally agreed that positive emotions are more commonly used in supporting organisations/products/service, and opponents express more negative emotions to persuade others (Hovy *et al*., 2021), and higher level of either type is a strong predictor of sharing behaviours (Berman *et al*., 2019). More importantly, some researchers propose that the impact of content emotions on sharing is more substantial compared with the quality of the argument, i.e., analytic (Weismueller *et al*., 2022). The elaboration likelihood model proposed by Petty and Cacioppo (1986) helps to explain how different emotions can influence the impact of information in different conditions (Rocklage *et al*., 2018). For example, once negative emotions are aroused, negative clues are intensified and elaborated, i.e., special attention will be paid only to these cues and the irrelevant information are more likely to be ignored (Baron *et al*., 1994). However, if both positive and negative emotions exist in the text, the ones of which positive emotions are predominant might trigger more shares (Weismueller *et al*., 2022).

It is worth highlighting that researchers also notice the phenomenon of emotionality backfire, in other words, under some circumstances, extreme polarity of emotions may lead to opposite effects because readers might doubt the actual helpfulness (Rocklage and Russell, 2020) and persuasiveness (Tucker, 2015) of the information. Therefore, in this study of online CCB, the impact of both positive and negative emotions will be explored:

> Hypothesis 9a: Positive emotions in online CCB will have negative impact on virality.

Hypothesis 9b: Negative emotions in online CCB will have positive impact on virality[11].

3.2.2.6 Use of question mark, exclamation mark and emoji

Twitter, being a popular social platform, has its own limitations. One of them is the word count limit[12]. Some challenges in conducting sentiment analysis are caused by inherent characteristics of short messages, such as wrong spelling, misspellings, grammatical mistakes, unfinished arguments, ununified abbreviations of words, etc. Thus, researchers highlight the importance of specific punctuations especially when analysing short and informal messages since they can to some extent work as the supplementary when the mentioned problems exist in short texts (Kiritchenko *et al*., 2014). More importantly, punctuations use can also reflect the emotions the writers want to express (Lee, 2021).

Apart from the insufficient or ambiguous cues because of the word limit, the paralinguistic factors of are sensitive clues for readers to understand the message by anonymous senders (Lea and Spears, 1992). Given that amplifiers such as facial expressions, change in speed and tone, and body language are missing in online platforms, punctuations become one of the most critical signals (Hancock, 2004). Thus, some researchers highlight the importance of using degree-relevant symbols along with attitudinal words to conduct sentiment analysis (Jang *et al*., 2013). Although punctuations are usually excluded when analysing, the nonstandard punctuations, such as exclamation mark and question mark are considered to have some particular and non-negligible impacts (Hancock, 2004; Vandergriff, 2013).

The functions of exclamation mark and question mark have been studied in advertising study and recently in sentiment analysis since researchers agree that these signals help to express different meanings (Lanham, 1991; McArthur, 1992: 394). According to the literature, exclamation marks are used for various purposes, such as attention attract (De Jans *et al*., 2018), information highlight (Vaičenonienė, 2006), “excitability” express (Waseleski, 2006), tone emphasize (Naveed *et al*., 2011), energy expression (Thelwall *et al*., 2010), and meaning double confirmation

[11] Based on the dictionary of sentiment words and its structure, several types of negative affect (i.e., anxiety, anger, sad and swear) are tested in the study. See Section 5.5.3 for detailed explanation.

[12] The initial Tweet length limited to 140 characters. Now according to Twitter’s latest regulation, most of the “text content of a Tweet can contain up to 280 characters”.

(McArthur, 1992). Previous studies also compared emotions of short paragraphs, finding that just adding one exclamation mark can to a large extent explain the expressed mood immediately, and this effect is further enhanced if repeated marks are used (Thelwall *et al*., 2010). The basic function of question mark is no doubt to interpret a sentence as a question, which may trigger readers to consider the relevant information (Howard, 1988). Besides, information senders use question marks because they expect to receive more response (Naveed *et al*., 2011) since addressing and responding to questions are one of the most frequent communication forms (Howard, 1988). Moreover, question marks sometimes have the same function as exclamation marks which express the level of surprise (Adeyemo, 2013), or indicate interrogation (mostly with negative attitude) when following uncertain or negative moods (Dresner and Herring, 2010).

In addition, emoji is regarded as the manifestation of nonverbal elements which works as the supplement or replacement of verbs (Luangrath *et al*., 2017) and neural study has proven that people will have neural response to visual paralanguage such as emoji (Churches *et al*., 2014). Thus, emoji can work as the proxy for the emotion the author want to express (Kaye *et al*., 2016). Given that emotional arousal of the content is the predictor of content virality (Herhausen *et al*., 2019), it is reasonable that use of emoji may increase the probability of content virality.

According to the rhetorical theory, using rhetoric symbols tend to attract the reader/audience’s attention and more likely to trigger their reactions (Scott, 1994), and it is found to increase responses in marketing (Delbaere et al., 2011) and social communication contexts (Aljukhadar et al., 2020). This effect is found more profound when the information to process is effort-consuming and motivation required (Petty and Cacioppo, 1986). Therefore, when exposing to huge amounts of complaints, readers may be attracted by symbols such as exclamation mark, question mark and emoji, which are easy to process and may trigger their responses. Extant literature find that the higher retweet actions take place when the Tweets are ended in question mark, however, similar outcome is not founded in those ending in exclamation mark (Lin and Peña, 2011). When polarity of contents is considered, computer science researchers find that positive tone sentences with more exclamation marks are more favourable (receive more “like”s) by readers (Teh *et* *al*., 2015). To further explore the impact of using exclamation mark, question mark and emoji on the virality, this research proposes that:

Hypothesis 10: Using more exclamation marks in online complaints will have positive impact on the virality.
Hypothesis 11: Using more question marks in online complaints will have positive impact on the virality.
Hypothesis 12: Using more emoji in online complaints will have positive impact on the virality.

3.3 Topics of Complaining

Consumers may complain for various reasons (Thøgersen *et al*., 2009), and current studies already prove that the ways and density of consumer complain might be diverse because of the differences in reasons (Grégoire *et al*., 2010; Herhausen *et al*., 2023). However, when studying the contents of complaints, simple statistics on single words may lead to confusing results since the unstructured data can contain complex word pairs, thus, understanding the topic or main idea of the text, which can clarify the interaction of words, is warranted (Büschken and Allenby, 2016). Based on the assumption that informative cues can be observed through the text, extant literature study the impact of topics on some outcomes, such as consumer's understanding process of the product (Zhao *et al*., 2013), predicting product sales (Ghose *et al*., 2012) and product attributes (Archak et *al*., 2011). Furthermore, literature on general CCB has proven that type of failure serves as indicator of complainer's behaviour (Grappi *et al*., 2013; Grégoire *et al*., 2018) as well as reader's perception and reaction (Gunarathne *et al*., 2017). It would be helpful to conduct topic modelling for better understanding the reasons for posting and sharing negative eWOM (Hu *et al*., 2019). Meanwhile, it is also worth highlighting that the attributes of the test are diverse among and within topics (Berger and Milkman, 2012), thus, the interaction between the complaint topic and the attributes of complaint may also influence the virality. Thus, this research proposes that:

Hypothesis 13: Different topics of online complaints will lead to differences in virality.
Hypothesis 14: The attributes (physical and psychological) will moderate the impact of complaint topic on virality.

3.4 Characteristics of Complainers (Number of Followers)

Among the important traits of information quality, the credibility of source is a critical criterion (Chaiken, 1980). Source credibility is receiver's perception of the communicator's level of believability (O'Keefe, 1990), and as subjective perception rather than objective description, credibility is determined by various factors (Westerman *et al*., 2014). Although there is no confirmed categorisation, credibility is usually evaluated by information receiver's assessment of the sender's expertise, trustworthiness: to what extent the sender is telling the truth and the goodwill: actual intention of the sender (Westerman *et al*., 2014). However, in online, especially social environment, the assessment of credibility becomes more challenging. It is observed that online reviews are usually inferior to traditional WOM in terms of their credibility because of anonymity (Park *et al*., 2007). Unlike the offline WOM, of which the sender's identity is more vivid and more observable, lack of the cues of online reviewers makes the judgment rather limited (Park and Lee, 2009). It is worth highlighting that measure senders' competence is not easy, thus, the limited number of accessible cues seem to be the remaining parameter. Number of followers is one of the visible and influential indicators. Although it cannot represent the profession of the information sender, at least it reflects that the visibility (Cheng and Ho, 2015) and prestige (Toubia and Stephen, 2013) of the sender is higher. In other words, others might regard this sender being representative or authority, and worth being listened to some extent. More importantly, the number of followers is not only the attribute of the user, but also the consequence of the user's previous posts (Toubia and Stephen, 2013).

One of the key elements for virality is how people are aroused in social environments. According to behavioural contagion theory (Stephenson and Fielding, 1971), one may spontaneously mimic others' behaviours (Ogunlade, 1979). For example, people choose the colour and style of fashion products by following the choice of their friends. These behaviours take place in society either accompanied by or without emotion spread (Wheeler, 1966), but it is important that the followers share similar conditions or emotions with the one they mimic, and more importantly the follower would perceive the one they mimic have a positive identity (Ogunlade, 1979). Thus, for the followers, those who they follow or have more followers, tend to be a proper model because of the positive perception of them. The ones who have wider networks can influence in various ways, such as convincing or advising (Weimann, 1994). Furthermore, those who have more followers have a latent and indirect range of reach as their followers also have their own networking. In online CCB context, if the popular social media users complain about an organisation or share negative WOM, the followers who share the similar opinion with them may take imitative behaviour. In general, with larger number of followers, the cumulative results may become viral. Thus, this study proposes that:

Hypothesis 15: The number of complainer's followers will have a positive impact on the virality.

3.5 Characteristics of the Organisation

3.5.1 Number of Followers

Number of followers can to some extent shows the popularity of the organisation/brand, meanwhile, may also reflect how wide the reach the WOM can be (De Veirman *et al*., 2017). Studies have found evidence that stronger brands are to some extent protected by their brand equity when facing attacks (Ahluwalia *et al*., 2000), unluckily, weaker brands that do not have this buffering (Erdem and Swait, 1998).

However, large number of followers can also be a tricky factor when negative WOM takes place. Although it is assumed that most of the followers are "friends" of the organisation/brand (Kim *et al*., 2014), the type and level of the connections/relationships between consumer and organisation can be diverse (Fullerton, 2003). Specifically, consumers may attach with the organisation just for calculative commitment, i.e., for economic and/or functional purpose. In these occasions, they seem to be "friends" just because they have no better opinions or the barrier to exit is too high (Bansal *et al*., 2004). So, it is understandable that some consumers follow the organisation just because they are (potential) consumers (with no matter positive, neutral or negative attitude). And larger organisations/brands have more followers not only because they are more popular, but also because they receive more scrutiny from the society and more likely to be targeted (Roberts, 2003).

Last but not the least, as channels for users to communicate with the organisation, organisation's social media accounts also have the function to gather and connect the (potential) followers no matter they follow the organisation for what purpose.

Within this community, information can be discussed and diffused more swiftly and frequently compared with traditional WOM channels, which only covers those in one's own network (Herhausen *et al*., 2019). Thus, it is predictable that once negative eWOM is posted, it is more likely to be shared if the involved organisation/brand has more followers. Thus, it is proposed that:

> Hypothesis 16: The number of the involved organisation/brand's followers will have positive impact on the virality of the online complaint.

3.5.2 Total Number of Tweets and Replies

Organisation/brand post on social media for exposure and interact with consumers and obviously higher number of Tweets posted reflect organisation/brand's activeness, meanwhile, higher number of (all) replies to consumers can to some extent show organisation cares about interaction with consumers. However, if the ratio of replies to negative comments are low, will leave negative impression on consumers, especially if they reply to more positive comments (Wang and Chaudhry, 2018). Consumer will doubt the organisation's attempt to admit their responsibility and think organisations are using replies as a chance to promote themselves, thus, they may share the negative eWOM to warn the organisation (Wang and Chaudhry, 2018). Therefore, this research proposes that:

> Hypothesis 17: Ratio of organisational response to online complaints will have negative impact on virality.

3.5.3 Ratio of negative Tweets Received

In line with the social learning theory, people can learn from others' behaviours during their interaction and use the learned pattern and criteria to alter their own judgement (Alexandrov *et al*., 2013; Bandura and Walter, 1977). This phenomenon is more widely found when the audience have limited knowledge of the situation, they observe and learn from previous consumers' attitudes and behaviours, which may even overcome their initial perceptions. Gradually, the whole audience group tend to have similar opinions (Chen et al., 2011). When observers have inadequate knowledge of the dissatisfying experience being complained by others, they will rely on other evidence to change their attitudes. The overall density of the complaints (compared with all UGCs) works as the clue that more consumers tend to have negative perception of the product/service, and they would also believe that complain about the relevant product/service is reasonable. Therefore, negativity spiral has been found among complainers sometimes, i.e., the more consumers are exposed to negative WOM, the more likely they will participate in it (Hewett *et al*., 2016; Hogreve *et al*., 2019). This phenomenon is also found when audience are exposed to both positive and negative information, and negative WOM is more influential and more likely to trigger sharing behaviours (Anderson, 1998). Therefore, this research posit that the overall sentiment about the organisation will be perceived as negative if the ratio of negative eWOM is higher (Nguyen *et al*., 2020), which might not only catch the eyes of consumers but also "encourage" them to take actions such as share and like the complaints. Thus, this study posits that:

> Hypothesis 18: Ratio of online complaints (of the organisation/brand) will have positive impact on the virality.

3.6 Characteristics of Organisational Reply

3.6.1 Reply versus No reply

For Twitter eWOM, the harm of complaint publicization (if the organisation respond to the complaint, it will be pinned at the top of the Twitter page until a new Tweet is posted, which might lead to more exposure (Golmohammadi *et al*., 2021). However, not responding is regarded as the dismissal of the consumers, which may trigger more negative attitudes and actions (Wang and Chaudhry, 2018). Thus, most of the literature suggest organisations provide response to show their concern for consumers which cannot only help to improve the satisfaction of the complainer but also leave a good impression on bystanders in case the situation getting out of control (e.g., Herhausen *et al*., 2019; Sparks *et al*., 2016). Therefore, the hypothesis is proposed:

> Hypothesis 19: Responding (compared with no responding) to negative eWOM will decrease the probability of virality.

3.6.2 Time Gap between Post and Reply

The timeliness of response is a critical dimension of organisational reaction to complaints (Davidow, 2003). Complainers expect the organisation can respond to them promptly because they regard the waiting time as psychological investment (Hogreve *et al*., 2017). Thus, delayed response will largely increase complainer's perceived input and decrease the satisfaction with recovery (Cambra-Fierro *et al*., 2015). Signalling theory and justice theory can explain how observers will perceive the response timeliness. Other consumers may regard the prompt response to complaints as a signal that the organisation concern about its consumers (Cambra-Fierro *et al*., 2015; Ringberg *et al*., 2007). Meanwhile, justice theory highlights that the feeling of injustice can be influenced by the input/output ratio (Weitzl and Einwiller, 2020). Thus, other consumers' empathy are more likely to be triggered if they notice the complainer has been waiting long for organisational response. Thus, this study proposes:

> Hypothesis 20: Time gap between the complaint post and organisational response will have positive impact on the virality.

3.7 Conceptual Framework

The research framework based on the hypotheses are as follows (Figure 9).

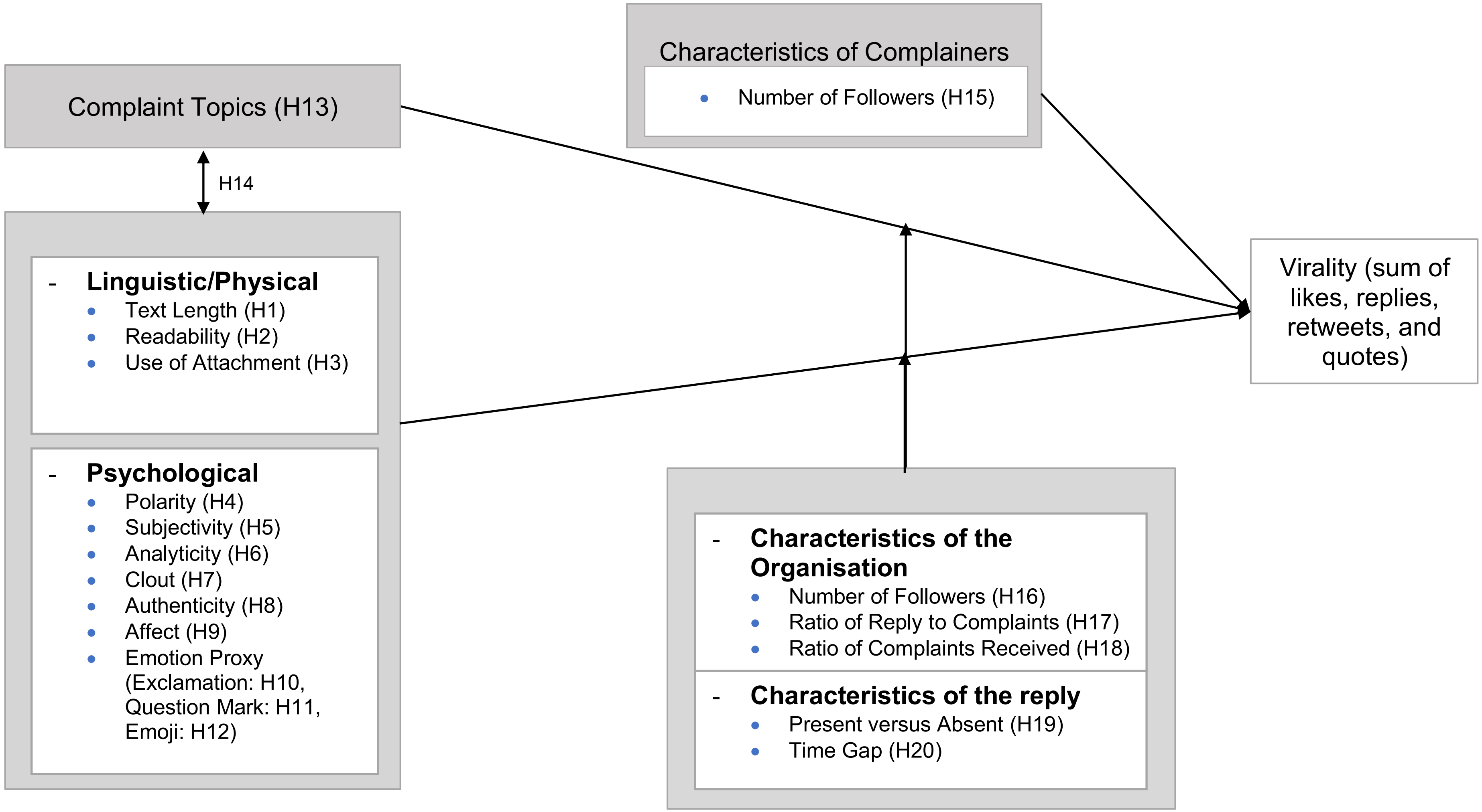


Figure 9 Research Framework

CHAPTER 4 RESEARCH METHODOLOGY

4.1 Introduction

This chapter introduces the design and procedure of empirical data collection method systematically and logically. This chapter starts with the philosophy and approach of this study; then, demonstrates the applied strategy and technique correspondingly. The setting of the empirical study is presented finally.

Being inherently diverse in the definition and typology of data (Bartunek *et al*., 1993), selecting appropriate research method and acquiring data is a comprehensive process (Bryman and Bell, 2011) for the purpose of problem-solving and knowledge-creating (Grinnell, 1993). Rather than randomly collecting data for unconvincing purposes and reasons (Walliman and Baiche, 2011), adopting systematic, scientific, and duplicatable methods is a must to examine the research questions and assess the importance and impact of the research (Burns, 1997). On this basis, the study will take into account the focus and target of the research according to the onion model (Saunders *et al*., 2009), to ensure the suitability and validity of the research method.

4.2 Research Philosophy

Distinguishing and clarifying the research philosophy should be put at the first stage (Carson *et al.*, 2001) to consolidate the conduct and evaluation of the research (Deshpande, 1983). Research philosophy is generically regarded as the nature and the development of knowledge (Saunders and Lewis, 2012). The importance of the philosophical understanding can hardly be ignored since it helps researchers to clarify their reflective role in the process of theory contribution and practice (Easterby-Smith *et al*., 2021; Saunders *et al*., 2009). Besides, philosophical knowledge assist researchers to assess the feasibility of their design and adjust it out of the constraints of their own knowledge and subject discipline (Easterby-Smith *et al*., 2021).

4.2.1 Ontology and Epistemology

Paradigm classification mainly focuses on ontology and epistemology (Easterby-Smith *et al*., 2021). Ontology refers to the nature of reality (Easterby-Smith *et al*., 2021), in other words, the characteristics of things caused/formed because of their inherent nature (Guarino *et al*., 2009). For business researchers, ontology focus more on the theories of the observable nature (Bell *et al*., 2015; Remenyi *et al*., 1998), which are independent of the researcher's existence (Easterby-Smith *et al*., 2021). Epistemology, on the other hand, explores the theories of knowledge and the scientific investigation into the physical and social environment (Easterby-Smith *et al*., 2021) and in business research, it refers to the known theories and what can be learned in social reality (Bell *et al*., 2015). Epistemological standpoints concern whether the reality can be investigated with the help of acceptable principles and knowledge (Bell *et al*., 2015) and how to prove the learned theories are legitimate (Blaikie, 2019; Crotty, 1998). As summarised by Carson *et al.* (2001) that ontology describes the reality while epistemology reflects the connections between the researcher and the reality. These basic beliefs on the one hand affect researchers' understanding of the subject domain and further influence their methodological choice (Deshpande, 1983), on the other hand, reflect the researcher's unique standpoint (Saunders *et al*., 2009). Researchers termed various philosophical standpoints following the nature and development of knowledge, for example, Crotty (1998) divided them into positivism, interpretivism, critical inquiry and post-modernism. However, Bryman (2004) argue that interpretivism and positivism are core perspectives. The inconsistence in cognitions may lead to misunderstanding and confusion, therefore, it is essential for researchers to clarify the standpoint for further explanation (Crotty, 1998). This study, as mentioned, follows the framework proposed by Saunders, Lewis and Thornhill (2019) which is in line with Bryman's (2004) typology.

4.2.2 Realism, Positivism, and Interpretivism

Ontological opinions debate on whether social entities are objective existence and realism is one of the key positions (Sayer, 1999; Lundberg and Young, 2005). Realism, according to its literal meaning, believe that reality can be understood by proper research methods and realism researchers tend to deny the importance of theory in science (Hunt, 1990). It distinguishes the differences between reality and the view of the reality (Carson *et al*., 2001). Therefore, individual's perception works as the window to reflect the reality (Healy and Perry, 2000). Two key assumptions of the realism are the reality is separate from how it is described, and same research methods are applicable to different science domains (Bell *et al*., 2015). In business studies, realism is frequently used to explore the underlying aspects of behaviours (Ackroyd and Fleetwood, 2000), such as value, attitude, and culture. However, one contentious aspect lies in the limitation of human's scientific cognition, which cannot fully describe the reality (Healy and Perry, 2000). As the "fallacy of realism" describes, realists believe they can distinguish whether their knowledge can describe the reality even without knowing what reality is (Peter, 1992).

Epistemology aims to explore the theory of knowledge (Creswell, 2009; Easterby-Smith *et al*., 2021) and the two mainstream epistemological paradigms are interpretivism and positivism. Interpretivism claims that the reality is shaped by the participants (Bryman and Bell, 2011). In other words, the meaningful interpretations of human's activities influence human's understanding of the world (Blaikie, 2019). The research focus of interpretivists are human's different impacts on the social entities (Saunders *et al*., 2009) and how to interpret these impacts (Belk, 2007). Interpretive perspectives argue that causalities are not the only way to investigate social science because of the subjectivity and complexity of social entities (de Vaus, 2009). Interpretivists distinguish the objects of social and natural science and highlight the autonomy of social beings (Bell *et al*., 2015). Researcher's own experience and personal understanding of the world, rather than scientific laws and regulations, guide the exploration of knowledge (Gill and Johnson, 1991). The main purpose of interpretivism is to understand how and why the behaviours are displayed (Bell *et al*., 2015) and qualitative methods are frequently adopted by interpretivism researchers (Malhotra, 2002).

Positivism (theory-testing paradigm), initiated by Comte (1855), believes in the objectivity, repetitiveness, and externalities of things and highlights the importance of empirical validation from observed realities (Easterby-Smith *et al*., 2021). In other words, knowledge is only convincing and meaningful if it can be proven by experience (Blaikie, 2019). Thus, positivism highlights that things should be evaluated by objective measurement rather than rely on subjective perceptions or intuitions (Easterby-Smith *et al*., 2008). A common target of positivism is to explore the underlying causality of realities (Saunders *et al*., 2009), and more specifically, the interpretation of behaviours in social science (business). Sharing some commons with realism, positivism insists on the use of repeatable data collection and processing routines (Bell *et al*., 2015), meanwhile highlights that findings come from logical and scientific proof (Macionis and Gerber, 2011). Thus, positivists tend to apply analytical methods, i.e., hypothesis testing and theory testing (Carson *et al*., 2001) to explore the underlying causality or mechanism (Malhotra, 2002).

Furthermore, positivism also asks for the independence of results (Remenyi *et al*., 1998), thus, requiring researchers to minimize their impacts on the results (Bell *et al*., 2015; Healy and Perry, 2000).

4.2.3 Theoretical Standpoint of the Current Research

Although there is no best philosophical standpoint for business research, it is necessary to choose a more reliable and valid practice of the approach according to the purpose, characteristics, and potential consequences of the research. Among various philosophies, positivism is the most appropriate one for this research because of the following reasons. First, the research investigates the effects of different individual and situational impacts on the virality of online complaints, in other words, determining the causalities are the key targets of this study, which is also the considerations of positivists. Meanwhile, the potential impact of these factors can be explained by extant theories and literature, thus, the hypothesis testing can be regarded as the knowledge testing in this study. Second, as a common behaviour, online complaining and its potential outcome – online firestorm/virality fulfil the primary assumption of positivism that the realities and phenomena are repetitive and observable. Specifically, because of the traits of online complaining platforms and the definition of virality (see Chapter 2 for definition and characteristics), all potential variables are visible, meanwhile, the quantity of complaints can be enormous, and the traits of complaints share some traits in common. Thus, also related to the following reason for adopting positivist approach that several hypotheses are proposed and tested to figure out the underlying causalities, meanwhile, a repeatable, unbiased and consistent method is critical to capture and analyse the data. Finally, this study is interested in customers' organic complaints and bystanders' spontaneous reactions, it is vital for the researcher to avoid any possible impact on the research subject, which also fulfils the requirements of the positivism research.

To be more specific, considering the research aim of this thesis – to identify and test the factors which may contribute to the complaint virality – scientific and unbiased research needs to be conducted. First of all, the hypotheses are proposed either based on existing theories (i.e., theory testing) or extant literature (i.e., knowledge repetition). Meanwhile, studying the structure and relationships by secondary data from open platforms can to some extent guarantee the objectivity and generalisability of an unbiased research. Specifically, data choosing process follows the repeatable steps, and all potential causality can be captured. Meanwhile, the measurement and analysis process adopt and test the reliability of multiple repeatable and common analytics methods, finally, compare the performance of different techniques, which can to large extent provide a more reliable result. Last but not the least, in accordance with positivists, the impact of researcher's own participation should be minimised. Therefore, 1) the philosophy and design of this research relies on the theories and literature rather than the researcher's own experience, meanwhile, respect the nature of the research target; 2) the conducting of this study strictly follows the scientific research process proposed by literature in both marketing and data science domains and using logical comparison and screening methods to draw the final conclusion. With the help of the above techniques, the level of objectivity, repetitiveness and generalisability can largely increase.

4.3 Research Approach

Research approaches can be classified as deductive and inductive according to the relationship between theory and research (Bryman and Bell, 2011). Deductive approaches apply strategies to test theoretical hypotheses while inductive studies propose a reversed approach which concludes the theories or generalizations from domain-related observations (Hunt, 2014; Saunders *et al*., 2009). Causality explanation is one of the main functions of deduction, thus, concepts formulation and data collection are critical to fulfill it. The deduction starts from theory-derived hypotheses, then clarifies measurement, tests hypothesis, and review the results for theory confirming (Robson, 1993). Since the deductive approach is frequently adopted to explore causal laws, meanwhile, its solid structure ensures the reliability and replicable (Gill and Johnson, 1991), which makes it 'the dominant research approach' (Saunders *et al*., 2009: 124). Meanwhile, since its first introduction by Glaser and Strauss (1967), it has been a strong approach to theory development (Bryman and Bell, 2011). It is also worth mentioning that the entities included in the study should be measurable and researchable (Bell *et al*., 2015).

Induction, on the contrary, refers to theory developing or knowledge constructing by data analytics (Saunders *et al*., 2009). The key function of induction is to infer and generalize the regulations and theory based on the observations. Compared with deductive studies, inductive approaches may have better operationalization when dealing with complex or non-obvious interactions (Bell *et al*., 2005), therefore, it enables the research with more changeable process and flexible constructs (Saunders *et al.*, 2009). From when this approach was proposed by Glaser and Strauss (1967), it has been regarded as effective in terms of theory-generating.

Based on the consideration of the logical relationship between theory and research, this thesis will adopt the deductive approach since it aims to determine the factors which will trigger or hinder the virality of the online complaints with the help of existing theories. With this purpose in mind, several hypotheses are raised according to the mentioned theories and extant literature. Followed by scraping online data and clarifying their interactions, the thesis will be able to decide whether the observations prove the theory or whether there are other unexplained phenomena beyond the known situations.

4.4 Research Strategy

Although the understanding and distinguishing of research approach is critical, deduction and induction sometimes go simultaneously and may contain each other (Bell *et al*., 2005). Thus, it is believed that the criteria of strategy choosing is whether it can meet the target of the research or not rather than according to the blunt classifications especially that previous studies have proven qualitative methods (such as interview, case study and archival research) are not always applied for induction (Saunders *et al*., 2009).

Therefore, although different strategies (e.g., survey, experiment, case study, etc.) can be implemented, this study will adopt the more appropriate method to fulfill the actual goals. The study aims to investigate the determinants of virality of online complaints and whether organisation's effort can hinder the impact to some extent. The characteristics of online complaints meet the standard of big data (Lycett, 2013; Erl, Khattak and Buhler, 2016), i.e., the enormous volume of online complaints, high velocity (data change an update swiftly), and considerable variety (for example, they may contain different contents, or take place on multiple platforms). Given the mentioned points, it is more appropriate to focus on the cumulative effects rather than in-depth investigating into single/several cases. The main reasons are as follows. First, as the content and purpose of the online complaints are diverse, the involved samples may not be representative enough when comparing with the whole population if the sample size is not large enough. Second, regarding the virality, which is the result of social/community behaviours, it is impossible for the subjects of qualitative research (no matter they are complainers, bystanders, or organisations) to verify or summarize the impact of their own group, not to mention the understanding of other parties. Third, online complaints can happen and develop on any platform at any time, and its impacts vary over time, which make it difficult for single or a group of subjects to observe and follow. In short, this research will employ quantitative method, big data analytics specifically, for data collecting and analysing. In particular, secondary data is used as the main data source. Secondary data refers to the data which is initially collected for other purpose and then captured and analysed for specific research target. It is also worth mentioning that secondary data may composed with raw data and compiled data (Saunders *et al*., 2009). The raw data of the online complaints will be collected with the help of web scrapy techniques, then they will be cleaned and processed for further analysis.

4.5 Summary of Research Methodology

In general, to answer the research question in a scientific way, this thesis takes the positivism perspective to investigate what physical and psychological attributes of online complaints cause virality. In other words, this thesis explores the causality by independent and unbiased observation of the research target (i.e., online complaints). Furthermore, this study follow the common procedures of deductive method strategy, starting from the theory- and knowledge-based assumptions (i.e., what factors may influence complaint virality, supported by theories and/or extant literature), then testing hypotheses. Finally, taking the nature of the research target (i.e., virality refers to the cumulative high amount of users' reactions) and the purpose of results generalisation (i.e., investigating general pattern of user's reaction rather than individual level behavioural intentions) into consideration, quantitative method is applied to collecting and analysing data.

CHAPTER 5 RESEARCH DESIGN

5.1 Introduction

Online CCB content analysis was based on the user-generated complaints on social platforms, meanwhile, taking the characteristics of the platform into consideration. Twitter was chosen as the single research context rather than conducting the studies across the platforms (see section 5.2 for more detailed explanation of this decision). Furthermore, the data collection was not limited to scraping the initial complaints but also included the full conversation among the complainer, bystanders, and the organisation to capture the impacts of the complaint, the interactions between different parties, as well as the complaint handling strategies. Besides, text mining and sentimental analysis was carried out with the help of Linguistic Inquiry and Word Count dictionary and probabilistic topic modelling.

5.2 Research Context

Since online CCB has diverse characteristics, forms, and purposes because of the traits of different platforms and different users, it is more realistic to conduct the research on one specific channel rather than synthesize all data sources together. The following paragraphs will introduce the background information of Twitter and explain the reason why it was chosen as the target platform in this study.

5.2.1 Twitter introduction

Social media like Facebook and Twitter have irreversibly become critical components of interpersonal communication (Berman *et al*., 2019; Toubia and Stephen, 2013). In United States of America for example, Facebook and Twitter ranked first and the sixth of social network usage in 2022 (Statista, 2023b; Figure 10) and number of Twitter user has remained and continues to be above 300 million from 2019 to 2024 (Statista, 2023c; Figure 11).[13] Furthermore, Twitter also facilitates connections between consumers and brands and with other consumers (Weitzl and Hutzinger, 2017) because consumers tend to be active and brands are more attachable and engaging on Twitter compared with on Facebook (Culotta and Cutler, 2016).

[13] 2023 and 2024 data are estimated.

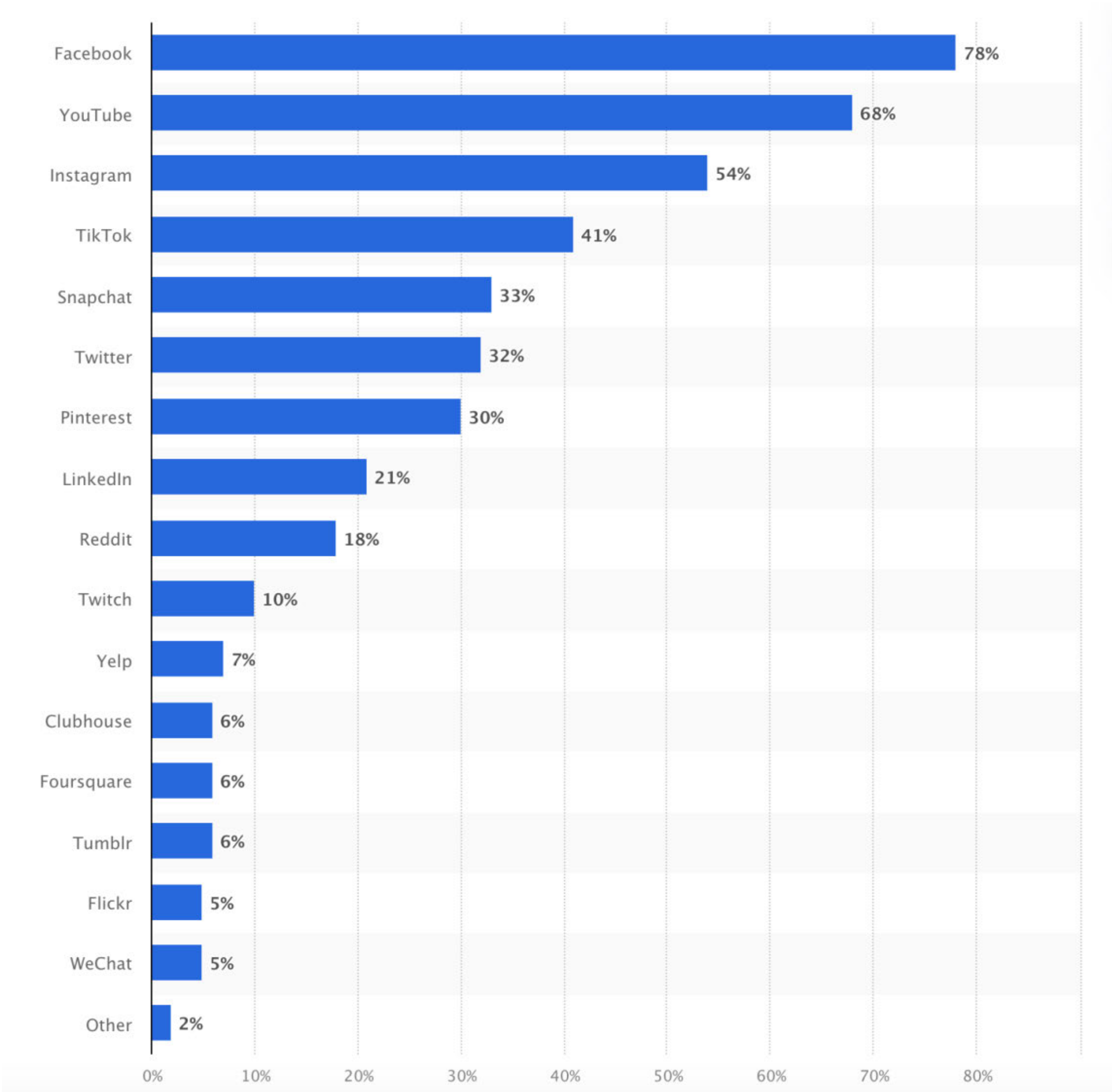


Figure 10 Social media usage in the U.S. in 2022

Source: Statista (2023b)

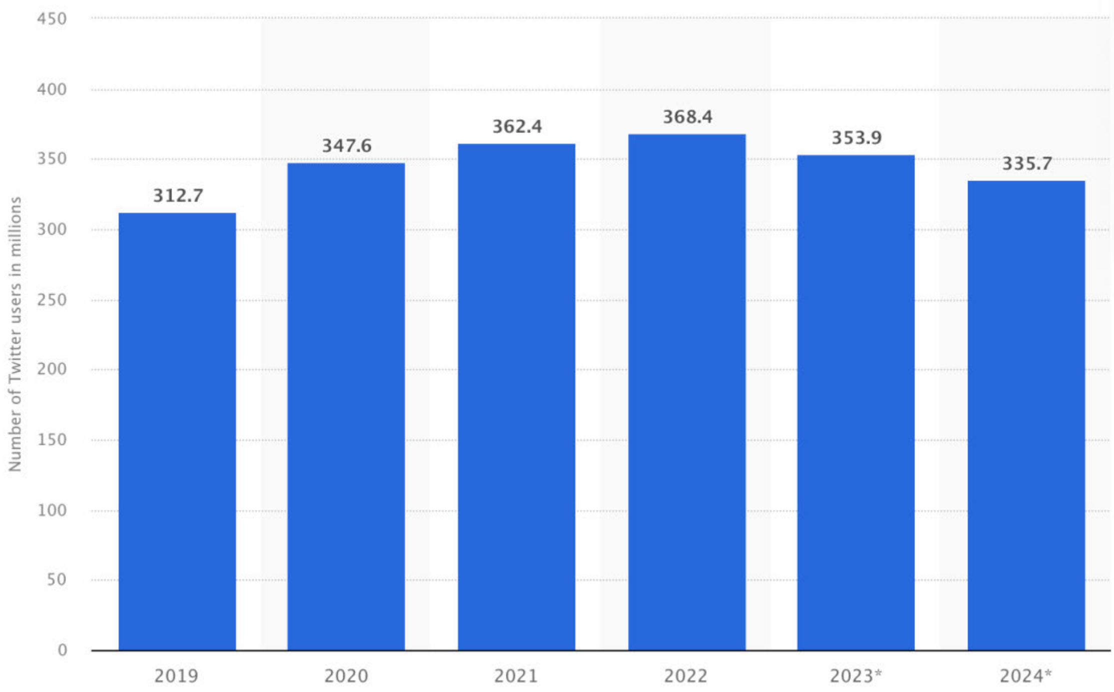


Figure 11 Number of Twitter users worldwide from 2019 to 2024 (in millions)
Source: Statista (2023c)

The attractiveness of Twitter as an online communication channel for both consumers and brands are as follows. Connections on Twitter are more public compared with other platforms (Toubia and Stephen, 2013), for example, user A can follow and contact user B and have access to user B's homepage, including timeline, followers and following, etc. although B did not follow user A. However, Facebook allows fine-grained controls for each of the posts, in other words, the access to posts can be limited (Debatin *et al*., 2009). The transparency of followers of Twitter accounts improves the relationship strength as users can express their social image by showing who and which brand they are following, which also bridges the brand image with social network (Naylor *et al*., 2012). Meanwhile, compared with Facebook, Twitter provides users the opportunity to keep anonymity to some extent, therefore, users pay more attention to the content of communication rather than who is communicating (Hughes *et al*., 2012). Without the restriction of social pressure, attracting new followers on Twitter is to large extant decided by the content posted (Shriver *et al*., 2013; Toubia and Stephen, 2013).

Communication on Twitter has also attracted the interest of researchers from various domains, including but not limited to computer science (Lassen and Brown, 2011; Singh and Kumari, 2016), linguistics (McKay, 2020), communication (Colleoni *et al*., 2014), information system (Oliveira *et al*., 2017; Sinha *et al*., 2020) as well as marketing (Culotta and Cutler, 2016; Ma *et al*., 2015; Rossi and Rubera, 2021; Schoenmueller *et al*., 2023). Thus, this study also adopted Twitter as the focal platform since extant literature already proven that the nature of Twitter provides adequate scale for social networking and content analysis (Tubia and Stephen, 2013).

5.2.2 Twitter Scraping: Advantages and Shortcomings

Research context choice is a comprehensive process since each scenario has its own advantages and limitations (see Table 3 which compares the directly accessible variables on various platforms). Twitter was used as the target platform for online CCB analysis in this research for the following reasons. First, social media (Facebook and Twitter) provide both customers' and organisational reviews. Specifically, the precise commenting time makes possible the insights into the speed of organisational response and collecting longitudinal data for comprehensive time frame (Herhausen *et al*., 2019). Meanwhile, social media allows the observation of bystanders' interaction with both the complainer and the organisation, which helps researchers to understand the impact and outcome of both the complaints and response approach. However, as interactive platforms, the primary function of social media is communication, therefore, the valance of review is latent which makes it impossible to establish a baseline for evaluating the subjectivity of the individual comment (Minnema *et al*., 2016).

Table 3 Summary of variables on different platforms

	Platform	Twitter	Facebook	Yelp	Trustpilot	TripAdvisor	Amazon
Product/service information	Type/category	Yes	Yes	Yes	Yes	Yes	Yes
	Average rating	No	No	Yes	Yes	Yes	Yes
Complaint	Text	Yes	Yes	Yes	Yes	Yes	Yes
	Date	Yes	Yes	Yes	Yes	Yes	Yes
	Time	Yes	Yes	No	No	No	No
	Rating/star	No	No	Yes	Yes	Yes	Yes
	Attachment	Yes	Yes	Yes	No	Yes	Yes
	Verification	No	No	No	Yes	No	Yes
Complainer information	Username	Yes	Yes	Yes	Yes	Yes	Yes
	Followers/friends	Yes	No	Yes	No	Yes	No
	Location	Yes	Yes	Yes	Yes	Yes	Yes
	Certification/level	No	No	Yes	No	Yes	Yes
	Previous review	No	No	Yes	Yes	Yes	Yes
	Rating distribution	No	No	Yes	Yes	Yes	Yes
Organisational response	Text	Yes	Yes	Yes	Yes	Yes	No
	Date	Yes	Yes	Yes	Yes	Yes	No
	Time	Yes	Yes	No	No	No	No
	Name/title of responder	Yes	Yes	Yes	Yes	Yes	No
Organisation information	Username	Yes	Yes	Yes	Yes	Yes	No
	Followers/friends	Yes	Yes	No	No	No	No
	Location	Yes	Yes	Yes	No	Yes	No
	Certification/level	Yes	Yes	No	Yes	Yes	No
	Previous review	Yes	Yes	Yes	Yes	Yes	No
	Rating distribution	No	Yes	Yes	Yes	Yes	No
	Behaviours (usefulness, like, etc.)	Yes	Yes	Yes	Yes	Yes	No

Bystanders' reaction to complaint	Conversation	Yes	Yes	No	No	No	No
	Date and time	Limited (only replies)	Limited (only comments)	No	No	No	No
Bystanders' reaction to organisational reply	Behaviours (usefulness, like, etc.)	Yes	Yes	No	No	No	No
	Conversation	Yes	Yes	No	No	No	No
	Date and time	Limited (only replies)	Limited (only comments)	No	No	No	No

Second, some review platforms (e.g., Yelp and TripAdvisor) provide more detailed customer information, including their level/certification on that specific platform, their previous review and overall rating distribution. For bystanders, these clues can help them to evaluate the helpfulness of the review (Cheng and Ho, 2015). Meanwhile, from the organisations' perspective, the authenticity of the reviewer and the degree of trustworthiness can be inferred from this information since detecting fake online reviews is one of the most critical steps in complaint management (Proserpio and Zervas, 2017). Nevertheless, unlike the unconfined conversations on social media, the interaction between complainers and bystanders on these platforms tend to be limited to the "like" of the usefulness/helpfulness of complaints. Furthermore, complainers' reactions toward the recovery and bystanders' attitude toward the organisations (and their responses) are nonexistent on these platforms, in other words, the effectiveness of the recovery attempt might be challenging for researchers to implement.

Third, some online service agencies and online retailers (such as Amazon) would verify the comments, which improves the reliability to a certain degree. Most of the online retailers (Amazon and eBay for instance), however, have no responses from either the seller or the platform, while the service agencies merely provide relative limited customer information, although the organisational responses are available if they are provided. Besides, the investigations on bystanders' reactions are constrained because of the similar restrictions as the review websites.

Based on the outcomes from the comparison, complaints on Twitter were chosen as the research target, however, it is worth mentioning that strengths and weaknesses are coexistent. One of the considerable challenges is the complex process to clean the useless data and convert unordered online information into structured and manageable information (Moens, 2006). Another difficulty of Twitter scraping is judging the authenticity of the complaints (Barhorst *et al*., 2020) since Twitter provides no verification on either the complaint or the complainer. However, illegitimate complaining behaviours (Kim *et al*., 2010) and bots-written reviews (Lugosi and Quinton, 2018) do exist in reality. Even worse, fake information usually spreads more swiftly than the real posts (Vosoughi *et al*., 2018).

While, compared with the shortcomings, Twitter scraping might be more rewarding than other types of websites and other social media. With more intensive social interactions (Ma *et al*., 2015), Twitter enables multiple parties, including complainers, bystanders, and organisations to participant in real-time communications (Gunarathne *et al*., 2017), which might lead to far reaching social influence and crisis, such as firestorms, which have been frequently ignored by previous studies (Herhausen *et al*., 2019). Meanwhile, the organisational response rate is relatively high on Twitter (Einwiller and Steilen, 2015) and this ensures us to have adequate data for analyzing the organisations' recovery attempt and the subsequent influence on both complainers and observers. Moreover, the use of hashtags on social media not only enables customers to post brand-oriented comments but also assists researchers to capture the related topics of the target brand. Notably, it is one dimension of Tweet informativeness, which can to some extent affect the probability of retweeting (Tan *et al*., 2014).

Contrasting with other social media, e.g., Facebook, Twitter also has some advantages in terms of research. First, although they both work as instant communication platforms, Facebook users tend to carry out social connections with friends (Smith *et al*., 2012), share more vivid content of their daily life and use its Messenger as one-to-one communication tool (Papacharissi, 2009). Meanwhile, a certain proportion of Twitter are brand-related (Ma *et al*., 2015) because the 280-word limits (was 140 before November 2017) make it impossible to discuss several topics in one Tweet (Jansen *et al*., 2009) and the length helps to decrease the complexity of reading and improve the convenience and speed of posting (Smith *et al*., 2012). More importantly, because of its better accessibility, Twitter is given higher expectation from complainers (Istanbulluoglu, 2017) which indicates that organisational responses on Twitter might have more significant impact on complainers' attitude. Furthermore, the number of Facebook friends is unavailable owing to the constraints on its API (Herhausen *et al*., 2019), in other words, it is difficult to evaluate complainers' social influence, which is expected to explain the purpose of online complaining and expectations of organisational responses to some extent (Gunarathne *et al*., 2017).

Therefore, as one of the dominant social media, Twitter provides a convenient platform for customers to share their negative consumption experience (Shen and Sengupta, 2018) and communicate with other customers (Raval, 2020), and triggered empathy and resonation might further cause firestorm. Besides, Twitter presents an opportunity for organisations to monitor, manage and react to customers' comments (Zhu and Zhang, 2010). More importantly, organisations are encouraged, and they do take active part in these public conversations (Schweidel and Moe, 2014), in addition, customers are more likely to get satisfied responses on Twitter compared with offline complaining (Istanbulluoglu *et al*., 2017).

5.2.3 Industry Choice

Hospitality again becomes an attracting and increasing market post Covid-19, with global hospitality market reached almost 4.7 trillion U.S. dollars in 2023 and is estimated to increase one more trillion in 2027 (Statista, 2023d). The management and research on hotel guest satisfaction/dissatisfaction has been studies since 1970s (Xiang *et al*., 2015), specifically, hospitality has attracted a great deal of attention when studying CCB and SFR (Ben *et al*., 2023; Du *et al*., 2014). According to the Net Promoter Score (NPS)[14] in 2021, hotels ranked the third among all the industries (Statista, 2023e; Figure 12), which also confirms that hospitality is an industry heavily rely on WOM and highlights the necessity to improve (or maintain satisfying) hotel guests experience. As an interactive industry, the importance of monitoring and participating in social media communication has become a critical task for hospitality (Fan and Niu, 2016) because of the increasing impact of UGC (Browning *et al*., 2013) and the complexity and diversity of hotel experience can be described on social media (Hu *et al*., 2019; Xiang *et al*., 2015). The profound understanding of complaints is believed can effectively improve service quality and guest satisfaction, which may further reflect in the revenue (Hu *et al*., 2019). Meanwhile, it can also help hotels to optimise their service system and wisely allocate their resources (Xu and Li, 2016). In sum, this study focus on hospitality and expecting to collect comprehensive complaint data and organisational response as hotels tend to concern consumer satisfaction according to the mentioned reasons.

[14] NPS is an index to measure consumer satisfaction level and the higher score means consumers are more likely to recommend the product/service and brand to others.

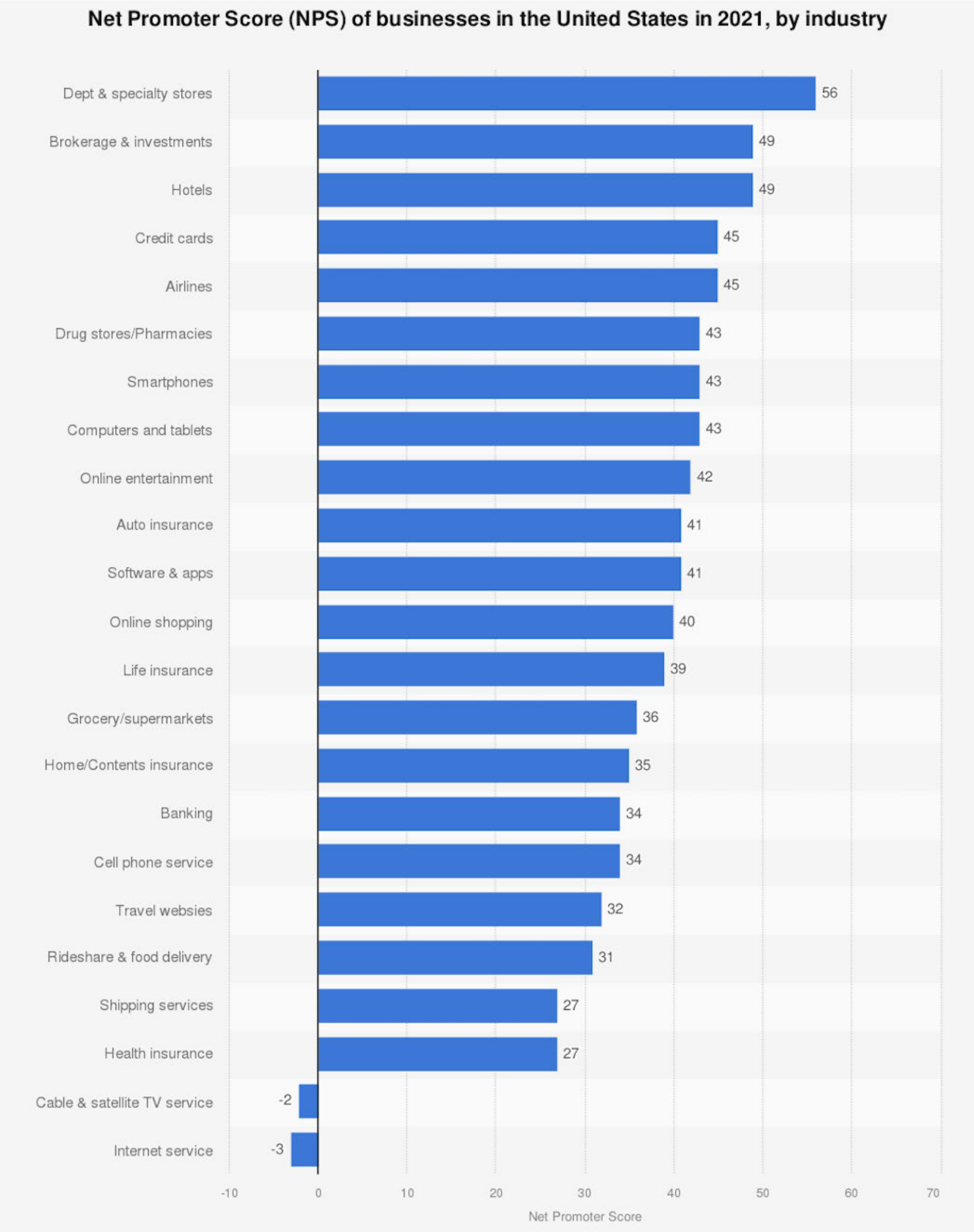


Figure 12 Net Promoter Score of industries in the U.S. in 2021

Source: Statista (2023e)

5.3 Sampling Procedures

To address the research questions, the data collection started from verified organisation's pages and customers' posts on Twitter by using Twitter's API (application programming interface). Since the characteristics of organisations are believed to contribute to variance in both their response strategy (Smith and Karwan, 2010) and customers' expectations (Wirtz and McColl-Kennedy, 2009), content virality and organisational response are expected to take place more frequently if the involved organisation has a larger scale (Chen and Hambrick, 1995). Meanwhile, for the text analysis purpose, texts only written in English were included in the final dataset since this is not only the author's working language and more importantly, one of the most widely focused and trained language when conducting natural language processing (NLP). Only UK- and US- based hotels and the international chain hotels of which branches are mostly located in English speaking countries with large amounts of followers were included in this study, ensuring that most of the conversations are written in English and most of the complainers and bystanders are from English-speaking countries or to some extent familiar with English reading and writing. In total, 28 hotel brands were included in the sample set, then, the author collected posts from 00:00:00 am, 1st January 2022 to 00:00:00 am, 1st February 2023 (13 months). Specifically, the Tweets posted during 00:00:00 am, 1st January 2022 to 00:00:00 am, 1st January 2023 (12 months) were focal tweets for text analysis, meanwhile, 13 months of retweet, reply, like and quote data was collected considering the lagging of subsequent organisational responses and bystanders' reactions. The scraped contents including a) detailed user-initiated Tweets related to these organisations/brands; b) these customers Twitter profile data, including description, number of followers and tweets, etc.; c) the timeline on the brand's official pages; d) the profile of the brand page, including ID, description, and number of followers, etc. The structure of collected data and examples can be seen in Appendix A. The number of each brand account's followers is more than 50,000 which to some extent provides the ground for potential online CCB virality.

Then, Tweepy was applied to access the user-initiated Tweets relevant to the focal brands in 2022, which returned a corpus of 453,058 Tweets in total[15]. After that, Tweets which fulfil the following criteria were excluded: a) only retweeting other Tweets with no valid text for analysis (n = 221,627) and b) non English written Tweets (n = 39,558), returning the Tweets for further cleaning and classification, n = 191,873. Apart from the Tweets for text analysis, Tweets on brand's timeline were also collected for analyzing the organisational response (n = 25,311 [00:00:00 am, 1st January 2022 to 00:00:00 am, 1st January 2023]). In addition, an extra one month

[15] Tweepy is one of the Python libraries to scrapy Twitter data recommended by Twitter (Tools and libraries, no date), which has also been used in marketing research (e.g., Hovy, Melumad and Inman, 2021). See detailed information of applied software/dictionary in Appendix B.

(00:00:00 am, 1st January 2023 to 00:00:00 am, 1st February 2023) user Tweets (n = 36,891 and brand Tweets (n = 1,790) were scraped.

5.4 Data Pre-processing

The basic of text mining, especially sentiment analysis (which will be conducted in the following steps), is to retrieve useful information (Serrano-Guerrero *et al*., 2015). However, the raw data collected from social media tend to be unstructured and voluminous (Baesens, 2014; Büschken and Allenby, 2016), and noise and errors are common in UGCs (Gandomi and Haider, 2015). Thus, data pre-processing is critical in NLP tasks to guarantee better analysis outcome and dimensionality reduction (Birjali *et al*., 2021). According to the extant data science (e.g., Birjali *et al*., 2021; Singh *et al*., 2022) and marketing literature (e.g., Berger *et al*., 2020; Roelen-Blasberg *et al*., 2023), the collected corpus was processed for data tokenization, stemming/lemmatization, and cleaning (see Table 4 for the summary of methods applied in this study). The following sections will further introduce and compare the commonly used methods/dictionaries used in each step of the NLP data pre-preparation pipeline.

Table 4 Methods used in data pre-processing steps of this study

Process	Applied dictionary and/or method	Explanation and/or rationale
Text tokenization	Python split() method	Breaking the sentences into units which can be analyzed by NLP (Deng and Liu, 2018; Wang *et al*., 2022).
Text normalization: Lemmatization	NLTK (Natural Language Toolkit) – WordNet Lemmatizer	Removing the root to reduce the inflectional forms of words for further analysis. Lemmatization was used in this study since it takes the context and information of the word into consideration rather than roughly “chop the roots off” (Pramana *et al*., 2022; Wang *et al*., 2022; Zhong and Schweidel, 2020).
Stopwords filter	NLTK - stopwords	The unimportant and uninformative words were not included for natural language

		processing (Birjali *et al*., 2021; Wang *et al*., 2022)

5.4.1 Text Tokenization

The first step of NLP is to distinguish the basic units (words to be specific), which is now an uncontentious convention of linguistic processing (Che and Zhang, 2018; Webster and Kit, 1992). The method to convert paragraphs into sentences and/or words is called tokenization (Baesens, 2014). Some common methods of Tokenization and the sample outcome is listed in Table 5. The sample text used here was randomly chosen from the corpus (".@HolidayInn can you please take a look at this photo and let me know your policy on grown men taking photos of other people's children without their consent? 😅 My work travel puts me in Holiday Inns two or three times a week (dm me for my @IHGRewards number.) Until I know... https://t.co/4WGoa5fNCb"). To ensure that all linguistically necessary and meaningful tokens are included (e.g., emoji) and avoid inappropriate separation (e.g., split elements before and after apostrophe), meanwhile taking the size of corpus into consideration, split() method was applied in this study. Furthermore, all words were lowercased for further normalization process (Kim *et al*., 2019; Porter, 1980).

Table 5 Common tokenization methods

Method	Output	Description, pros and cons	Sample execution duration
Python built-in .split()	['.@HolidayInn', 'can', 'you', 'please', 'take', 'a', 'look', 'at', 'this', 'photo', 'and', 'let', 'me', 'know', 'your', 'policy', 'on', 'grown', 'men', 'taking', 'photos', 'of', 'other', 'people's', 'children', 'without', 'their', 'consent?', '😅', 'My', 'work', 'travel', 'puts', 'me', 'in', 'Holiday', 'Inns', 'two', 'or', 'three', 'times', 'a', 'week', '(dm', 'me', 'for', 'my', '@IHGRewards', 'number.)', 'Until', 'I', 'know...', 'https://t.co/4WGoa5fNCb']	Description: Use white space to separate text. Pros: Shortest executing duration. Won't have unnecessary separations. Cons: Won't separate punctuation symbols.	0:00:00.000739
NLTK – word_tokenize	['.', '@', 'HolidayInn', 'can', 'you', 'please', 'take', 'a', 'look', 'at', 'this', 'photo', 'and', 'let', 'me', 'know', 'your', 'policy', 'on', 'grown', 'men', 'taking', 'photos', 'of', 'other', 'people', '’', 's', 'children', 'without', 'their', 'consent',	Description: String processing library based. Pros: Able to separate punctuation symbols.	0:00:02.644383

	'?', '😅', 'My', 'work', 'travel', 'puts', 'me', 'in', 'Holiday', 'Inns', 'two', 'or', 'three', 'times', 'a', 'week', '(', 'dm', 'me', 'for', 'my', '@', 'IHGRewards', 'number', '.', ')', 'Until', 'I', 'know', '...', 'https', ':', '//t.co/4WGoa5fNCb']	Cons: Can be time-consuming when analyzing large corpus. Unnecessary separation, e.g., apostrophe (’) in “people’s”.	
spaCy	['.@HolidayInn', 'can', 'you', 'please', 'take', 'a', 'look', 'at', 'this', 'photo', 'and', 'let', 'me', 'know', 'your', 'policy', 'on', 'grown', 'men', 'taking', 'photos', 'of', 'other', 'people', '’s', 'children', 'without', 'their', 'consent', '?', '😅', 'My', 'work', 'travel', 'puts', 'me', 'in', 'Holiday', 'Inns', 'two', 'or', 'three', 'times', 'a', 'week', '(', 'dm', 'me', 'for', 'my', ' ', '@IHGRewards', 'number', '.', ')', 'Until', 'I', 'know', '...', 'https://t.co/4WGoa5fNCb']	Description: Library-based text processing method. Pros: Support word vectors. Cons: Can be time-consuming when analyzing large corpus. Less flexible. Unnecessary separation, e.g., apostrophe (’) in “people’s”.	0:00:02.452410
Gensim	['HolidayInn', 'can', 'you', 'please', 'take', 'a', 'look', 'at', 'this', 'photo', 'and', 'let', 'me', 'know', 'your', 'policy', 'on', 'grown', 'men', 'taking', 'photos', 'of', 'other', 'people', 's', 'children', 'without', 'their', 'consent', 'My',	Description: Library-based text processing method. Pros: Work for large dataset.	0:00:00.085137

	'work', 'travel', 'puts', 'me', 'in', 'Holiday', 'Inns', 'two', 'or', 'three', 'times', 'a', 'week', 'dm', 'me', 'for', 'my', 'IHGRewards', 'number', 'Until', 'I', 'know', 'https', 't', 'co', 'WGoa', 'fNCb']	Cons: Unnecessary separation, e.g., separating the hyperlinks and cannot process emoji.	

5.4.2 Text Normalization

Tokenized words are still complex for analysis since they are in various grammatical forms (Kennedy *et al*., 2021), in other words, words with suffixes or inflections. To improve the accuracy of NLP and maximizing the captured word forms (Luangrath *et al.*, 2023), transforming words into basic form (root) has become a prescriptive step since early computational linguistics studies (Berger *et al*., 2020; Lovins, 1968). There are two main techniques, namely stemming and lemmatization. Stemming is a rule-based approach, simply put, cutting down the suffixes from words without considering the actual meaning (Kennedy *et al*., 2021). For example, “cars” and “automobile” are stemmed into “car” and “automobile” respectively although they have the same meaning. However, “caring” is also stemmed to “car” although the initial meaning is irrelevant. While lemmatization is a dictionary-based method, which will return the complete form of the word meanwhile considering the meaning of the word (Poria *et al*., 2018) and the word-related context (Berger *et al*., 2020; Birjali *et al*., 2021). Thus, “cars” and “automobile” are both lemmatized to “automobile” and “caring” is lemmatized into “care”. Thus, despite the faster processing speed of stemming, lemmatization was used in this study for more accurate outcome. Similar with the tokenization process, lemmatization also has various popular toolkits. In Table 6, lists some common methods of lemmatization by Python and the outcome examples (the same sample text as the tokenization) and Wordnet Lemmatizer with POS tagging was applied in this study since it returned the expected outcome by comparison.

Table 6 Common lemmatization methods

Method	Output	Pros and Cons	Sample execution duration
NLTK - Wordnet Lemmatizer	['.@HolidayInn', 'can', 'you', 'please', 'take', 'a', 'look', 'at', 'this', 'photo', 'and', 'let', 'me', 'know', 'your', 'policy', 'on', 'grown', 'men', 'taking', 'photo', 'of', 'other', 'people's', 'child', 'without', 'their', 'consent?', '😅', 'My', 'work', 'travel', 'put', 'me', 'in', 'Holiday', 'Inns', 'two', 'or', 'three', 'time', 'a', 'week', '(dm', 'me', 'for', 'my', '@IHGRewards', 'number.)', 'Until', 'I', 'know...', 'https://t.co/4WGoa5fNCb'][*]	Pros: Coding-wise, it is simple and flexible. Cons: Under lemmatization. For example, "taking" is not lemmatized into 'take' as expected.	0:00:01.442567
NLTK - Wordnet Lemmatizer with POS (Part-of-speech) tag[16]	['.@HolidayInn', 'can', 'you', 'please', 'take', 'a', 'look', 'at', 'this', 'photo', 'and', 'let', 'me', 'know', 'your', 'policy', 'on', 'grown', 'men', 'take', 'photo', 'of', 'other', 'people's', 'child', 'without', 'their', 'consent?', '😅', 'My', 'work', 'travel', 'put', 'me', 'in', 'Holiday', 'Inns', 'two', 'or', 'three', 'time', 'a',	Pros: Improve the performance of basic Wordnet Lemmatizer. Cons: Coding-wise, less flexible.	0:00:00.086153

[16] POS tagging refers to a grammatical classification method which decreases the ambiguity of words in NLP (Collobert *et al.*, 2011). Simply put, it labels the part-of-speech of each word according to the context (Deng and Liu, 2018).

	'week', '(dm', 'me', 'for', 'my', '@IHGRewards', 'number.)', 'Until', 'I', 'know...', 'https://t.co/4WGoa5fNCb']		
TextBlob Lemmatizer	['.@HolidayInn', 'can', 'you', 'please', 'take', 'a', 'look', 'at', 'this', 'photo', 'and', 'let', 'me', 'know', 'your', 'policy', 'on', 'grown', 'men', 'taking', 'photo', 'of', 'other', 'people's', 'child', 'without', 'their', 'consent?', '😅', 'My', 'work', 'travel', 'put', 'me', 'in', 'Holiday', 'Inns', 'two', 'or', 'three', 'time', 'a', 'week', '(dm', 'me', 'for', 'my', '@IHGRewards', 'number.)', 'Until', 'I', 'know...', 'https://t.co/4WGoa5fNCb']	Pros: Executing faster. Cons: Under lemmatization. For example, "taking" is not lemmatized into 'take' as expected.	0:00:00.000350

*The examples here only demonstrate the lemmatization performance without tokenization. In this study, the lemmatizer was applied after tokenization.

5.4.3 Text Cleaning

The final step of the pre-processing is the text cleaning, including the stop words removal and the exclusion of unwanted text according to the research target. Stop words, such as conjunctions, articles, and prepositions, although in extremely high frequency, has no contribution to the meaning and sentiment of the text, thus, need to be removed (Baesens, 2014; Birjali *et al*., 2021). Meanwhile, given the traits and structure of Tweets, some unnecessary elements (e.g., hyperlinks) were removed since they will become noise when conducting NLP (see Table 7 for the details and explanations). After refining the texts based on the listed regulations, text with less than 3 words (n = 17,913) were excluded to ensure the meaningfulness of the text. Regarding the words per unit (word count of each Tweet in this case), the NLP outcome is more likely to be influenced by potential noise if the word count is low (Humphreys and Wang, 2018). For short UGCs on social media, Tirunillai and Tellis (2012) suggest only include the posts which have at least 10 words, while Herhausen *et al*. (2019) keep the reviews with no less than 3 words since a sentence grammatically requires the fundamental elements including a subject, a verb, and an objective to be understood by readers. In this study, since meaningless and unnecessary words, such as stop words were already removed from Tweets before analysis, the later regulation was adopted to remove the Tweets less than 3 words.

Table 7 Elements removed from raw Tweets

Elements to remove	Rationale	Example
Stopwords	Stopwords are commonly used in sentences, however, have no impact on sentiment analysis or topic modeling.	the, is, to
@[A-Za-z0-9]	At sign and the following hotel name are removed because a) they have no valid meaning for analyzing; b) for more accurate text word count; c) exclude the potential impact of specific brand name (e.g., Hotel name	@Marriott

	"Premierinn" will be regarded as positive when conducting sentiment analysis after stemming.	
Brand name	Hotel names are removed because a) they have no valid meaning for analyzing; b) exclude the potential impact of specific brand name (e.g., Hotel name "Premierinn" will be regarded as positive when conducting sentiment analysis after stemming.	Marriott
Non-necessary punctuations	Only the potential influential punctuations (e.g., have emotional meanings: question mark and exclamation mark) are included.	Comma, underscore, dash, etc.
# signal	Hashtag signal is removed and only the topics following Hashtags are kept for further investigating.	#Rewardspoints -> Rewardspoints, #StandWithUkraine, #rubbishcustomerservice
Hyperlinks	Hyperlinks are noise for analysis.	https://t.co/4WGoa5fNCb

5.4.4 Sentiment Analysis and Final Dataset

Finishing the data pre-processing, sentiment analysis was conducted to distinguish the polarity of the Tweets. There are various methods to extract sentiments and it is not realistic to apply and compare all of them. Thus, three common and well-performed (Aljedanni *et al.*, 2022; Hutto and Gilbert, 2014) methods which are widely used in latent marketing and data science literature were employed to classify the returned Tweets (n = 173,960) into positive, neutral, and negative. Table 8 demonstrates the details of dictionary/method and the sentiment score of the sample text (the same example used for tokenization), and Table 9-10 show the reliability test of these methods. The Cronbach's Alpha testing shows that the overall a is higher than 0.70 (a = 0.802), confirming the reliability of the applied methods (Pallant, 2020). Meanwhile, the values in Cronbach's Alpha if Item Deleted are all lower than the overall score, thus, the measurements of sentiment score by different methods are reliable. Since this research is only interested in online CCB, thus, the sample set only collected Tweets which are classified as negative. To improve the validity of the study, only the intersections of no less than two methods (i.e., the review was regarded as negative according to the outcome of at least two methods) were included in the final dataset, which returned N_negative = 29,317 and the average word count of these text is 25.20 (SD = 13.97)[17].

Table 8 Dictionary/method for sentiment analysis

Method	Description	Examples	Sample score
vaderSentiment	A rule-based and lexicon-based framework (Borg and Boldt, 2020; Hutto and Gilbert, 2014). Sentiment scores range lie between [-1, +1].	Hartmann *et al*. (2019); Klostermann *et al*. (2018); Luangrath, Xu and Wang (2023)	0.37
TextBlob	A lexicon based NLTK framework relies on pre-defined dictionary (Aljedanni *et al*., 2022). Polarity scores range from [-1, +1].	Aljedaani *et al*. (2022); Shi *et al*. (2022); Wang *et al*. (2022); Yu *et al*. (2022)	0.20
Linguistic Inquiry and Word Count (LIWC)	A lexicon-based software (Herhausen *et al*., 2019; Pennebaker *et al*., 2007). Positive and negative tone scores are present in percentage, ranging from [0, +100]. The polarity score is the gap between positive	Crolic *et al*. (2022); Herhausen *et al*. (2019)	3.33

[17] At the data pre-processing stage, to ensure the meaningfulness of included Tweets (for sentiment analysis), Tweets which have more than 3 words after removing the stop words and other meaningless elements were included in final dataset. The subsequent sentiment analysis was all conducted on this processed dataset. While given that some linguistic attributes of tweets, such as word count, words per sentence and number of big words are also focal variables, the measurement of these variables were performed to the raw data (i.e., without pre-procession except removing the hyperlinks). In general, processed text were used for sentiment analysis while descriptive statistics were conducted on raw data. See section 5.5.2 explanation for linguistic attributes measurement.

	and negative tone score, i.e., if the positive score is higher than negative score, the overall tone is regarded as positive in this study.		

Table 9-10 Reliability test output – sentiment analysis dictionary (n = 173,960)

Reliability Statistics

Cronbach's Alpha	N of Items
.802	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Textblob_score*	.0000000	3.211	.623	.754
Vader_score	.0000000	3.006	.702	.670
LIWC_gap	.0000000	3.225	.618	.760

* Results are calculated after standardization since the scores have different range.

5.5 Measurement

5.5.1 Virality

The principal variable of research interest is the *virality* of online complaints. In line with the definition (see section 2.4.5 Virality of online CCB), virality is regarded as the cumulative amount of other audience/reader's behaviours, thus, measured by the sum of retweets, replies, likes, and quotes a Tweet receives on Twitter (platform) in this study (Herhausen *et al.*, 2019)[18]. The negative Tweets are

[18] The definition of virality is non-unified. Specifically, some researchers regarded it as the cumulative effect of information adopting and sharing (Fichman, 1992; Garg et al., 2011), this definition highlights the range of the information spread. While the other definition focus on the speed of spread, thus, some researchers describe virality as the high frequency and speed of information spread (Tellis et al., 2019). As the time stamp of Twitter is non-accessible, this thesis sums up the number of retweets, replies, likes, and quotes. On the other hand, consumer engagement refers to individual's attitude and action toward a specific context (Dessart et al.,

retweeted M = 0.75 (SD = 30.32), liked M = 4.01 (SD = 138.77) and quoted M = 0.09 (SD = 4.99) times on average, and furthermore, they received M = 0.71 (SD = 8.37) replies on average (see Table 11 for descriptive statistics). The total number of retweets, replies, likes, and quotes are closely correlate (all higher than 0.8) as shown in correlation matrix in Table 12, which enables the measurement of a composite dependent variable (Herhausen *et al*., 2019; for the detailed distribution of retweets, replies, likes and quotes, see Appendix C). Given that the extreme values and the massive data range, a constant was added, and log-transformation was applied to measure virality (De Vries *et al*., 2012; Herhausen *et al*., 2019).

Table 11 Descriptive statistics for Tweets receive retweets, replies, likes, quotes and the overall virality

		retweets	replies	likes	quotes	*virality*
N	Valid	29317	29317	29317	29317	29317
	Missing	0	0	0	0	0
Mean		.75	.71	4.01	.09	5.56
Std. Deviation		30.320	8.369	138.771	4.994	178.007
Skewness		138.777	110.167	105.819	163.598	115.325
Std. Error of Skewness		.014	.014	.014	.014	.014
Kurtosis		21902.948	15296.647	14867.806	27567.860	17128.593
Std. Error of Kurtosis		.029	.029	.029	.029	.029
Minimum		0	0	0	0	0
Maximum		4823	1212	19425	842	26302

2016), and it is demonstrated in either customer's interaction with the focal brand (Brodie et al., 2011) or the psychological bond in the customer-organisation relationship (Sashi, 2012). In this thesis, based on the definition and taking the structure of attainable Twitter data, the focus is the cumulative Twitter user's reaction to each complaint targets the specific brands. Specifically, the measurement of virality: 1) calculate the number of behavioural reactions each complaint received; 2) regardless the emotional bond between the customer and organisation; 3) is interested in the cumulative number of each complaint rather than the individual's perception.

Table 12 Correlation matrix of total number of retweets, replies, likes and quotes

	(1)	(2)	(3)	(4)
(1) retweets	1.000			
(2) replies	.875	1.000		
(3) likes	.873	.894	1.000	
(4) quotes	.964	.889	.853	1.000

5.5.2 Linguistic Attributes of Complaints

Word count of the Tweets in this study was measured by the LIWC text-mining dictionary (see Appendix D). It is worth noting that the measurements of linguistic attributes were conducted on the unprocessed Tweets (i.e., only hyperlinks are removed, and words are not stemmed) as readers' understanding and perception of Tweets are based on the raw text. The readability of text was calculated by using the popular readability formula (see Sawyer *et al*., 2018 for review) with the help of linguistic attributes (see Table 13 for details). LIWC general descriptor categories were used to capture the word count, word per sentence (called "WPS" in LIWC, and $\frac{Word\ Count}{Sentence\ Count}$ in formulas), percentage of big words (named "BigWords" in LIWC, and ($\frac{Difficult\ Words}{Word\ Count} \times 100$) in formulas). Number of characters and syllables were calculated by python built-in function len() (Character Count = len(text) – Word Count - 1) and syllables.estimate() function of PyPI (Python Package Index).

Table 13 Summary of readability calculation

Name of formulas	Formulas	Interpretation	Reference studies
Flesch-Kincaid (Kincaid *et al*., 1975)	$206.835 - 1.015\left(\frac{Word\ Count}{Sentence\ Count}\right) - 84.6\left(\frac{Total\ Syllables}{Word\ Count}\right)$	The higher score means easier to read and negative scores indicate the sentences are long.	Hong and Hoban，2022； Sawyer *et al*., 2018; Sridhar and Srinivasan, 2012
Dale-Chall (Dale and Chall, 1984)	$0.1579\left(\frac{Difficult\ Words}{Word\ Count} * 100\right) + 0.0496\left(\frac{Word\ Count}{Sentence\ Count}\right)$	Note that if the proportion of difficult words is more than 5%, need to add 3.6365 to the raw score for adjustment. The lower score means easier to read.	Dale-Chall *et al*., 2021; Zierau *et al*., 2022
Gunning fog (Gunning, 1952)	$0.4\left[\left(\frac{Word\ Count}{Sentence\ Count}\right) + 100\left(\frac{Difficult\ Words}{Word\ Count}\right)\right]$	The lower score means easier to read.	Sridhar and Srinivasan, 2012; Yin *et al*., 2017
ARI (Automated readability index, Smith and Sender, 1967)	$4.71\left(\frac{Character\ Count}{Word\ Count}\right) + 0.5\left(\frac{Word\ Count}{Sentence\ count}\right) - 21.43$	Note that non-integer scores need to be transferred to the closest integer, e.g., both 9.1 and 9.6 are converted to 10. The lower score means easier to read.	Borah *et al*., 2020; Melumad *et al*., 2021; Ransbotham *et al*., 2019; Tamaddoni *et al*., 2023

The scores by different methods correlated closely, see Table 14 for the correlation of readability score calculated by different methods. Furthermore, reliability test shows the good reliability of these methods, and Table 15-16 show the reliability test outcome. The overall Cronbach's Alpha larger than 0.70 (a = 0.942), and the values in Cronbach's Alpha if Item Deleted are all lower than the overall score indicating that none of these readability measurements need to be removed. In other words, the measurements of readability are consistent. Given that the high reliability of these methods and the different ranges of the data, this study just used one of them in analysis, and since the Cronbach's Alpha if item deleted is lowest for Gunning fog score, it was adopted in this study. Finally, although the attachment such as picture, video and external links are not able to be controlled or analysed (Herhausen *et al*., 2019), since they may be helpful for the content vividness, it is still worth investigating the impact of attachment use. This variable was obtained by Twitter API and coded into dummy (1 = attachment used, -1 = attachment absent).

Table 14 Correlation matrix of readability scores

	(1)	**(2)**	**(3)**	**(4)**
(1) Dale-Chall	1.000			
(2) Flesch-Kincaid[1]	.765	1.000		
(3) Gunning fog	.893	.805	1.000	
(4) ARI[2]	.689	.811	.857	1.000

[1] Flesch-Kincaid score has opposite regulation with other methods; thus, the score was multiple by -1 to change the direction.

[2] Given that the ranges of scores are different, all scores were standardized before analysis.

Table 15 Reliability statistics of readability scores

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.942	.942	4

Table 16 Item-total statistics of readability scores

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Zscore(Dale-Chall)	.0000461	7.946	.833	.843	.934
Zscore(Flesch-Kincaid)	.0000318	7.881	.848	.739	.929
Zscore(Gunning_fog)	.0000263	7.532	.931	.910	.902
Zscore(ARI)	.0000384	7.928	.837	.820	.932

5.5.3 Psychological Attributes of Complaints

The analyticity, clout and authenticity of texts were measured by existing summary language variable of LIWC dictionaries (Pennebaker *et al*., 2015). Specifically, analyticity score variable is a factor analytical technique which analyses function words, wherein lower scores refer to softer and more friendly expression while texts with higher scores are regarded as more logical (Boyd and Pennebaker, 2015). Meanwhile, authenticity in recent linguistic studies tends to focus on the social performance (Markowitz *et al*., 2023), in other words, whether the text is social cautious (low score) or without social inhibitions (high score). Subjectivity analysis was conducted by Python TextBlob package and the subjectivity score ranging from 0 to +1. Polarity of text is measured by the gap between positive and negative tone based on LIWC, ranging from -100 to +100. With premise that the Tweets are negative, positive score indicates that the proportion of words belong to the dictionaries of positive emotions and words relevant to positive emotions are higher than the negative ones[19], while negative score means opposite. Furthermore, the higher absolute value implies higher polarity (either positive or negative) of the text.

The intensity of emotion expressed by the Tweets were demonstrated by the proportion of affect words by using LIWC since it enables both general sentiment analysis as well as fine-grained negative emotion categorization (Herhausen *et al*., 2019). To be more specific, LIWC provides hierarchical category of “Affect”, which is composed with three subcategories, positive tone, negative tone, emotion and swear words. “Tone” dictionaries include both words describing emotions (e.g., sad, happy) but also words relevant to emotions (e.g., cake, funeral). The “Emotion”

[19] Since three different methods are applied for sentiment analysis, and the intersection of at least two out of the three outcomes is regarded as negative. Thus, the score of positive tone might be higher than negative tone in some case, which occupies 0.8% of the complaint dataset in this study. For example, one Twitter user posted “Wtf @Marriott @MarriottBonvoy @CourtyardHotels we would like some answers https://t.co/lqeTXj7VnY”, the Vaderscore and Textblob score both regard it as negative, however, with a very strong positive word “like” in this sentence, the overall LIWC positive score is higher than the negative score.

group is subdivided into positive emotion and negative emotion, furthermore, negative emotions are classified into “anxiety”, “anger” and “sad” (see Figure 13 for the construct of “Affect” dictionaries). Words may be classified into multiple categories and subcategories. For example, word “hate” belongs to the lowest hierarchy “Anger” and the subcategory “Negative Emotion”, as well as the overall “Affect” dictionary. To avoid the potential multicollinearity problem, the affective words analysis in this study only included the non-repetitive variables, i.e., positive emotion, anxiety, anger, sad and swear words. Furthermore, the use of question mark, exclamation and emoji were measured with the help of LIWC functions (number of question mark, exclamation and emoji divided by word count).

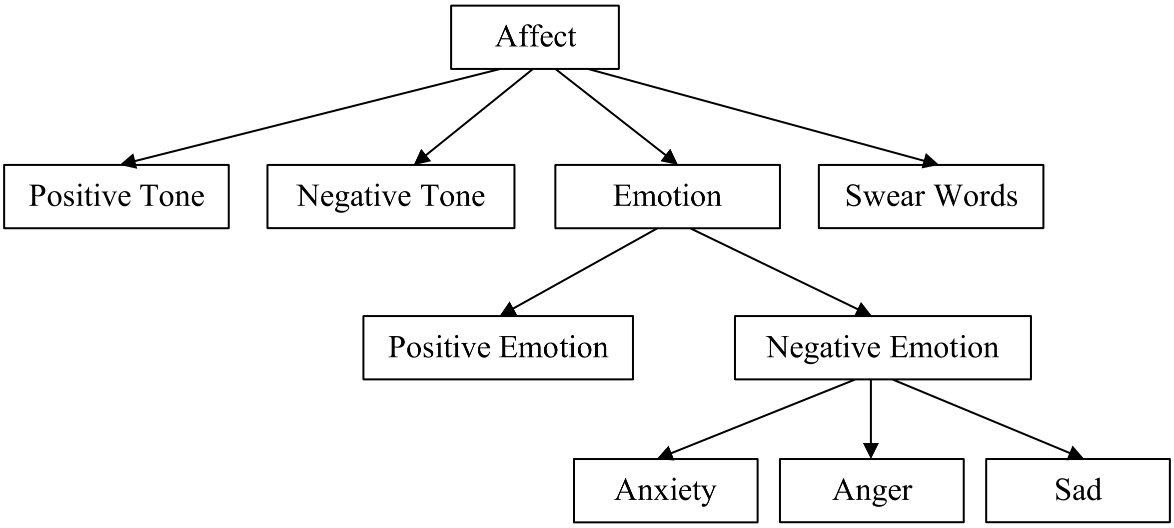


Figure 13 Construct of “Affect” dictionaries

Source: Byod *et al*. (2022)

5.5.4 Topic Modelling of Complaints

Complaints in online environment are rich and diverse, and the text interpretation techniques have been evolving over the decades. The earlier studies mainly relied on researchers’ expertise (Manickas and Shea, 1997; Zhou *et al*., 2014), however, traditional statistical methods are found not applicable for several reasons. First, biases are unavoidable thus make the findings non-replicable; meanwhile, raw data such as online UGCs are unstructured, which is difficult for manually processing. Finally, the extremely large volume of content brings more challenge to text understanding (Guo *et al*., 2017). Taking these shortcomings into considerations, computer-based techniques are taking over nowadays (Büschken and Allenby, 2016). Common methods including analyzing frequency of words (Archak *et al*., 2011; Lee and Bradlow, 2011) and using probabilistic model (Büschken and Allenby, 2016). The word-frequency method in this study, was conducted by LIWC, which provides both social-psychological and common-topic dictionaries (e.g., social behaviours, culture, lifestyle, physical, and perception). It is worth mentioning that as a supervised learning method which heavily rely on priori experience and labelled data (Van Engelen and Hoos, 2020), the limitations of using LIWC dictionary are undeniable although the convenience is also obvious. The dictionary works as the black box, which makes the interpretation challenging. For example, if the "Lifestyle" topics are found more likely to go viral, what exactly are these lifestyle topics about are unknown because words in dictionary are inaccessible. The other problem with LIWC dictionary is caused by its algorithm, which only calculate the frequency of topic words but ignore the interactions and contexts. However, there are a lot of overlaps between topics and one Tweet may contain several topics, which requires the investigation on the combination of words rather than count the numbers. Therefore, LIWC dictionary is only used to confirm the necessity of topic modelling, i.e., to investigate whether various topics may explain the variance in virality, and more advanced method will be applied to confirm the exact themes of complaining.

A simple and most widely (Büschken and Allenby, 2016; Zhong and Schweidel, 2020) used model for Bayesian topic modelling is Latent Dirichlet Allocation (LDA). LDA uses the variational exception maximization algorithm to estimate the maximum likelihood of the text. allows texts to have multiple topics and each of the words has its own weight in each of the topics (Zhong and Schweidel, 2020). Here is an example to demonstrate the mechanism (See Figure 14). There is a corpus of online reviews. Assume that there are N "topics", which are composed with common words (see the lower level of the figure), and each of the reviews is expected to be formed as follows. To determine the topic, the first step is to choose the distribution (the histogram in the middle). After that, choose the topic assignment for each word (the highlights in text) based on the corresponding topic words (the lower level). By LDA, the probability of topics for each of the review can be obtained to infer the topic. Figure 15 demonstrates the deductive topic proportion (illustrative, with more topic names added which is not shown in the figure of example description) for the third example review shown in Figure 14.

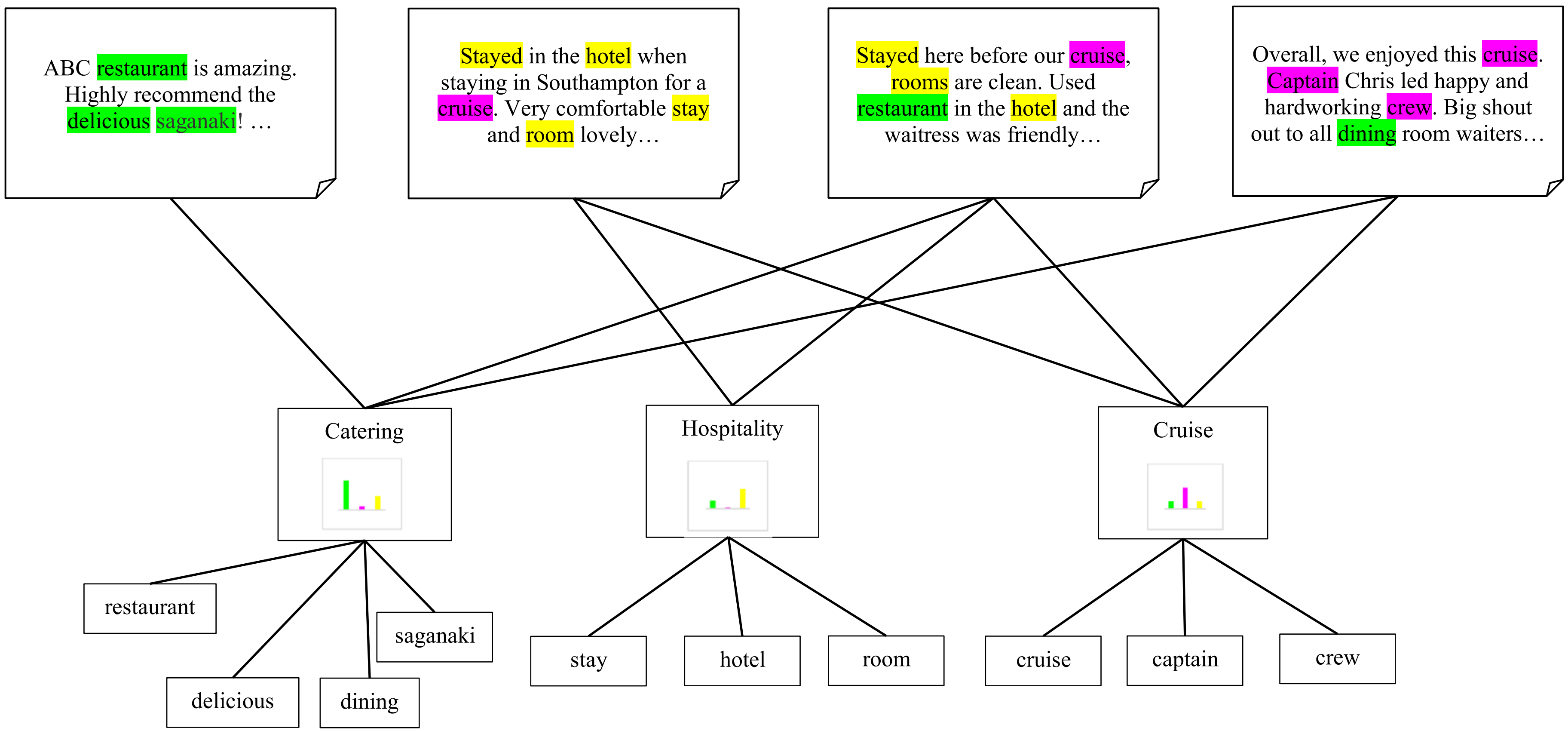


Figure 14 Example of texts and the intuitions of LDA

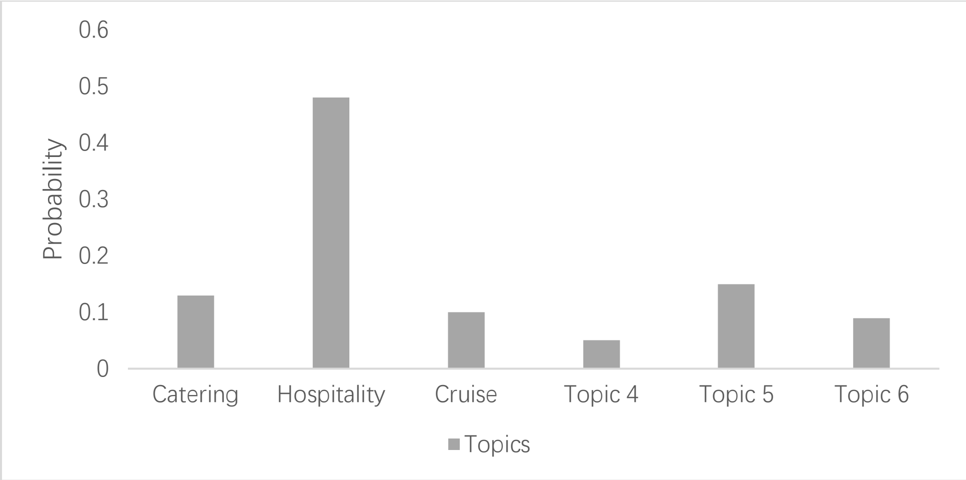


Figure 15 Inference with LDA

Considering the workload of LDA, this study will use dictionary-based method as an exploration to check the potential virality variance caused by topics. Given that the inaccessibility of the dictionary details (i.e., the keywords are unknown) and the Tweet may have multiple scores for different topics (e.g., one Tweet may be scored 10 for "social", 12 for "culture" and 11 for "perception", then it is difficult to determine what exactly is the topic), the outcome is not interpretable by using dictionary. Therefore, if the virality is found influenced by topic words, the study will further adopt algorithms to determine the appropriate number of topics and conduct LDA for a more precise, meaningful and context-based topic modelling.

5.5.5 Characteristics of Complainers

The number of complainer's followers was obtained via Twitter's API, and after adding a constant (to ensure the outcomes are positive), the data was log-transformed since the massive data range and the extreme numbers of followers (see descriptive statistics in Chapter 6).

5.5.6 Characteristics of Organisation/brand

The number of organisation/brand followers and the amount of organisation/brand's Tweets were captured by Twitter API. To measure the ratio of organisational response to complaints, the author divided the number of replied complaints by the total number of replied Tweets (regardless their sentiment). Specifically, the time span of reply starts from 00:00:00 am, 1st January 2022 to 00:00:00 am, 1st February 2023 (1 month more than the end time of complaint data) to cover the time-lag. The overall ratio of negative Tweets each brand received was calculated by comparing the number of negative Tweets with total number of Tweets the organisation/brand received 00:00:00 am, 1st January 2022 to 00:00:00 am, 1st January 2023.[20, 21]

5.5.7 Characteristics of Organisational Reply

Whether the organisation responded to the complaint was captured via Twitter API with the help of Tweepy package and then dummy coded (1 = response provided, -1 = response absent). The time gap between the complaint posted and the organisational response (if provided) was calculated and shown in hours (see Chapter 6 for descriptive statistics).

[20] The total number of Tweets and total number of replied Tweets focus on Tweets with more than 3 words and written in English.

[21] To detect the potential interference, time series analysis was also demonstrated to check whether there is negativity spiral phenomenon or seasonal/cyclical fluctuation. See Appendix F for visualisation of the outcomes.

5.5.8 Summary of Measurement

The source and operations of variables as well as relevant studies are listed in Table 17.

Table 17 Summary of variables and measurements in this study

Variable	Operationalization	Measurement	Source	Related Studies
Dependent Variable				
Virality	Sum of retweets, replies, likes, and quotes each tweet received from other customers when the data was collected, and logarithmic transformed.	Sum of retweets, replies, likes and quotes	Twitter API	Herhausen *et al*., 2019
Independent Variable				
Subjectivity	Python – TextBlob library: Sentiment subjectivity of the Tweet; range from 0 to 1; a larger ratio indicates a more subjective Tweet	TextBlob subjectivity score	Text mining	Giatsoglou *et al*., 2017; Micu *et al*., 2017
Polarity	Gap between LIWC dictionary “positive tone” and “negative tone”.	Proportion of positive tone keywords – Proportion of negative tone keywords	Text mining	Herhausen *et al*., 2019
WC (word count)	Word count of the text.	LIWC word count	Text mining	Berger and Milkman, 2012; Melumad *et al*., 2019

Analytic	LIWC dictionary "analytic" for complaints (number of matching words, represented as proportion of total word count).	Proportion of LIWC analytic score	Text mining	Woodard *et al*., 2021
Clout	LIWC dictionary "clout" for complaints (number of matching words, represented as proportion of total word count).	Proportion of LIWC clout score	Text mining	Pilny *et al*., 2019
Authentic	LIWC dictionary "authentic" for complaints (number of matching words, represented as proportion of total word count).	Proportion of LIWC authentic score	Text mining	Cheung *et al*., 2009
Affect	LIWC dictionary "affect" for complaints (number of matching words, represented as proportion of total word count).	Proportion of LIWC emotion score: • Positive • Anxiety • Anger • Sad • Swear	Text mining	Herhausen *et al*., 2019
Readability	Difficulty of reading. Use Gunning fog index (for English): a higher value indicates the higher requirement of the readers education level to understand the text.	Gunning fog score	Text mining	Sawyer *et al*., 2008
Question mark	Represented as proportion of total word count.	Proportion of question mark	Text mining	Lin and Peña, 2011

Exclamation mark	Represented as proportion of total word count.	Proportion of exclamation mark	Text mining	Teh *et al*., 2015
Number of brand followers	Number of brand page followers when data collected.	Number of the brand's followers on Twitter	Twitter API	Herhausen *et al*., 2019
Number of complainer followers	Number of complainer followers when data collected.	Number of the complainer's followers on Twitter	Twitter API	
Organisation response to conversation	Whether the organisation respond to the complaint Twitter ID or not. Binary variable dummy coded.	"1 – response provided", "-1 – response absent"	Twitter API	Herhausen *et al*., 2019
Gap between Tweets posted and organisational response	Time difference shown in hours.	Gap between when the complainer posted the Tweet and when the organisation respond to the Tweet (in hours)	Twitter API	Herhausen *et al*., 2019
Topic (Bayesian topic model)	Sklearn Latent Dirichlet Allocation (two different topic modelling method adopted to confirm the validity of the classification).	Categorical variable coded by LDA	Text mining	Tirunillai and Tellis, 2014
Topic (dictionary-based)	Priori word-category approach: LIWC basic and expanded dictionary multi-hierarchy topic words, including first hierarchy "drives", "cognition", "social",	Proportion of LIWC topic words	Text mining	Herhausen *et al*., 2019

	“general topics”, “states”, “motive”, “perception”, “time orientation”, “conversation” and some lower hierarchy topics (number of matching words, represented as proportion of total word count).			

CHAPTER 6 MODEL TESTING AND COMPARISON

6.1 Descriptive Statistics and Data Robustness Checks

Prior to presenting the results, a summary of descriptive statistics is demonstrated in Table 18 and the frequency for all categorical variables is shown in Table 19, which together present all measurements used in this study. Before estimating models, several checks were conducted to ensure the data is robust. First, the Pearson correlation analysis was conducted to measure the direction and strength between two variables. The results of correlation analysis on main variables (see Table 20) show that all values are lower than 0.7 as expected (Pallant, 2020), thus, all variables are retained for further analysis. Furthermore, collinearity diagnostics was conducted to detect potential multicollinear problems. Results in Table 21 show that the variance inflation factor (VIF) values are lower than 10, and the average of VIF values is 1.68 (not considerably higher than 1), indicating that the risk of multicollinearity is not substantial (Alin, 2010; Pallant, 2020). Noting that the cut-off points for the value of multicollinearity is contentious and some researchers propose that VIF should not exceed 5 (Alauddin and Nghiem, 2010). It is suggested that the rule of thumb should take the context into consideration (O'Brien, 2007). Since the VIF of organisational response rate is 5.52 and based on the research purpose that this study can be adequately comprehensive, organisational response rate is kept as one independent variable for further exploration.

Table 18 Descriptive statistics for all numerical variables used in this study

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Dependent Variable									
Virality	29317	0	26302	5.56	178.007	123.270	.014	17128.593	.029
Independent Variable									
Linguistic attributes of complaint									
Word Count	29317	3	64	25.20	13.968	.276	.014	-1.055	.029
Readability Gunning	29317	.40	45.20	13.3094	5.8876	.481	.014	.425	.029
Psychological attributes of complaint									
Subjectivity	29317	.00	1.00	.4805	.3308	-.044	.014	-1.173	.029
Polarity	29317	-100.00	28.57	-9.8944	10.0274	-1.613	.014	4.872	.029
Analytic	29317	1.00	99.00	48.4449	32.9445	-.027	.014	-1.450	.029
Clout	29317	1.00	99.00	46.1391	35.8375	.226	.014	-1.354	.029
Authentic	29317	1.00	99.00	47.6775	41.0169	.103	.014	-1.730	.029
emo_pos	29317	.00	50.00	.2658	1.7647	11.079	.014	167.681	.029
emo_anx	29317	.00	40.00	.2887	1.9601	9.738	.014	116.859	.029
emo_anger	29317	.00	66.67	.9808	3.5477	5.415	.014	38.585	.029

emo_sad	29317	.00	66.67	.6504	2.9676	7.797	.014	90.535	.029
swear	29317	.00	100.00	1.3458	5.1254	5.781	.014	46.991	.029
Question Mark	29317	.00	266.67	2.1747	7.0513	7.627	.014	126.924	.029
Exclamation	29317	.00	871.43	3.1047	13.1101	26.817	.014	1473.138	.029
Emoji	29317	.00	820.00	1.7889	11.2227	32.417	.014	1779.429	.029
Topic (supervised)									
Cognition	29317	.00	100.00	11.0930	10.8875	1.216	.014	2.373	.029
Social	29317	.00	100.00	17.2989	13.8180	1.079	.014	2.116	.029
Culture	29317	.00	66.67	2.9557	6.22118	2.929	.014	11.801	.029
Lifestyle	29317	.00	100.00	7.8439	8.74370	1.449	.014	3.828	.029
Physical	29317	.00	75.00	3.1734	6.43110	3.157	.014	14.851	.029
Perception	29317	.00	80.00	9.7424	9.67173	1.168	.014	1.967	.029
Organisational response									
Time_gap(hour)	3043	.0078	2187.4567	24.1801	93.2545	13.749	.044	250.846	.089
Characteristics of organisation									
Brand followers	28	51209	377210	136421.5714	92240.9267	1.522	.441	1.335	.858
Ratio of complaints	28	.0366	.3220	.1355	.0689	.493	.441	.264	.858
Response rate	28	.0000	.4505	.1186	.1022	1.171	.441	2.531	.858
Characteristics of complainer									

Number of complainer's followers	29317	0	2190244	2631.95	25309.234	41.339	.014	2617.980	.029

Table 19 Frequency tables of all categorical variables used in this study (N = 29,317)

			Frequency	Percent	Valid Percent	Cumulative Percent
Attachment	Valid	Absent	23974	81.8	81.8	81.8
		Present	5343	18.2	18.2	100.0
		Total	29317	100.0	100.0	
Organisational Response	Valid	Absent	26082	89.0	89.0	89.0
		Present	3235	11.0	11.0	100.0
		Total	29317	100.0	100.0	

Table 20 Correlation matrix of main variables

Variable	M	SD	N	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
1. Virality (log)	5.56	178.01	29317																										
Brand controls																													
2. Brand followers (log)	12.11	0.69	28	.03																									
3. Ratio of complaints	0.14	0.07	28	-.07	.04																								
4. Response rate	0.12	0.10	28	.04	.40	.10																							
Author control																													
5. Author followers (log)	5.06	2.28	29317	.29	.07	-.08	.00																						
Linguistic attributes of complaint																													

6. Word count	25.20	13.97	29317	.08	-.05	.03	.07	-.08																					
7. Readability G	13.31	5.89	29317	-.01	-.10	.19	-.06	-.08	.16																				
Psychological attributes of complaint																													
8. Subjectivity	0.48	0.33	29317	.01	.05	-.14	.09	.02	.03	-.16																			
9. Polarity	-9.89	10.02	29317	.08	.01	-.09	.05	.01	.44	.00*	.08																		
10. Analytic	48.44	32.94	29317	-.05	-.11	.14	-.10	-.10	-.01	.34	-.21	-.07																	
11. Clout	46.14	35.84	29317	-.01	.02	.04	.00	-.06	-.05	.10	-.09	-.09	.18																
12. Authentic	47.68	41.02	29317	.06	.02	-.13	.08	.05	.23	-.18	.08	.23	-.23	-.34															
13. Emotion_positive	0.27	1.76	29317	-.01	.02	-.02	.01	.03	-.02	-.06	.06	-.03	-.05	-.05	.01														
14. Emotion_anxiety	0.29	1.96	29317	.01	.02	-.02	.00*	.04	-.06	-.04	.02	-.10	-.04	-.01	-.01	.00													
15. Emotion_anger	0.98	3.55	29317	.00	.05	-.02	.01	.03	-.09	-.02	.06	-.19	-.05	.03	-.05	.00	-.02												
16. Emotion_sad	0.65	2.97	29317	-.02	.03	-.04	.01	.01	-.07	-.06	.08	-.14	-.05	-.02	-.01	.03	-.01	-.04											
17. Swear	1.35	5.13	29317	-.03	.06	-.03	.01	.02	-.19	-.16	.11	-.01	-.03	-.16	-.07	-.01	-.02	-.01	-.03										
18. Question	2.17	7.05	29317	.01	.06	-.03	.03	.03	-.13	-.12	.01	-.04	-.11	.01	-.04	-.02	.02	.04	.00	.08									
19. Exclamation	3.10	13.11	29317	-.02	.02	-.05	.03	-.02	-.11	-.08	.02	-.07	-.02	.02	.00*	.00	.01	.01	-.01	.03	.05								
20. Emoji	1.79	11.22	29317	.01	.00	-.02	-.03	.03	-.10	-.02	-.02	-.05	.02	-.01	-.03	-.01	.00	.00	.01	.12	.01	.05							
Topic (supervised)																													
21. Cognition	11.09	10.89	29317	.04	.01	-.10	.06	.06	.06	-.13	.13	.11	-.38	-.21	.21	.14	.03	.01	.01	-.05	.07	-.03	-.04						
22. Social	17.30	13.82	29317	-.04	.02	.15	-.03	-.05	-.11	.05	-.11	-.25	-.01	.50	-.27	-.04	-.05	.10	-.03	-.03	.01	.01	-.01	-.12					
23. Culture	2.96	6.22	29317	-.05	-.05	.22	-.06	-.05	-.05	.26	-.22	-.15	.22	.08	-.21	-.04	-.03	.00*	-.06	-.05	.02	-.03	-.01	-.14	.16				
24. Lifestyle	7.84	8.74	29317	-.03	-.07	.04	.04	-.09	.14	.20	-.01	.09	.16	.09	-.05	-.03	-.05	-.05	-.03	-.07	-.04	-.02	-.02	-.11	.00*	-.02			
25. Physical	3.17	6.43	29317	-.04	-.05	.03	-.06	.00*	-.07	.03	-.12	-.13	.12	.00*	-.10	-.02	-.01	-.05	-.04	.09	-.03	.00*	.01	-.13	-.01	.08	-.07		
26. Perception	9.74	9.67	29317	.04	.03	-.07	.04	.03	.14	-.16	.03	.14	.02	-.07	.47	.03	-.02	-.06	-.01	-.04	-.03	-.01	-.03	-.01	-.21	-.14	-.05	.01	
Organisational response																													
27. Post_response gap (hour)	24.18	93.25	3043	.00	-.09	.01	-.05	-.02	.00*	.03	-.02	.01	.00	.02	.01	-.01	.01	.02	-.02	-.01	-.03	-.01	-.01	.02	.06	.05	.01	.00	-.01

* Only two decimals kept, .00 with * indicates the value is negative, however, shows .00 after rounding

Table 21 Collinearity diagnostics results for all numerical variables

Model		Collinearity Statistics	
		Tolerance	VIF
1	(Constant)		
	Zscore(LNBrand_follower)	.255	3.926
	Zscore(neg_rate)	.504	1.986
	Zscore(res_rate)	.181	5.522
	Zscore(LNauthor_followers)	.943	1.061
	Zscore(WC)	.735	1.360
	Zscore(Gunning)	.858	1.165
	Zscore(Subjectivity)	.932	1.073
	Zscore(Polarity)	.730	1.370
	Zscore(Analytic)	.732	1.366
	Zscore(Clout)	.614	1.630
	Zscore(Authentic)	.632	1.583
	Zscore(emo_pos)	.973	1.028
	Zscore(emo_anx)	.965	1.036
	Zscore(emo_anger)	.907	1.103
	Zscore(emo_sad)	.918	1.089
	Zscore(swear)	.898	1.114
	Zscore(Cognition)	.826	1.211
	Zscore(Social)	.657	1.523
	Zscore(Culture)	.936	1.069
	Zscore(Lifestyle)	.898	1.114
	Zscore(Physical)	.927	1.078
	Zscore(Perception)	.701	1.426
	Zscore(QMark)	.945	1.058
	Zscore(Exclam)	.961	1.041
	Zscore(Emoji)	.960	1.042
	Zscore(gap_hour)	.981	1.020

6.2 Multiple Regression

Given that the structure of raw data was unclear, a basic regression model was tested to explore the variables. Regression analysis one of the common techniques to investigate the relationship between variables and propose models, and when there are more than one regressor variable involved, the model is called multiple regression model (Montgomery *et al*., 2021). Given that the large number of potential predictors in this study, statistical regression procedures were applied to retain predictive results (Pallant, 2020). The decision of inclusion and exclusion of variables purely relies on the statistics computation, rather than the interpretation of the variable in statistical regression (Tabachnick and Fidell, 2013), which enables to return more objective results. Specifically, statistical regression has three versions, namely forward selection, backward elimination, and stepwise regression (Pallant, 2020).

Forward selection starts with the assumption that there is no regression model and only intercepts come into effect and the purpose of this procedure is to find appropriate regressors (Montgomery *et al*., 2021). Initially, no variable is included in the equation and sequentially adds one independent variable at a time, starting from the one with the highest simple correlation with the dependent variable, meanwhile checks whether it meet the inclusion criteria and keep (permanently)/remove them from the equation. Then, the variable with second highest correlation with dependent variable adjusted by the first regressor (also called partial correlation) is tested. This step is repeated until the last independent variable is tested. Backward elimination works with diametrically opposite procedures by including all variables and computing the F or t statistic and then sequentially remove the variables with the smallest partial F or t value compared with preselected cut off F value (Montgomery *et al*., 2021). Finally, stepwise regression is the combination of the forward and backward versions (Efroymson, 1960), simply put, it will add the independent variable into the model but also delete it whenever it can no longer significantly change the F value. Stepwise regression is more frequently used when predicting equation because it maximises the included independent variables meanwhile excludes the variables no longer have significant contribution to the equation which has been added previously (Pallant, 2020). Therefore, in line with the research aim of this study, stepwise method was adopted for multiple regression in this study.

The following Table 22 shows the stepwise linear regression models, and the highest R Square indicates that the model describes the data better (for the reasons of brevity, details of the model with and without outliers can be seen in Appendix G). Table 23 presents the results of model 19 ($R^2 = 0.102$). With all of the independent variables entered and evaluated, number of author's followers ($b = 0.29$, $t(29297) = 50.67$, $p < .001$), word count ($b = 0.07$, $t(29297) = 11.39$, $p < .001$), rate of organisatinal response to negative Tweets ($b = 0.03$, $t(29297) = 5.0$, $p < .001$), presence of attachment ($b = 0.05$, $t(29297) = 7.79$, $p < .001$), tone polarity ($b = 0.02$,

$t(29297) = 3.77$, $p < .001$), presence of organisational response to the negative Tweet ($b = 0.03$, $t(29297) = 6.13$, $p < .001$) and clout of the text all have strong positive impacts on virality (($b = 0.04$, $t(29297) = 5.51$, $p < .001$), meanwhile, percentage of negative Tweets ($b = 0.02$, $t(29297) = 3.77$, $p < .001$), level of analytical thinking of the text ($b = -0.03$, $t(29297) = -4.05$, $p < .001$), physical objective ($b = -0.03$, $t(29297) = -5.11$, $p < .001$), lifestyle ($b =-0.02$, $t(29297) = -3.69$, $p < .001$), and social relevant topic words ($b = -0.02$, $t(29297) = -3.38$, $p < .001$) will significantly decrease the virality. Besides, number of brand's followers ($b = 0.02$, $t(29297) = 2.46$, $p < .05$), level of text readability ($b = 0.01$, $t(29297) = 2.10$, $p < .05$) and using words belong to perception dictionary ($b = 0.01$, $t(29297) = 2.45$, $p < .05$) will have significantly positive impact on virality while use of positive emotion words ($b = -0.02$, $t(29297) = -2.90$, $p < .01$), sad emotion expressed in text ($b = -0.1$, $t(29297) = -2.42$, $p < .05$), level of text subjectivity ($b = -0.01$, $t(29297) = -2.08$, $p < .05$), and use of exclamation marks ($b = -0.01$, $t(29297) = -1.97$, $p < .05$) will reduce the possibility of complaint virality.

Table 22 Part of the stepwise linear regression model (n = 29,317)[22]

Model Summary[t]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.285[a]	.081	.081	.9586	.081	2589.517	1	29315	.000
2	.301[b]	.091	.091	.9535	.010	312.478	1	29314	<.001
3	.306[c]	.094	.094	.9520	.003	94.225	1	29313	<.001
4	.309[d]	.095	.095	.9513	.001	46.121	1	29312	<.001
5	.311[e]	.097	.097	.9504	.002	53.215	1	29311	<.001
6	.313[f]	.098	.098	.9499	.001	31.168	1	29310	<.001
7	.314[g]	.099	.098	.9495	.001	27.549	1	29309	<.001
8	.315[h]	.099	.099	.9492	.001	23.450	1	29308	<.001
9	.316[i]	.100	.100	.9489	.000	14.820	1	29307	<.001
10	.317[j]	.100	.100	.9487	.001	16.422	1	29306	<.001
11	.317[k]	.101	.100	.9486	.000	8.573	1	29305	.003
12	.318[l]	.101	.101	.9484	.000	9.784	1	29304	.002
13	.318[m]	.101	.101	.9483	.000	9.133	1	29303	.003
14	.318[n]	.101	.101	.9482	.000	6.228	1	29302	.013
15	.319[o]	.102	.101	.9481	.000	6.046	1	29301	.014
16	.319[p]	.102	.101	.9480	.000	5.119	1	29300	.024
17	.319[q]	.102	.101	.9480	.000	4.418	1	29299	.036
18	.319[r]	.102	.101	.9479	.000	4.888	1	29298	.027
19	.320[s]	.102	.102	.9479	.000	3.893	1	29297	.048

a. Predictors: (Constant), Zscore(LNauthor_followers)

s. Predictors: (Constant), Zscore(LNauthor_followers), Zscore(WC), Zscore(neg_ratio), Zscore(res_rate), attachments, Zscore(Polarity), Res_tweet, Zscore(Physical), Zscore(Clout), Zscore(Lifestyle), Zscore(Social), Zscore(Analytic), Zscore(emo_pos), Zscore(emo_sad), Zscore(LNBrand_follower), Zscore(Subjectivity), Zscore(Perception), Zscore(Gunning), Zscore(Exclam)

t. Dependent Variable: Zscore(LNvirality)

[22] Only the critical part of the variable description is included in this table, see full table in Appendix H-1.

Table 23 Coefficient table of model 19 (n = 29,317)[23]

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
19	(Constant)	.083	.010		8.040	<.001
	Zscore(LNauthor_followers)	.285	.006	.285	50.669	.000
	Zscore(WC)	.073	.006	.073	11.388	<.001
	Zscore(neg_ratio)	-.059	.006	-.059	-9.891	<.001
	Zscore(res_rate)	.032	.006	.032	5.003	<.001
	attachments	.061	.008	.047	7.792	<.001
	Zscore(Polarity)	.024	.006	.024	3.770	<.001
	Res_tweet	.058	.009	.036	6.132	<.001
	Zscore(Physical)	-.029	.006	-.029	-5.111	<.001
	Zscore(Clout)	.036	.007	.036	5.508	<.001
	Zscore(Lifestyle)	-.021	.006	-.021	-3.689	<.001
	Zscore(Social)	-.023	.007	-.023	-3.377	<.001
	Zscore(Analytic)	-.026	.006	-.026	-4.054	<.001
	Zscore(emo_pos)	-.016	.006	-.016	-2.896	.004
	Zscore(emo_sad)	-.014	.006	-.014	-2.423	.015
	Zscore(LNBrand_follower)	.016	.006	.016	2.459	.014
	Zscore(Subjectivity)	-.012	.006	-.012	-2.079	.038
	Zscore(Perception)	.014	.006	.014	2.447	.014
	Zscore(Gunning)	.013	.006	.013	2.097	.036
	Zscore(Exclam)	-.011	.006	-.011	-1.973	.048

a. Dependent Variable: Zscore(LNvirality)

The focus of this study is the virality of negative Tweets, thus, extremity plays a critical role in analysis which requires more attention. Considering the extremes and range of number of author's followers, multiple linear regression of without outliers was also conducted for robustness check (n = 28,287). According to the model summary (Table 24), R-squared of the final model 18 is 0.103 and the results are demonstrated in Table 25. The linear regression result shows that number of author's followers (b = 0.29, t(228268) = 50.00, p < .001), word count (b = 0.07, t(228268) = 10.86, p < .001), presence of attachment (b = 0.05, t(228268) = 8.35, p < .001), rate of organisational response to negative Tweets (b = 0.03, t(228268) =

[23] Only Model 19 is presented here, and the full table of all models can be found in Appendix H-2.

4.49, $p < .001$), gap between positive and negative tone ($b = 0.02$, $t(228268) = 3.44$, $p < .001$), presence of organisational response to the negative Tweet ($b = 0.03$, $t(228268) = 5.47$, $p < .001$) and clout of the text ($b = 0.04$, $t(228268) = 5.96$, $p < .001$) all have strong positive impacts on virality which replicate the result when outliers are included in the dataset; meanwhile, the negative impact of percentage of negative Tweets ($b = -0.06$, $t(228268) = -9.55$, $p < .001$), use of physical objective relevant words ($b = -0.03$, $t(228268) = -4.68$, $p < .001$), level of analytical thinking ($b = -0.02$, $t(228268) = -3.13$, $p < .001$), and lifestyle relevant topic words ($b = -0.02$, $t(228268) = -3.90$, $p < .001$) on virality are further proven. Besides, number of brand's followers ($b = 0.01$, $t(228268) = 2.24$, $p < .05$), text authenticity ($b = 0.02$, $t(228268) = 2.28$, $p < .05$), and text readability have significantly positive impact on virality at $p < .05$ while use of social topic words ($b = -0.02$, $t(228268) = -3.29$, $p = .001$), expressing positive emotion ($b = -0.02$, $t(228268) = -3.00$, $p < .05$) and sad emotions ($b = -0.01$, $t(228268) = -2.40$, $p < .05$), and use of exclamation marks ($b = -0.01$, $t(228268) = -2.01$, $p < .05$) will reduce the possibility of complaint virality.

Table 24 Part of the stepwise linear regression model of dataset with no outliers (n = 28,287)[24]

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.287[a]	.083	.083	.9689	.083	2546.880	1	28285	.000
2	.303[b]	.092	.092	.9639	.009	293.268	1	28284	<.001
3	.308[c]	.095	.095	.9624	.003	90.449	1	28283	<.001
4	.310[d]	.096	.096	.9617	.001	41.852	1	28282	<.001
5	.313[e]	.098	.098	.9608	.002	53.651	1	28281	<.001
6	.314[f]	.099	.099	.9603	.001	29.358	1	28280	<.001
7	.316[g]	.100	.099	.9599	.001	22.264	1	28279	<.001
8	.317[h]	.100	.100	.9596	.001	21.334	1	28278	<.001
9	.317[i]	.101	.100	.9593	.000	15.440	1	28277	<.001
10	.318[j]	.101	.101	.9591	.001	16.980	1	28276	<.001
11	.319[k]	.102	.101	.9589	.000	8.765	1	28275	.003
12	.319[l]	.102	.101	.9588	.000	7.998	1	28274	.005
13	.320[m]	.102	.102	.9587	.000	10.001	1	28273	.002

[24] Only the variable description of focal model is included in this table, see full table in Appendix H-3.

14	.320[n]	.102	.102	.9586	.000	5.520	1	28272	.019
15	.320[o]	.102	.102	.9585	.000	4.808	1	28271	.028
16	.320[p]	.103	.102	.9585	.000	4.352	1	28270	.037
17	.321[q]	.103	.102	.9584	.000	4.153	1	28269	.042
18	.321[r]	.103	.102	.9584	.000	4.631	1	28268	.031

r. Predictors: (Constant), Zscore(LNauthor_followers), Zscore(WC), Zscore(neg_ratio), attachments, Zscore(res_rate), Zscore(Physical), Zscore(Polarity), Res_tweet, Zscore(Clout), Zscore(Lifestyle), Zscore(emo_pos), Zscore(Social), Zscore(Analytic), Zscore(emo_sad), Zscore(LNBrand_follower), Zscore(Exclam), Zscore(Authentic), Zscore(Gunning)

Table 25 Coefficient table of model 18 (n = 28,287)[25]

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
18	(Constant)	.073	.011		6.865	<.001
	Zscore(LNauthor_followers)	.305	.006	.286	50.002	.000
	Zscore(WC)	.073	.007	.072	10.856	<.001
	Zscore(neg_ratio)	-.058	.006	-.058	-9.547	<.001
	attachments	.066	.008	.051	8.346	<.001
	Zscore(res_rate)	.029	.007	.029	4.488	<.001
	Zscore(Physical)	-.027	.006	-.027	-4.682	<.001
	Zscore(Polarity)	.023	.007	.023	3.436	<.001
	Res_tweet	.053	.010	.033	5.468	<.001
	Zscore(Clout)	.042	.007	.041	5.955	<.001
	Zscore(Lifestyle)	-.023	.006	-.023	-3.897	<.001
	Zscore(emo_pos)	-.017	.006	-.017	-2.999	.003
	Zscore(Social)	-.023	.007	-.023	-3.286	.001
	Zscore(Analytic)	-.021	.006	-.021	-3.313	<.001
	Zscore(emo_sad)	-.014	.006	-.014	-2.402	.016
	Zscore(LNBrand_follower)	.015	.007	.014	2.237	.025
	Zscore(Exclam)	-.011	.006	-.011	-2.009	.045
	Zscore(Authentic)	.015	.007	.015	2.281	.023
	Zscore(Gunning)	.014	.006	.014	2.152	.031

a. Dependent Variable: Zscore(LNvirality)

Table 26 summarises the independent variables included in the model of both dataset with and without outliers. Comparing the results when outliers were included and excluded, the overall model is robust which shows the predominant impact of

[25] Only Model 18 is presented here, and the full table of all models can be found in Appendix H-4.

the number of the complainer's followers on the virality of negative Tweet. Linguistic attributes, word count and readability as well as emotional expressions and proxies also found to increase or decrease the possibility of complaint virality. Meanwhile, topic keywords are also found to be critical regressors. Finally, organisational performance, such as the percentage of negative Tweets, number of brand's followers and organisational response to complaint are found to be potential factors.

Table 26 Robustness check (independent variables in models with/without outliers)

	With outliers (n = 29,317)		**Without outliers** (n = 28,287)	
	Standardized Coefficients Beta	Sig.	Standardized Coefficients Beta	Sig.
Author followers (log)	.285	.000	.286	.000
Word count	.073	<.001	.072	<.001
Ratio of complaints	-.059	<.001	-.058	<.001
Ratio of organisational response to complaints	.032	<.001	.029	<.001
Attachment presence	.047	<.001	.051	<.001
Polarity	.024	<.001	.023	<.001
Organisational response presence	.036	<.001	.033	<.001
Physical	-.029	<.001	-.027	<.001
Clout	.036	<.001	.041	<.001
Lifestyle	-.021	<.001	-.023	<.001
Social	-.023	<.001	-.023	.001
Analytical thinking	-.026	<.001	-.021	<.001
emo_positive	-.016	.004	-.017	.003
emo_sad	-.014	.015	-.014	.016
Brand follower (log)	.016	.014	.014	.025
Subjectivity	-.012	.038		NS
Perception	.014	.014		NS

Readability Gunning	.013	.036	.014	.031
Exclamation mark	-.011	.048	-.011	.045
Authenticity		NS	.015	.023

6.3 Logistic Regression

Considering that the range of the virality is large, and there is no confirmed algorithm for virality evaluation, to distinguish the viral and non-viral Tweets is a tough task. Although virality was coded by the sum of retweets, replies, likes, and quotes, it is still unclear what is the boundary of virality. Thus, it is necessary to code the virality and conduct logistic regressions to investigate the probability of virality. It is worth mentioning the impact of brand-level difference in content virality. For instance, Twitter users are more interactive and engaging when discussing some brands, therefore, the total number of retweets, likes, replies and quotes are overall high whether the contents are positive or negative. Thus, to measure the virality, the coding was conducted at the brand level (De Vries *et al*., 2012; Herhausen *et al*., 2019), in other words, comparing the sum of retweets, likes, replies and quotes of negative comments with all English Tweets on each brand Twitter page (see Appendix E for descriptive statistics of sum of received retweets, likes, replies and quotes of negative Tweets and all English written Tweets). For each of the brands, comparing the sum of retweets, replies and likes per negative Tweets with average + 3SD of the Tweets referring each brand, and considering the variable is highly skewed, values were log-transformed. The values were coded into dummy, “1 – viral” and “0 – non-viral”. To conduct the logistic regression and test the model fit, the dataset was randomly split into 70% training data (n = 20,522) and 30% test data (n = 8,795) stratified by the dummy.

SPSS forward logistic regression was first applied to examine the impact of various factors on the likelihood that the negative Tweet would go viral on the training dataset. Omnibus test indicates the stepwise model performance by comparing with the previous model. As shown in Table 27, the performance of Model 1 (Step 1) is significantly increased compared with Model 0 (no variables included in the equation), and Model 2 is better than Model 1, and so on. The final model containing all predictors which were statistically significant, c^2 (9, N = 20,522) = 643.60, p < .001, indicating that the model was able to distinguish the viral and non-viral Tweets.

Hosmer and Lemeshow test results (Table 28) also confirmed the fit of the model (Pallant, 2020), with significance value of the final model (Model 9) higher than 0.05. The model as a whole can explain 20.2% of the variance in virality (see Table 29).

Table 27 Omnibus tests of model coefficient (Training)

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	573.809	1	<.001
	Block	573.809	1	<.001
	Model	573.809	1	<.001
Step 2	Step	17.499	1	<.001
	Block	591.308	2	<.001
	Model	591.308	2	<.001
Step 3	Step	10.583	1	.001
	Block	601.891	3	<.001
	Model	601.891	3	<.001
Step 4	Step	8.813	1	.003
	Block	610.703	4	<.001
	Model	610.703	4	<.001
Step 5	Step	9.408	1	.002
	Block	620.111	5	<.001
	Model	620.111	5	<.001
Step 6	Step	5.996	1	.014
	Block	626.108	6	<.001
	Model	626.108	6	<.001
Step 7	Step	5.083	1	.024
	Block	631.191	7	<.001
	Model	631.191	7	<.001
Step 8	Step	6.973	1	.008
	Block	638.164	8	<.001
	Model	638.164	8	<.001
Step 9	Step	5.436	1	.020
	Block	643.600	9	<.001
	Model	643.600	9	<.001

Table 28 Hosmer and Lemeshow test (Training)

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	20.028	8	.010
2	18.528	8	.018
3	19.754	8	.011
4	15.049	8	.058
5	13.672	8	.091
6	13.546	8	.094
7	16.980	8	.030
8	10.765	8	.215
9	11.174	8	.192

Table 29 Model summary (Training)

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	2831.418[a]	.028	.180
2	2813.919[a]	.028	.186
3	2803.336[a]	.029	.189
4	2794.523[a]	.029	.192
5	2785.115[a]	.030	.195
6	2779.119[a]	.030	.197
7	2774.036[a]	.030	.198
8	2767.063[a]	.031	.200
9	2761.627[a]	.031	.202

a. Estimation terminated at iteration number 8 because parameter estimates changed by less than .001.

Table 30 lists the details of categorial variables coding. As shown in Table 31, nine independent variables are found that significantly influence the virality. The most critical factor is the number of author's followers, with an odds ratio of 3.74, indicating that negative Tweets posted by authors who have higher number of followers were more than three times more likely to go viral. The odds ratio of 0.60 for attachment absence was less than 1, referring that the virality were 0.6 times less likely to happen if the attachment was absent. In brief, number of author followers, absence of organisational response to the Tweet, word count, clout tone of the text, anger expressed in text and ratio of negative Tweet response to organisation's whole timeline Tweets would increase the probability of virality.

Meanwhile, absence of attachments, using exclamation marks, and referring words relevant to physical conditions were found hinders the negative Tweets going viral. The model was saved then applied to the testing dataset (n = 8,975) for model fit evaluation and robustness check. The value of AUC (area under the curve) is 0.758, indicating the forward logistic regression model retained by training data fits the testing data well with AUC higher than 0.7 (Hosmer *et al*., 2013). See Appendix I for AUC table and visualisation of ROC (receiver operating characteristic) Curve.

Table 30 Codings of categorical variables

Categorical Variables Codings

		Frequency	Parameter coding (1)
Res_tweet	-1 - absent	18242	1.000
	1 - present	2280	.000
attachments	-1 - absent	16747	1.000
	1 - present	3775	.000

Note: This coding is also applicable to the further analysis

Table 31 Variables in the equation

Variables in the Equation (Training)[26]

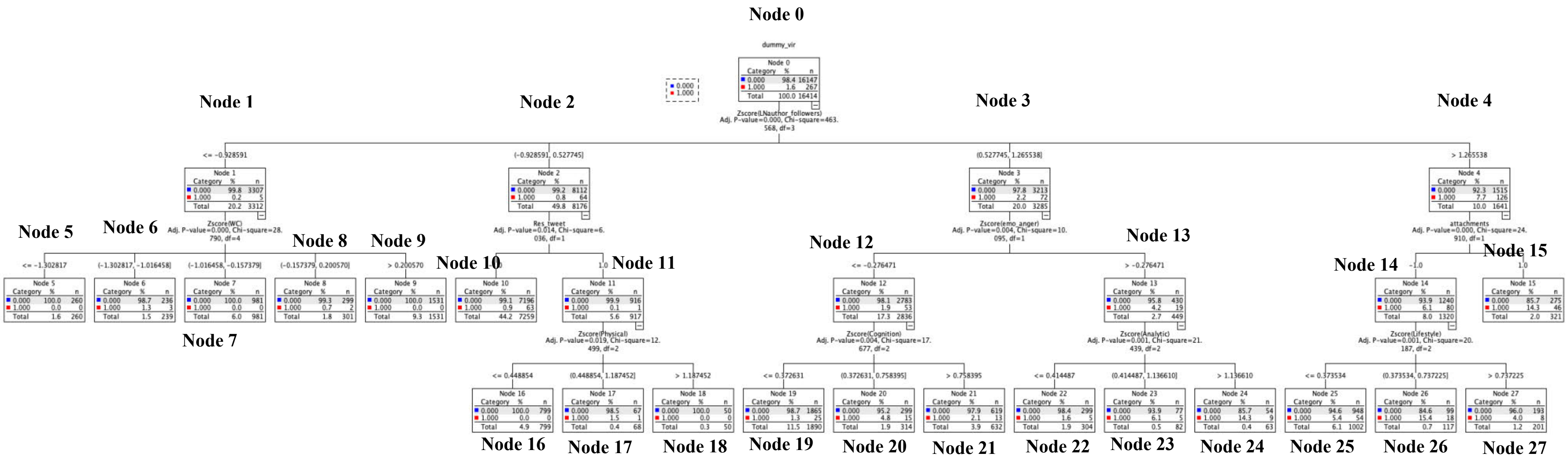
		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 9	Zscore(res_rate)	.121	.056	4.642	1	.031	1.128	1.011	1.259
	Zscore(LNauthor_followers)	1.319	.058	512.661	1	<.001	3.739	3.336	4.192
	Zscore(WC)	.232	.058	15.853	1	<.001	1.262	1.125	1.415
	Zscore(Clout)	.158	.057	7.626	1	.006	1.172	1.047	1.311
	Zscore(emo_anger)	.115	.046	6.173	1	.013	1.122	1.025	1.228
	Zscore(Exclam)	-.315	.137	5.282	1	.022	.730	.558	.955
	Zscore(Physical)	-.161	.073	4.798	1	.028	.852	.738	.983
	attachments(1)	-.510	.134	14.388	1	<.001	.600	.461	.782
	Res_tweet(1)	.746	.246	9.217	1	.002	2.109	1.303	3.414
	Constant	-5.292	.271	381.832	1	<.001	.005		

[26] Only Model 9 is presented here, and the full table of all models can be found in Appendix H.

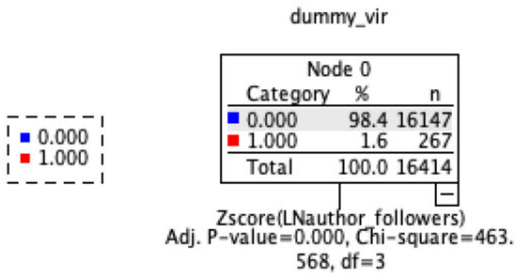
6.4 Decision Tree Classification and Other Non-linear Regression

The tested models all based on the assumption that the relationship between independent and dependent variables are linear, and all ignored the potential bias caused by outliers/extreme values. Given that the structure and interrelationship between variables are unknown because of the characteristics of social media, and extreme values are focal targets in this study which cannot be simply excluded, more robust models are required to overcome the shortcomings of the linear models. To estimate whether a complaint will go viral or not is a typical binary classification, and the most common methods are logistic regression and classification trees, and they are proven to have acceptable predictive function (Neslin *et al*., 2006; Risselada *et al*., 2010). To conduct the classification tree, data was randomly split into 70% training and 30% testing stratified by the dummy virality. To ensure the validity of the model, random assignment was applied for split-sample validation (i.e., 80% of the training data, n = 16,147, were used as model training and 20% of the training data, n = 4,042, were left to further confirm the model). Figure 16-17 demonstrate the model including details of the nodes, variables, significance level and split values of the Tree model for training and testing[27]. The saved model was then tested with the testing dataset (n = 8,795) and the AUC = 0.765 which indicating the acceptable model prediction (see Appendix J for AUC table and visualisation of ROC).

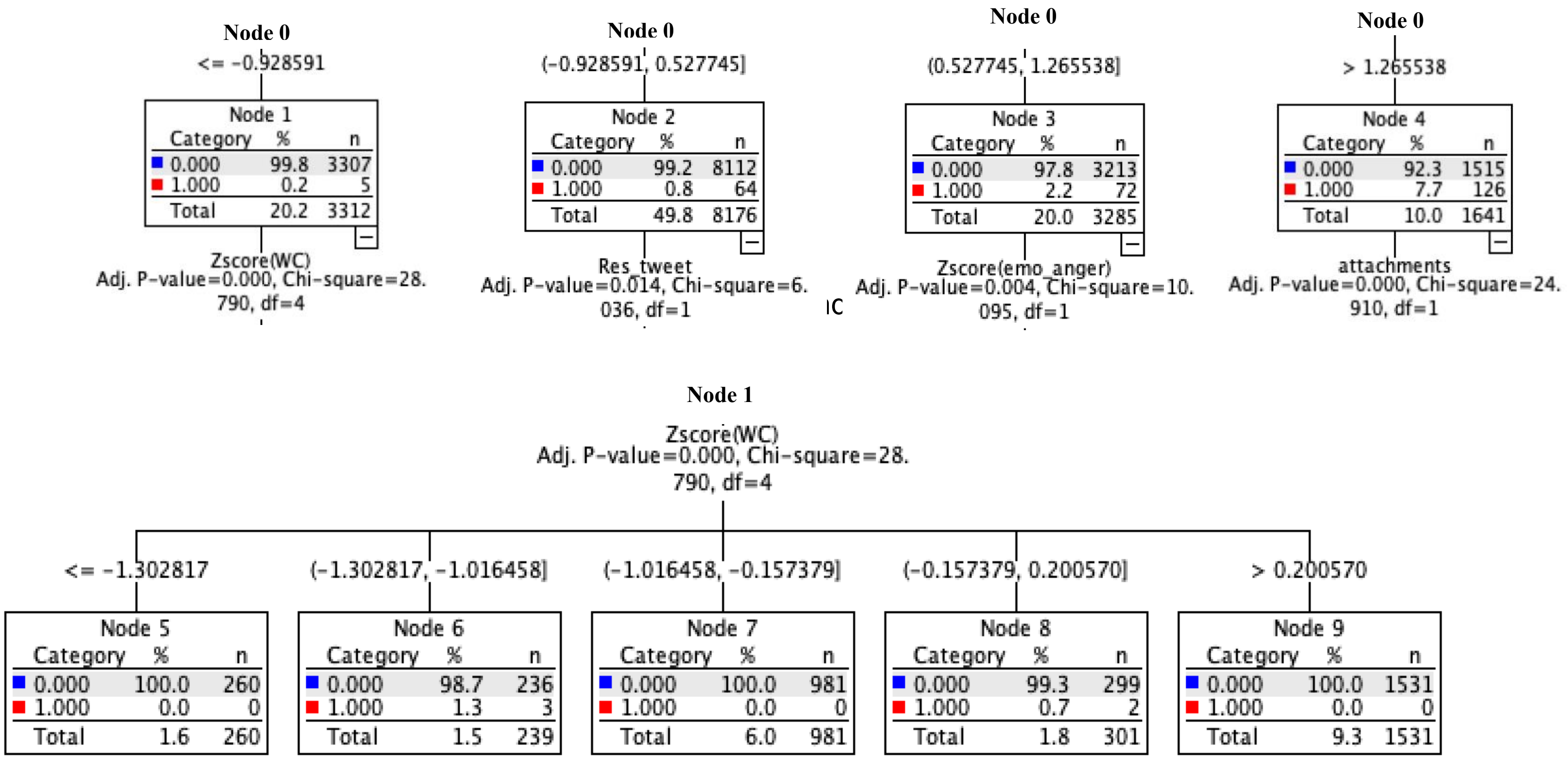
[27] Due to the large scale of the tree model and restriction of page layout, high-definition images of nodes are demonstrated with the upper level of nodes highlighted.

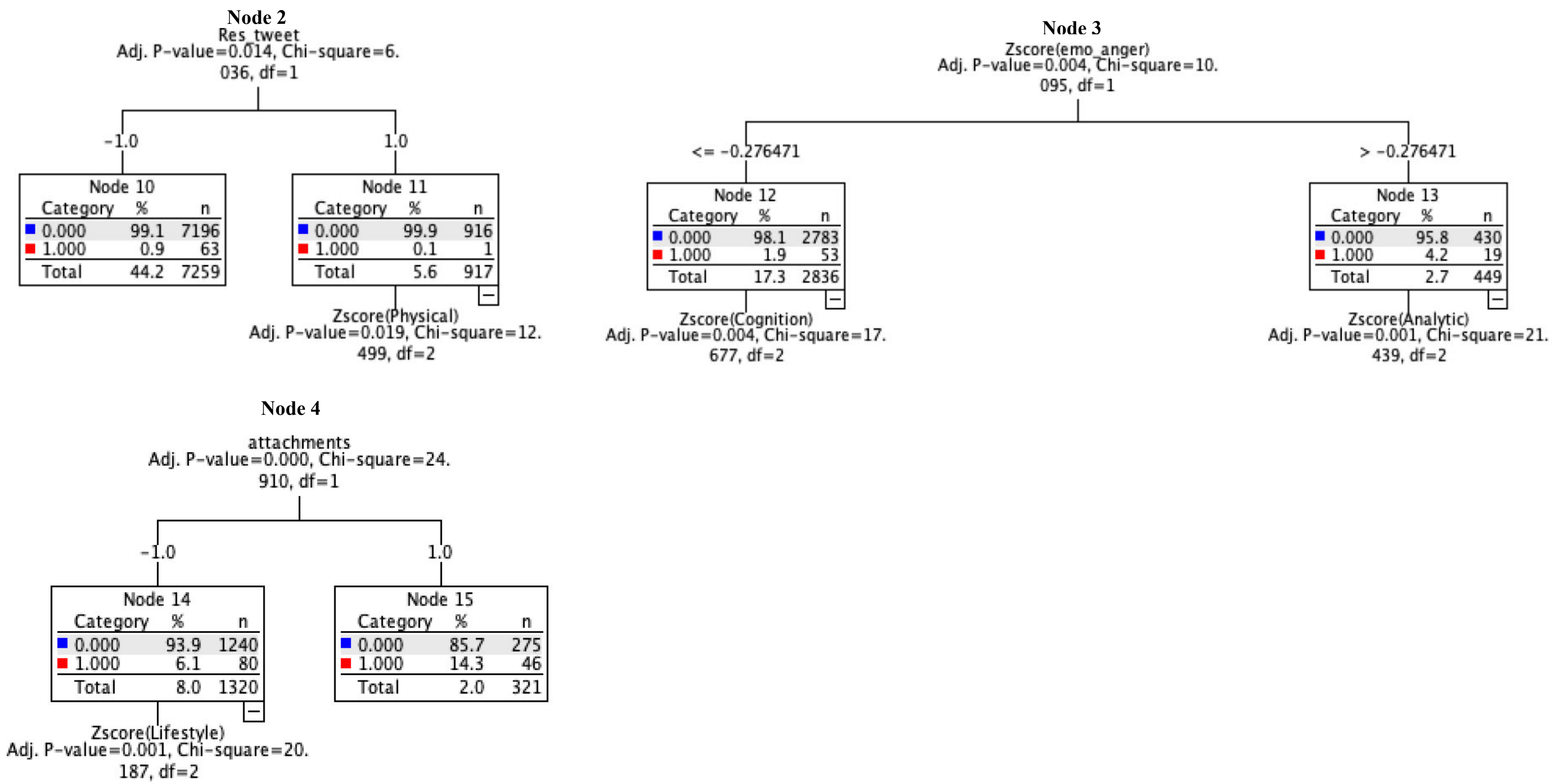


Level 0: Virality



Level 1: Author_follower




Node 2
Res_tweet
Adj. P-value=0.014, Chi-square=6.036, df=1
-1.0
1.0
Node 10
Category % n
0.000 99.1 7196
1.000 0.9 63
Total 44.2 7259
Node 11
Category % n
0.000 99.9 916
1.000 0.1 1
Total 5.6 917
Zscore(Physical)
Adj. P-value=0.019, Chi-square=12.499, df=2
Node 3
Zscore(emo_anger)
Adj. P-value=0.004, Chi-square=10.095, df=1
<= -0.276471
> -0.276471
Node 12
Category % n
0.000 98.1 2783
1.000 1.9 53
Total 17.3 2836
Zscore(Cognition)
Adj. P-value=0.004, Chi-square=17.677, df=2
Node 13
Category % n
0.000 95.8 430
1.000 4.2 19
Total 2.7 449
Zscore(Analytic)
Adj. P-value=0.001, Chi-square=21.439, df=2
Node 4
attachments
Adj. P-value=0.000, Chi-square=24.910, df=1
-1.0
1.0
Node 14
Category % n
0.000 93.9 1240
1.000 6.1 80
Total 8.0 1320
Zscore(Lifestyle)
Adj. P-value=0.001, Chi-square=20.187, df=2
Node 15
Category % n
0.000 85.7 275
1.000 14.3 46
Total 2.0 321

Level 3: Physical, cognition, analvtic. and lifestyle

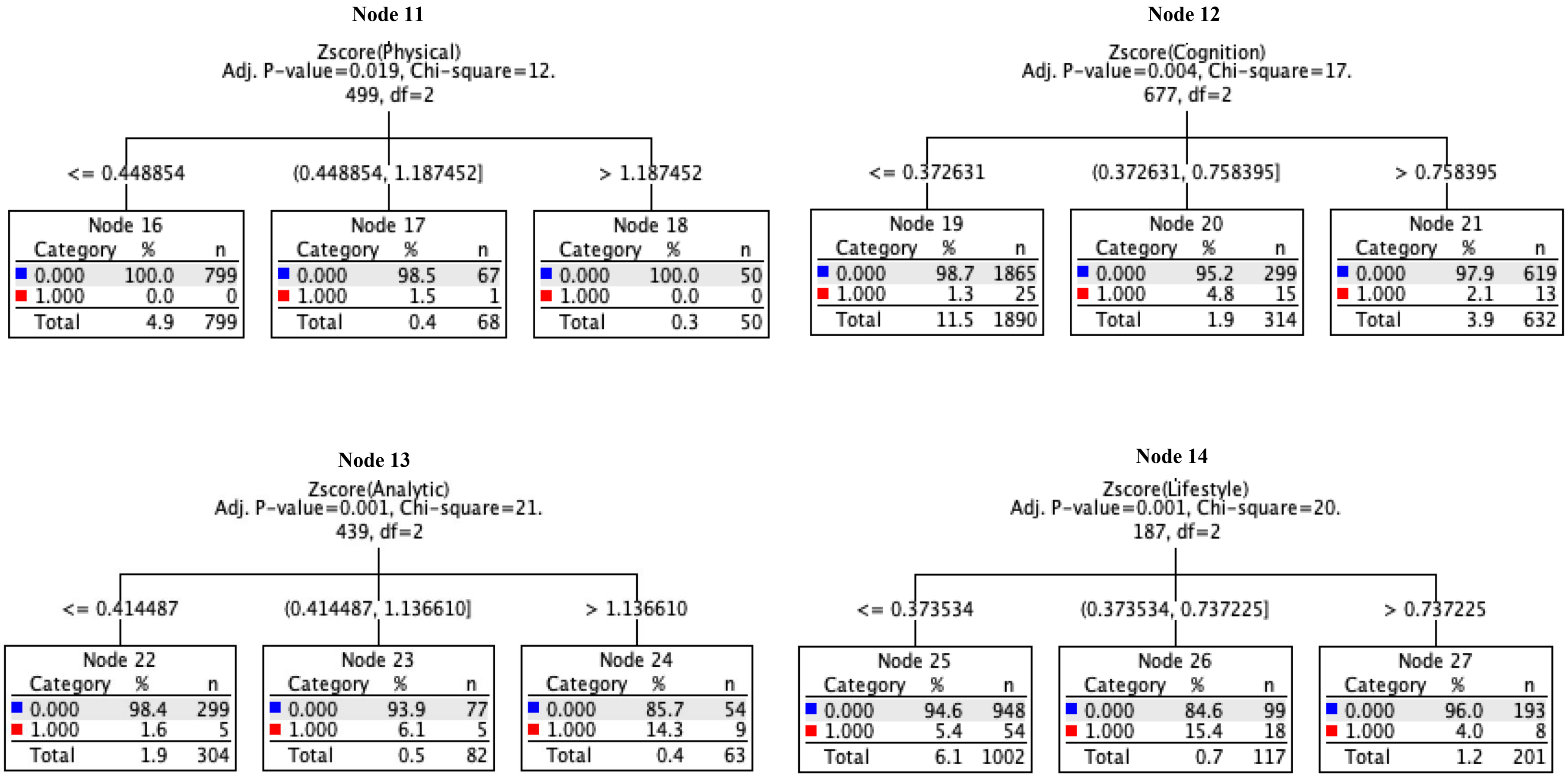
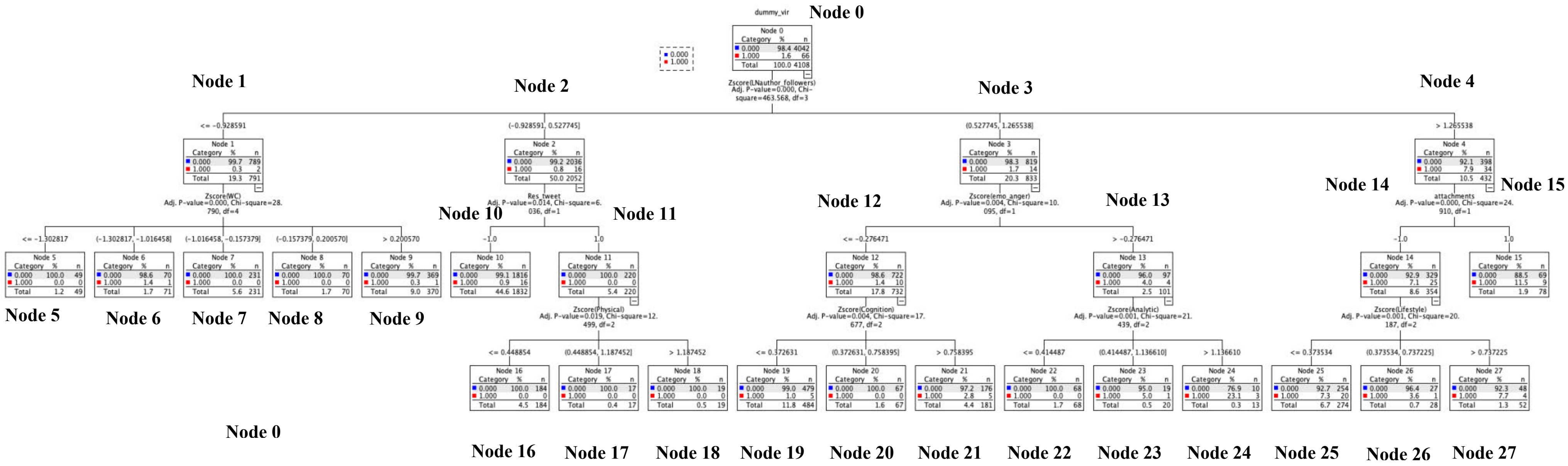
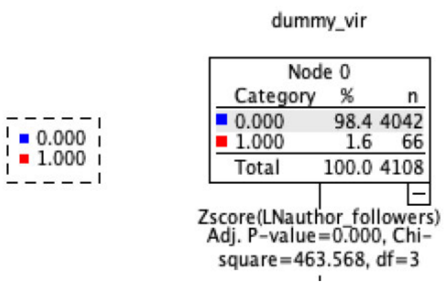


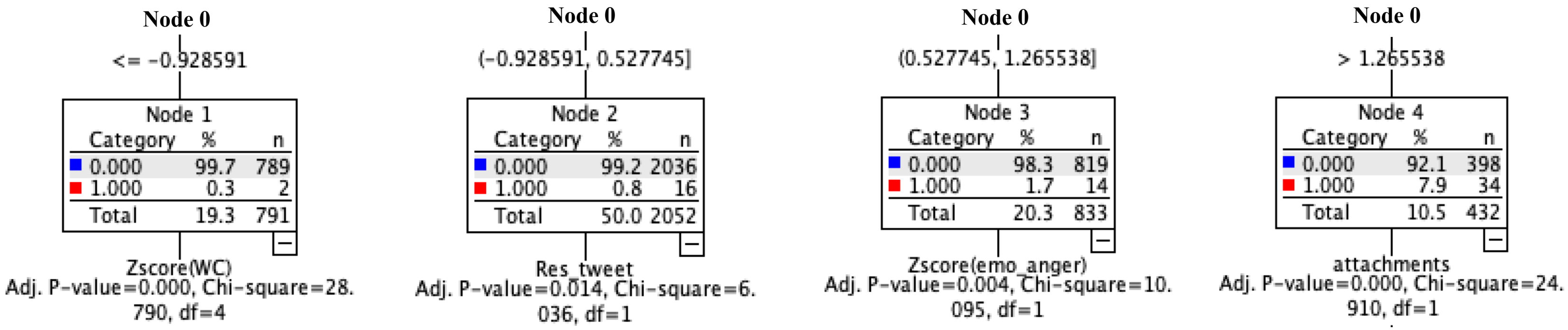
Figure 16 Classification tree (Training)



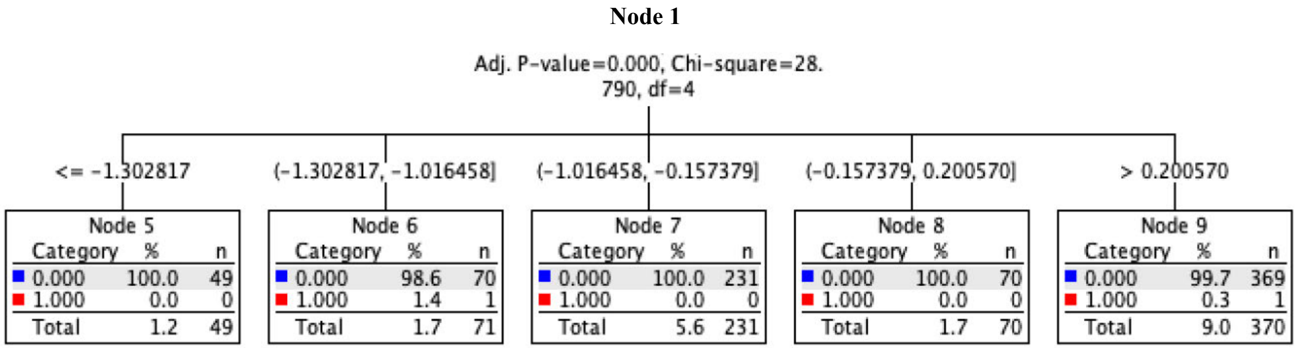
Level 0: Virality



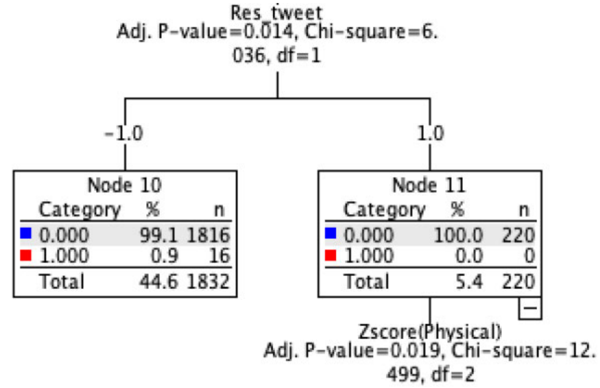
Level 1: Author_follower



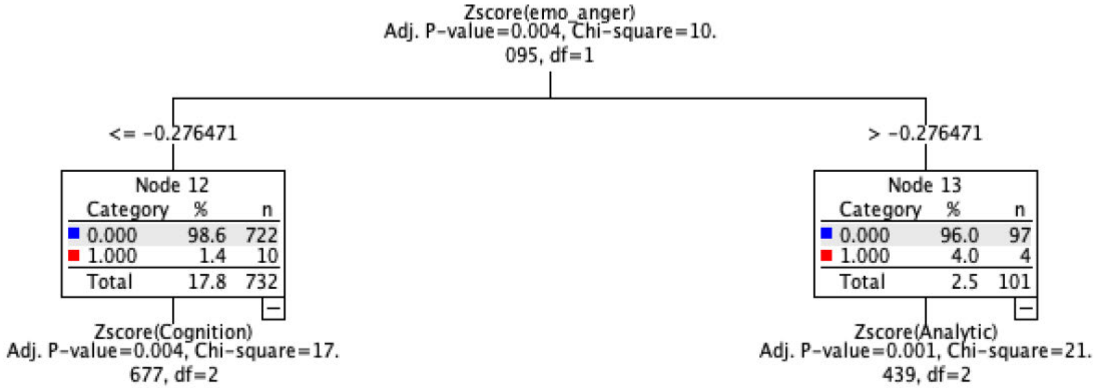
Level 2: Word count, respond to the negative Tweet, anger, and attachments



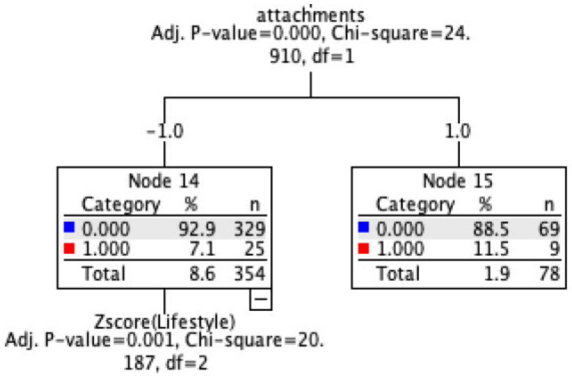
Node 2



Node 3



Node 4



Level 3: Physical, cognition, analytic, and lifestyle

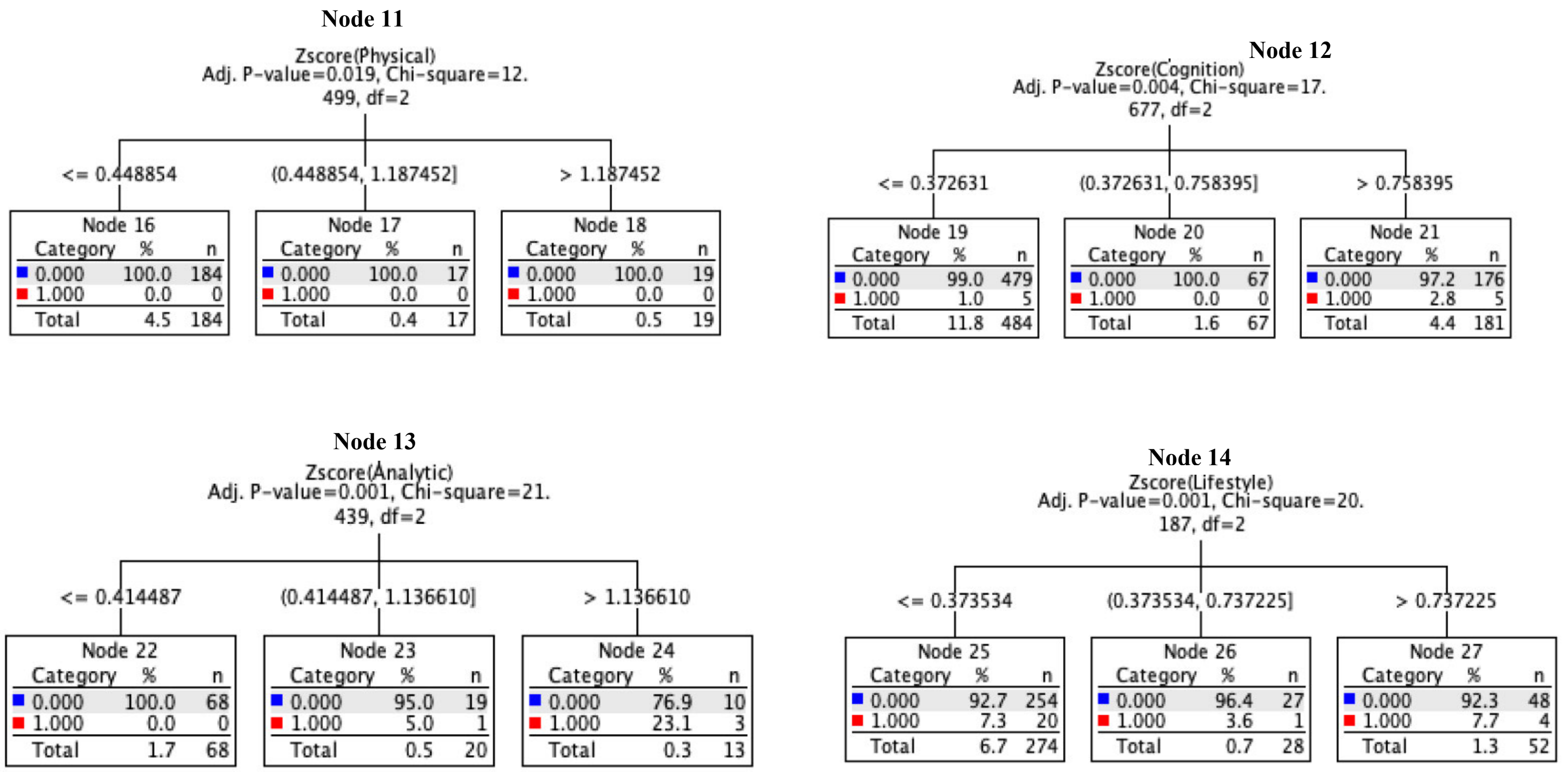


Figure 17 Classification tree (Testing)

According to the results of training model, the classification tree has the maximin 3 depths and 27 terminal nodes. The most critical predictor independent variable is the number of author's followers, Node 1-4 show that the possibility of negative Tweets posted by ZLNauthor_followers higher than 1.266 (around 2,800 followers) going viral will be 9.625 times higher than those ZLNauthor_followers among -0.929 and 0.528 (around 20 to 500 followers). Node 5-9 are sub-nodes of Node 1, which show that if the negative Tweet is posted by one with the fewest number of followers, word count may come into effect when predicting the virality. Although the similar pattern is found in testing data, given that the number of the viral content under Node 1 is limited, the generalization of the results is doubtful. Among the Twitter posters who have the second lowest number of followers, whether the organisation respond to the negative Tweet will determine whether the content will go viral or not as presented in Node 10 and 11 of both training and testing data[28]. Anger emotion expressed in Tweets is a critical variable for the complainers who have relative higher number of followers (approximate 500 to 2,800), and the probability of complaint virality is doubled when the density of anger is higher (Node 12 and 13). Among the low-anger contents, those using moderately cognitive words tend to go viral (Node 19-21) while for the high-anger texts, higher level of analytical thinking will trigger virality (Node 22-24). Finally, for those Twitter users who have more followers (more than 2,800), using attachments can double the possibility of content virality (Node 14 and 15), meanwhile, when the proportion of lifestyle relevant topic words is medium, the negative Tweets are more likely to go viral even without attachments (Node 25-27). Similar classifications of upper levels (Node 0-15) and Node 22-24 are proven in testing data, however, not replicable for Node 16-21 ("Physical" and "Cognition") and Node 25-27 ("Lifestyle"). This unfit might be caused by the limited number of samples in these groups, which will be strongly disturbed by noise and heavily rely on the value of single case.

One shortcoming of tree classification cannot be ignored in this study is the low percentage of the Tweet which are regarded as "viral", because brand differences were controlled when coding the dummy. Although it is undeniable that daily user-brand interaction can be different across brands (e.g., 100 replies may be viral for some brands but rather common for other brands), as everyone have access to

[28] Node 11 contains only one viral Tweet, which was further classified by the use of physical objective relevant words. However, the sub-nodes will not be discussed in text and this criterion will be applied to other similar nodes as well.

these Tweets and able to participate in the conversation (which is also the key difference compared with Facebook brand community studied by Herhausen *et al*. (2019)), bystanders' attitude and actions may not be influenced by the activeness of the brand and other Twitter users. Thus, random forest regression was also conducted to explore the non-linear relationship between the predictors and the more generalised numerical dependent variable. Python sklearn.model_selection package is used to randomly select the 70% training data and 30% testing data, and RandomForestRegressor estimator of sklearn.ensemble function trained and tested the regression model. Besides, out-of-bag (OOB) sampling is also conducted to evaluate the stability of the model and detect the risk of overfitting (Schwartz *et al*., 2014). Figure 18 ranked the significant independent variables according to their importance in descending order. Number of the Twitter user's follower is no doubt the most critical predictor, followed by the level of readability and word count and some other psychological characteristics such as subjectivity, analytical thinking, using social-relevant topic words, etc. The overall R-square of this mode is 0.17 and the OOB R-square is 0.18, indicating that around 18% of variance can be explained by this random forest regression model[29].

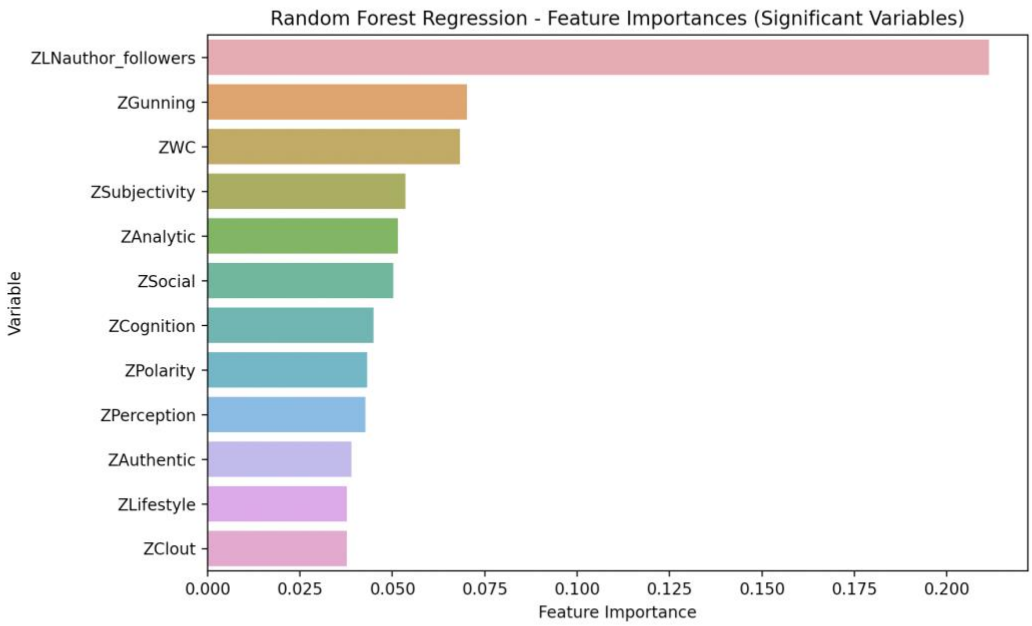


Figure 18 Significant variables of random forest regression

[29] The algorithm and process of random forest are rather complex, and the length of final equation is extremely large (more than 6.5 million bytes) which will not be discussed or demonstrated in this thesis. Same with the gradient boosting regression conducted later.

6.5 Other Model Tests

As random forest regression build decision trees parallelly and independently (Chen and Chen, 2020), it tend to be biased or strongly influenced by extreme situations since the final model is built on the average of the trees (Hastie *et al*., 2009). Therefore, gradient boosting regression, a machine learning approach for prediction by combining tree models (Friedman, 2001), was also conducted in this study. The models are sequentially built, and the later models will try to minimise the errors in previous model, thus, it is believed to have higher accuracy compare with random forest regression (Sahin, 2020). Similar as the process of random forest regression, after splitting the data, GradientBoostingRegressor estimator of sklearn.ensemble function was applied to train and test the model, and the R-square is 0.1708. For robustness checking, K-fold cross-validation was utilised with the help of cross_val_score and KFold functions in sklearn.model_selection, and considering the massive number of samples, K was set to 5. As shown in Table 32, the average R-square of the 5 folds is 0.1596, which is quite close to the overall model R-square. Meanwhile, the standard deviation of the R-squared across 5 folds is low, which is 0.022, indicating the consistence across the folds and the model is reliable. The visualisation of the significant independent variables is shown in Figure 19 and the number of the complainer's followers is predominately influence the virality, meanwhile word count and use of attachments are two relative important predictors.

Table 32 R-squared of 5 folds

Times of fold	R-squared
1	0.1770
2	0.1286
3	0.1795
4	0.1762
5	0.1368
Average R-squared across 5 folds: 0.1596	
Standard Deviation of R-squared across 5 folds: 0.0222	

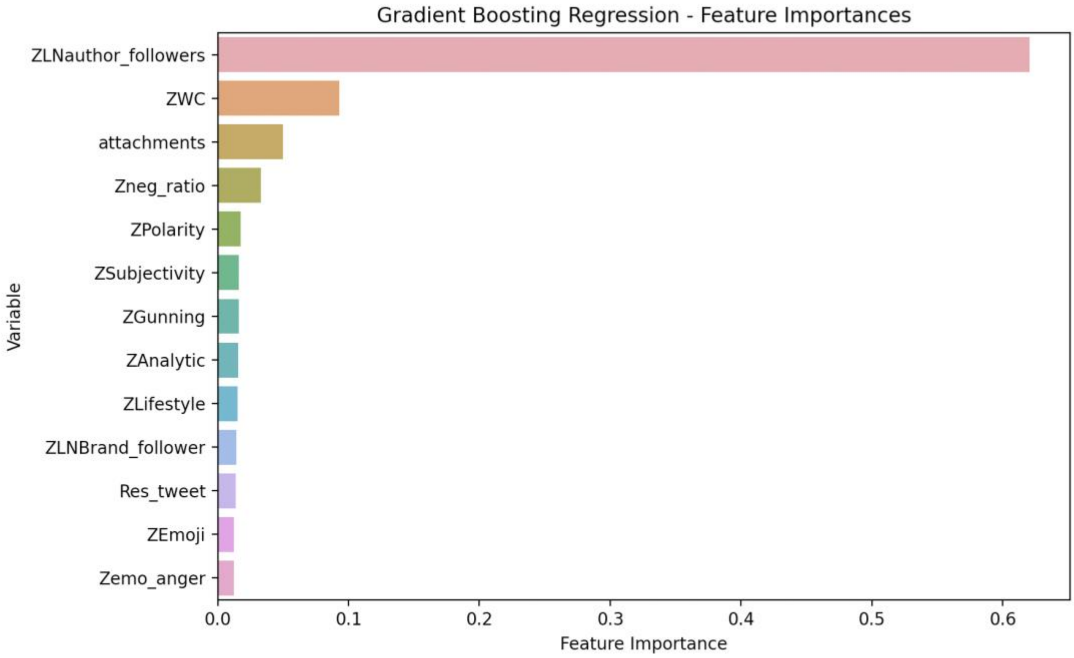


Figure 19 Significant variables of gradient boosting regression

6.6 Model Summary and Discussion

In the previous sections, several different models are introduced and tested. Table 33 summarises the significant variables in different models and model performances. Among the various models, logistic regression performed better, which can explain 20% of the variance. Meanwhile, random forest regression and gradient boosting regression all have the R-squared values higher than 0.17. For a more robust outcome, the following analysis will only include the significant independent variables proven by most of the three methods (logistic regression, random forest regression and gradient boosting regression) for further exploration (see Table 34 for significant variables tested by different methods)[30]. Table 35 summarises the research hypotheses testing results. In general, the results confirmed the influence of both content and non-content attributes on the complaint virality. This indicates that Twitter user's behaviours (retweet, comment, and like) towards complaints follows the perception of both heuristic and systematic routines rather than rely on single dimension of information.

[30] Note that only the variables which have significant impact in two out of the three models are included in final results.

Table 33 Summary of significant variables in equation and model performance

Model	Significant variables	Variance explained	Robustness testing method
Stepwise multiple regression (full dataset, n = 29,317)	Characteristics of complainer: number of followers. Characteristics of the brand: ratio of negative Tweets brand received$^{(-)}$, rate of organisational response to negative Tweets, number of followers. Organisational response provided. Physical attributes/structure of the Tweet: word count, use of attachments, readability. Psychological attributes of the Tweet: tone polarity, subjectivity$^{(-)}$, clout, analytical thinking$^{(-)}$, positive emotions$^{(-)}$, sad emotions$^{(-)}$. Topic-relevant words: physical$^{(-)}$, lifestyle$^{(-)}$, social$^{(-)}$, perception. Emotion proxy: use of exclamation$^{(-)}$.	R-square = 0.102	Mutual verification
Stepwise multiple regression (no extreme values, n = 28,287)	Characteristics of complainer: number of followers. Characteristics of the brand: ratio of negative Tweets brand received$^{(-)}$, rate of organisational response to negative Tweets, number of followers.	R-square = 0.103	

	Organisational response provided. Physical attributes/structure of the Tweet: word count, use of attachments, readability. Psychological attributes of the Tweet: tone polarity, clout, analytical thinking$^{(-)}$, authenticity, positive emotions$^{(-)}$, sad emotions$^{(-)}$. Topic-relevant words: physical$^{(-)}$, lifestyle$^{(-)}$, social$^{(-)}$. Emotion proxy: use of exclamation$^{(-)}$.		
Logistic regression (full dataset, n = 29,317)	Characteristics of complainer: number of followers. Characteristics of the brand: rate of organisational response to negative Tweets. Organisational response provided$^{(-)}$. Physical attributes/structure of the Tweet: word count, use of attachments. Psychological attributes of the Tweet: clout, anger emotions. Emotion proxy: use of exclamation$^{(-)}$. Topic-relevant words: physical$^{(-)}$.	R-square = 0.202	Random sampling, model training and evaluation, AUC = 0.758
Tree classification*	Characteristics of complainer: number of followers. Organisational response provided. Physical attributes/structure of the Tweet: use of attachments.	Estimate = 0.12	Random sampling, AUC = 0.765

	Psychological attributes of the Tweet: anger emotions, analytical thinking. Topic-relevant words: cognition, lifestyle.		
Random forest regression	Characteristics of complainer: number of followers. Physical attributes/structure of the Tweet: readability, word count, use of attachments. Psychological attributes of the Tweet: subjectivity, tone polarity, analytical thinking, authenticity, clout. Topic-relevant words: social, cognition, perception, lifestyle.	R-square: 0.172	Random sampling, OOB R-square = 0.181
Gradient boosting regression	Characteristics of complainer: number of followers. Characteristics of the brand: ratio of negative Tweets brand received, number of followers. Organisational response provided. Physical attributes/structure of the Tweet: readability, word count, use of attachments. Psychological attributes of the Tweet: subjectivity, tone polarity, analytical thinking, anger emotions. Emotion proxy: emoji. Topic-relevant words: lifestyle.	R-square: 0.171	Random sampling, Cross validation, Average R-squared = 0.160, SD = 0.022.
Multi-layer perceptron (MLP) neural	-	R-squared = 0.054	-

network regression**			
Support vector machine (SVM)	-	R-squared = 0.092	-

(-) In multiple linear regression and logistic regression models, the negative superscript indicating the negative impact of independent variable on dependent variable.

* The valence of variables in following models are not demonstrated since these methods tend to categorise the values rather than look at the valences.

** Other machine learning methods, such as MLP and SVM was also trained and tested, however, as the R-squared are much lower, significant variables were not listed.

Table 34 Significant variables in high R-squared models

	Logistic	Random forest	Gradient boosting
Number of complainer’s followers	√	√	√
Rate of response to negative Tweets	√	×	×
Number of brand’s followers	×	×	√
Ratio of negative Tweets received	×	×	√
Organisational response provided	√	×	√
Word count	√	√	√
Readability	×	√	√
Use of attachments	√	√	√
Subjectivity	×	√	√
Tone polarity	×	×	√
Clout	√	√	×
Analytical thinking	×	√	√
Authenticity	×	√	√
Emotion: anger	√	×	√
Emotion proxy: exclamation	√	×	×
Emotion proxy: emoji	×	×	√
Topic: physical	√	×	×
Topic: social	×	√	×
Topic: cognition	×	√	×
Topic: perception	×	√	×
Topic: lifestyle	×	√	√

Table 35 Summary table of hypotheses testing outcomes in previous models and the hypotheses will be tested in following analysis

Hypotheses		Outcome/progression
Hypothesis 1	The length of online complaints will have positive impact on the virality.	H1 marginally supported. In general longer CCB will have positive impact, while for the complainer who has very low number of followers, relative shorter and extremely longer complaints are more likely to go viral.
Hypothesis 2	Higher readability of online complaints will have positive impact on the virality.	H2 supported.
Hypothesis 3	Adding attachments to online complaints will have positive impact on virality.	H3 supported.
Hypothesis 4	The tone polarity of online complaints will have positive impact on the virality.	H4 not supported.
Hypothesis 5	Subjectivity level of the online complaint will have negative impact on virality.	H5 supported.
Hypothesis 6	Analytical online complaints will be more likely to go viral.	H6 supported.
Hypothesis 7	Clout of the online complaint will have negative impact on virality.	H7 not supported. However, clout is found have positive impact.

Hypothesis 8	Authenticity of the online complaint will have positive impact on virality.	H8 supported.
Hypothesis 9a	Positive emotions in online CCB will have negative impact on virality.	H9a not supported.
Hypothesis 9b	Negative emotions in online CCB will have positive impact on virality.	H9b partly supported. Only anger is found have positive impact.
Hypothesis 10	Using more exclamation marks in online complaints will have positive impact on the virality.	H10 not supported.
Hypothesis 11	Using more question marks in online complaints will have positive impact on the virality.	H11 not supported.
Hypothesis 12	Using more emoji in online complaints will have positive impact on the virality.	H12 not supported.
Hypothesis 13	Different topics of online complaints will lead to differences in virality.	H13 to be tested.
Hypothesis 14	The attributes (physical and psychological) will moderate the impact of complaint topic on virality.	H14 to be tested.
Hypothesis 15	The number of complainer's followers will have positive impact on the virality.	H15 supported.

Hypothesis 16	The number of the involved organisation/brand's followers will have positive impact on the virality of the online complaint.	H16 not supported.
Hypothesis 17	Ratio of organisational response to online complaints will have negative impact on virality.	H17 not supported.
Hypothesis 18	Ratio of online complaints (of the organisation/brand) will have positive impact on the virality.	H18 not supported.
Hypothesis 19	Responding to online complaints will decrease the probability of virality.	H19 supported.
Hypothesis 20	Time gap between the complaint post and organisational response will have positive impact on the virality.	H20 to be tested.

As predicted, number of complainers is a predominant factor of complaint virality (H14 supported) which prove the snowballing effect in social relationship and communication (Arif *et al*., 2016). Besides, the complaint virality is found hindered if organisational responses provided (H18 supported), which to some extent agrees with the findings in previous study on negative Facebook by Herhausen *et al*. (2019). Some physical characteristics are critical predictors of virality, indicating that these obvious signals work as the heuristic cues to influence readers' attitude and guide their behaviours (Weitzl and Hutzinger, 2017). Specifically, using attachment will help increasing the possibility of virality (H3 supported) and complaints with larger word count (H1 supported) tend to go viral. It is also worth mentioning that the word count can significantly contribute to virality particularly when the complainer has extremely low number of followers. This further support the idea that longer contents tend to reduce the ambiguity caused by information asymmetries and provide more evidence for reader's evaluation (Javornik *et al*., 2020), especially when the level of uncertainty is high (Brunner *et al*., 2019), e.g., the identity of the complainer is unclear.

The psychological elements of the text, also impact the complaint virality. Subjective complaints are less likely to go viral (H5 supported) because they tend to be affective expression or even emotional venting, rather than cognitive and accurate description (Anand *et al*., 1988) and they are generally regarded as more negative than reality (Zhao *et al*., 2019). Thus, it is understandable that readers are reluctant to support the extremely subjective complaints because sharing negative information may harm one's image, and this effect will be reinforced if the information is rather irrational. Extant literature claim that the spread of information is not limited to the spread of contents but also the contagion of emotions (Berger, 2014), emotional empathy will trigger information receiver's behavioural intentions (de Campos Ribeiro *et al*., 2018). Complaints undoubtedly express negative emotions and previous studies prove the emotions in complaining have discrete types, such as sad, disappointed and anger (Strizhakova *et al*., 2012). The findings of this study indicate that diverse negative emotions perform differently in terms of promoting negative Tweets. Anxiety and sadness are found have no impact on virality while angry expressions increase the possibility of the negative Tweets being retweeted, replied and liked (H9b supported). These results are consistent with the observation that different emotions can trigger different psychological activation (Smith and Ellsworth, 1985). Higher arousal will stimulate actions while lower arousal emotions are accompanied by relaxation and will soothe the nerve (Berger and Milkman, 2012; Heilman, 1997). Therefore, the intensity of anger, a well-recognised high arousal emotion, has positive impact on the virality of negative Tweets. However, in contrast to hypothesis 7, level of clout expressed in Tweets has positive impact on virality which illustrates that more confident tones and expressions in communication tend to become persuasive and receive more support (Schwardmann and Van der Weele, 2019). While level of authenticity (i.e., whether unnecessary inhibitory expressions are used in social communication) is found positively affect the virality as more authentic the conversation is, less communication restriction it has (Markowitz *et al*., 2023), which benefits the spread of complaints. Meanwhile, analytical complaints are found more likely to go viral because these contents have clear logic and tend to fit better with the readers from a relatively individual cultural background (Kumar *et al*., 2022)[31].

Apart from the tested hypotheses, there are still some unanswered research questions, meanwhile some shortcomings with the current methods need further improvement/remediation. First, results of diverse models show different impacts of multiple topic words although not always consistent. However, since the LIWC topic dictionary is a “black box” and the exact word in that box is unknown, the meaning of the topics is uninterpretable. Meanwhile, LIWC processing reliable sentiment analysis (Herhausen *et al*., 2019), however, regarded as not always applicable for topic modelling (Hartmann *et al*., 2019). Thus, LDA will be adopted for topic modelling in the following chapter to solve the unfinished tasks. Second, it is understandable that complainers may complain about different topics in different styles/tones/expressions (Grégoire *et al*., 2010), however, most of the regression models (tested in this chapter) tend to ignore the potential interactions between the physical/psychological characteristics of the text and the topic of the text but look them as variables in the same dimension/ hierarchy. In the next chapter the moderating effects will also be tested.

[31] The focal hotels are predominantly UK and US based, and the included Tweets are all written in English.

CHAPTER 7 FURTHER ANALYSIS

7.1 Introduction

In chapter 6, exploratory analyses are introduced and compared to figure out the significant independent variables. Results show that the number of author's followers can largely influence the complaint virality. Meanwhile, physical attributes of complaints, including word count and use of attachments also contribute to virality. Some of the psychological attributes are also critical. Density of anger and clout will have positive impacts while subjectivity will have opposite influence. Furthermore, organisational response can effectively decrease the probability of virality.

As mentioned in previous chapter, there are several research questions (Whether the complaint topic will lead to variance of virality? Whether time gap between complaint post and organisational response will have impact on virality?) remain unanswered because of the complex structure of data and some technical restrictions. This chapter aims to solve these problems with the help of other techniques and models. In the following sections, two main streams of analysis will be conducted: a). whether the timing of response will have impact on virality; and b). whether there are interactional impacts of complaint topic and the physical/psychological characteristics of complaint on virality.

7.2 Impact of Response Timing

The other unanswered question is whether the timing of response will have impact on virality[32]. The Tweets which received organisational response (n = 3,038, see Table 36 descriptive statistics for time gap between complaint posted and replied) were separated for analysis and the result of exploratory regression (Table 37) indicates that the time gap between the posted timing and response timing has no significant impact on virality.

Table 36 Descriptive statistics for time gap between Tweet posted and responded (in hours)

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
gap_hour	3038	.0078	2187.4567	24.1802	93.3297

Table 37 Direct effect of time gap (between Tweet posted and replied) on virality

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.007	1	.007	.017	.897[b]
	Residual	1185.079	3036	.390		
	Total	1185.085	3037			

a. Dependent Variable: Zscore(LNvirality)

b. Predictors: (Constant), Zscore(gap_hour)

To further confirm the finding, time gap was grouped according to the practical meaning ("1 – less than 1 day", "2 – 1 to 3 days", "3 – 3 days to 1 week", "4 – more than 1 week"). One-way analysis of variance (ANOVA) result (see Table 38) shows that the impact of response time gap on virality was not significant at the $p < .05$ level for the four conditions ($F(3, 3034) = 1.38$, $p = 0.25$). It is worth noting that although the overall variance is insignificant, huge differences in virality can be found between the Tweets being replied within 3 days and more than 3 days (see Table 39 for details).

[32] Here the exploratory analysis only investigates the direct effect of response timing.

Table 38 One-way ANOVA result

ANOVA

Zscore(LNvirality)

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1.619	3	.540	1.384	.246
Within Groups	1183.466	3034	.390		
Total	1185.085	3037			

Table 39 Descriptives of ANOVA

	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
				Lower Bound	Upper Bound		
1 (less than 1 day)	.1626	.6191	.0125	.1381	.1871	-.7160	6.3413
2 (1-3 days)	.1753	.6193	.0311	.1141	.2365	-.7160	7.7962
3 (3 days – 1 week)	.2702	.6917	.0611	.1492	.3911	-.7160	5.7546
4 (more than 1 week)	.2271	.7301	.0959	.0351	.4191	-.7160	2.8533
Total	.1700	.6247	.0113	.1478	.1923	-.7160	7.7962

To confirm this finding, the gap hours were re-coded into two groups ("1 – less than 3 days" and "2 – more than 3 days") and run the one-way ANOVA again. As shown in the descriptions (Table 40) and ANOVA result table (Table 41), whether the organisation replied to the negative Tweet within 3 days or more than 3 days can lead to differences in virality (M_{within_3} = 0.164, SD = 0.619; $M_{more\_than\_3}$ = 0.257, SD = 0.702; $F(1, 3036) = 3.823$, $p = 0.05$). The above analysis to some extent proves that delayed response to the complaint will increase the possibility of virality, thus, it will be introduced as one of the potential moderators to test in the next section. Therefore, the complaint virality will significantly increase when the time gap (between the complaint post and organisational response) is more than 3 days. Thus, hypothesis 19 is marginally supported.

Table 40 Descriptives of ANOVA (re-grouping)

Zscore(LNvirality)

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
1 (within 3 days)	2852	.1644	.6190	.0116	.1416	.1871	-.7160	7.7962
2 (more than 3 days)	186	.2568	.7022	.0515	.1552	.3583	-.7160	5.7546
Total	3038	.1700	.6247	.0113	.1478	.1923	-.7160	7.7962

Table 41 One-way ANOVA result (re-grouping)

ANOVA

Zscore(LNvirality)

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1.490	1	1.490	3.823	.051
Within Groups	1183.595	3036	.390		
Total	1185.085	3037			

7.3 Differences between Topics

Results of the previous models confirm that apart from various linguistic and psychological attributes of complaints, use of topic relevant words are also found to be critical predictors of virality although the specific keywords and text meanings are unknown. This section will conduct topic modelling to enhance the comprehension of the complaining content and unveil the variations in virality among different topics. Sklearn LatentDirichletAllocation function was imported to run the variational Bayes algorithm for topic modelling. Determining the number of topics is a fundamental but controversial step, as LDA has no prior group number, various methods, such as convenient/default choices, visual observation, and more scientific parameters are used to determine the number of topics (Kunc *et al.*, 2018). In this study, convenience-based choice and visual inspection are conducted together and then the performance of different model is also computed by statistical values. Prior to undertaking the LDA, it is imperative to carry out the task-specific data cleaning process. Apart from the commonly used stopwords, brand names and the word “hotel” and its synonyms are also excluded because they are high in frequency but exist in most of the Tweets targeting/referring hospitality brands. The findings of some extant studies provide the reference for the range of groups, for example, Hu *et al*. (2019) extracted 29 sub-topics under 5 categories by analysing more than 27,000 hotel reviews while 18 topics are confirmed by Guo *et al*. (2017) study on more than 266,000 reviews. However, since these studies including both positive and negative reviews, the single valence data collected for this thesis may have less topics. Meanwhile, the focal platforms in previous studies have less limitation on maximum word count, which physically enables more diverse and complex topics to be posted compared with Twitter. Thus, it is understandable that the number of topics in this study might be lower. Generally, the convenience choices are mostly multiples of 10 (e.g., 10, 20, 50), thus, the tested number k was set to 5, 10, 15 and 20 in the first round of test to roughly determine the range of the topic number[33]. Meanwhile, the results will be visualised for comparison. Figure 20 and 21 show the word clouds when k = 5 and 10[34]. Comparing the word clouds, it is obvious that similarity between topics become higher when the k value increases, and many overlaps make the performance and interpretation of the topics doubtful[35]. Therefore, the selecting of k range from 2 to 10 in this study (see Appendix O for word clouds).

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[33] On the basis of extant studies and considering the attributes of Tweets, the tested k was set to relatively low number, meanwhile, for finer-grained result, 5 and 15 were also tested.

[34] Word clouds of k = 15 and 20 are demonstrated in Appendix L as they are not considered/analysed in the following processes (reasons will be explained).

[35] More rigorous methods also used to confirm this finding, see Appendix M and N for coherence score and perplexity score (will be discussed later). Note that calculation of these scores is time-consuming, it is impossible to test all k values. Thus, in the exploratory stage, only set the range to start, limit, step = 5, 26, 5 to see the trends. As shown in the figures, the coherence score reached the highest when k = 10 and the perplexity score keep increasing with the k value.

Figure 20 Word cloud of the 15 most frequently used words in different topics (k = 5)

Figure 21 Word cloud of the 15 most frequently used words in different topics (k = 10)

To determine the topic number scientifically and precisely, coherence score and perplexity score are implied to test the probability analysis appropriateness. Coherence score is a frequently used criteria to evaluate the model interpretation, and in LDA, it measures the degree of semantic similarity among words within the topic (Hu *et al*., 2019; O'callaghan *et al*., 2015). Larger coherence score represents higher similarity. Perplexity score algebraically represents the geometric mean of the reciprocal of the likelihood per-word (Cao *et al*., 2019) and lower scores indicating better model performance (Griffiths and Steyvers, 2004). Figure 22 and Figure 23 present the coherence and perplexity when k is set to the integer range from 2 to 10 (including) and it is obvious that when k = 3, the coherence score is the highest while the perplexity score is the lowest. Another model with relatively higher coherence and lower perplexity is when k = 5.

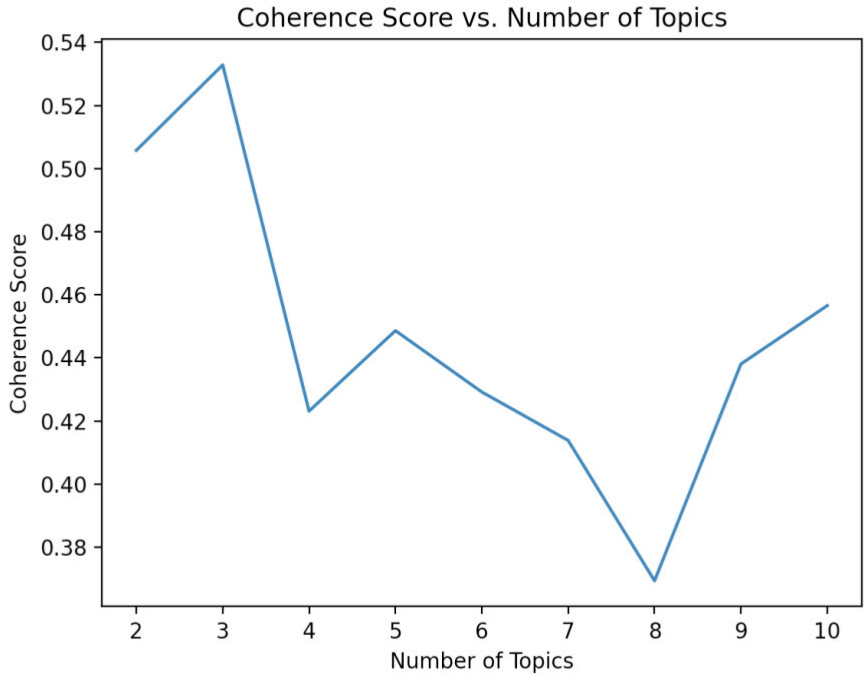

Figure 22 Coherence score of topic modelling (k range from 2 to 10)

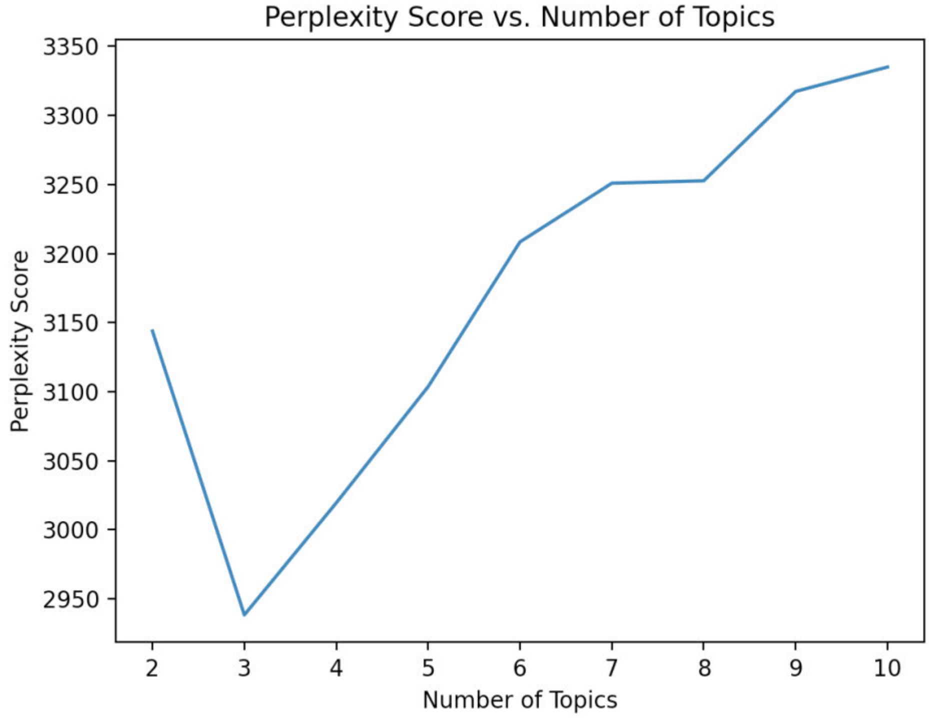

Figure 23 Perplexity score of topic modelling (k range from 2 to 10)

However, the other key aspect of topic modelling is the interpretability, therefore, the categories will be manually checked to determine the final model. Figures 24 and 25 show the 20 most frequently used words in each topic when k = 3 and 5[36]. According to the combination of high frequency words, topics can be summarised as “politics: Ukraine and Uganda”, “ethnicity: racist”, and “service” when k = 3 and categorised as “politics: Uganda”, “ethnicity: racist”, “service: room”, “politics: Ukraine”, and “service: reservation” when k = 5. The vividness of 5-topic modelling is evident; thus, the following analysis will sacrifice the accuracy to some extent but expect more meaningful outcomes.

[36] The visualisation of k = 5 (Figure 25) is slightly different from Figure 20 because different random state number were applied, and different numbers of words were demonstrated. Appendix O also demonstrate word clouds for k range in (2, 10) (including 10).

Figure 24 Word cloud of the 20 most frequently used words in different topics (k = 3)

Figure 25 Word cloud of the 20 most frequently used words in different topics (k = 5)

After determining the topic number, the Tweets share common word probabilistic distributions/Dirichlet are grouped together. One-way ANOVA on complaint virality revealed the significant difference between topics (M_1 = -0.35, SD = 0.70; M_2 = 0.06, SD = 1.12; M_3 = 0.04, SD = 0.91; M_4 = -0.10, SD = 1.07; M_5 = 0.04, SD = 0.93; $F(4, 29312) = 86.50$, $p < .001$). Table 42 demonstrates the descriptive statistics of the topics.

Furthermore, post-hoc Tukey HSD (Table 43) test finds that the mean scores for Topic 1 and Topic 4 were significantly different from Topic 2, 3, and 5 while the differences between among Topics 2, 3 and 5 were not significant. To sum up, the results of ANOVA confirm the topic-wise virality differences. The politics related complaints, although always trending and popular on social media[37], are less likely to go viral when brands/organisations involved, compared with complaints which describe terrible service. Obviously, not all political complaints receive less support and not all complaints on service are substantially shared, the interactions between complaint topics and other attributes need to be explored. Moderating effects will be tested in next section.

Table 42 Descriptive statistics of negative Tweets topics (k = 5)

Descriptives

Zscore(LNvirality)

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound	Minimum	Maximum
1	1997	-.3489	.6970	.0156	-.3795	-.3183	-.7160	10.9292
2	8719	.0620	1.1210	.0120	.0385	.0855	-.7160	10.3274
3	8116	.0432	.9116	.0101	.0234	.0630	-.7160	13.6808
4	4324	-.0982	1.0693	.0163	-.1301	-.0663	-.7160	10.4500
5	6161	.0373	.9330	.0119	.0141	.0607	-.7160	10.2032
Total	29317	.0000	1.0000	.0058	-.0114	.0114	-.7160	13.6808

“1- politics: Uganda”, “2 - ethnicity: racist”, “3 - service: room”, “4 - politics: Ukraine”, and “5 - service: reservation”

[37] “War in Ukraine” was the most mentioned topics across multiple social media in 2022 (Statista, 2023f). See Appendix P for detail.

Table 43 Post Hoc test results

Multiple Comparisons

Dependent Variable: Zscore(LNvirality)

Tukey HSD

(I) topic5	(J) topic5	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	2	-.4109*	.0247	<.001	-.4781	-.3436
	3	-.3921*	.0248	<.001	-.4598	-.3243
	4	-.2507*	.0269	<.001	-.3241	-.1773
	5	-.3862*	.0256	<.001	-.4561	-.3164
2	1	.4109*	.0247	<.001	.3436	.4781
	3	.0188	.0153	.737	-.0231	.0606
	4	.1602*	.0185	<.001	.1097	.2106
	5	.0246	.0165	.570	-.0205	.0698
3	1	.3921*	.0248	<.001	.3243	.4598
	2	-.0188	.0153	.737	-.0606	.0231
	4	.1414*	.0187	<.001	.0903	.1925
	5	.0058	.0168	.997	-.0400	.0517
4	1	.2507*	.0269	<.001	.1773	.3241
	2	-.1602*	.0185	<.001	-.2106	-.1097
	3	-.1414*	.0187	<.001	-.1925	-.0903
	5	-.1356*	.0197	<.001	-.1894	-.0817
5	1	.3862*	.0256	<.001	.3164	.4561
	2	-.0246	.0165	.570	-.0698	.0205
	3	-.0058	.0168	.997	-.0516765	.0400
	4	.1356*	.0197	<.001	.0817479	.1894

*. The mean difference is significant at the 0.05 level.

7.4 Moderating Effects

This section aims to test the moderating effects which are divided into two main processes according to the type of variables. Two-way ANOVA tests were performed to investigate the categorical moderators; meanwhile, moderation analyses were run by using SPSS PROCESS Model 1 (Hayes, 2013) to investigate the interactive effects of complaint topics and the physical/psychological attributes (continuous variables) of the complaint on virality.

7.4.1 Interaction between Topic and Use of Attachment

A two-way ANOVA analysis reveals the significant interactive effect of topic and use of attachment on complaint virality was significant ($F(4, 29307) = 36.33$, $p < 0.001$). The direct effect of topic ($F(4, 29307) = 66.79$, $p < 0.001$) and attachment ($F(1, 29307) = 54.61$, $p < 0.001$). The use of attachment has positive impact on complaint virality for topic 2-5, however, decreases the virality of topic 1 (see Table 44 for descriptive statistics and Figure 26 for visualisation).

Table 44 Descriptive statistics for 5 topics and use of attachment

Topic	1 – Attachment present			-1 – Attachment absent		
	N	Mean	Std. Deviation	N	Mean	Std. Deviation
1	1611	-.417	.564	386	-.067	1.045
2	900	.386	1.428	7819	.025	1.074
3	1429	.207	1.088	6687	.008	.865
4	703	-.024	1.320	3621	-.113	1.013
5	700	.373	1.327	5461	-.006	.860
Total	5343	.041	1.149	23974	-.009	.963

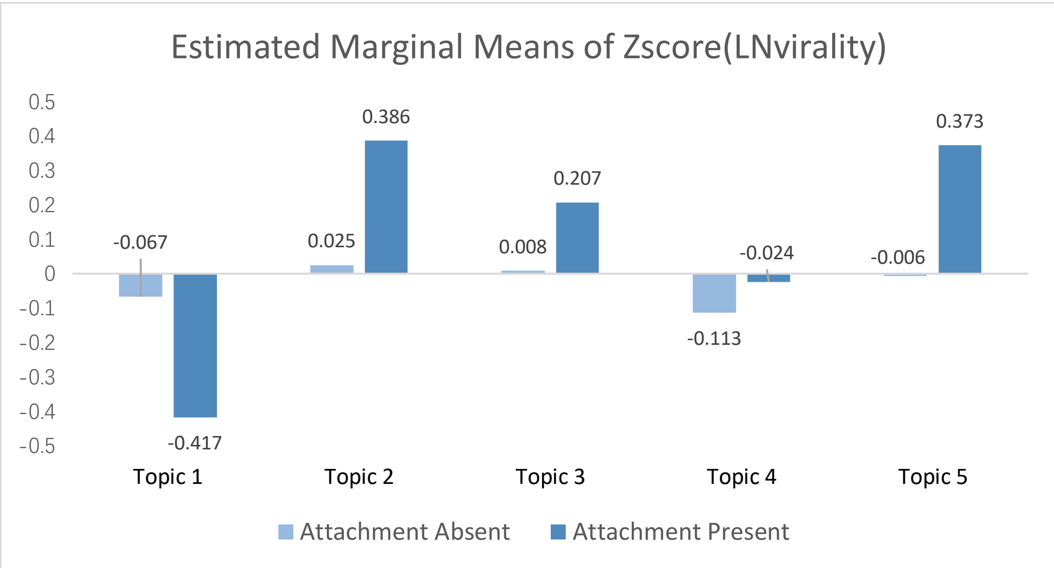

Figure 26 Effect of topics and use of attachment on virality

7.4.2 Interaction between Topic and Word Count

The moderation analysis run by PROCESS Model 1 (IV = complaint topic; Moderator = word count; DV = virality), see Table 45 for the coding of categorical independent variable[38]. The interaction between complaint topic and word count on complaint virality was significant (X_1: $b_1 = 0.28$; SE = 0.04; t = 7.35; p = 0.000; X_2: $b_2 = 0.25$; SE = 0.04; t = 6.35; p = 0.000; X_3: $b_3 = 0.27$; SE = 0.04; t = 6.63; p = 0.000; X_4: $b_4 = 0.24$; SE = 0.04; t = 6.22; p = 0.000). The conditional indirect effects of the complaint topic on virality were significant when the word count was average

[38] This coding of categorical independent variable will be used as default in this chapter unless there are other ad hoc statements.

(conditional indirect X_1: $b_1 = 0.43$; Boost SE = 0.03; 95% CI [0.38, 0.48]; X_2: $b_2 = 0.37$; Boost SE = 0.03; 95% CI [0.32, 0.42]; X_3: $b_3 = 0.29$; Boost SE = 0.03; 95% CI [0.23, 0.34]; X_4: $b_4 = 0.38$; Boost SE = 0.03; 95% CI [0.33, 0.43]) or high (X_1: $b_1 = 0.81$; Boost SE = 0.06; 95% CI [0.70, 0.93]; X_2: $b_2 = 0.71$; Boost SE = 0.06; 95% CI [0.59, 0.82]; X_3: $b_3 = 0.66$; Boost SE = 0.07; 95% CI [0.53, 0.78]; X_4: $b_4 = 0.71$; Boost SE = 0.06; 95% CI [0.59, 0.83]). For complaint Topic 2, 3, and 5, the conditional indirect effect was also significant (compared with Topic 1 as the reference) when the word count was low (X_1: $b_1 = 0.16$; Boost SE = 0.04; 95% CI [0.08, 0.24]; X_2: $b_2 = 0.14$; Boost SE = 0.04; 95% CI [0.06, 0.23]; X_4: $b_4 = 0.15$; Boost SE = 0.04; 95% CI [0.06, 0.24]), however, not significant for Topic 4 when the word count was low (X_3: $b_3 = 0.03$; Boost SE = 0.04; 95% CI [-0.05, 0.12]). To sum up, the word count moderates the impact of topic difference on complaint virality when the word count is average and high, however, only moderates the impacts of some (non-political) topics when the word count is lower (see Figure 27).

Table 45 Coding of categorical independent variable for moderation analysis

5 topics	X1	X2	X3	X4
1	0	0	0	0
2	1	0	0	0
3	0	1	0	0
4	0	0	1	0
5	0	0	0	1

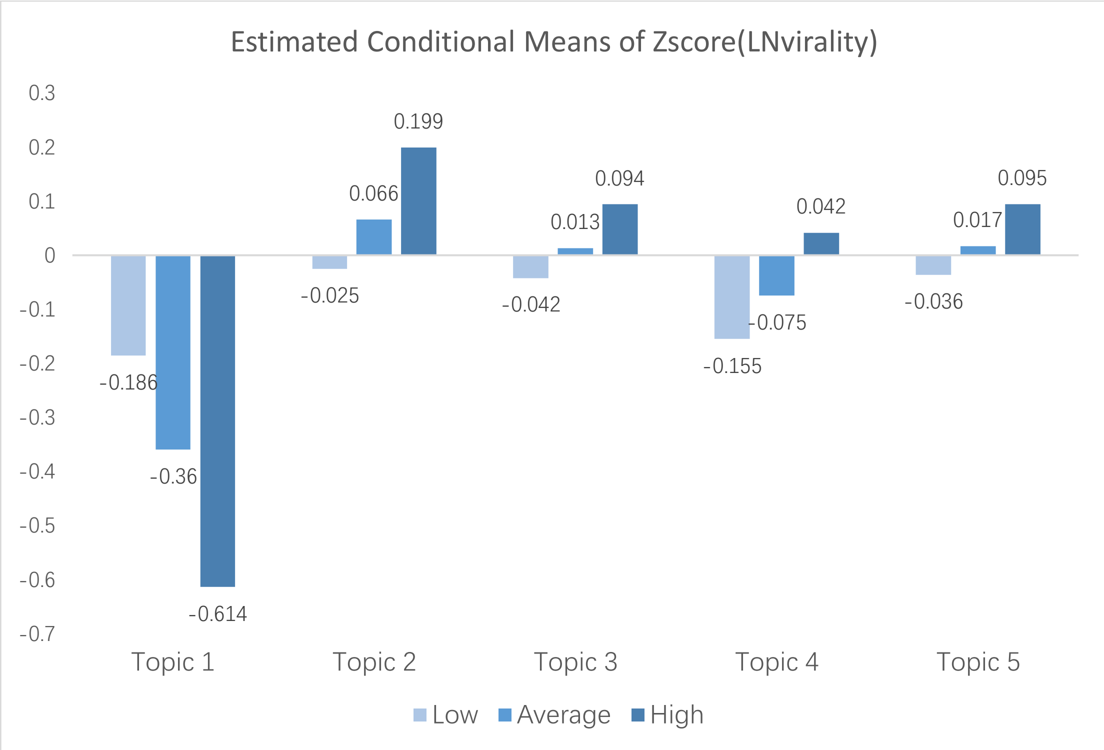

Figure 27 Effect of topics and word count on virality

7.4.3 Interaction between Topic and Subjectivity

The moderation analysis (IV = complaint topic; Moderator = subjectivity; DV = virality) confirmed that interaction between complaint topic and complaint subjectivity on the virality was significant (X_1: b_1 = -0.18; SE = 0.03; t = -5.14; p = 0.000; X_2: b_2 = -0.14; SE = 0.04; t = -3.99; p = 0.000; X_3: b_3 = -0.10; SE = 0.04; t = -2.80; p = 0.005; X_4: b_4 = -0.18; SE = 0.04; t = -5.04; p = 0.000). The conditional indirect effects of the complaint topic on virality were significant when the subjectivity was low (conditional indirect X_1: b_1 = 0.56; Boost SE = 0.03; 95% CI [0.50, 0.63]; X_2: b_2 = 0.48; Boost SE = 0.04; 95% CI [0.41, 0.55]; X_3: b_3 = 0.29; Boost SE = 0.03; 95% CI [0.22, 0.35]; X_4: b_4 = 0.54; Boost SE = 0.04; 95% CI [0.47, 0.61]) and average (X_1: b_1 = 0.29; Boost SE = 0.04; 95% CI [0.21, 0.38]; X_2: b_2 = 0.27; Boost SE = 0.04; 95% CI [0.19, 0.36]; X_3: b_3 = 0.14; Boost SE = 0.05; 95% CI [0.05, 0.22]; X_4: b_4 = 0.27; Boost SE = 0.04; 95% CI [0.18, 0.35]). However, it was not significant when the level of subjectivity was high (X_1: b_1 = 0.10; Boost SE = 0.08; 95% CI [-0.05, 0.25]; X_2: b_2 = 0.12; Boost SE = 0.08; 95% CI [-0.03, 0.27]; X_3: b_3 = 0.02; Boost SE = 0.08; 95% CI [-0.13, 0.18]; X_4: b_4 = 0.07; Boost SE = 0.08; 95% CI [-0.08, 0.221]). In sum, the subjectivity moderates the impact of topic difference on complaint virality only when the level is low and average (see Figure 28).

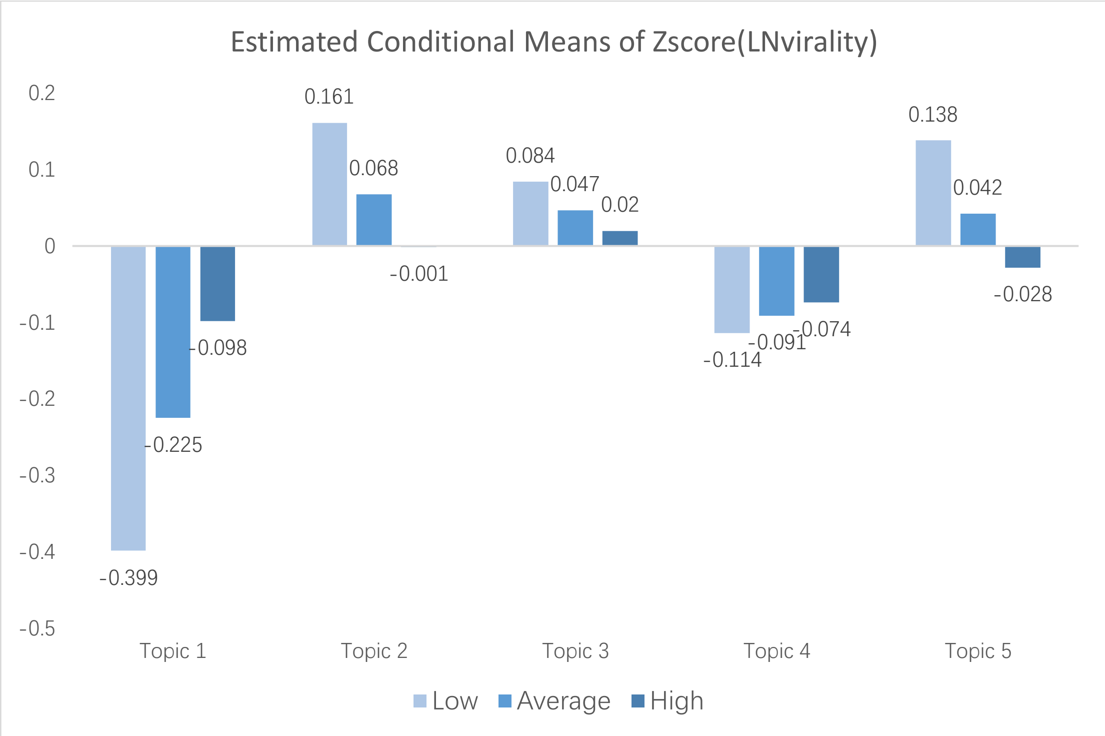

Figure 28 Effect of topics and subjectivity on virality

7.4.4 Interaction between Topic and Clout

The moderation analysis (IV = complaint topic; Moderator = clout; DV = virality) found that interaction between some topics and clout score on the virality were insignificant (X_1: b_1 = -0.02; SE = 0.03; t = -0.70; p = 0.48; X_2: b_2 = -0.05; SE = 0.04; t = -1.45; p = 0.15) while significant impact were proven among some topics (X_3: b_3 = -0.08; SE = 0.04; t = -2.22; p = 0.03; X_4: b_4 = -0.07; SE = 0.04; t = -2.01; p = 0.04). However, the conditional indirect effects of the complaint topic on virality were significant no matter when the clout was low (conditional indirect X_1: b_1 = 0.45; Boost SE = 0.05; 95% CI [0.34, 0.55]; X_2: b_2 = 0.46; Boost SE = 0.05; 95% CI [0.36, 0.57]; X_3: b_3 = 0.37; Boost SE = 0.06; 95% CI [0.25, 0.48]; X_4: b_4 = 0.48; Boost SE = 0.06; 95% CI [0.37, 0.59]), average (X_1: b_1 = 0.42; Boost SE = 0.03; 95% CI [0.37, 0.48]; X_2: b_2 = 0.41; Boost SE = 0.03; 95% CI [0.36, 0.46]; X_3: b_3 = 0.28; Boost SE = 0.03; 95% CI [0.22, 0.34]; X_4: b_4 = 0.40; Boost SE = 0.03; 95% CI [0.35, 0.46]) and high (X_1: b_1 = 0.38; Boost SE = 0.05; 95% CI [0.28, 0.48]; X_2: b_2 = 0.33; Boost SE = 0.05; 95% CI [0.23, 0.43]; X_3: b_3 = 0.15; Boost SE = 0.05; 95% CI [0.05, 0.26]; X_4: b_4 = 0.29; Boost SE = 0.05; 95% CI [0.19, 0.40]). In sum, the clout moderates the impact of topic differences between Topic 4 (“politics: Ukraine”) and Topic 5 (“service: reservation”) on complaint virality, while the clout conditional moderates the impact at all different levels (see Figure 29).

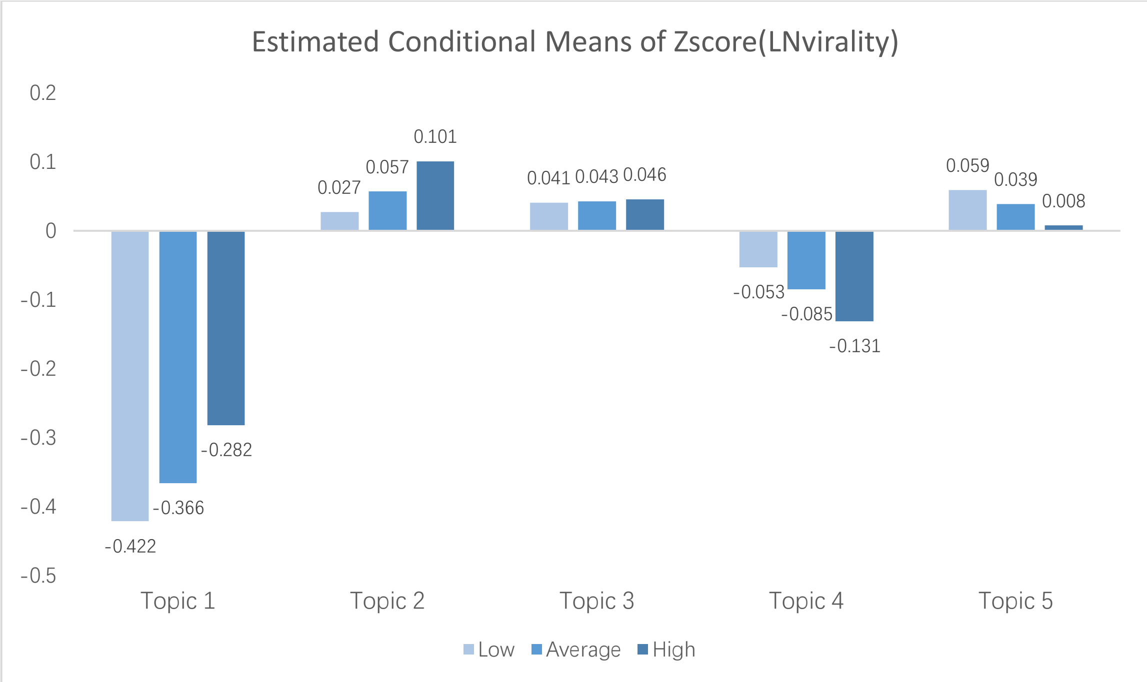

Figure 29 Effect of topics and clout on virality

7.4.5 Interaction between Topic and Anger Emotion

The moderating effect analysis (IV = complaint topic; Moderator = anger emotion; DV = virality) revealed that the interaction between some topic and anger on the virality were insignificant (X_4: b_4 = -0.05; SE = 0.03; t = -1.57; p = 0.12) while significant impacts were proven among some topics (X_1: b_1 = -0.07; SE = 0.03; t = -2.54; p = 0.01; X_2: b_2 = -0.07; SE = 0.03; t = -2.35; p = 0.02; X_3: b_3 = -0.08; SE = 0.03; t = -2.98; p = 0.00). The conditional indirect effects of the complaint topic on virality were significant when the anger emotion was low (conditional indirect X_1: b_1 = 0.42; Boost SE = 0.03; 95% CI [0.37, 0.47]; X_2: b_2 = 0.41; Boost SE = 0.03; 95% CI [0.36, 0.46]; X_3: b_3 = 0.27; Boost SE = 0.03; 95% CI [0.22, 0.33]; X_4: b_4 = 0.40; Boost SE = 0.03; 95% CI [0.34, 0.45]), average (X_1: b_1 = 0.41; Boost SE = 0.03; 95% CI [0.36, 0.45]; X_2: b_2 = 0.39; Boost SE = 0.03; 95% CI [0.34, 0.44]; X_3: b_3 = 0.28; Boost SE = 0.03; 95% CI [0.20, 0.30]; X_4: b_4 = 0.38; Boost SE = 0.03; 95% CI [0.33, 0.43]) and high (X_1: b_1 = 0.34; Boost SE = 0.04; 95% CI [0.27, 0.41]; X_2: b_2 = 0.32; Boost SE = 0.04; 95% CI [0.24, 0.40]; X_3: b_3 = 0.17; Boost SE = 0.04; 95% CI [0.09, 0.24]; X_4: b_4 = 0.34; Boost SE = 0.04; 95% CI [0.26, 0.42]). Therefore, the anger emotion moderates the impact of topic differences between Topic 2 (“ethnicity: racist”), Topic 3 (“service: room”) and Topic 4 (“politics: Ukraine”) on complaint virality. Meanwhile, it moderates the impact of topic difference on complaint virality at different anger levels (see Figure 30).

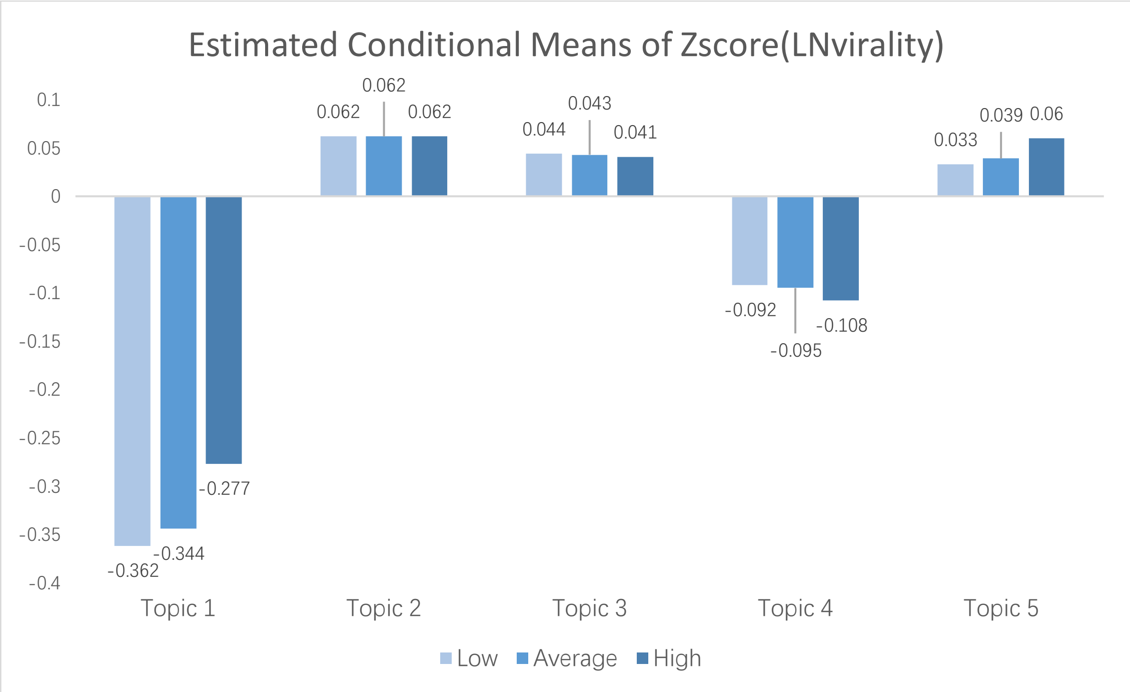

Figure 30 Effect of topics and anger on virality

7.6 Discussion

The unanswered questions and the hypotheses untested in Chapter 6 are conducted. First, both classification tree and logistic regression were conducted to explore whether organisations follow some certain patterns to decide whether to reply to negative Tweets or not. Results of these two models confirm that word count is the key factor of organisational response, which is coincidentally similar with the impact on virality. The findings suggest that word count is a signal for all readers, no matter they are potential consumers or staff of the organisation/brand, to evaluate the value of the text. This is also in line with the attention-based view and signalling theory that richer information is believed to be more observable and valuable (von Janda *et al*., 2021). On the other hand, subjective and authentic Tweets are found being answered, which is different from the pattern of virality.

Response timing is also critical in explaining the variance of virality (H19 supported). Specifically, the divider of the time gap between Tweet posted and organisation replied is three days, in other words, negative Tweets are more likely to go viral if being answered after 3 days compared with being replied within 3 days. This result confirmed the importance of timely responses to complaints (Golmohammadi *et al*., 2021; Zhou *et al*., 2014) because the waiting time is regarded as non-financial input (Hogreve *et al*., 2017). Prompt responses are found effective to weaken the virality because when the negative Tweet reaches the new reader, he/she finds the organisation has already responded which can to some extent restore the injustice situation caused by the organisation's failure, and level of injustice can be a strong predictor of actions (Balaji *et al*., 2016). Meanwhile, the response timing is also a signal for readers to evaluate the organisation's procedure and policy performance (Wirtz and McColl-Kennedy, 2010).

Afterwards, LDA was applied to model the topic of the negative Tweets. Five topics are returned, among which there are 2 political Tweets, one criticising the symposium held in their branches in Canada inviting some Ugandan leaders and the other topic blaming the hotels which are still doing business in Russia during the Ukraine War. The service quality topics are about the awful environment of the room, some reservation problems, and some unpleasant interactive experience including racism. By comparing the virality among these topics, it is obvious that the actual living experience at hotels are more likely to go viral especially when the complainer mentioned discrimination, followed by room reservation failures. However, it is interesting to find that political topics were not viral when related to specific brands and situational political issues (e.g., boycotting the symposium) are less supported compared with long-term topics (e.g., blame the business in Russia). The variance in virality caused by topic indicate that readers evaluate the Tweets by its core information (Cheng and Ho, 2015). Finally, ANOVA and moderating analysis were carried out to test the moderating effects of the linguistic/psychological attributes on the relationship between topic and virality. Results show that word count, using attachment and level of subjectivity moderate the impact of all topics. Furthermore, clout is found only moderating the Ukraine War and the failure relevant room environment and discrimination while intensity of anger emotion moderates most of the topics except the horrible experience such as racism. In sum, the impact of topic difference on virality is moderated by the linguistic and psychological characteristics of the text. Table 46 summarises the hypotheses tested in this chapter.

Table 46 Summary of hypotheses testing outcomes in this chapter

Hypotheses	Support / Not support
H13: Different topics of online complaints will lead to differences in virality.	Support

H14: The attributes (physical and psychological) will moderate the impact of complaint topic on virality.	Support
H20: Time gap between the complaint post and organisational response will have positive impact on the virality.	Support

CHAPTER 8 DISCUSSION AND CONCLUSION

8.1 General Discussion

This chapter summarises the findings of the empirical study. This thesis was initialized to figure out the factors which will influence the negative eWOM virality, meanwhile investigate the organisational response strategy and its impact on virality. By scraping and analysing the Tweets referring 28 hotel brands and the timelines of these brands in 2022, the findings proven the significant impacts of content and non-content attributes of the online complaints and the characteristics of organisation's response on virality. Specifically, the predominant factor of the virality is the number of the complainer's followers, followed by some obvious physical cues, including the word count of the Tweet and whether the attachment is used or not. Besides, psychological attributes of the Tweet are also found come into effect. Clout (social confidence) as well as high-arousal emotion - anger, will increase the virality, while the subjectivity will hinder the possibility of virality.

Topic modelling was also conducted to understand and categorise the content of negative Tweets. According to the suggestions by statistical methods and the manually meaning analysing and comparing, five main topics are confirmed and the significant differences in virality variance are found across topics. Specifically, the dissatisfied experience with previous stay at hotel are more likely to go viral, among which the service experience with discrimination and terrible room conditions are two main issues worth manger's concerning. Failure of reservation is also a topic which is frequently complained and may become contagious. Interestingly, the politics relevant topics are less likely to be supported by other Twitter users, this is not consistent with the overall trend on Twitter in 2022. Furthermore, this study also aims to explore the information processing pattern with the help of dual-process theory. According to the moderating analysis of the complaint topic and the linguistic/psychological attributes of the complaint, this study proven that Twitter users will use both central and peripheral cues to guide their actions.

Finally, the effectiveness of organisational response is also investigated. Results show that responding to negative Tweets can hinder the virality to some extent. However, further exploration on response timing indicates that prompt response is critical and the tipping point in this case is three days. In other words, responding to the complaints within three days can effectively decrease the possibility of virality.

Table 47 summarises all hypotheses in this thesis.

Table 47 Summary table of hypotheses testing outcomes in this thesis

Hypotheses		Outcome and Relevant Analysis
Hypothesis 1	The length of online complaints will have positive impact on the virality.	H1 marginally supported. In general longer complaints will have positive impact, while for the complainer who has very low number of followers, relative shorter and extremely longer complaints are more likely to go viral. (Section 6.6)
Hypothesis 2	Higher readability of online complaints will have positive impact on the virality.	H2 supported. (Section 6.6)
Hypothesis 3	Adding attachments to online complaints will have positive impact on virality.	H3 supported. (Section 6.6)
Hypothesis 4	The tone polarity of online complaints will have positive impact on the virality.	H4 not supported. (Section 6.6)
Hypothesis 5	Subjectivity level of the online complaint will have negative impact on virality.	H5 supported. (Section 6.6)
Hypothesis 6	Analytical online complaints will be more likely to go viral.	H6 supported. (Section 6.6)
Hypothesis 7	Clout of the online complaint will have negative impact on virality.	H7 not supported. However, clout is found have positive impact on virality. (Section 6.6)
Hypothesis 8	Authenticity of the online complaint will have positive impact on virality.	H8 supported. (Section 6.6)
Hypothesis 9a	Positive emotions in online CCB will have negative impact on virality.	H9a not supported. (Section 6.6)
Hypothesis 9b	Negative emotions in online CCB will have positive impact on virality.	H9b partly supported. Only anger is found have positive impact. (Section 6.6)
Hypothesis 10	Using more exclamation marks in online complaints will have positive impact on the virality.	H10 not supported. (Section 6.6)
Hypothesis 11	Using more question marks in online complaints will have positive impact on the virality.	H11 not supported. (Section 6.6)
Hypothesis 12	Using more emoji in online complaints will have positive impact on the virality.	H12 not supported. (Section 6.6)
Hypothesis 13	Different topics of online complaints will lead to differences in virality.	H13 supported. (Section 7.3)
Hypothesis 14	The attributes (physical and psychological) will moderate the impact of complaint topic on virality.	H14 supported. (Section 7.4)
Hypothesis 15	The number of complainer's followers will have positive impact on the virality.	H15 supported. (Section 6.6)

Hypothesis 16	The number of the involved organisation/brand's followers will have positive impact on the virality of the online complaint.	H16 not supported. (Section 6.6)
Hypothesis 17	Ratio of organisational response to online complaints will have negative impact on virality.	H17 not supported. (Section 6.6)
Hypothesis 18	Ratio of online complaints (of the organisation/brand) will have positive impact on the virality.	H18 not supported. (Section 6.6)
Hypothesis 19	Responding to online complaints will decrease the probability of virality.	H19 supported. (Section 6.6)
Hypothesis 20	Time gap between the complaint post and organisational response will have positive impact on the virality.	H20 supported. (Section 7.2)

8.2 Contributions

8.2.1 Theoretical Contributions

Extensive literature has confirmed the impact of online UGC on other potential consumer's attitude and behaviours at the individual's level (e.g., Allard *et al*., 2020; Minnema *et al*., 2016) while studies devoted to cumulative impacts of complaints on social media gradually attract researchers' attentions in recent years. Based on the research on CCB and SFR (e.g., Homburg *et al*., 2010), especially the recent literature on negative eWOM (e.g., Allard *et al*., 2020; Herhausen *et al*., 2019), this thesis integrating the influence of different parties in these online conversations to distinguish the potential triggers of complaint virality. This study assesses the attributes of complaints, complainers, involved organisations/brands and their impacts on readers' reactions towards the complaints about 28 hospitality brands' official Twitter accounts, which responds to calls for research on diverse characteristics of eWOM (Reimer and Benkenstein, 2016). Drawing from the recovery strategies from SFR studies, this study also explores the variance of virality caused by different recovery efforts. This thesis makes several significant theoretical contributions.

Generally, this study sheds light on the impact of diverse attributes on negative eWOM virality. First, the number of complainer's followers predominantly affects the virality, which proves the behavioural contagion effects (Stephenson and Fielding, 1971) in social communication, specifically, on social platforms. Twitter users may follow others for diverse reasons, however, the primary motivation is the interest in the accounts/users being followed, observing their social status and/or maintaining consistent communication channels (De Veirman *et al*., 2017). In general, social media users have higher reliability in the accounts/users they follow, and the level of trust is too large extent affected by the number of the followers these accounts/users have (Djafarova and Rushworth, 2017). Therefore, it is understandable that the complaints posted by the social media users who have larger number of followers are more likely to be believed, accepted and even supported by more people. According to the contagion effects, individual's supporting behaviours (e.g., adopting and spreading the information in this study) increases the probability of the information exposure (Hinz et al., 2011) and the larger number of followers means a wider coverage of information.

Second, in agreement with the signalling theory, the physical traits of the complaints are proven to be critical factors. Word count is sometimes controlled in experiments (e.g., Allard *et al*., 2020), however, it is worth noting that user's reading preference and habit on social media are different from reading/browsing other media such as newspapers, review websites and online forums. Whether the long Tweets would lead to readers' cognitive load or be perceived as informative description is unclear. Therefore, as suggested by researchers (e.g., Proserpio and Zervas, 2017; Zhu *et al*., 2021), this study explores the impact of these seemingly simple attributes, e.g., word count and content structure, to have a more comprehensive understanding of the textual contents. According to the signalling theory, signals are carriers of visible attributes (Spence, 2002) and especially effective in highly uncertain situations, such as online environment (Filieri *et al*., 2021). Information asymmetry is more serious when in virtual environments or describing intangible targets, such as service quality (Bansal and Voyer, 2000). Thus, the difficulty of understanding is largely increased owing to the inefficient in information in these circumstances while signals can help to interpret the abstract and subtle cues. However, not all signals are observable enough for understanding, and readers tend to ignore the signals which require more effort to be observed (Connelly *et al*., 2011). Using attachment and more word counts reflect the author's enthusiasm and effort in writing the complaint (Chevalier and Mayzlin, 2006), and they are both obvious signals which can be successfully conveyed and interpreted by the readers. Thus, this study advances the study on online complaint and content virality by highlighting the physical attributes as critical predictor of complaint virality. These attributes are direct and evident cues for reader's evaluation of the content, in other words, they provide more diagnostic function to diminish the information asymmetry and reflect the efforts of the complaint writing.

Third, the impact of psychological factors further enrich the CCB and UGC virality literature. Drawing on congruity theory, this study explores the impact of content subjectivity on the virality (Osgood and Tannenbaum, 1955). The level of dissonance between one's previously held opinions and the actual phenomenon will affect the acceptance level of the reality (Mattila and Wirtz, 2001; Olson and Ahluwalia, 2021). Therefore, readers are more likely to support the Tweets which are consistent with their perceptions and expectations. Subjective texts are always accompanied by more biased and unverified expressions (Ford *et al*., 1990), and sentiment wise, they tend to be more extreme (Zhao *et al*., 2019). Since sharing negative information will impact one's image, readers will take it seriously and compare the described situation with their prior perception. Subjective texts are less measurable compared with objective comments, thus, requires more efforts to processing and assessing subjective Tweets. The findings of this study prove the above point as the subjective Tweets are found less likely to be liked, retweeted or replied. In most cases, readers have no prior animosity against the brand, and the exaggerated Tweets will lead to larger congruity dissonance. In these cases, readers' engagements will be hindered because they are afraid of the abuse of social media and complaint management if they are incapable of evaluating or cannot legitimize the subjective failure description (Wirtz and McColl-Kennedy, 2010).

Furthermore, analytical complaints tend to go viral, and this finding contribute to both information processing and culture dimensions domains. It is believed that information understanding can be smoother if it fit the cognition better (Korfiatis *et al*., 2012). Therefore, whether the style and logic of the information can match the information processor's own knowledge will to large extent affect the difficulty of processing the information and further guide the behavioural intentions (Vessey and Galletta, 1991). Simply put, Twitter users are more likely to understand the complaints which can be more effectively and effortlessly processed, and their subsequent adopting reactions will be triggered if the information is understandable. Furthermore, considering the research context (the hotels based in UK and US) and research target (complaints written in English mostly by UK and US complainers), it is understandable that the style of complaints can easily fit most of the other audiences if it is in line with the thinking and linguistic styles of the UK and US Twitter users. As the analytical style of complaints tend to have clear logic and provide explanations of the incident, it can effectively match the understanding of the audience from high individualism culture background. Therefore, this study also expand the cognitive fit theory through the lens of cultural dimensions.

Fourth, extant studies tend to only highlight the impact of negative emotions when analysing complaints, however, ignore the potential emotionality backfire situations and the reality that different valences of emotional words may be mixed used in reality. The findings of this study fill these gaps by investigating the extremity and the mix of both emotion valences. On the one hand, positive emotions are found have no impact on virality or interfere the negative tones, which can be explained by ELM. Specifically, if the salient emotion is triggered, it will occupy the attention capacity to large extent (Eysenck, 1976) and reinforce the dominant emotion but weaken other cues (Baron *et al*., 1994; Rocklage *et al*., 2018), this phenomenon is rather universal if the overall emotion is negative (Baron *et al*., 1994; Eysenck, 1976). On the other hand, higher density of negative tone is more consistent with the entire negative emotional state of the complaint, which makes it more persuasive and contagious (Wegener and Petty, 1994). Furthermore, in line with Berger and Milkman (2012) and Herhausen *et al*. (2019) studies which investigate the content virality, this study confirms the generalisability of negative emotions triggering virality on a different social platform. These previous studies examine the non-UGC contents spread via email and negative Facebook posts within brand community, in other words, the range of information transmission is to some extent limited to a specific group of receivers with higher similarity in interest and attitudes. This study extends the findings about the influence of negative emotion to general Twitter users and draw the conclusion that high arousal negative emotion fuels the virality of the complaints. This proves that the social function of emotion that one is easily affected and persuaded by outward emotions, such as anger, will dramatically stimulate his/her further action (Rocklage *et al*., 2018) and spreading this emotion is a common choice because the information receiver is influenced and has the intention to persuade others (Andrade and Ho, 2009; Van Kleef, 2009).

Fifth, as suggested by prior studies (e.g., Herhausen *et al*., 2019; Ma *et al*., 2015), the impact of organisational response to cut off the diffusion of negative eWOM on social media. Advancing this emerging research across CCB and SFR domains, this study empirically confirms the effectiveness of general response strategy, i.e., respond or not. Organisations might face the complaint publicisation situation if responding to the complaints because the replies will show in the timeline and will stick at the top of the brand page until a new Tweet is posted (Golmohammadi *et al*., 2021). However, this study confirms that replying to complaints on Twitter is an effective way to decrease the probability of virality, and no response, as previous literature suggest should be always avoided (Wang and Chaudhry, 2018; Herhausen *et al*., 2019). The study also presents the evidence that timeliness of response is also a critical factor, which is consistent with prior knowledge (Homburg *et al*., 2015). Specifically, prompt responses are proved too large extent decrease the probability of complaint virality.

Last but not the least, this study advances the understanding of the information analysis process. Specifically, it enriches the literature on the arguments concerning the stimuli process and attitude persuasion routine by investigating the outcomes of content and non-content cues. Elaboration likelihood model (ELM) and heuristic-systematic model, being popular theoretical foundations for explaining the process and learning eWOM (Cheng and Ho, 2015), however, has an inherent shortcoming in terms of its differentiation between different routines. The boundary between central and peripheral routines can be simply summarised as the efforts required when processing information (Petty *et al*., 1997) and the choice is mainly determined by the capacity and motivation to devote efforts (Hansen *et al*., 2018). However, one's perception of his/her own capacity and motivation tend to be situational (Li *et al*., 2022), in other words, evaluating the required effort can be non-rational but instinctive in reality. Simply put, high and low effort is a subjective and unstable criterion for distinguishing the information processing routines.

The other main problem with ELM or heuristic-systematic model, is that the process is based on an assumption that cues at different levels cannot be processed simultaneously (Stiff, 1986). In other words, previous studies assume that one will only go through one path at a time, either carefully evaluate the quality and value of the information or instinctively react to the stimuli without considering the logic of the information (e.g., Weitzl and Hutzinger, 2017). In line with the idea of the dual-process, readers' capability for information evaluation is a key prerequisite. However, considering the anonymity of online complaint, recipients may be imperfectly informed what actually happened, thus, whether they are able to assess the value of the complaint is doubtful. The findings of this thesis, although cannot thoroughly distinguish the routines adopted at individual's level, challenge the bias in extant literature which overestimate the preference of a single route. Some researchers claim that readers may rely on the peripheral/heuristic process as the shortcut especially when they have access to huge amount of information (Van Lange *et al*., 2011; Weitzl and Hutzinger, 2017). However, sharing negative information on social media may harm the sender's self-image in public (Zhang *et al*., 2014), thus, being motivated to support the negative comments may not be a impulsive choice but actions after detailed information checking. On the other hand, it is believed that the central routine will gain the upper hand when readers have the ability and motivation to process the information elaborately (Hansen *et al*., 2018).

However, the motivation can be affected by observing social interactions and triggered by the situational stimuli (Relling *et al*., 2016), rather than being totally attribute to one's own subjective perceptions. In this study, topic/content of the complaint, can be regarded as the core information (Cheng and Ho, 2015) which require more logical understanding and analysis, are proven to influence the reader's actions (like, retweet, and reply). However, the variance caused by topic is also affected by other peripheral cues, such as the word count and negative emotion arousal. Previous studies have already investigated the impact of central and peripheral routes on information adoption (e.g., Barhorst *et al*., 2020; Filieri and McLeay, 2014), but not yet study whether actions will be triggered. By investigating the impact of various physical and psychological attributes of the complaint, complainer and the organisation, audiences' assessment and behaviours toward the complaint are proved not rely on single routine but multiple cues. And the test of interactive effect of physical and psychological effects further confirms the co-occurrence of central and peripheral stimuli on readers' active participation in negative eWOM. Taken together, this study emphasises the importance of considering diverse factors when studying the virality of contents as readers rely on multiple cues rather than single dimension to guide their actions.

8.2.2 Managerial Implications

Exploring the factors of negative eWOM virality and organisational response strategy, this study offering some managerial implications for marketing and service practice. Understanding and predicting complaint virality is a critical first step for organisations to prevent or weaken the threat of further spreading. However, diverse factors may fuel or hinder the probability of complaint virality. Therefore, for staff or manager who operate the brand/organisation official account, should consider the potential effects of multiple factors from a comprehensive perspective when predicting which complaints tend to go viral. In this thesis, by investigating and confirming multiple significant characteristics, both content and non-content factors are found critical.

In terms of the non-content factors, the top-priority takeaways for organisation is that managers need to prioritise the complainers who have more followers. Note that social media users sometimes assess and deduce the realiability of the UGCs based on the influence of the information publisher, meanwhile, complaints posted by those who have more followers have higher probability of content exposure.

Therefore, managers should keep an eye the complainers who have larger number of followers because their complaints may attract more participation. Although this suggestion might be regarded as the ‘common knowledge’, however may not always be practiced in reality.

Second, when assessing the contents, the managers should focus on physical characteristics (i.e., word count and attachment use) of the contents as they are obvious cues for readers to deduce and assess the failure situation and the complainers’ efforts. Managing complaints by physical attributes provides an accessible and swift way for any mangers with or without data mining techniques. Managers can observe the basic linguistic and structural attributes, word count of the Tweet and whether attachments such as GIF (Graphics Interchange Format), image and video is used, and quickly rule out the Tweets which are less likely to go viral.

Third, the findings of this study also recommend managers to classify the eWOM topics and focus on those which will trigger more participation and pay extra attention to the complaints relevant to these topics. This thesis provide some practical suggestions and workable techniques for organisation’s complaint management, which are applicable to organisations of different scales and have diverse data analytics capacities. In this study, dictionary-based (supervised learning) worked as the exploratory step and unsupervised learning provided a more interpretable result. This two-step method may inspire organisations to develop their own social media complaint topic modelling system by adopting this comprehensive process or choose one of them according to their own needs and dataset. For brands/organisations which have enough historical data, managers can train and test the existing data for creating own dictionary composed with common topic words, and automatically categorise new Tweets. If the brand/organisation has to process big data (high in volume, velocity and variety) but has insufficient archival data for model training, timely collecting data and conducting unsupervised topic modelling can be a practical method. While for the brand/organisation which has no busy traffic on social media, manually check and make use of prior industrial knowledge and experience can be an option.

Apart from the physical attributes and complaint topics, managers need to pay special attention to the Tweets have some specific psychological attributes simultaneously. Specifically, managers should be aware of the potential virality of complaints which are written in analytical and logical styles if the organisation is mainly operated in UK/US and most of the customers come from the highly individualism culture background. Meanwhile, the authenticity of the complaints can also influence the virality. Thus, the complaints written in less social inhibitory phrases and provide more informative information can ring the alarm to the managers that the complaints might be understood and spread by more audience. Furthermore, the density of high arousal emotions, such as anger, should also attract managers attention since they will cause emotional contagion and tend to be rather influential. However, managers do not need to worry about extremely subjective complaints as they are less likely to go viral although the descriptions may be vivid. It is worth noting that the dictionary-based approach used in this study can be applied to distinguish some specific types of emotions and semantics according to the organisation's needs, meanwhile, some reliable dictionaries developed by existing literature (e.g., Herhausen *et al*., 2019) and database published on machine learning platforms such as Kaggle can also be trained and tested for analysis. In other words, the analyses adopted in this study can be generalised to other marketing analytics projects. For example, for organisations which want to decrease the customer churn, maybe they are interested in providing recovery to the complainers who express lower anger because less efforts may require to make these complainers satisfied. Specifically, as both content (i.e., physical and psychological attributes and topic of complaint) and non-content (i.e., number of followers), managers should alert to the synthetic influences as the factors are found amplify each other. For example, if the Twitter users who have many followers post long negative Tweets with attachment and confidently described the situation and express their anger, managers should deal with the Tweets with extreme caution. Thus, this thesis suggests organisations to develop their own complaint management system which can measure the different attributes of the complaint and complainer and prioritise the complaints by their probability of going viral.

Upstanding complaints and predicting potential virality is just the first step of complaint virality preventing. As the findings suggest, responding to negative Tweets is an effective way to prevent or weaken the virality, however, timing is a critical dimension. The tipping point in this study is three days, in other words, reply within three days are found beneficial while delayed response cannot help stopping the virality (if the Tweet has the potential to go viral). Since this study focus on the hospitality accounts, brands of this industry can use this finding as a readily guidance, while for other industries, it is also helpful if they can figure out the turning point and timely respond to the negative Tweets. Hence, the author would also suggest organisations include the tipping point in their complaint response/customer sere system no matter they are using manual record book or developed their own automatic systems. It is also worth noting that brands can also alter the respond timing on different platforms as studies find user's social purpose and expectation of organisational response vary across platforms (Hughes *et al*., 2012; Istanbulluoglu, 2017). This can help organisations managing and prioritising the complaints on platforms which have larger traffic and more active users because as a matter of fact, organisations may not be able or willing to respond to all negative information on various platforms.

Knowing the critical factors of complaint virality and confirming that prompt response can to some extent dampen the virality, this thesis also shed light on the reality of organisational response to complaints. Analysing the organisational response strategy (i.e., what complaints are more likely to receive response from organisation) and comparing the virality model and organisational response pattern, the gap between organisation's strategy and the virality pattern is obvious. Both Twitter readers and managers are more likely to react to longer Tweets with attachment, however, they have opposite opinions of psychological attributes. Readers tend to support objective and more social confident Tweets while mangers will reply to subjective Tweets which are written in modest tone. In terms of negative emotions, strong arousal emotion, anger, is found trigger readers' actions. Meanwhile, managers prefer responding to sad Tweets rather than angry ones partly because they want to show they sympathy to the sad customers and avoid conflicts with angry customers. More importantly, managers ignore the number of followers of the complainer, which is found a strong predictor of virality. These differences can illustrate critical managerial implications for managers to alter their response strategy by coping with the complaint virality model. Therefore, this thesis urges organisations to collect the historical data and find the gap between organisational response and the virality pattern in their own industry and adjust their complaint management strategy accordingly.

8.3 Limitation and Future Research Directions

8.3.1 Research Limitations

The findings of this study are consistent with the opinion that complaint virality is affected by various factors and organisations need to respond timely to prevent situation exacerbation. Although this thesis answered some research questions which have not been well explored in extant literature and provided some practical methods for managers to solve the thorny issue, there are still some inefficient and limitations in this study.

Research wise, although this study attempt to integrate all potential factors, some characteristics are not included because of the technical and time limitations. For example, literature has already proven that gender of the complainer makes huge differences in terms of reader's and organisation's reactions (Proserpio *et al*., 2021). However, using the scraped data and several Kaggle gender classification dataset for model testing, the overall accuracy of the classifier is no higher than 70%, thus, makes it impossible to infer the complainer's gender for further analysis. Furthermore, situational factors are not considered in this study. Although no obvious cyclical patterns can be observed from the time-series visualization, being an industry which is heavily influenced by seasons, consumer's focus on hospitality can be a critical factor for the virality in different seasons. Furthermore, accessibility to time stamp remains an unsolved problem for this study. Twitter API does not provide access to time stamps of likes, retweets and quotes (i.e., they cannot be automatically captured by coding). The replies are time-stamped and the correlation between replies, retweets and likes are high according to the results and it is believed that these actions are evolving simultaneously (Rieder *et al*., 2015). However, given that the number of replies is the lowest among these four actions, relying on this single dimension maybe biased and not representative enough as reader's purpose of like and reply can be diverse which might also lead to different outcomes.

Meanwhile, some findings are inconsistent with the proposition which has been proven by previous literature and the underlying reasons are unclear. The authenticity is believed to be an important dimension for information evaluation; however, its impact is not significant according to the results. As the fraud detection algorithms are diverse and complex, only the dictionary-based method was applied, which might not be accurate enough. Besides, the use of emotion proxy, such as exclamation mark and emoji are found not affecting the virality although emoji is proven to affect information persuasiveness (e.g., Maiberger *et al*., 2023). This study cannot explain this unexpected outcome whether it is because of the content ambiguity or caused by the methodological deficiency. For example, whether the mix-use of symbols will lead to confusion when readers try to understand the mood of the complainer; whether differences in individual interpretation of emoji/punctuation can lead to different outcomes; whether the count of the proxies rather than the proportion (used in this study) is a better measurement is unclear. The reason why popular topics such as politics relevant complaints are not viral is another unanswered question. Some potential reasons may be explained by attribution theory, i.e., whether readers will mainly criticise the organisation (e.g., who is still running business in Russia) or blame the actual culprit of the incident (e.g., Russia) when there is organisation involved when discussing the political issues. Situational empathy may be another explanation that if the topic of complaint is similar to the reader's own experience or is relevant to the well-being, empathy is more likely to be triggered and the willingness to support the complaint will increase.

Finally, although the multicollinearity risk is ruled out in this study, the hierarchy and interconnection of variables are not investigated for several reasons. The number of hypotheses and included variables is relatively large and the structure of the model includes several parties, thus, calculating the indirect relationships between variables will be extremely time and calculation consuming. Meanwhile, most of the variables are latent variables processed by various algorithms/models, among which are uninterpretable black boxes. Thus, the accuracy of information is already unavoidable sacrificed in these processes to some extent, which will further cause deviations when analysing the hierarchies and testing the overall model. However, it is still worth investigating whether the variables are independent or not and exploring the potential synergies or offset effects. For example, more word means more detailed description, maybe it will also influence the emotion diversity and logic complexity; level of readability may also have impact on the analytical thinking, perceived communication confidence, and emotion expression, which are also potential factors of virality.

8.3.2 Directions for Future Research

Apart from the mentioned imperfections, here are some suggestions for future research to generalise and develop the findings. Theoretical wise, future research can jump out of the restrictions of the data structure. In other words, this thesis only examined the scraped complaints, the publishers of the complaints, and the accessible organizational information on Twitter. As the overall performance of the models are not high, although this is rather common when analysing raw data from social media, the possibility of whether other potential factors work behind the scenes cannot be excluded. For example, observer's priori perception and relation with the complainer/organisation may affect their attitude and behavioural intentions when exposed to complaints. Previous CCB and SFR studies have no conclusive opinions of the impact of priori relationship. For example, buffering effects of strong self-brand relationships are found hinder complaining behaviours (Kähr *et al*., 2016) while higher expectations of these customers might also lead to huge psychological gaps after service failure (Johnson *et al*., 2011). Thus, integrating relationship marketing constructs in study on observers' reactions can provide some fruitful and meaningful results. Based on this aspect, investigating bystander's previous interaction with the organisation and complaining behaviours by analysing their previous Tweets may help to have a better understanding of observer's motivation and purpose of supporting the complaints.

Furthermore, in line with the mentioned limitation that the underlying mechanism is unclear, which is also a common shortcoming with studies rely on big data, the author would suggest using mix-methods, such as lab or field experiments as supplementary studies to explore the reasons why the significant factors proven in this and previous can increase the virality. Meanwhile, experiments are also necessary for manipulating and controlling variables to clarify the interactions between variables and what are the key components of the content and non-content characteristics. Meanwhile, as the hypotheses were proposed on the basis of theories, the reason why some of the hypotheses are not supported need further studies to explain. For example, whether these factors have inherent conflicts or inhibiting effects on others can be explored by future research.

The other limitation of the thesis is the actual outcome (especially the harms) of complaint virality is unknown. There are some cases that viral complaints do not lead to disasters[39]. Therefore, future research can test the impact of complaint virality in longitudinal timeline and from diverse aspects. For example, investigating different dimensions of complaint diffusion, such as the frequency, speed and persistence of the spread and the actual participation behaviours (e.g., observers may comment to support the organisation, attack the complainer, and share the complaint with friends to mock the complainer) can help to predict potential harm of the complaint virality. Furthermore, researchers are encouraged to study the conditions that complaint virality escalate to offline crisis.

Methodological wise, data scraped in this study rely on the API provided by the Twitter development account, which 1) has some limitation to access full data; 2) set the daily and monthly usage limit; 3) has anti-scraping techniques which will continuously halt the process after a large amount of data is returned. More advanced scrapy methods are expected in future studies to enlarge the access of the data and improve the scrapy efficiency. Besides, the time-stamp problem is not solved in this study also because of the API restrictions which leaves a challenging but fruitful methodological improvement task for future studies. It is also worth mentioning that virality in this study is the sum of replies, retweets, likes and quotes, however, the purposes of these actions can be different for those participate in the conversation although they all contribute to the virality. Researchers can also study them separately to investigate the purpose to participate in these actions meanwhile explore which variables are the critical factors for specific action.

In terms of the research context, the scope of this study is limited to negative Tweets about hotel brands, future studies can apply the method to conduct a more comprehensive study across industries on various platforms. For example, findings of service and product brands may be different as the evaluation of the service

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[39] A passenger posted a photo of her seat next to the cabin door on a Ryanair flight and complained that she has paid for a window seat but the small window on the cabin door is not what she expected. The complaint attracted a lot of attention and Ryanair replied with the same photo but annotated the small cabin door window. Although the complaint and the humorous reply both went viral, it seems there is no definite threat to the brand. Interestingly, Twitter users seem to have opposite comments (Sly, 2022), such as “Technically, that’s a window”, “So much legroom and she’s complaining about the lack of a window on a 19 quid flight 😂”, “This whole ‘ignoring customer complaints under the guise of social media banter’ is getting tiring…” and “Omg haha I hate Ryanair but I love Ryanair”. See the conversation on Twitter: https://twitter.com/Ryanair/status/1569268623235231748?ref_src=twsrc%5Etfw%7Ctwcamp%5Etweetembed%7Ctwterm%5E1569268623235231748%7Ctwgr%5E128c024b799a3fcdc2e171d7d25213e6832a4463%7Ctwcon%5Es1_&ref_url=https%3A%2F%2Fd-2413597977765276930.ampproject.net%2F2311171837000%2Fframe.html

failure is more subjective while product failures tend to be measurable. Considering the data structure and user characteristics on social media are different, studies on Facebook or Instagram may also provide some interesting findings.

Last but not the least, this study only explored whether and when response will have impact on virality considering the overall response rate is not high. Since the effectiveness of response is found determined by multiple dimensions, future research can also continue exploring in this direction if more response data can be collected. For example, is there any difference if the complaint is responded by the official account or by the staff's account? In which conditions will organisations respond in accommodative or defensive tone and whether this will lead to variance in virality or not? Text mining techniques can also be applied to explore whether the linguistic attributes (e.g., linguistic similarity between the complainer and the responder, humorous responses, readability and logic of the response) can have any impact on reader's attitude towards the organisation. Since everyone can interact with each other on social media, researchers may also be interested in exploring how will the following interactions among the replies (complainer or brand supporter) change the direction of the conversation. For the viral complaints, whether the complainer's updates on the satisfied/dissatisfied recovery will lead to a new wave of virality can also be an interesting research topic.

Appendices

Appendix A: Structure and Example of Collected Data

Appendix A-1 User Tweets

Item Name	Description	Example
ID	ID of the tweet	162053112295762xxxx
User ID	ID of the Twitter user	32748902xxxx
Username	Name of the Twitter user	ABC123xxxx
User followers	The Twitter user's follower number	3975
User tweets	The total number of the user's tweets	1846
User description	User's own description	💙 Jazz lover.
User location	The location of the user	North Carolina, USA
Conversation ID	The ID of the whole conversation, and the tweets based on the same conversation share the same conversation ID.	162052764731822xxxx
Text	Full text of the Tweet.	@Marriott Solutions and resolutions are mandatory obligations with Fortune 500 Companies in providing customer satisfaction! Check out https://t.co/akQtFQ9bg5 (attached) "core values, ethics and business code of conduct." Cont'd 1/
Attachment	The attached media of the Tweet, shown in dictionary format.	{'media_keys': ['3_1620563233961811969', '3_1620563241079554049', '3_1620563249099079682', '3_1620563253473734658']}

Language	The (main) written language of the Tweet	2022 09 24 10:40:12
Created at	The time and date of the Tweet posted	2022 11 28 19:00:01
Retweets	Total number of retweets of this Tweet	2
Replies	Total number of replies of this Tweet	1
Likes	Total number of likes of this Tweet	8
Quotes	Total number of quotes of this Tweet	0
Reply to user ID	The ID of the user being replied in this Tweet.	19085xxxx
Reference Tweet	The ID of the referenced tweet and the type of reference, i.e., retweet, reply, like and quote.	[<ReferencedTweet id=158471745220601xxxx type=quoted, <ReferencedTweet id=158797870739377xxxx type=replied_to]

Appendix A-2 Brand Timeline

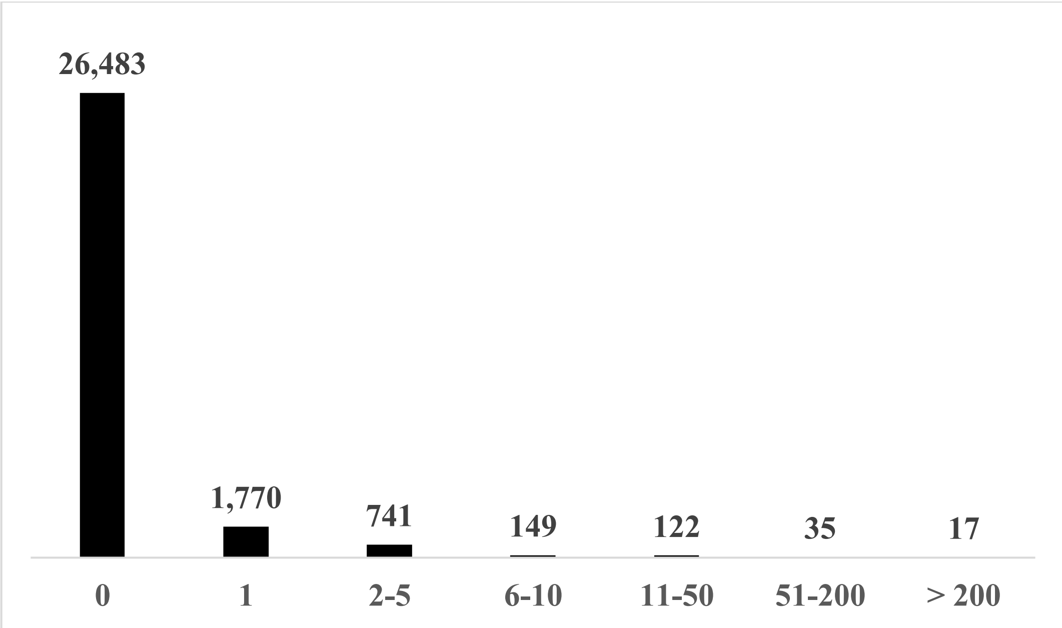
Item Name	Description	Example
User	Brand name	Marriott
User ID	ID of the brand account	14369314
ID	ID of the brand tweet	161288700921480xxxx
User followers	Number of the brand account followers	343600
User tweets	Number of the brand tweets on timeline	84700
Conversation ID	The ID of the whole conversation, and the tweets based on the same conversation share the same conversation ID.	161361177702289xxxx
Text	Full text of the Tweet.	@xxxx Yummy! It looks great 😋 Hope you enjoyed it. https://t.co/sYbZZw3npd
Created at	The time and date of the Tweet posted	2022 11 28 19:00:01
Retweets	Total number of retweets of this Tweet	2
Replies	Total number of replies of this Tweet	1
Likes	Total number of likes of this Tweet	8
Quotes	Total number of quotes of this Tweet	0
Reply to user ID	The ID of the user being replied in this Tweet by the brand.	131034604974838xxxx
Reference Tweet ID	The ID of the referenced tweet.	160869108032065xxxx

Appendix B: Applied Software and Dictionary

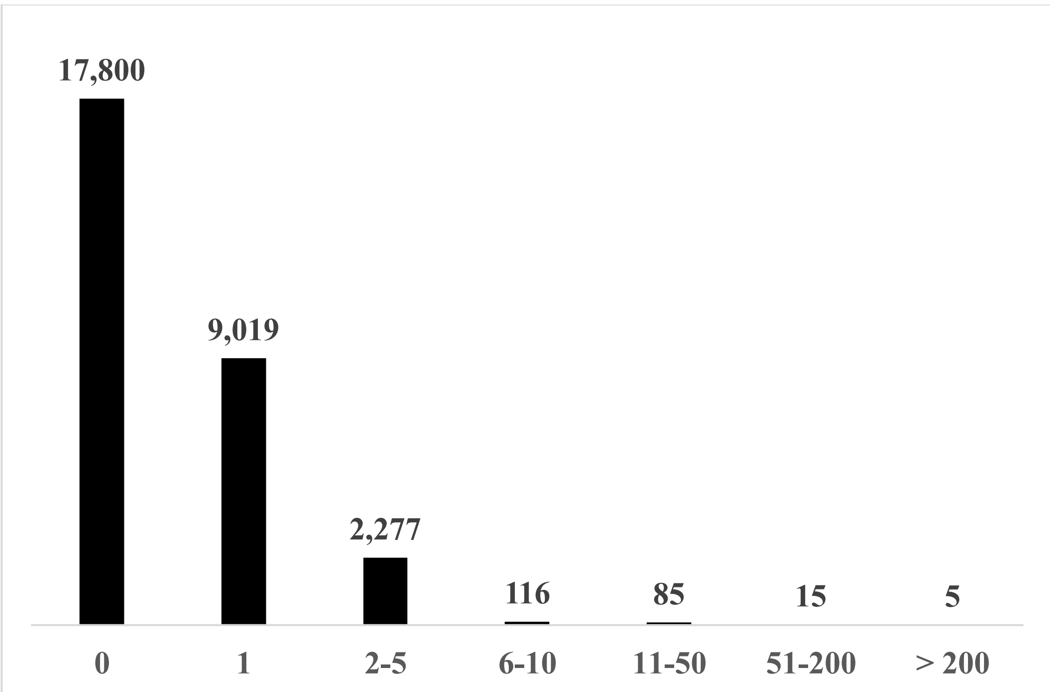
Name	Description	Reference	Source
Python	Programming language	Van Rossum and Drake (1995)	https://www.python.org/
Tweepy	Accessing Twitter API	Kunal *et al*. (2018)	https://www.tweepy.org/
NLTK	Natural language processing	Loper and Bird (2002)	https://www.nltk.org/
vaderSentiment	Sentiment analysis	Hutto and Gilbert (2014)	https://pypi.org/project/vaderSentiment/
TextBlob	Sentiment analysis	Shi *et al*. (2022)	https://textblob.readthedocs.io/en/dev/
sklearn	Machine learning library	Pedregosa *et al*. (2011)	https://scikit-learn.org/stable/
matplotlib	Plotting library	Hunter (2007)	https://matplotlib.org/
LIWC	Text analysis program	Tausczik and Pennebaker (2010)	https://www.liwc.app/
NumPy	Library for working with arrays	Harris *et al.* (2020)	https://numpy.org/
pandas	Data analysis library	McKinney (2011)	https://pandas.pydata.org/
seaborn	Visualization library	Waskom (2021)	https://seaborn.pydata.org/
SPSS	Statistical software	Field (2013)	https://www.ibm.com/products/spss-statistics

Appendix C: Distribution of the Number of Retweets, Replies, Likes, and Quotes

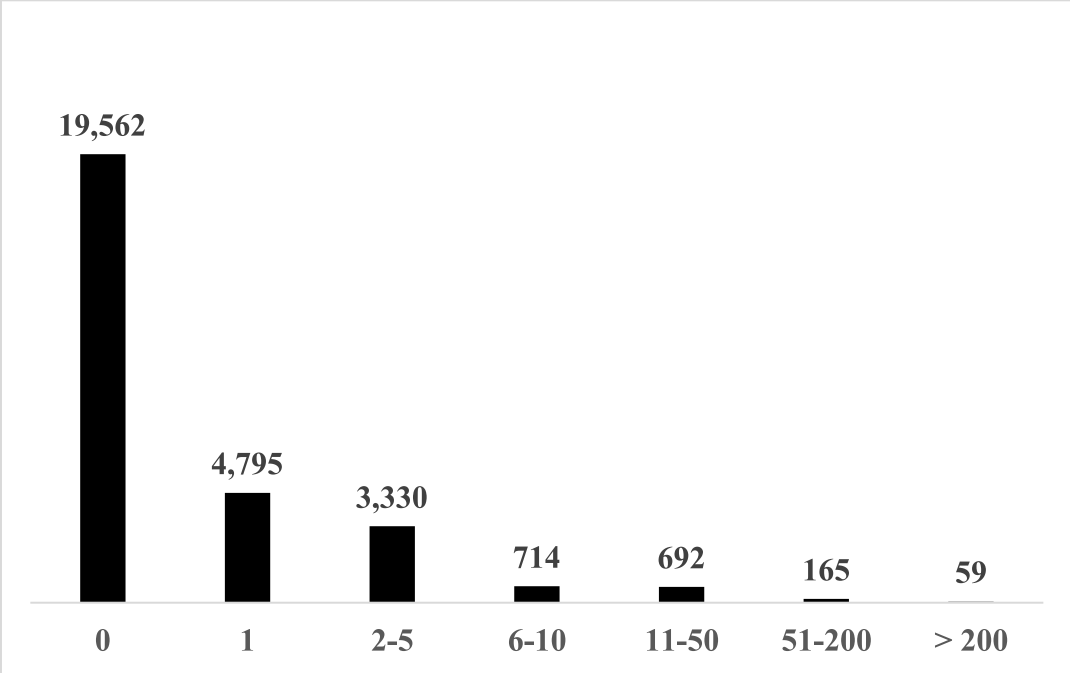
Appendix C-1: Distribution of Number of Retweets



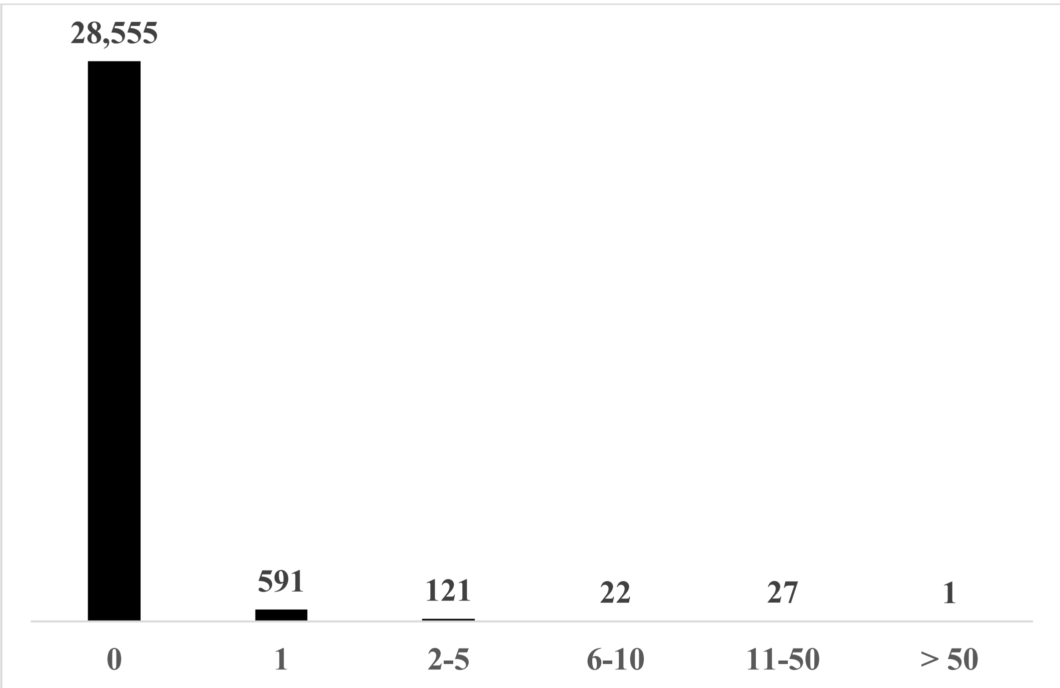
Appendix C-2: Distribution of Number of Replies



Appendix C-3: Distribution of Number of Likes



Appendix C-4: Distribution of Number of Quotes



Appendix D: LIWC-22 Language Dimensions

Category	Abbrev.	Description/Most frequently used examples
Summary Variables		
Word count	WC	Total word count
Analytical thinking	Analytic	Metric of logical, formal thinking
Clout	Clout	Language of leadership, status
Authentic	Authentic	Perceived honesty, genuineness
Emotional tone	Tone	Degree of positive (negative) tone
Words per sentence	WPS	Average words per sentence
Big words	BigWords	Percent words 7 letters or longer
Dictionary words	Dic	Percent words captured by LIWC
Linguistic Dimensions		
Total function words	function	the, to, and, I
Total pronouns	pronoun	I, you, that, it
Personal pronouns	ppron	I, you, my, me
1st person singular	i	I, me, my, myself
1st person plural	we	we, our, us, lets
2nd person	you	you, your, u, yourself
3rd person singular	shehe	he, she, her, his
3rd person plural	they	they, their, them, themsel*
Impersonal pronouns	ipron	that, it, this, what
Determiners	det	the, at, that, my
Articles	article	a, an, the, alot
Numbers	number	one, two, first, once
Prepositions	prep	to, of, in, for
Auxiliary verbs	auxverb	is, was, be, have
Adverbs	adverb	so, just, about, there
Conjunctions	conj	and, but, so, as
Negations	negate	not, no, never, nothing
Common verbs	verb	is, was, be, have
Common adjectives	adj	more, very, other, new
Quantities	quantity	all, one, more, some
Psychological Processes		
Drives	Drives	we, our, work, us
Affiliation	affiliation	we, our, us, help
Achievement	achieve	work, better, best, working
Power	power	own, order, allow, power

Cognition	Cognition	is, was, but, are
All-or-none	allnone	all, no, never, always
Cognitive processes	cogproc	but, not, if, or, know
Insight	insight	know, how, think, feel
Causation	cause	how, because, make, why
Discrepancy	discrep	would, can, want, could
Tentative	tentat	if, or, any, something
Certitude	certitude	really, actually, of course, real
Differentiation	differ	but, not, if, or
Memory	memory	remember, forget, remind, forgot
Affect	Affect	good, well, new, love
Positive tone	tone_pos	good, well, new, love
Negative tone	tone_neg	bad, wrong, too much, hate
Emotion	emotion	good, love, happy, hope
Positive emotion	emo_pos	good, love, happy, hope
Negative emotion	emo_neg	bad, hate, hurt, tired
Anxiety	emo_anx	worry, fear, afraid, nervous
Anger	emo_anger	hate, mad, angry, frustr*
Sadness	emo_sad	:(, sad, disappoint*, cry
Swear words	swear	shit, fuckin*, fuck, damn
Social processes	Social	you, we, he, she
Social behavior	socbehav	said, love, say, care
Prosocial behavior	prosocial	care, help, thank, please
Politeness	polite	thank, please, thanks, good morning
Interpersonal conflict	conflict	fight, kill, killed, attack
Moralization	moral	wrong, honor*, deserv*, judge
Communication	comm	said, say, tell, thank*
Social referents	socrefs	you, we, he, she
Family	family	parent*, mother*, father*, baby
Friends	friend	friend*, boyfriend*, girlfriend*, dude
Female references	female	she, her, girl, woman
Male references	male	he, his, him, man
Expanded Dictionary		
Culture	Culture	car, united states, govern*, phone
Politics	politic	united states, govern*, congress*, senat*
Ethnicity	ethnicity	american, french, chinese, indian
Technology	tech	car, phone, comput*, email*
Lifestyle	lifestyle	work, home, school, working
Leisure	leisure	game*, fun, play, party*
Home	home	home, house, room, bed

Work	work	work, school, working, class
Money	money	business*, pay*, price*, market*
Religion	relig	god, hell, christmas*, church
Physical	physical	medic*, food*, patients, eye*
Health	health	medic*, patients, physician*, health
Illness	illness	hospital*, cancer*, sick, pain
Wellness	wellness	healthy, gym*, supported, diet
Mental health	mental	mental health, depressed, suicid*, trauma*
Substances	substances	beer*, wine, drunk, cigar*
Sexual	sexual	sex, gay, pregnan*, dick
Food	food	food*, drink*, eat, dinner*
Death	death	death*, dead, die, kill
States		
Need	need	have to, need, had to, must
Want	want	want, hope, wanted, wish
Acquire	acquire	get, got, take, getting
Lack	lack	don’t have, didn’t have, *less, hungry
Fulfilled	fulfill	enough, full, complete, extra
Fatigue	fatigue	tired, bored, don’t care, boring
Motives		
Reward	reward	opportun*, win, gain*, benefit*
Risk	risk	secur*, protect*, pain, risk*
Curiosity	curiosity	scien*, look* for, research*, wonder
Allure	allure	have, like, out, know
Perception	Perception	in, out, up, there
Attention	attention	look, look* for, watch, check
Motion	motion	go, come, went, came
Space	space	in, out, up, there
Visual	visual	see, look, eye*, saw
Auditory	auditory	sound*, heard, hear, music
Feeling	feeling	feel, hard, cool, felt
Time orientation		
Time	time	when, now, then, day
Past focus	focuspast	was, had, were, been
Present focus	focuspresent	is, are, I’m, can
Future focus	focusfuture	will, going to, have to, may
Conversational	Conversation	yeah, oh, yes, okay
Netspeak	netspeak	:), u, lol, haha*
Assent	assent	yeah, yes, okay, ok
Nonfluencies	nonflu	oh, um, uh, i i

Fillers	filler	rr*, wow, sooo*, youknow

*Notes: “Words/Entries in category” refers to the number of different words and/or entries that make up the variable category.

Source: Boyd *et al*. (2022)

Appendix E: Descriptive Statistics of Sum of Retweets, Replies, and Likes

Appendix E-1: Descriptive Statistics of Sum of Retweets, Replies, and Likes for Negative Tweets of Each Brand

Descriptive Statistics[a]

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Brand 1	724	0	853	3.66	36.006	20.448	.091	453.601	.181
Brand 2	964	0	179	2.06	9.299	14.914	.079	245.557	.157
Brand 3	816	0	225	3.52	15.755	9.661	.086	110.182	.171
Brand 4	239	0	17	1.58	2.339	3.403	.157	14.551	.314
Brand 5	843	0	1379	7.55	77.732	15.637	.084	253.696	.168
Brand 6	327	0	30	1.35	2.312	7.704	.135	82.737	.269
Brand 7	199	0	140	3.90	12.393	7.912	.172	77.642	.343
Brand 8	228	0	12627	59.47	836.194	15.088	.161	227.755	.321
Brand 9	856	0	180	2.96	10.861	9.532	.084	113.854	.167
Brand 10	5070	0	1306	3.59	27.357	29.657	.034	1164.215	.069
Brand 11	1999	0	2659	5.90	71.372	30.692	.055	1050.079	.109
Brand 12	1720	0	564	2.54	17.778	23.092	.059	640.984	.118
Brand 13	576	0	585	2.29	24.624	23.166	.102	548.174	.203
Brand 14	372	0	564	3.62	31.368	16.019	.126	278.730	.252
Brand 15	128	0	8	.92	1.367	2.794	.214	10.197	.425
Brand 16	223	0	146	4.17	13.423	7.421	.163	65.686	.324
Brand 17	8787	0	26302	8.40	287.711	87.249	.026	7944.962	.052
Brand 18	833	0	428	4.04	24.387	14.134	.085	222.371	.169
Brand 19	56	0	32	2.75	6.495	3.571	.319	12.638	.628
Brand 20	26	0	79	10.08	21.126	2.608	.456	5.859	.887
Brand 21	94	0	51	2.40	5.830	6.688	.249	53.061	.493
Brand 22	1051	0	364	4.18	20.464	11.870	.075	168.699	.151
Brand 23	845	0	4291	7.73	148.098	28.741	.084	831.927	.168
Brand 24	104	0	29	2.27	4.720	4.304	.237	20.176	.469
Brand 25	377	0	902	5.31	47.161	18.422	.126	350.239	.251
Brand 26	180	0	93	3.48	9.616	6.516	.181	51.398	.360
Brand 27	1560	0	70	.92	3.177	13.004	.062	235.558	.124
Brand 28	112	0	40	1.96	4.851	5.437	.228	36.424	.453

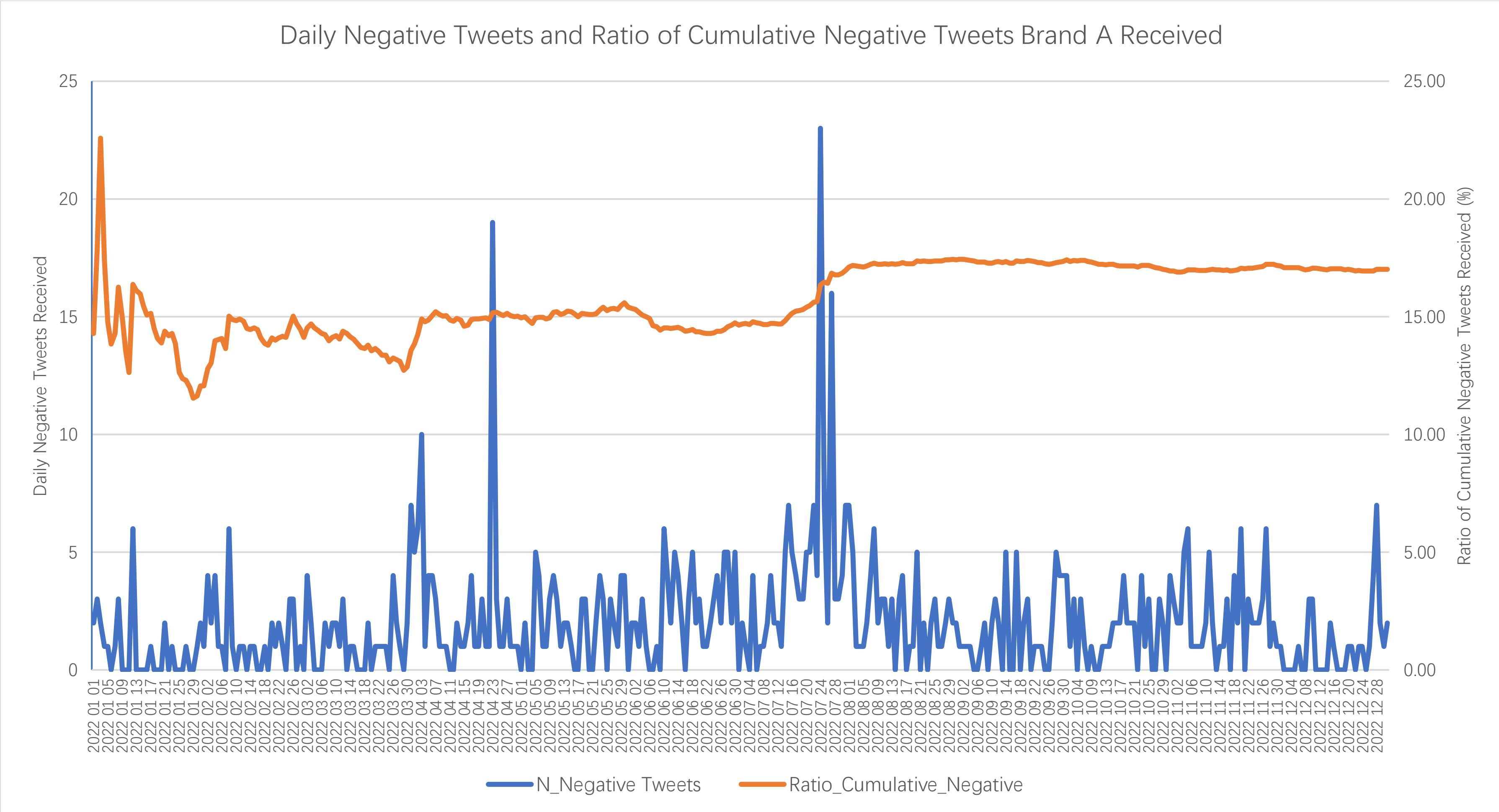
Appendix E-2: Descriptive Statistics of Sum of Retweets, Replies, and Likes for English Tweets of Each Brand

Descriptive Statistics[a]

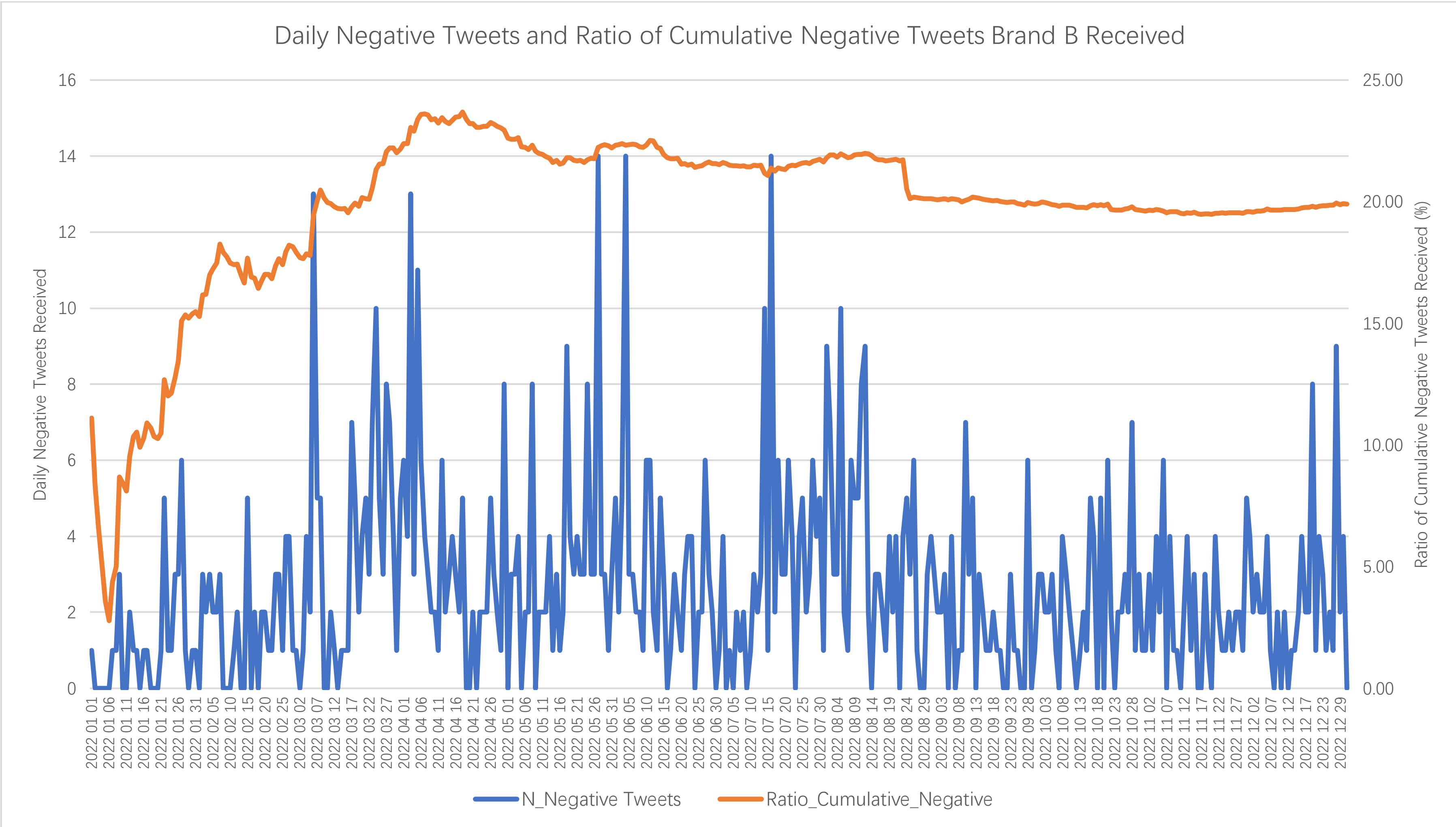
	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Brand 1	3619	0	853	2.45	17.836	35.268	.041	1529.328	.081
Brand 2	4844	0	639	1.99	16.671	28.915	.035	949.282	.070
Brand 3	5492	0	8902	14.56	217.691	25.220	.033	767.197	.066
Brand 4	1943	0	310	2.85	9.759	18.989	.056	530.417	.111
Brand 5	5470	0	2546	4.81	51.140	33.619	.033	1369.314	.066
Brand 6	2042	0	397	2.82	14.943	19.288	.054	432.226	.108
Brand 7	2560	0	920	3.98	21.963	30.315	.048	1199.199	.097
Brand 8	4803	0	12627	7.15	183.945	67.341	.035	4616.688	.071
Brand 9	5164	0	7199	13.89	179.684	28.427	.034	995.304	.068
Brand 10	26072	0	5807	4.45	58.003	73.442	.015	6748.517	.030
Brand 11	11408	0	3012	4.75	49.259	41.859	.023	2153.854	.046
Brand 12	9802	0	5372	4.92	71.171	55.130	.025	3969.463	.049
Brand 13	2620	0	590	2.67	17.757	27.773	.048	896.971	.096
Brand 14	2746	0	564	3.96	19.369	17.193	.047	397.617	.093
Brand 15	1217	0	99	1.91	5.525	9.221	.070	117.764	.140
Brand 16	3967	0	2479	4.37	43.605	48.034	.039	2641.890	.078
Brand 17	42218	0	45772	8.51	310.161	110.091	.012	13983.317	.024
Brand 18	8030	0	44440	21.25	554.804	67.052	.027	5175.418	.055
Brand 19	1190	0	9488	12.90	277.757	33.505	.071	1141.900	.142
Brand 20	711	0	815	5.31	34.148	19.795	.092	452.124	.183
Brand 21	869	0	2009	5.59	69.329	27.941	.083	806.111	.166
Brand 22	6478	0	6314	11.96	144.445	30.335	.030	1092.338	.061
Brand 23	4112	0	4291	4.99	73.782	50.329	.038	2815.574	.076
Brand 24	2617	0	2082	7.92	61.817	23.719	.048	677.744	.096
Brand 25	5291	0	1611	7.46	52.134	18.640	.034	435.494	.067
Brand 26	2197	0	1633	8.17	56.896	19.751	.052	475.651	.104
Brand 27	4870	0	751	2.62	18.069	26.672	.035	899.127	.070
Brand 28	1623	0	4382	9.10	113.521	35.691	.061	1362.027	.121

Appendix F: Time Series Analysis by Brands

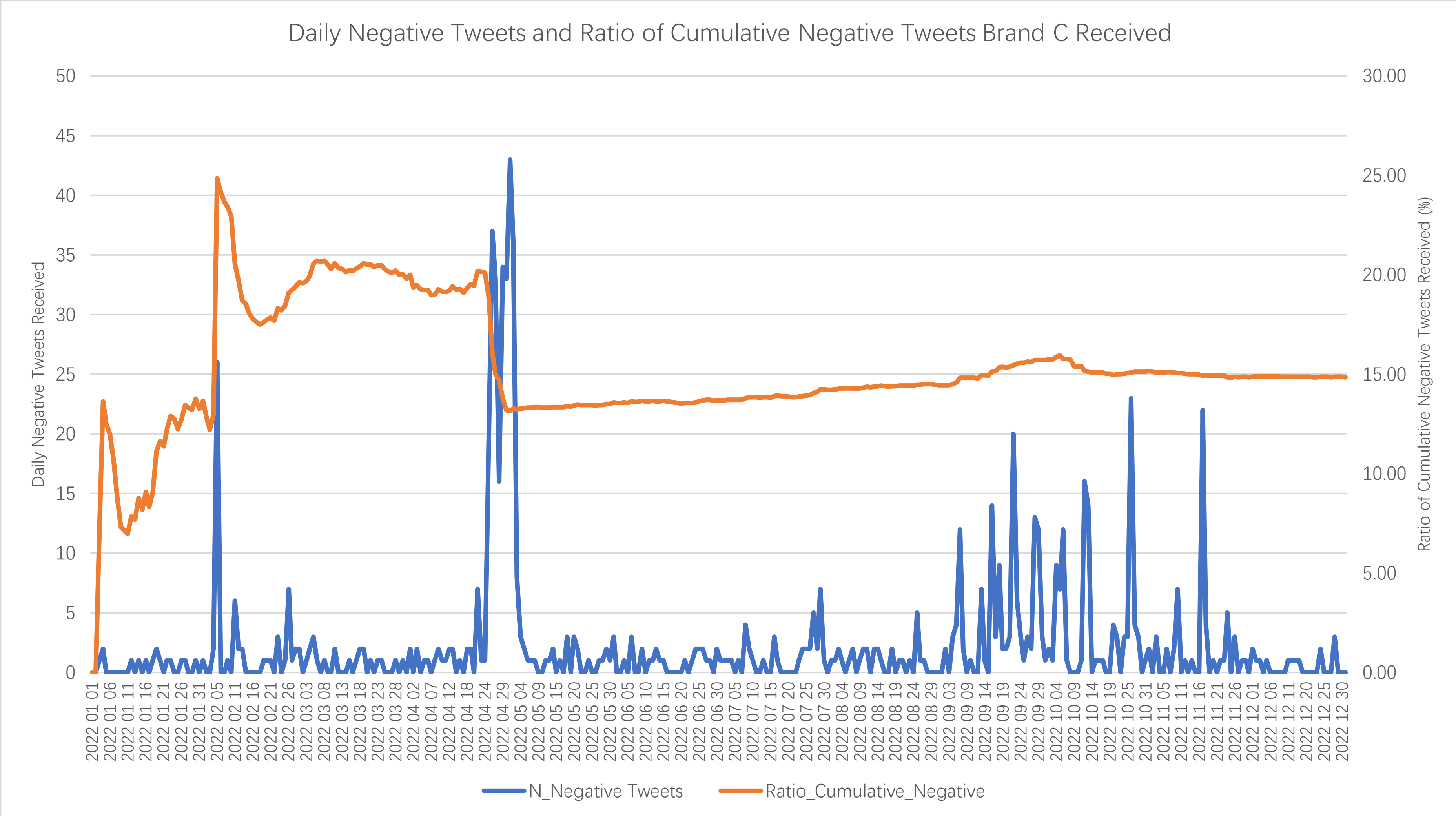
Appendix F-1: Time Series of Negative Tweets about Brand A



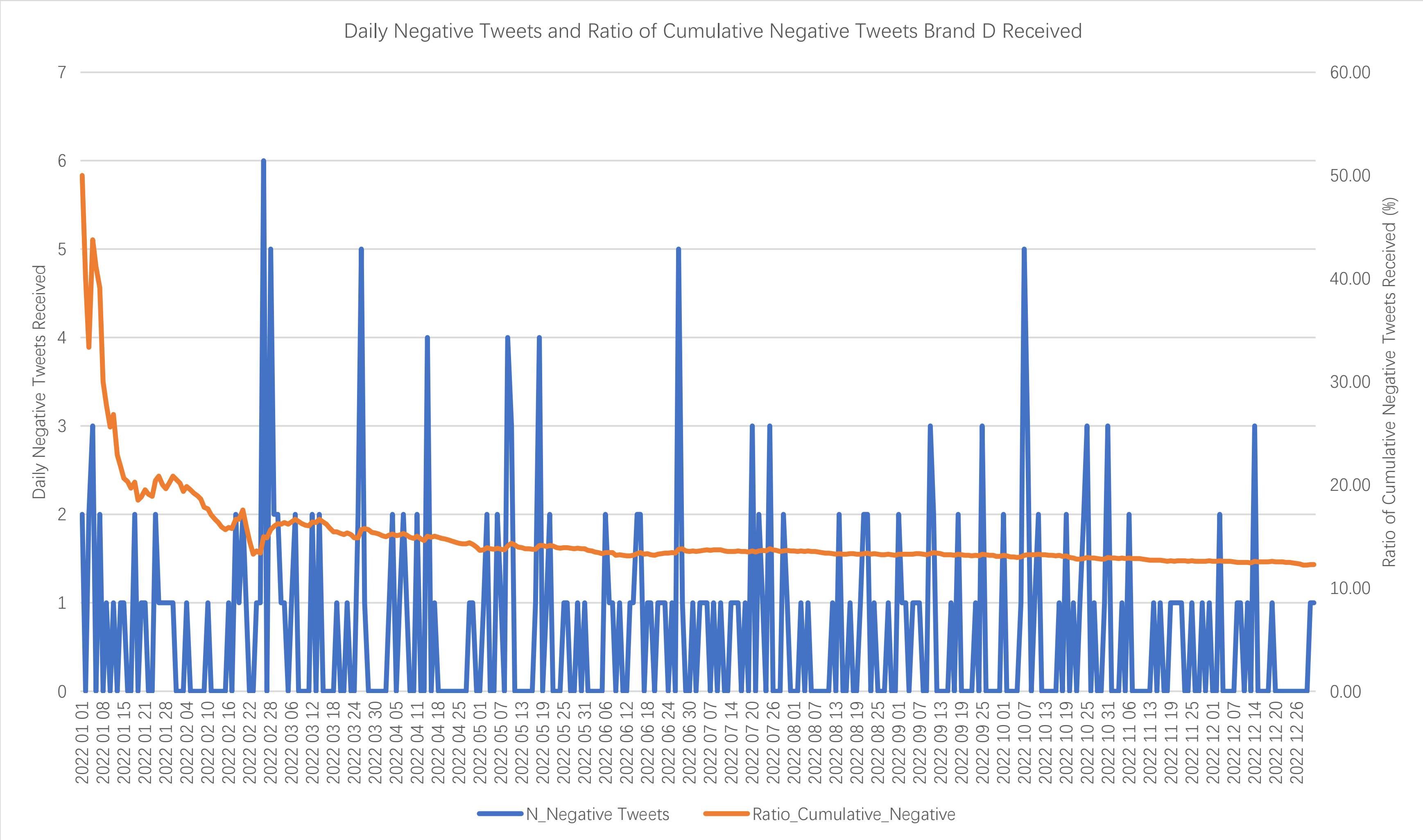
Appendix F-2: Time Series of Negative Tweets about Brand B



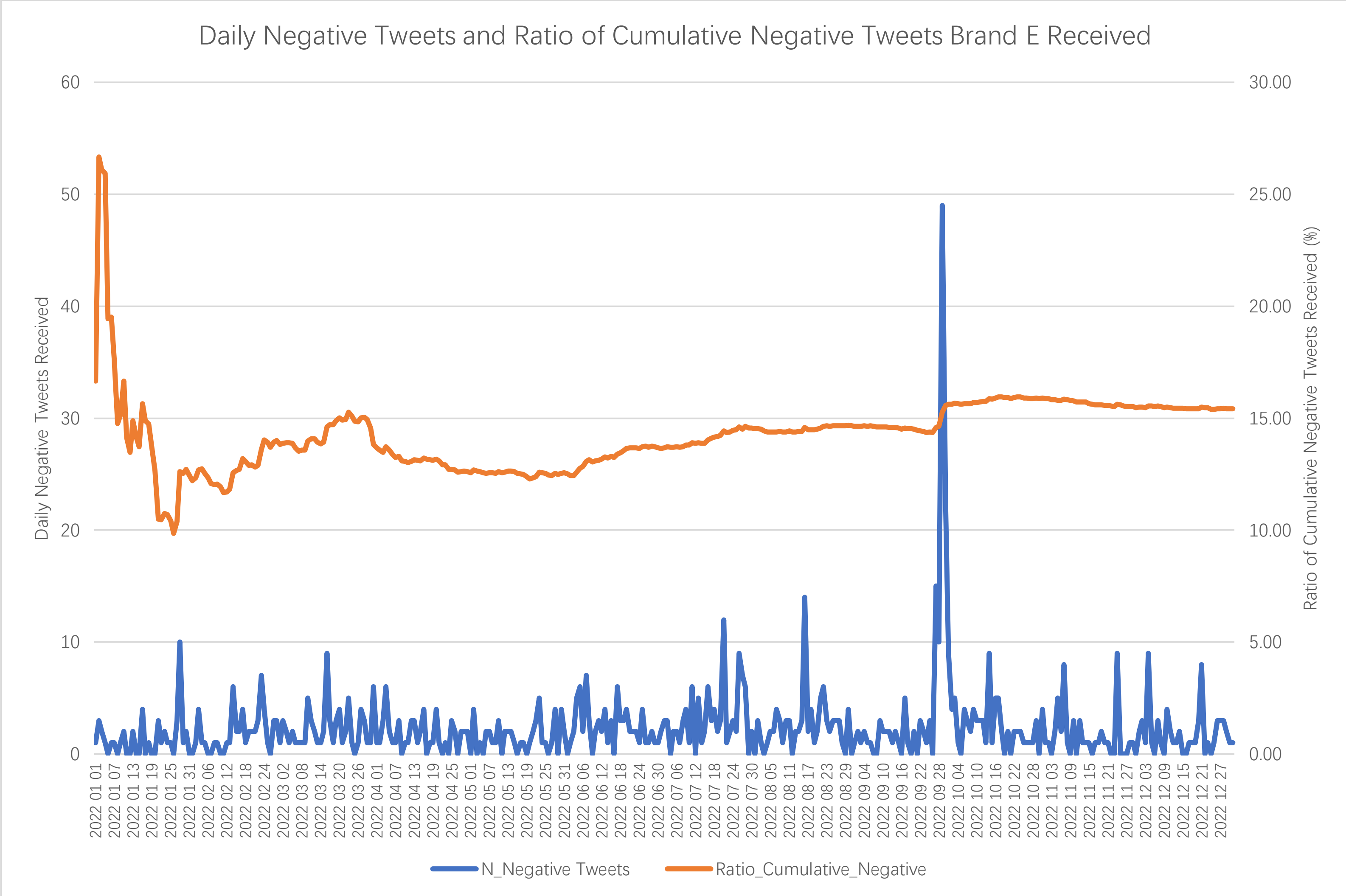
Appendix F-3: Time Series of Negative Tweets about Brand C



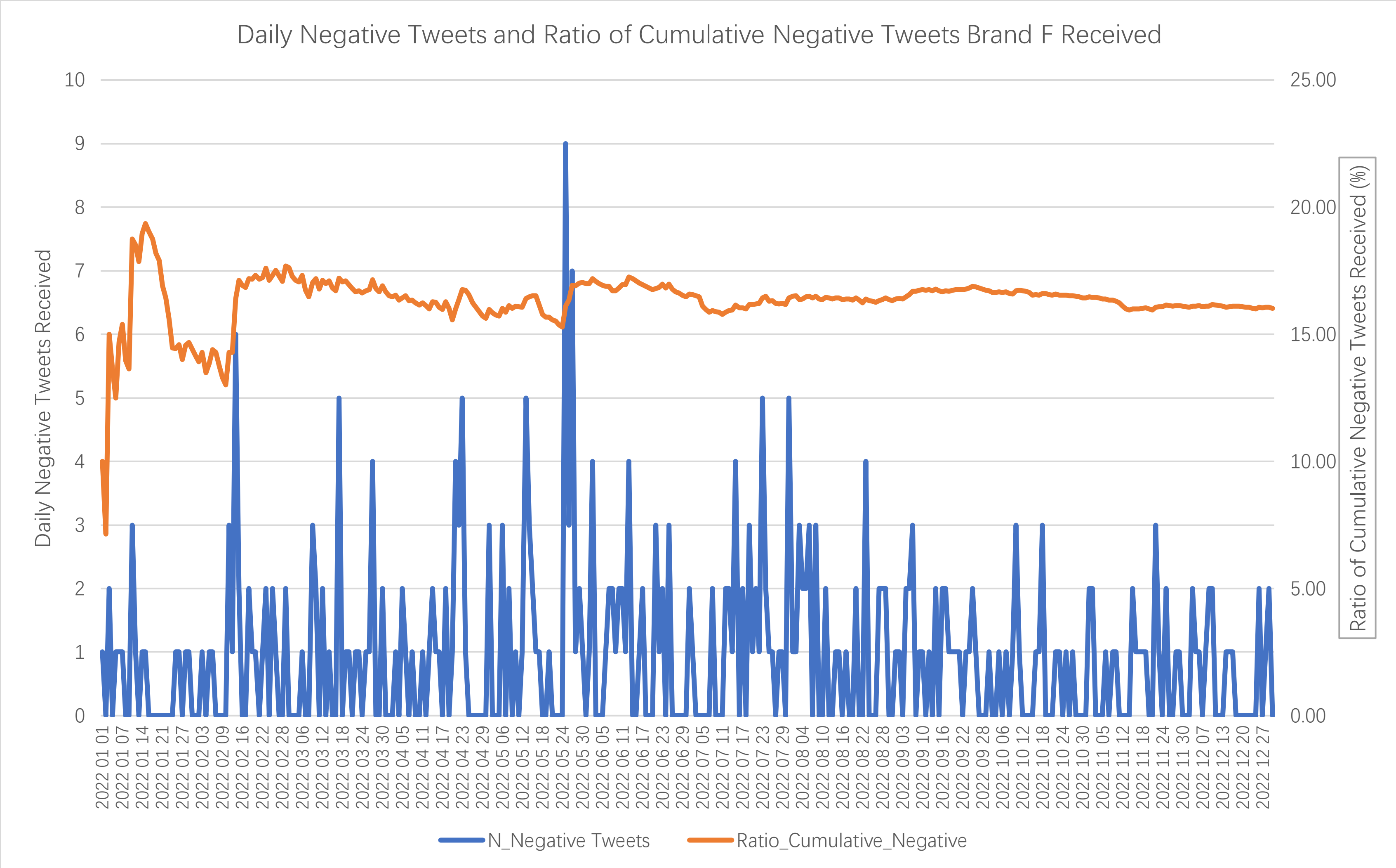
Appendix F-4: Time Series of Negative Tweets about Brand D



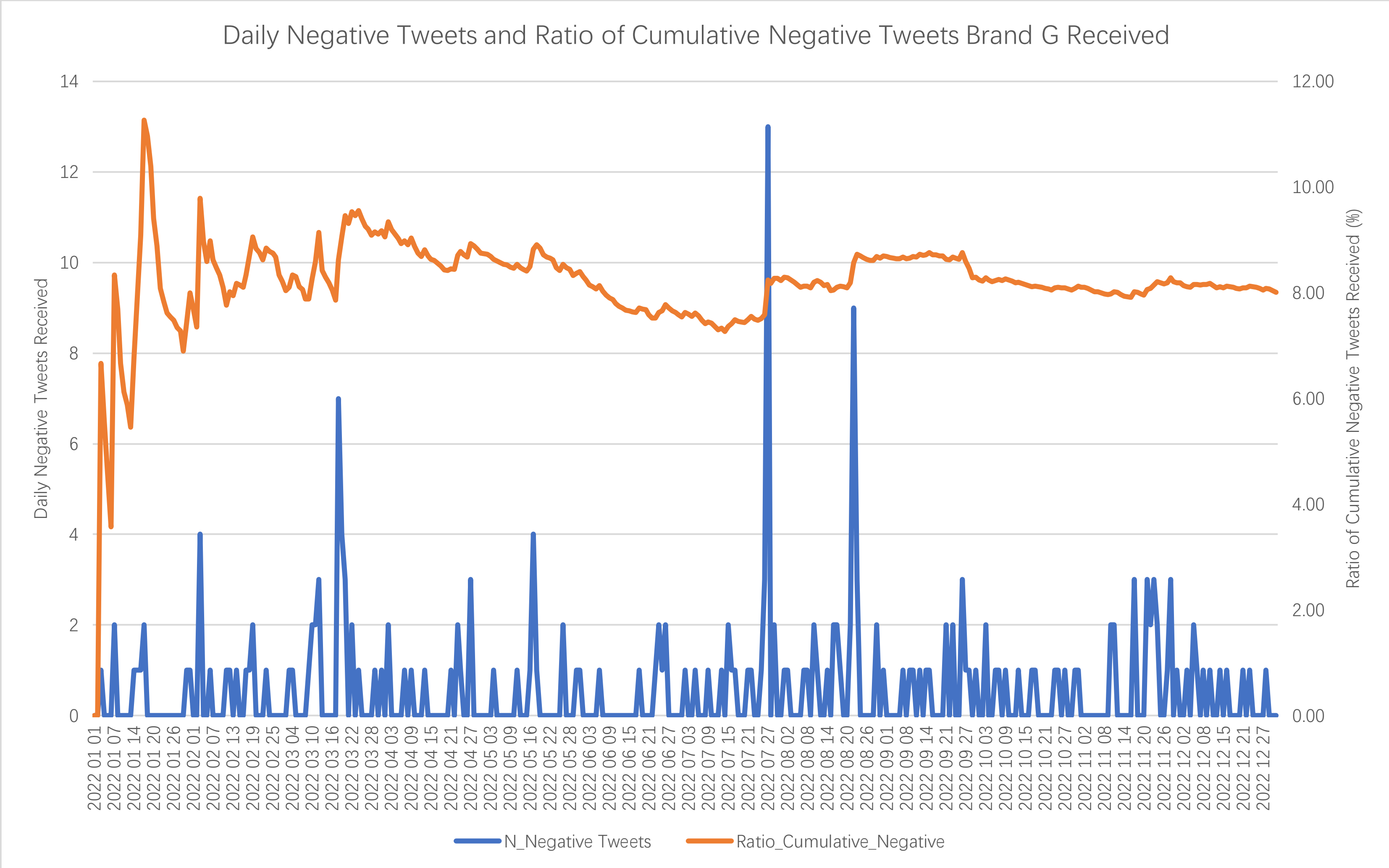
Appendix F-5: Time Series of Negative Tweets about Brand E



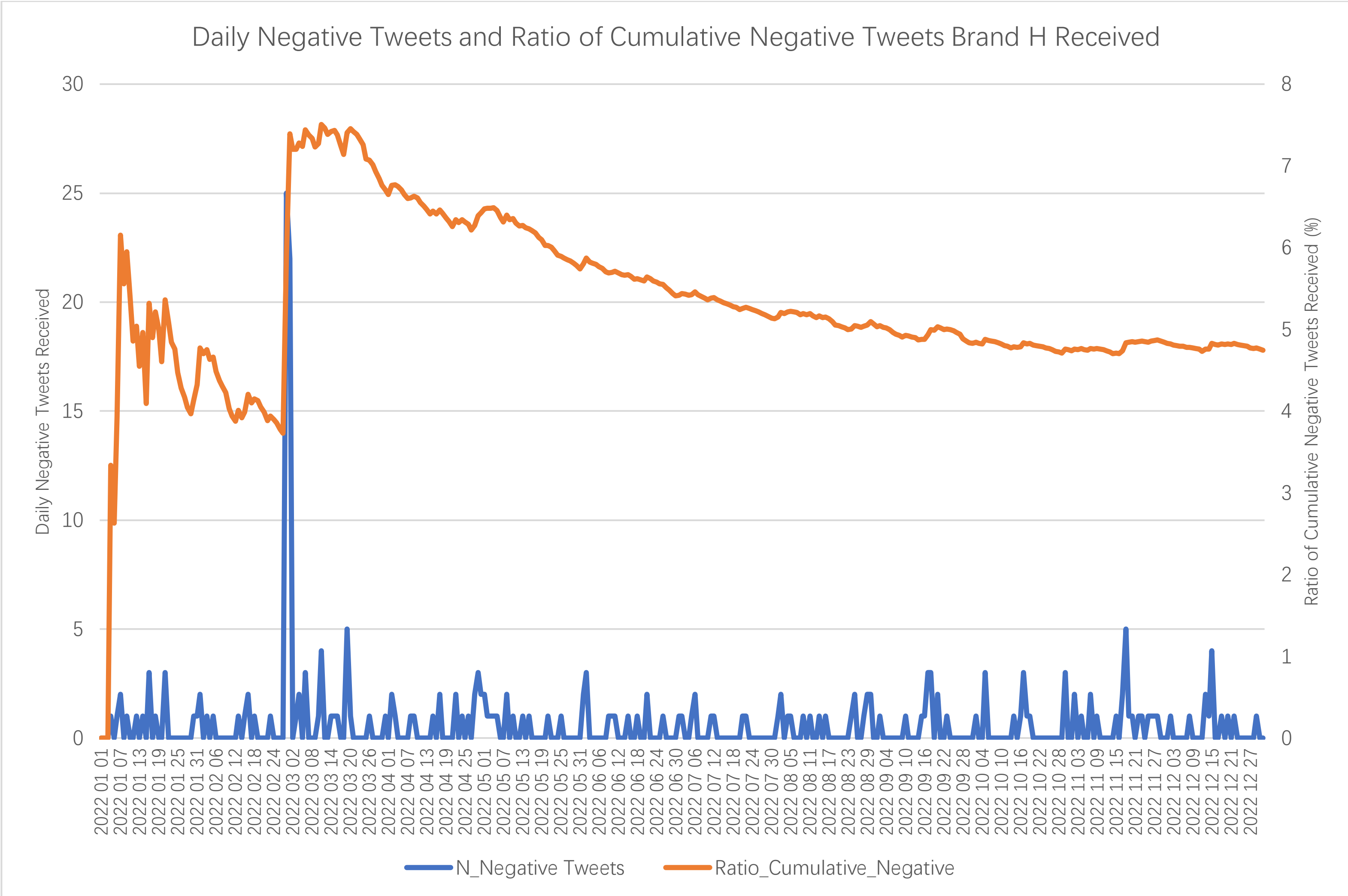
Appendix F-6: Time Series of Negative Tweets about Brand F



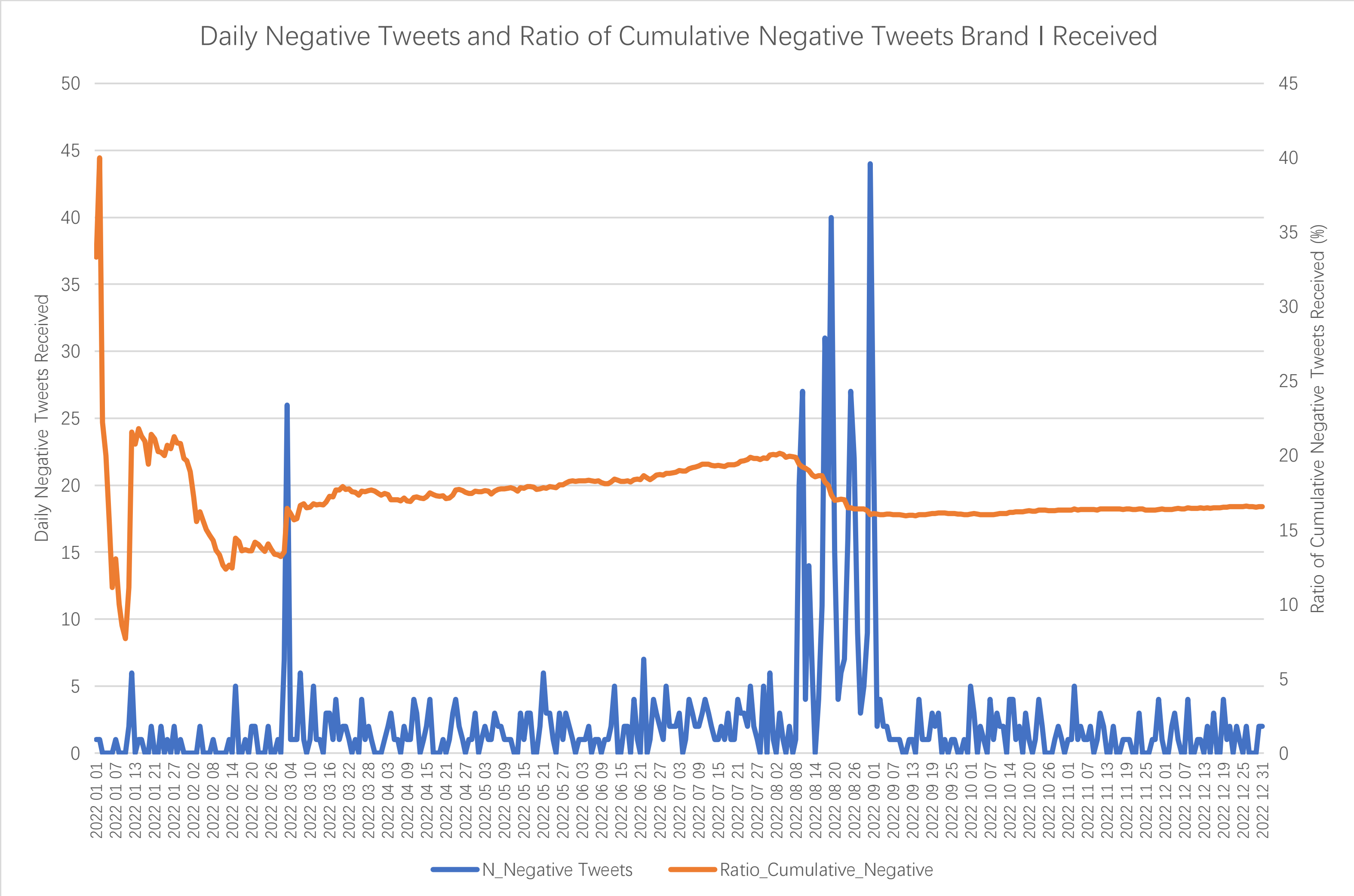
Appendix F-7: Time Series of Negative Tweets about Brand G



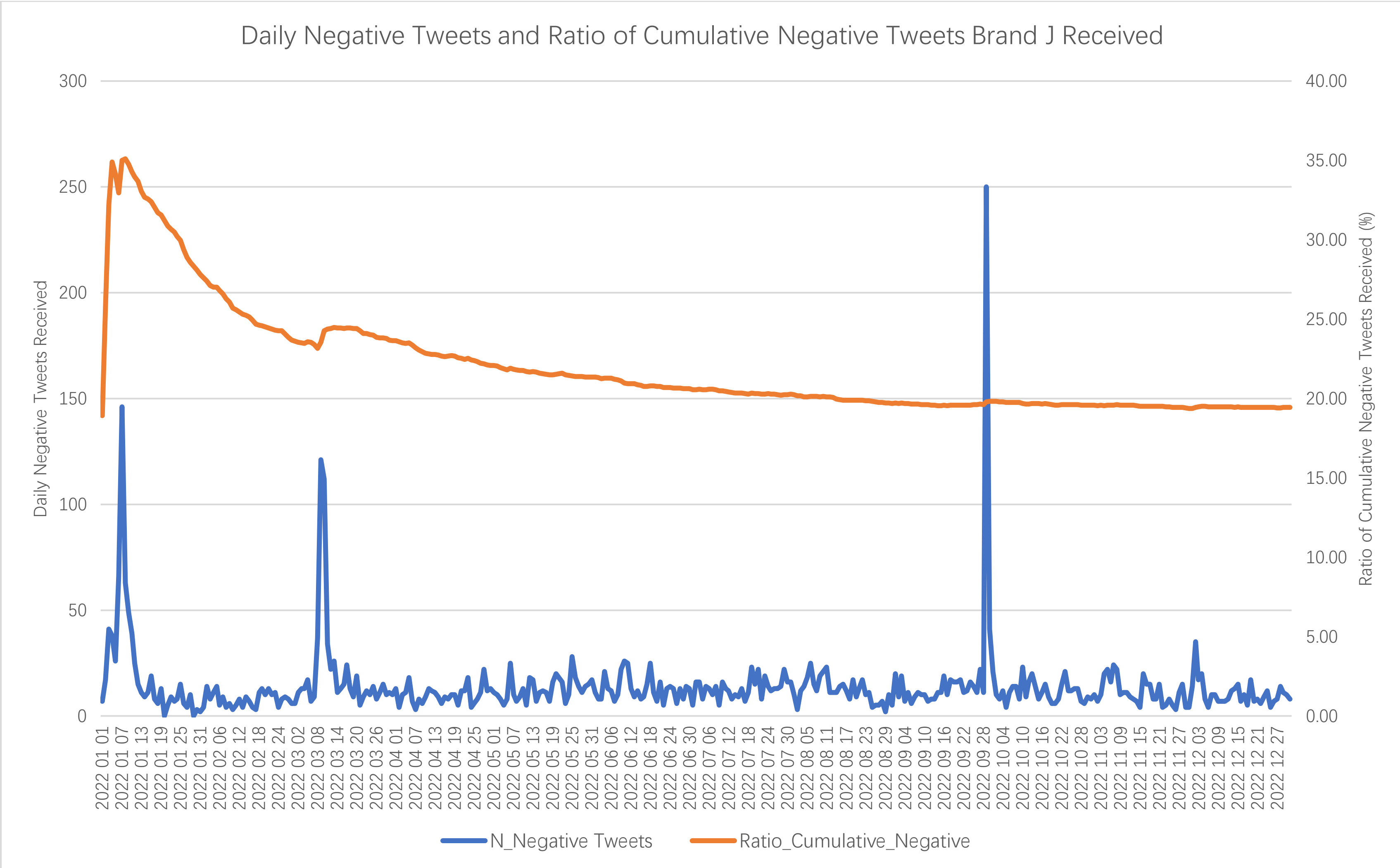
Appendix F-8: Time Series of Negative Tweets about Brand H



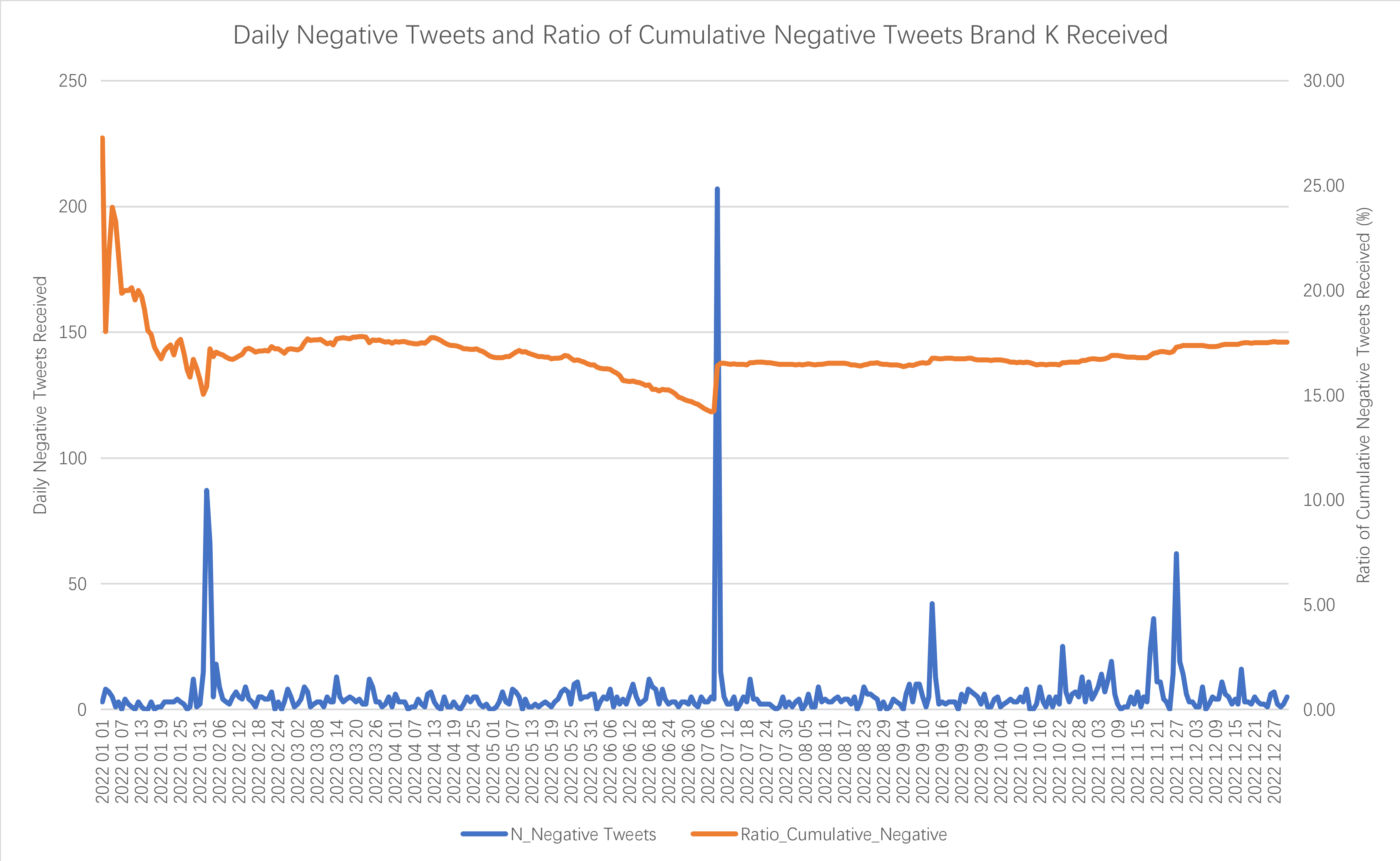
Appendix F-9: Time Series of Negative Tweets about Brand I



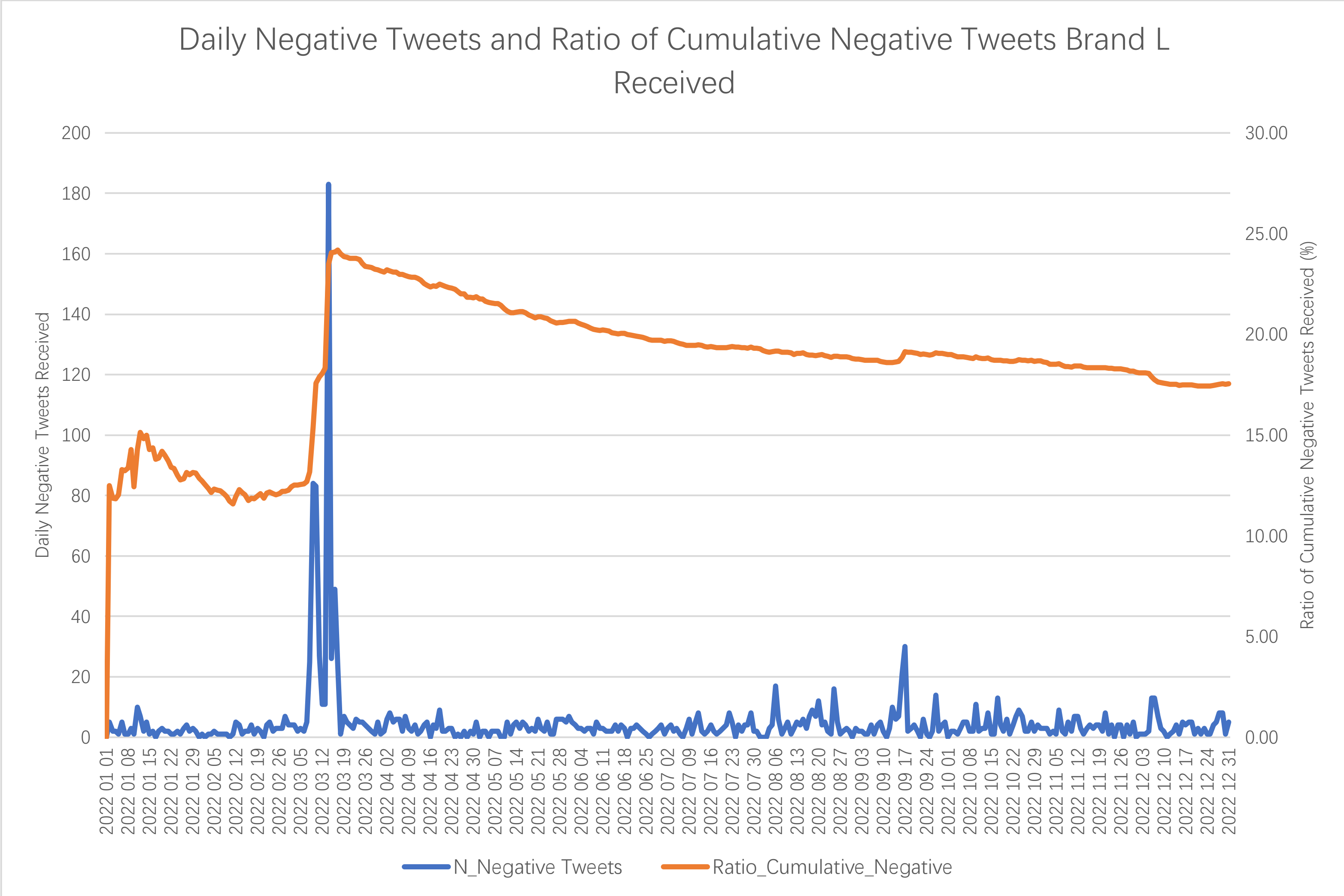
Appendix F-10: Time Series of Negative Tweets about Brand J



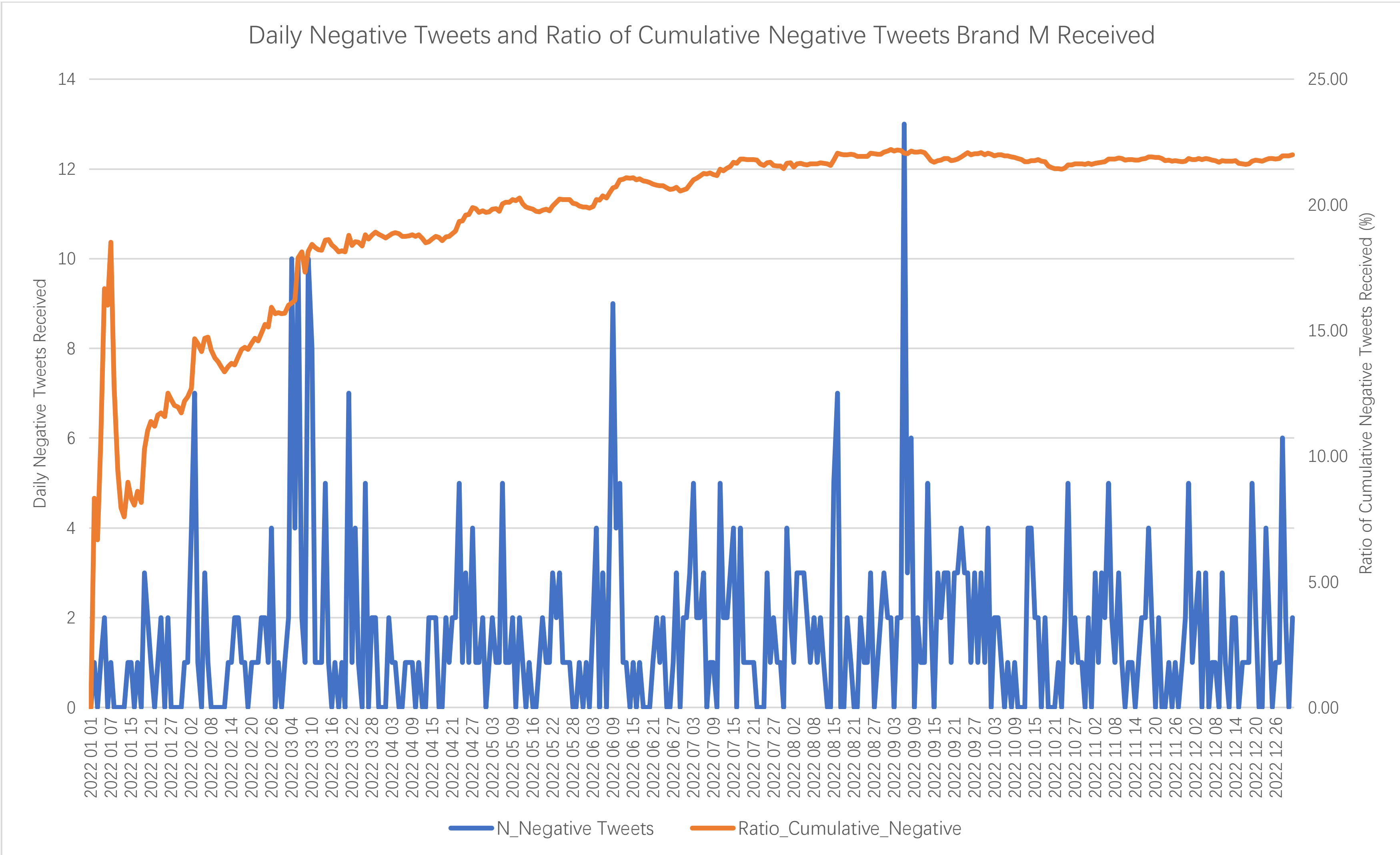
Appendix F-11: Time Series of Negative Tweets about Brand K



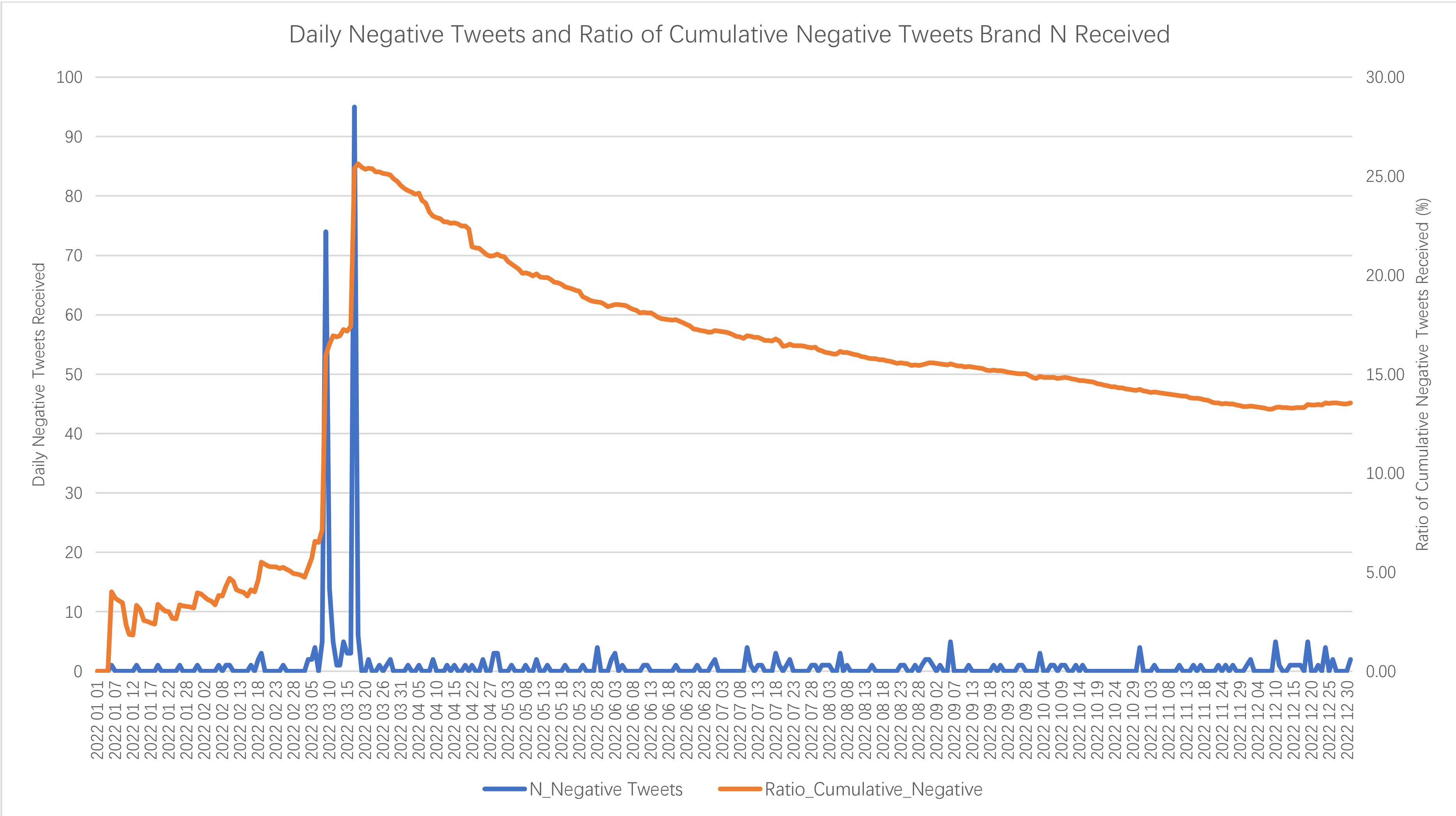
Appendix F-12: Time Series of Negative Tweets about Brand L



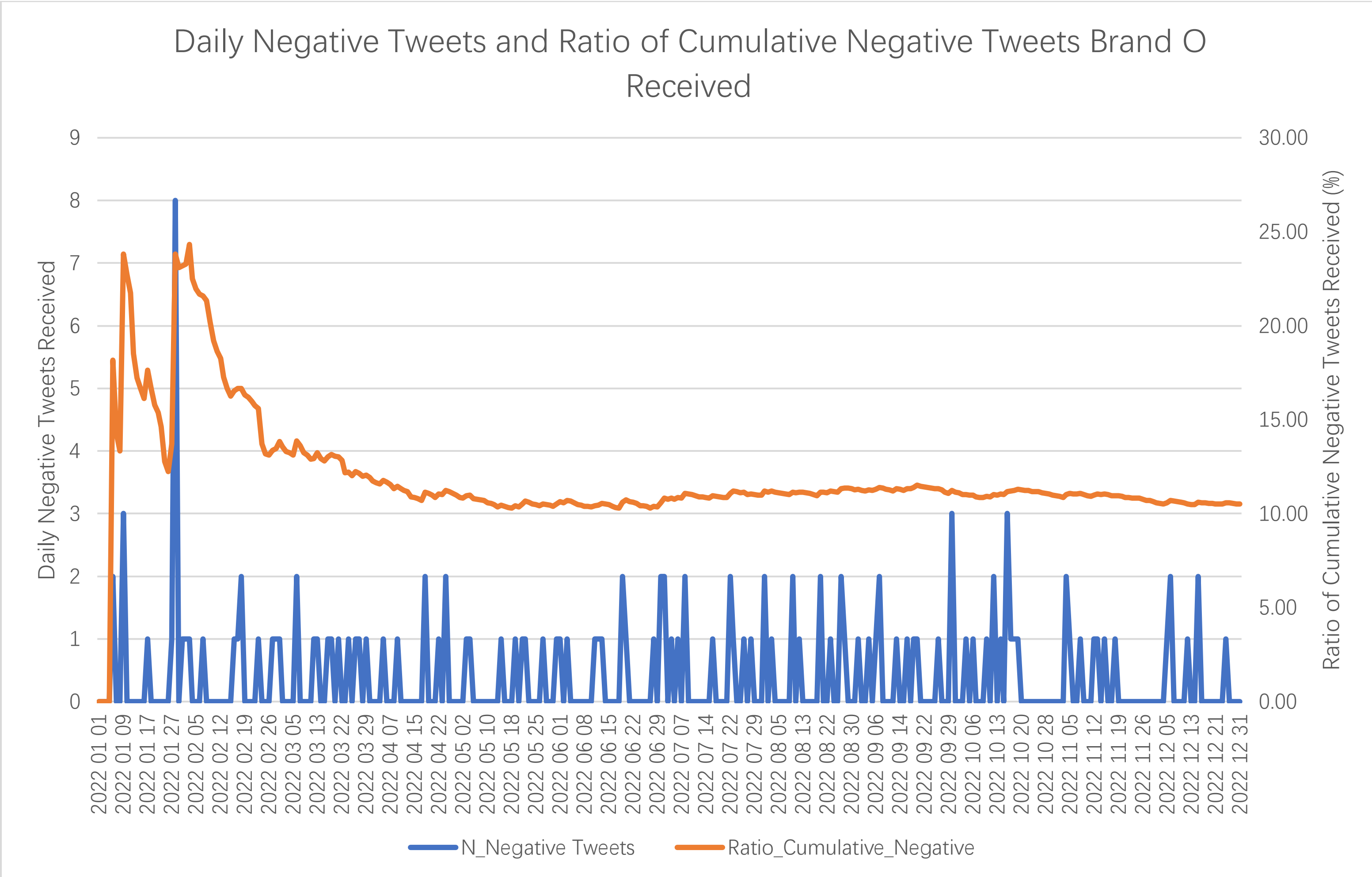
Appendix F-13: Time Series of Negative Tweets about Brand M



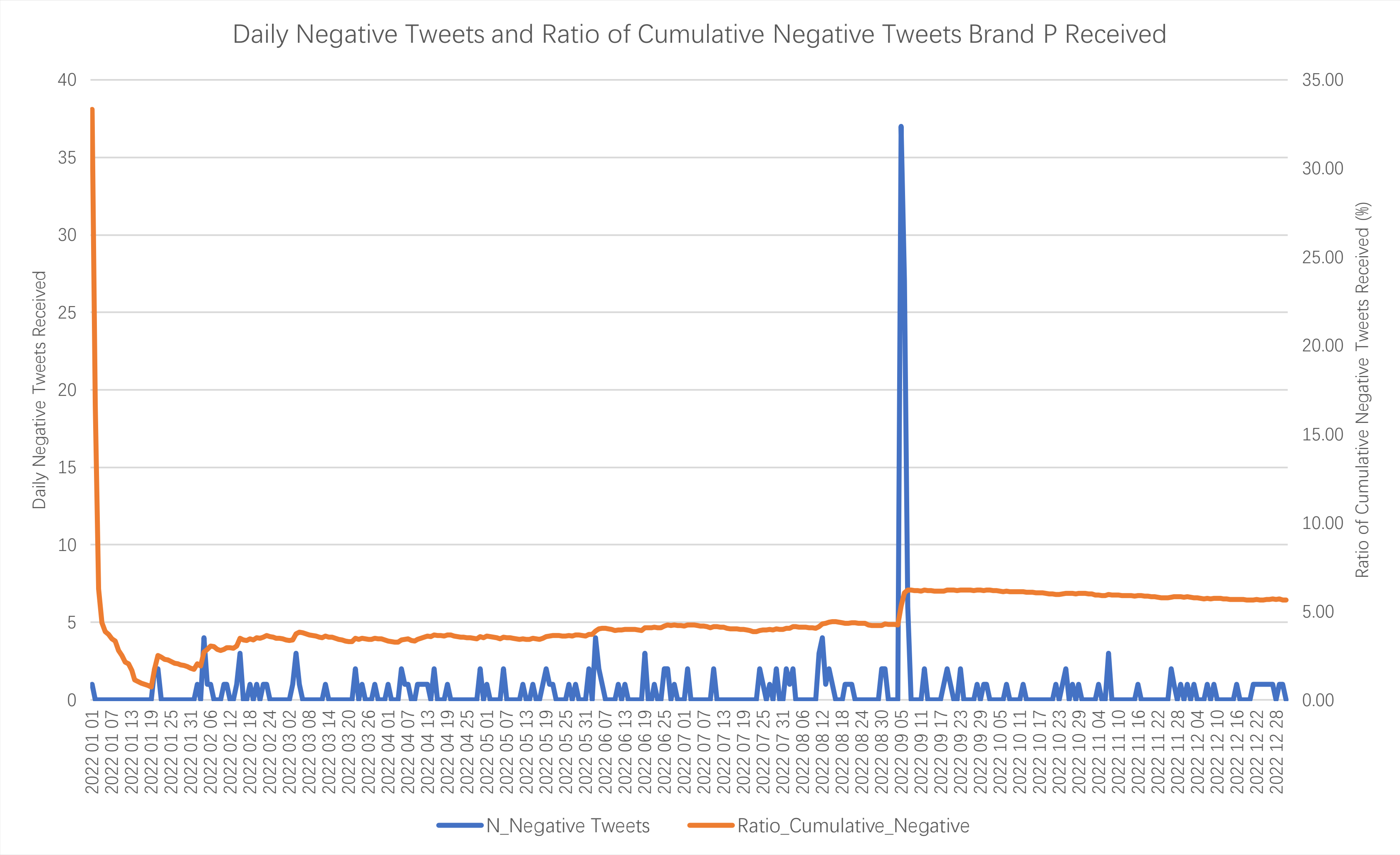
Appendix F-14: Time Series of Negative Tweets about Brand N



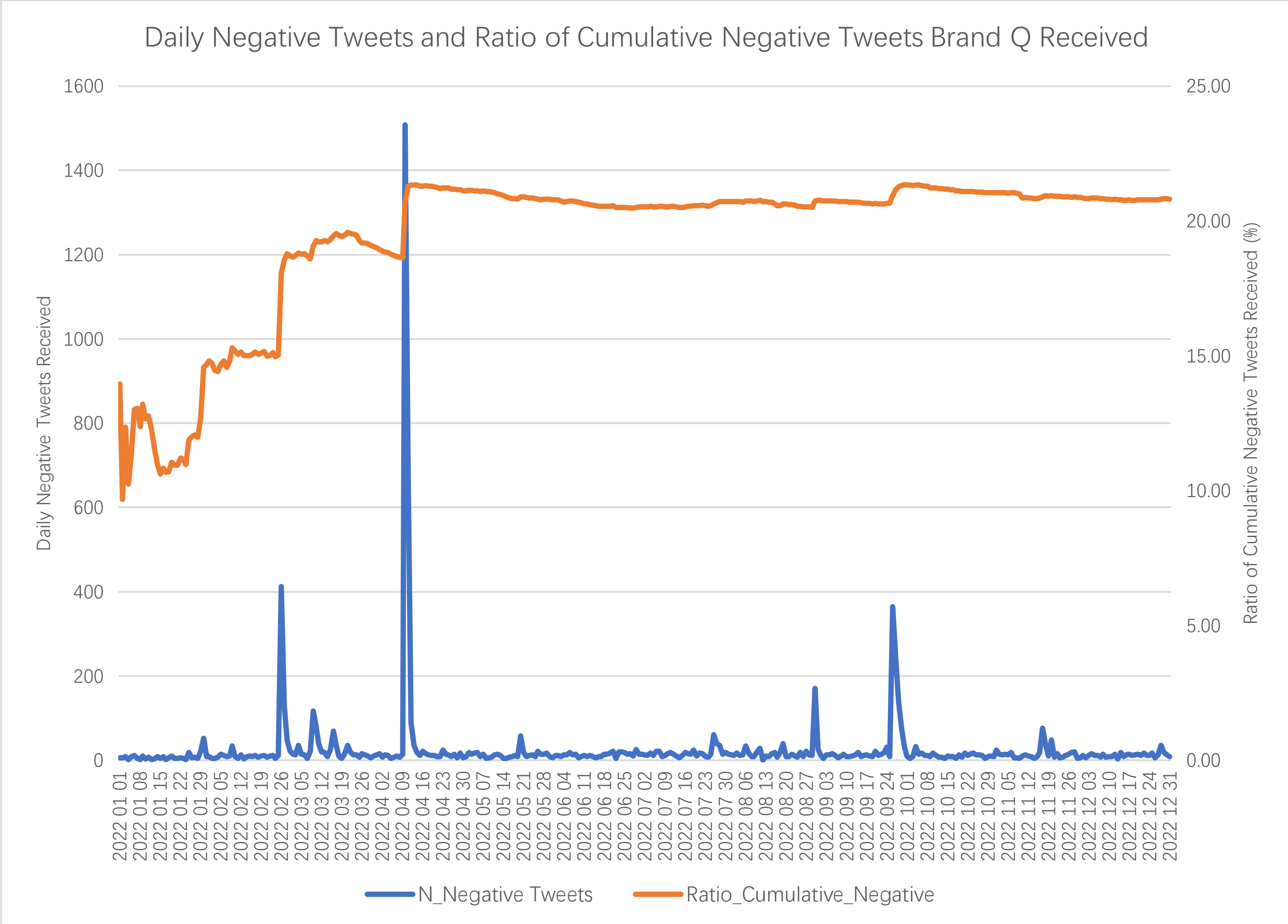
Appendix F-15: Time Series of Negative Tweets about Brand O



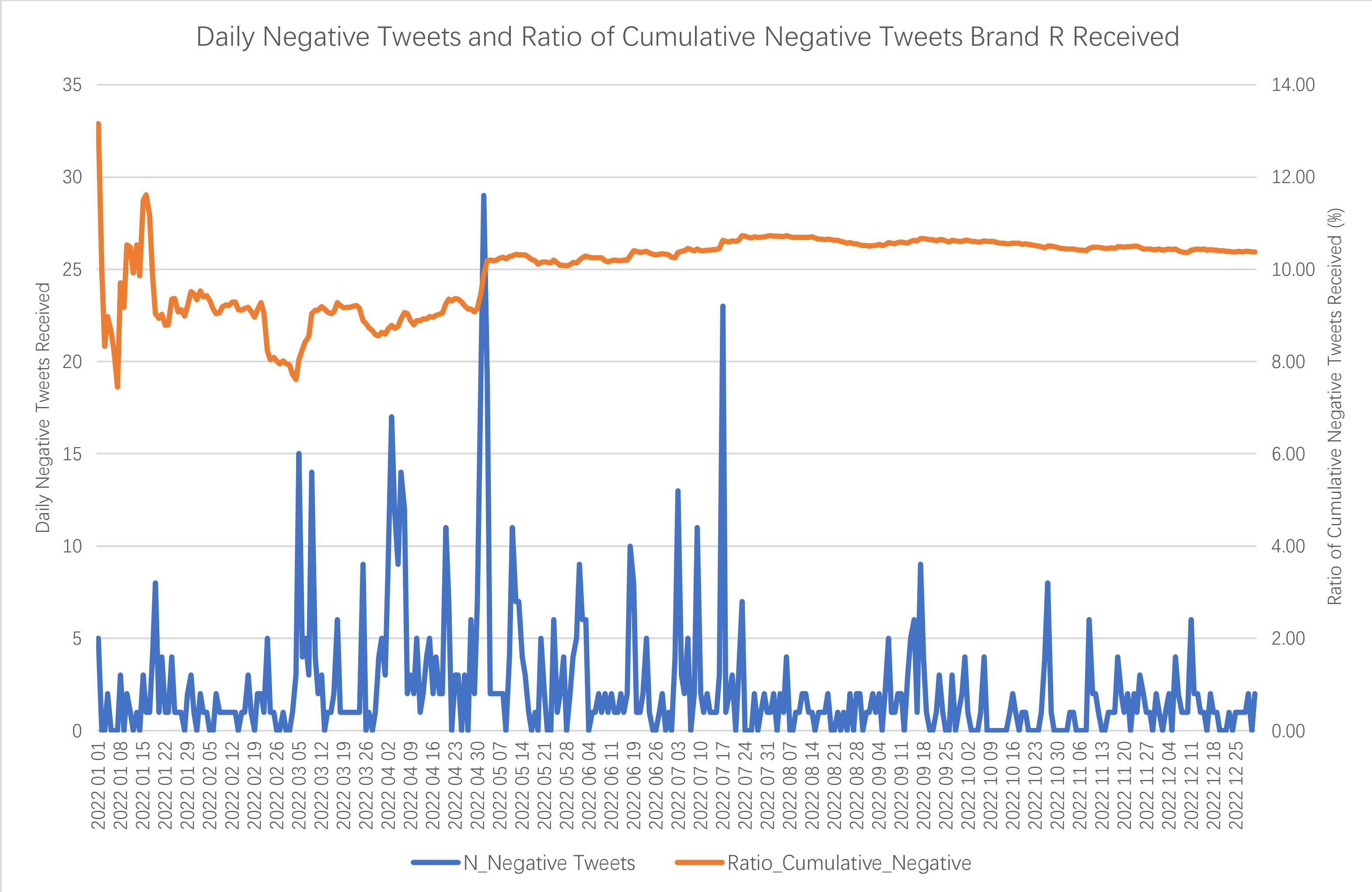
Appendix F-16: Time Series of Negative Tweets about Brand P



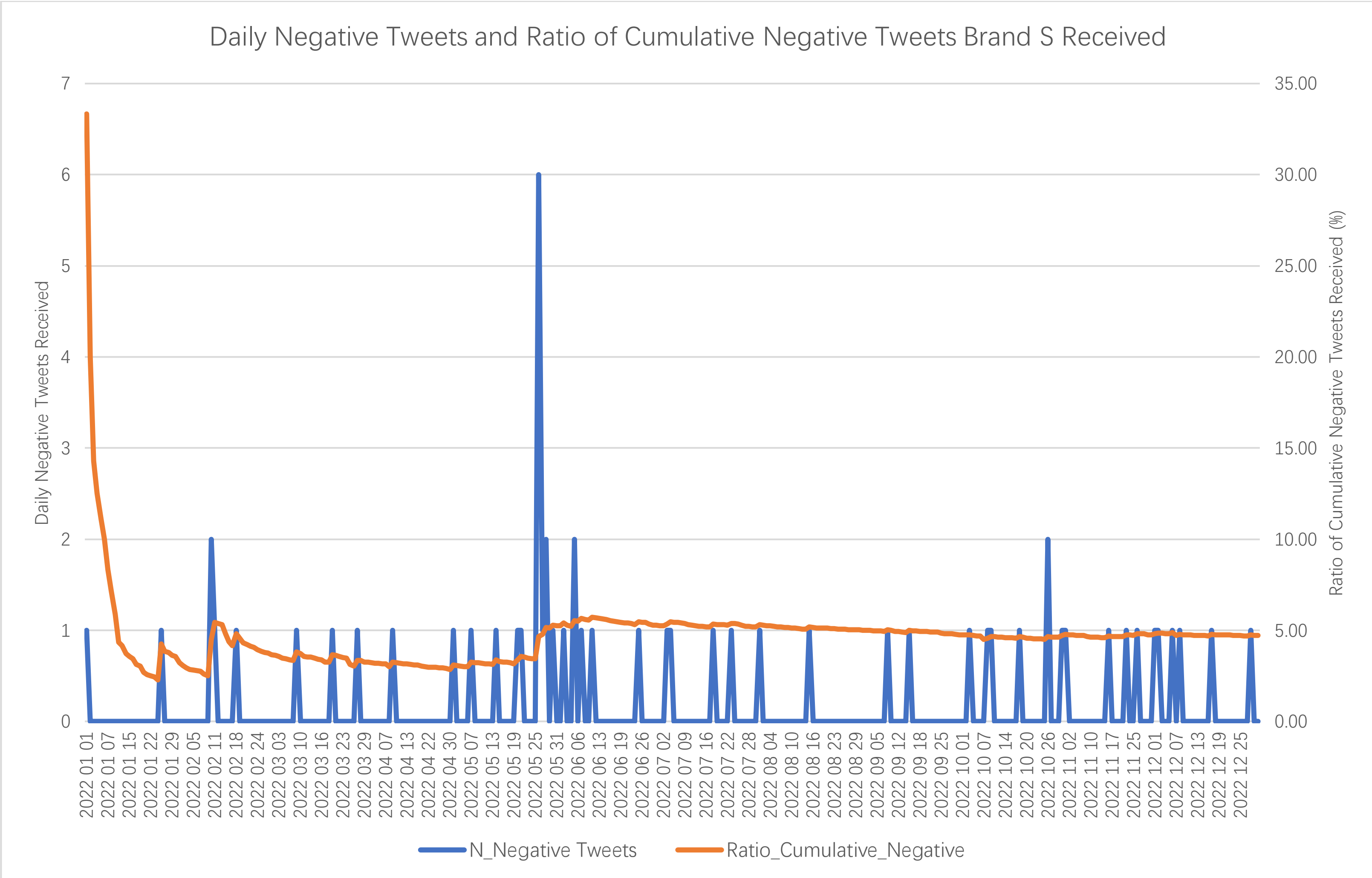
Appendix F-17: Time Series of Negative Tweets about Brand Q



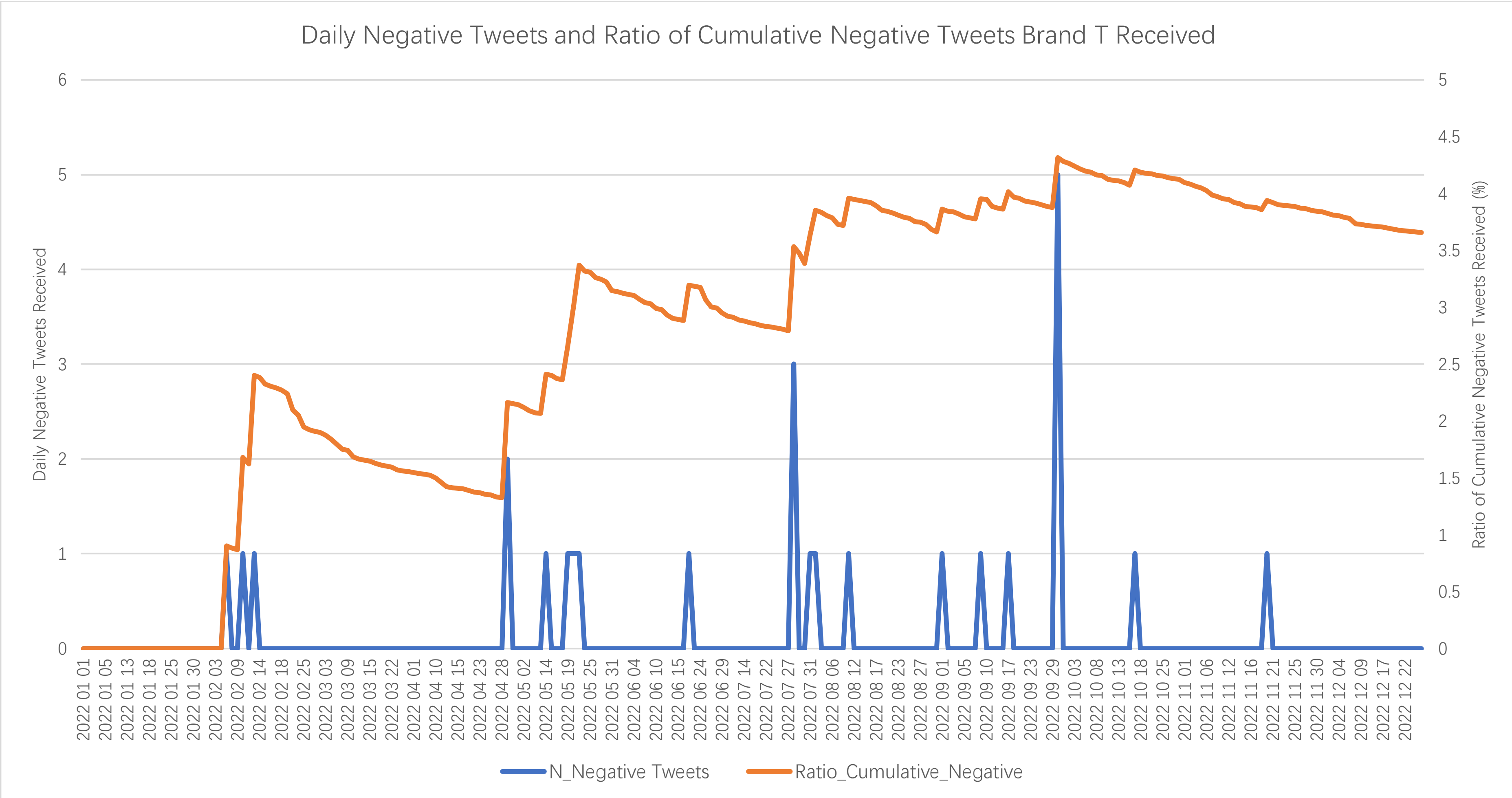
Appendix F-18: Time Series of Negative Tweets about Brand R



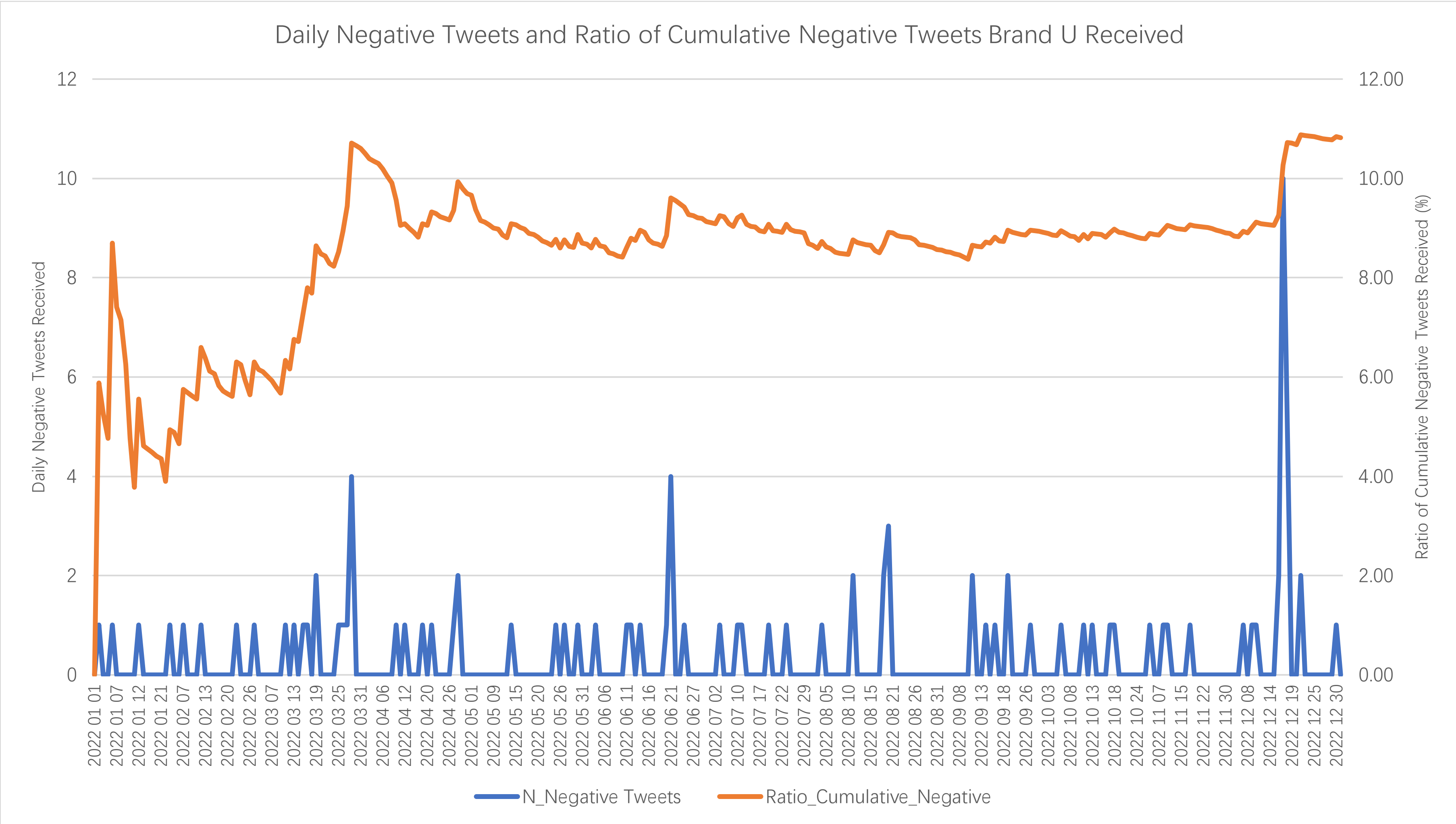
Appendix F-19: Time Series of Negative Tweets about Brand S



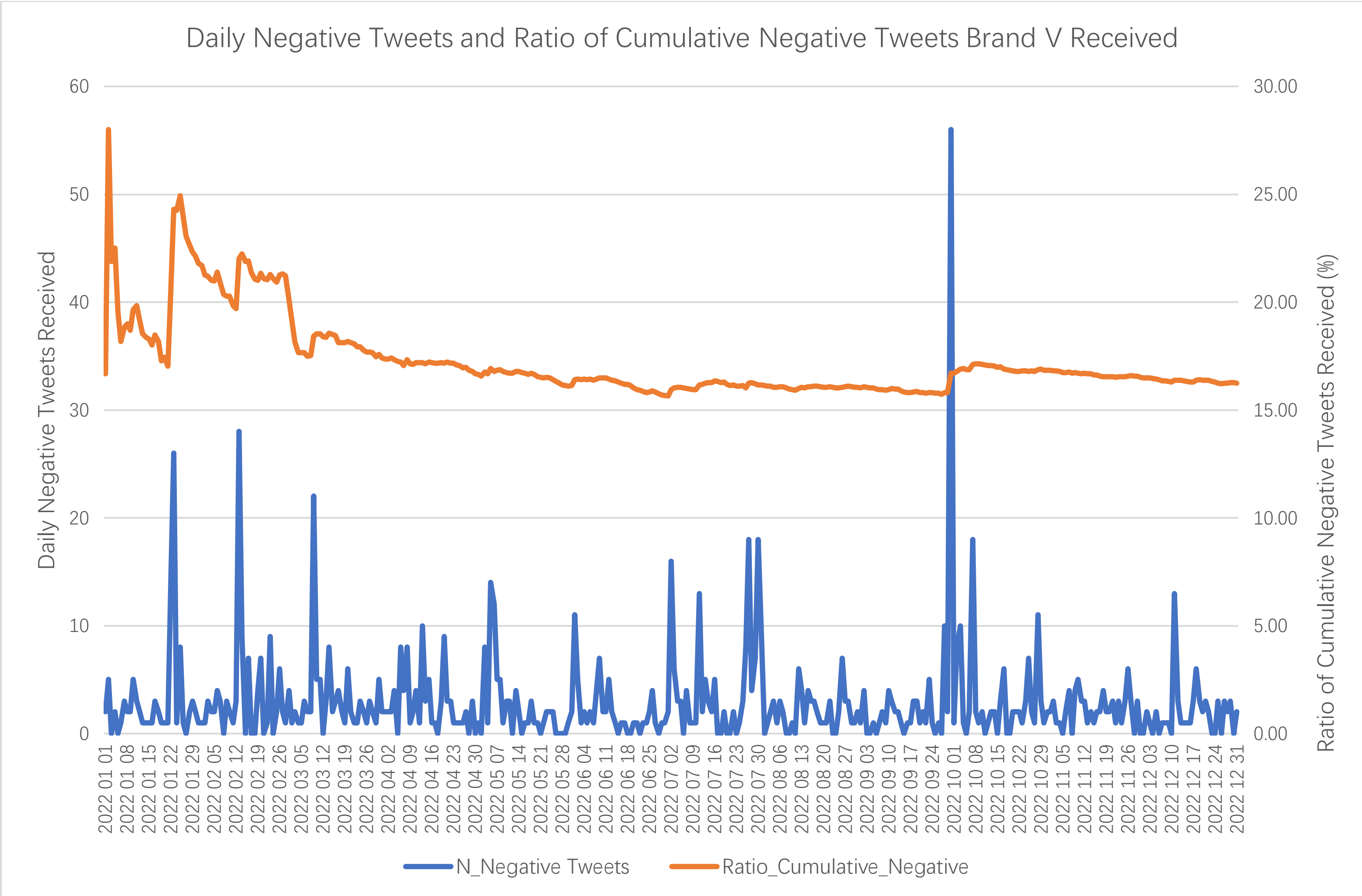
Appendix F-20: Time Series of Negative Tweets about Brand T



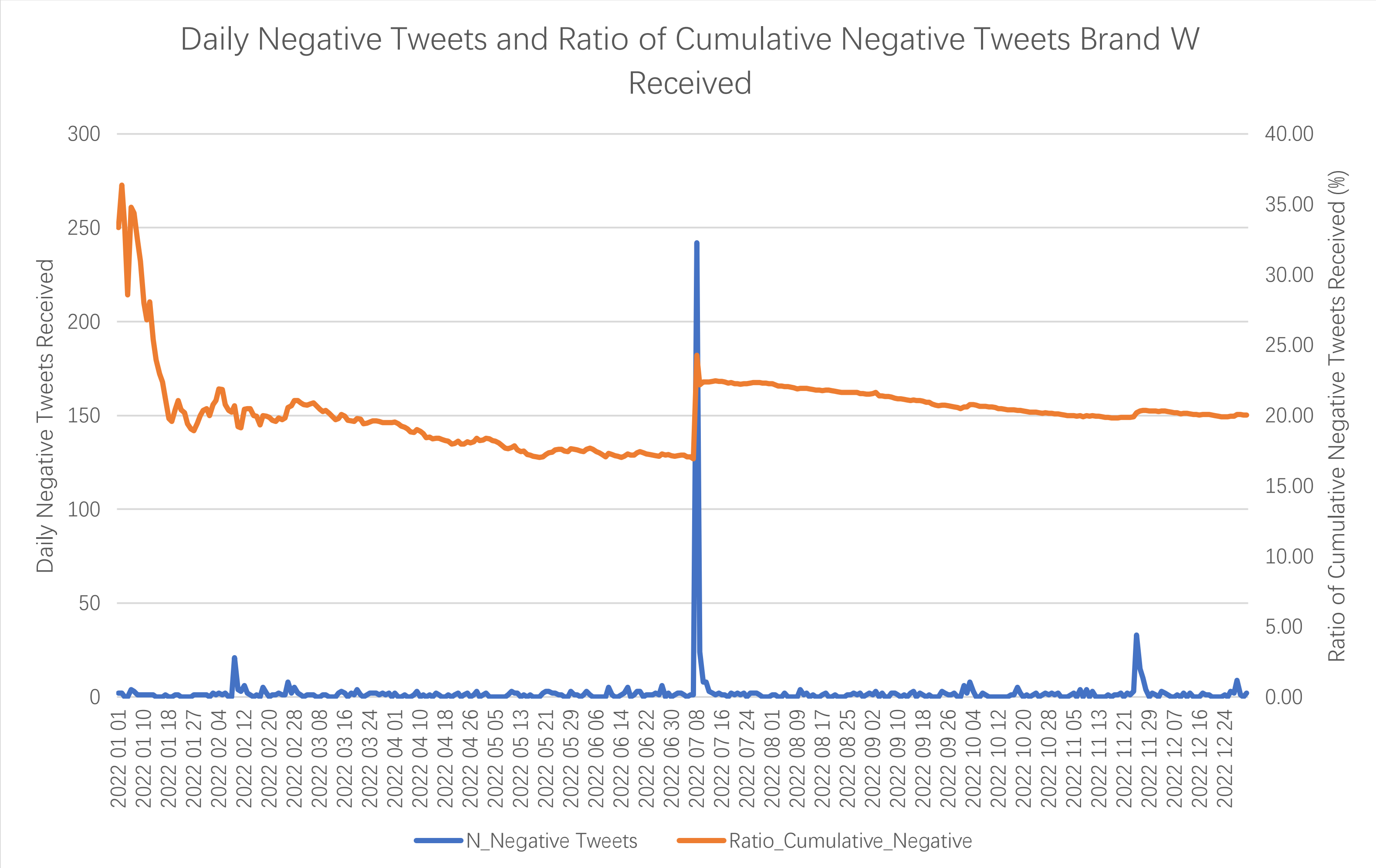
Appendix F-21: Time Series of Negative Tweets about Brand U



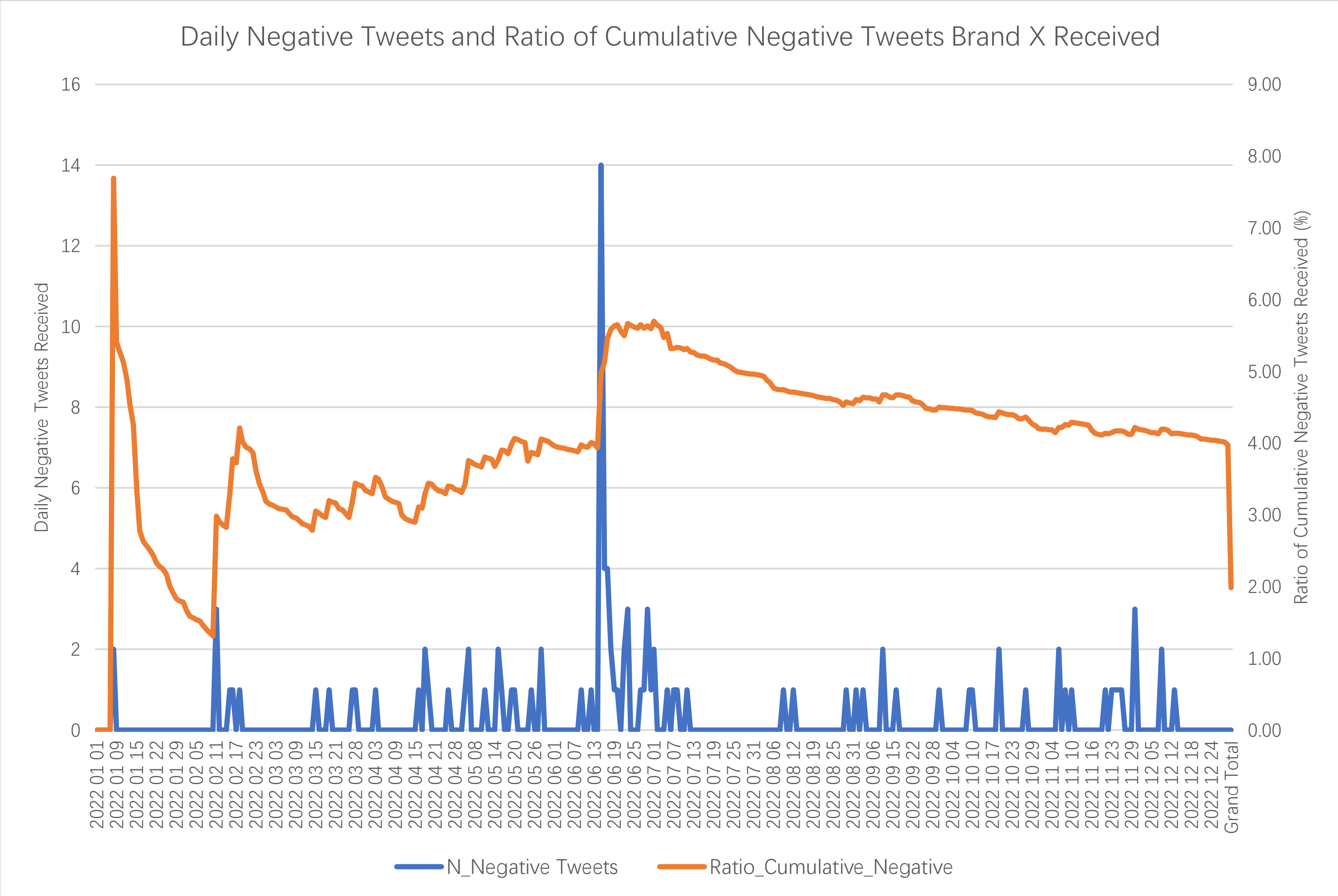
Appendix F-22: Time Series of Negative Tweets about Brand V



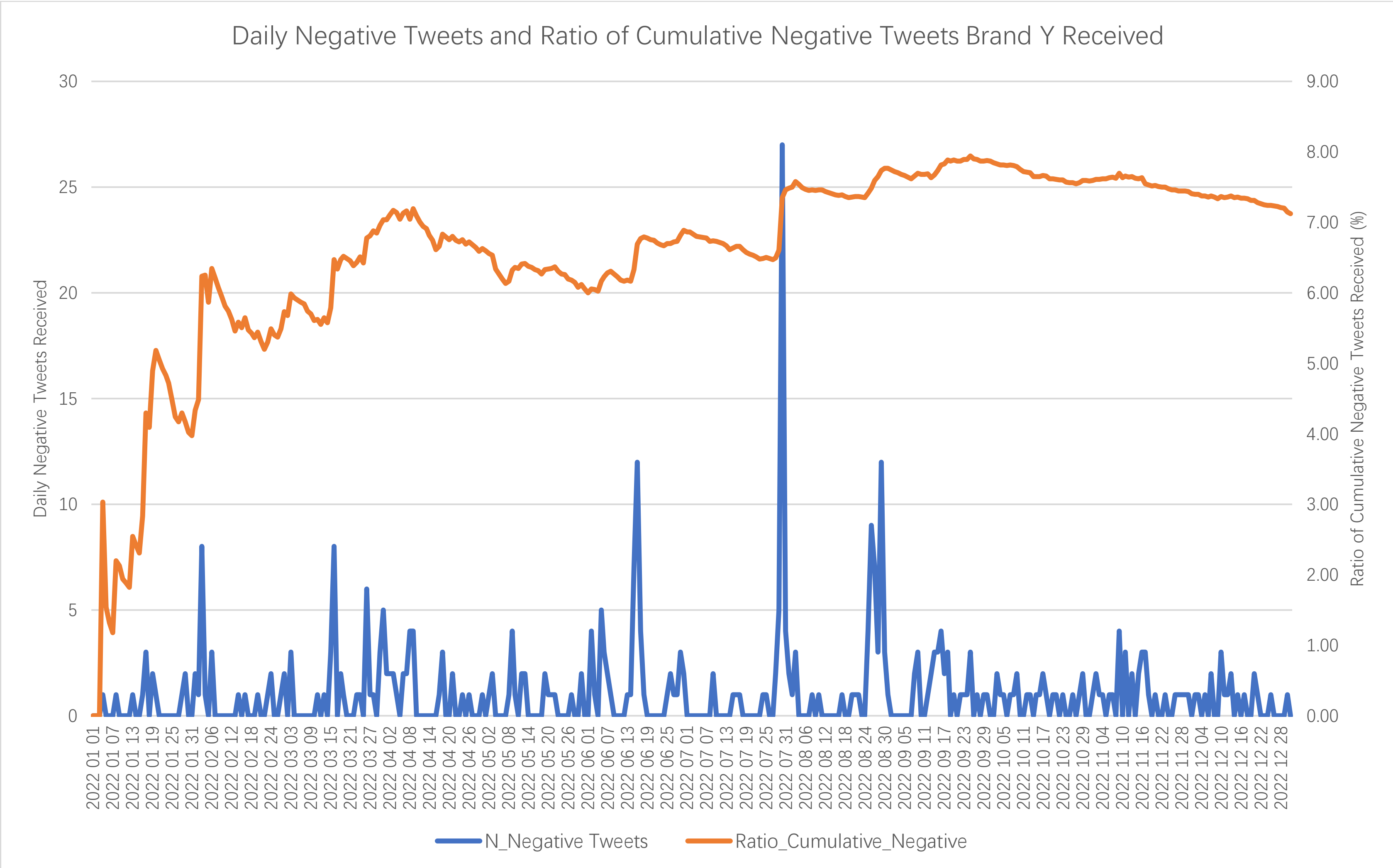
Appendix F-23: Time Series of Negative Tweets about Brand W



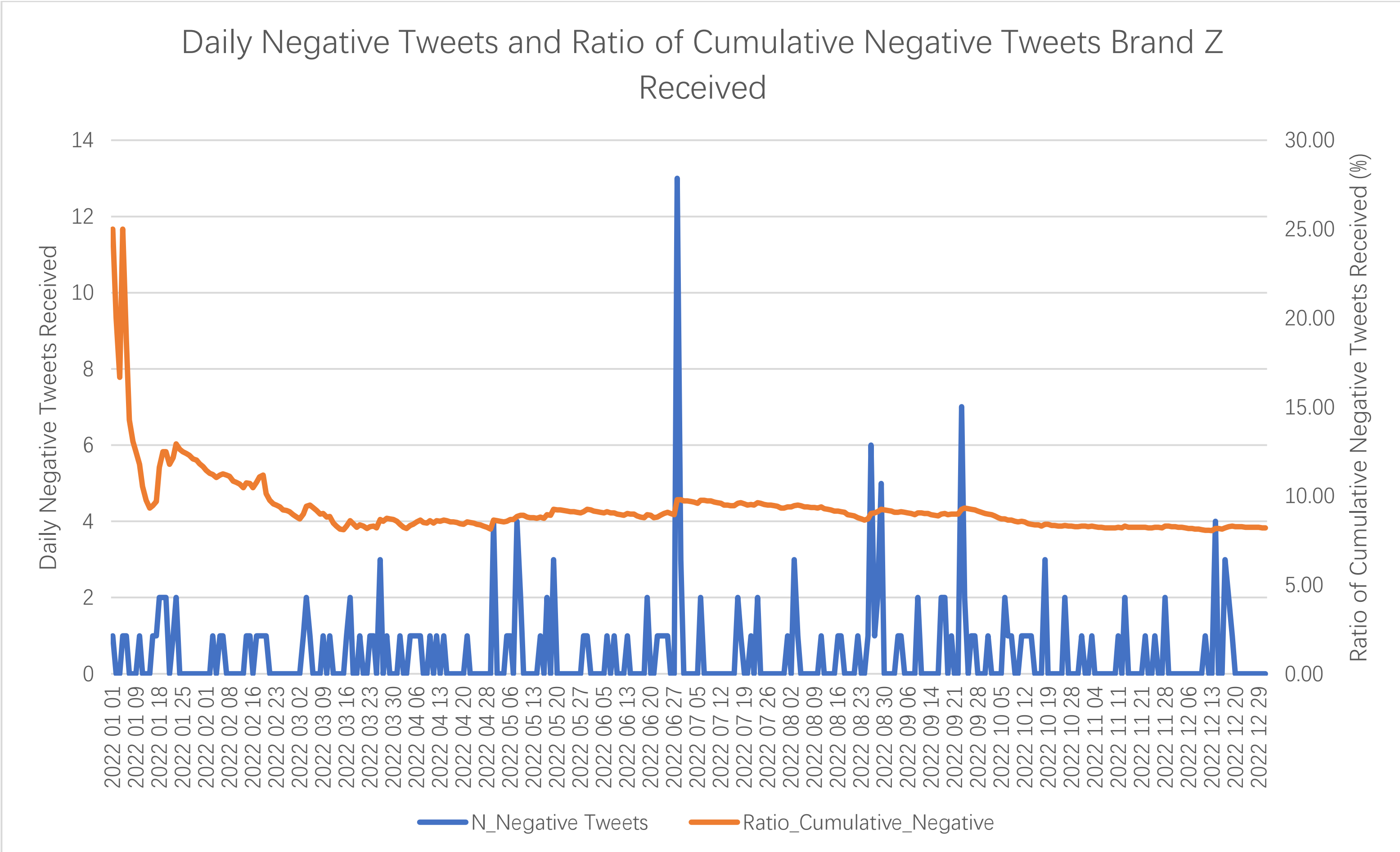
Appendix F-24: Time Series of Negative Tweets about Brand X



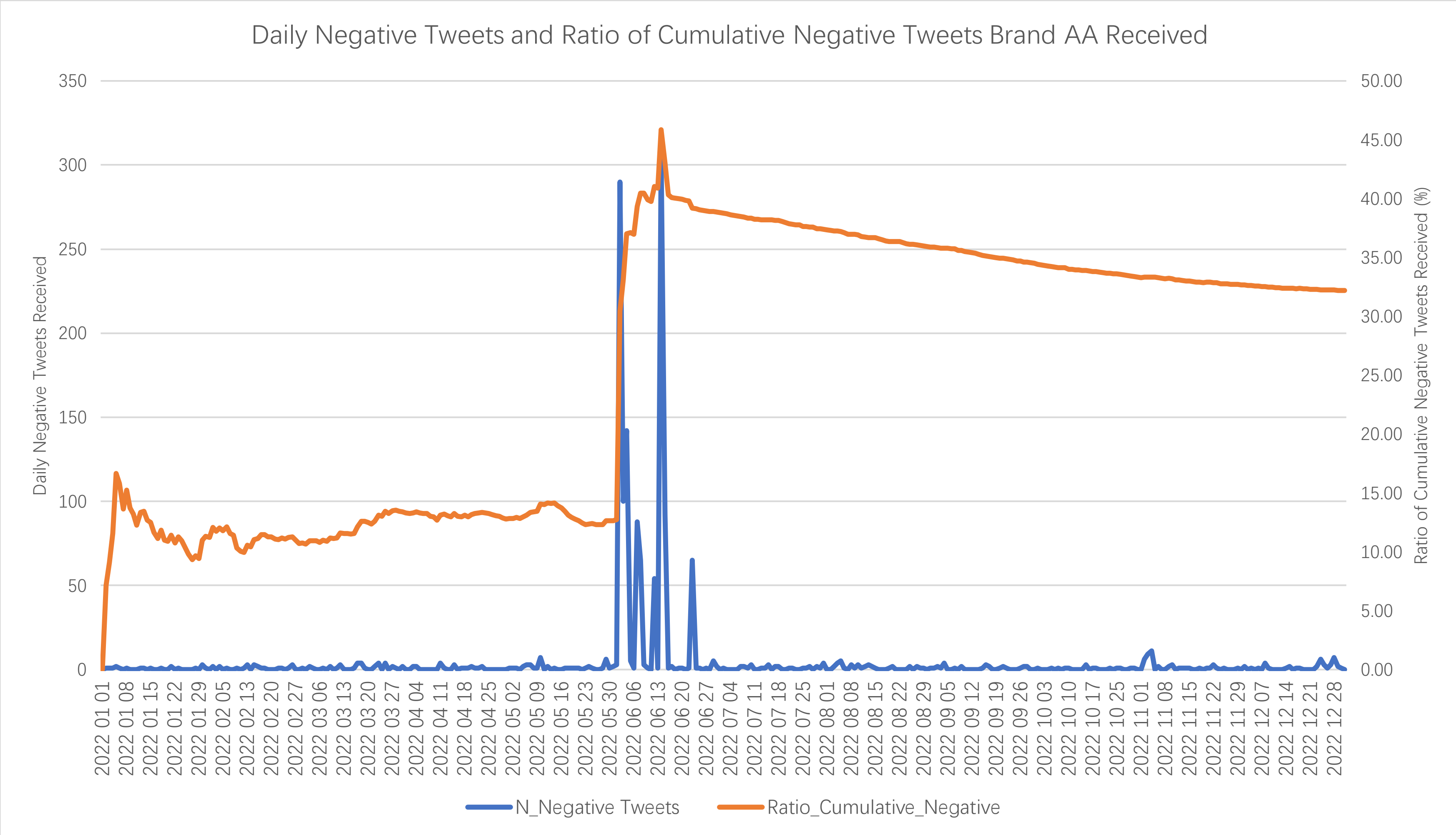
Appendix F-25: Time Series of Negative Tweets about Brand Y



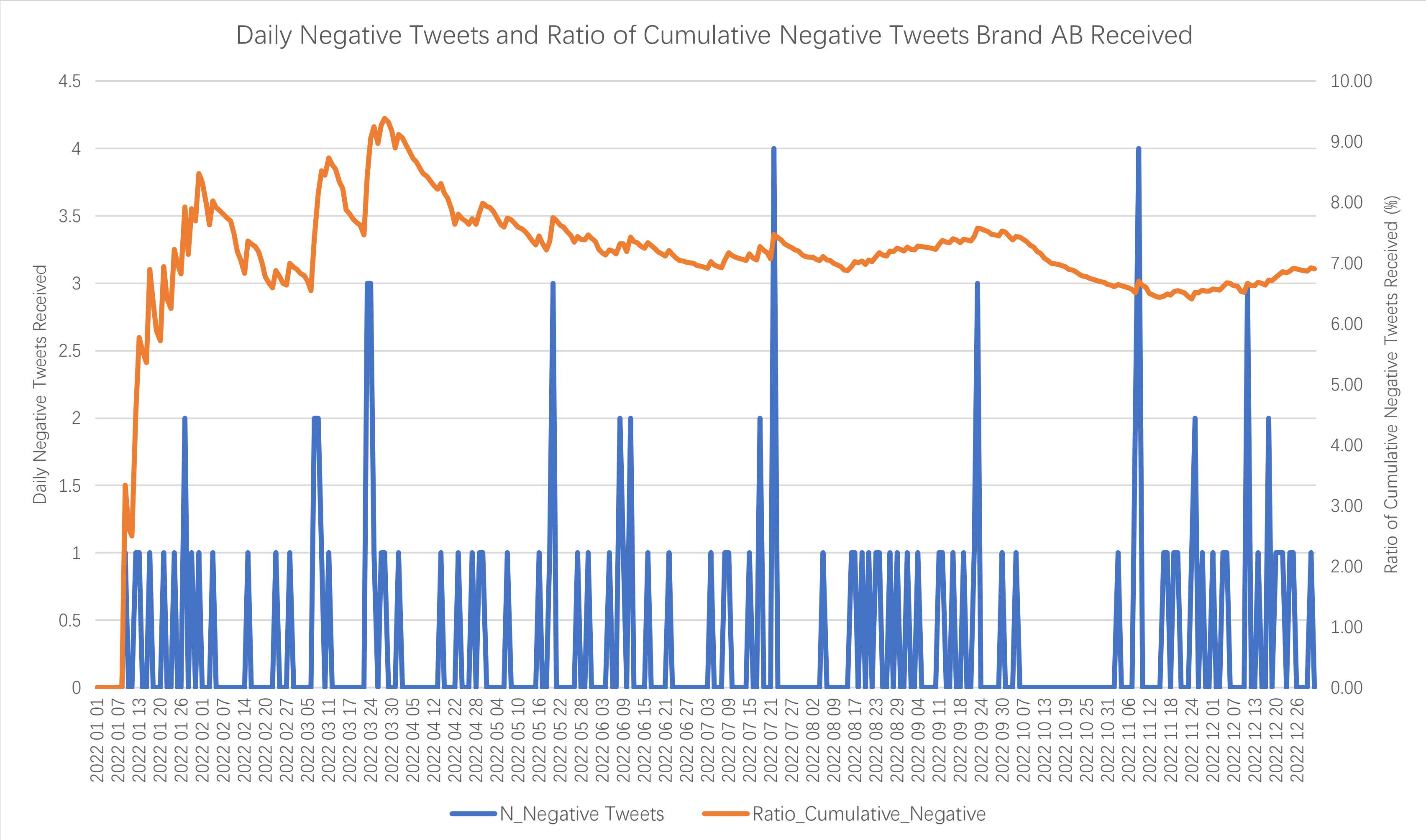
Appendix F-26: Time Series of Negative Tweets about Brand Z



Appendix F-27: Time Series of Negative Tweets about Brand AA



Appendix F-28: Time Series of Negative Tweets about Brand AB



Appendix G: Full Stepwise Linear Regression Model

Appendix G-1: Model Summary with outliers (n = 29,317)

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.285[a]	.081	.081	.9586	.081	2589.517	1	29315	.000
2	.301[b]	.091	.091	.9535	.010	312.478	1	29314	<.001
3	.306[c]	.094	.094	.9520	.003	94.225	1	29313	<.001
4	.309[d]	.095	.095	.9513	.001	46.121	1	29312	<.001
5	.311[e]	.097	.097	.9504	.002	53.215	1	29311	<.001
6	.313[f]	.098	.098	.9499	.001	31.168	1	29310	<.001
7	.314[g]	.099	.098	.9495	.001	27.549	1	29309	<.001
8	.315[h]	.099	.099	.9492	.001	23.450	1	29308	<.001
9	.316[i]	.100	.100	.9489	.000	14.820	1	29307	<.001
10	.317[j]	.100	.100	.9487	.001	16.422	1	29306	<.001
11	.317[k]	.101	.100	.9486	.000	8.573	1	29305	.003
12	.318[l]	.101	.101	.9484	.000	9.784	1	29304	.002
13	.318[m]	.101	.101	.9483	.000	9.133	1	29303	.003
14	.318[n]	.101	.101	.9482	.000	6.228	1	29302	.013
15	.319[o]	.102	.101	.9481	.000	6.046	1	29301	.014
16	.319[p]	.102	.101	.9480	.000	5.119	1	29300	.024
17	.319[q]	.102	.101	.9480	.000	4.418	1	29299	.036
18	.319[r]	.102	.101	.9479	.000	4.888	1	29298	.027
19	.320[s]	.102	.102	.9479	.000	3.893	1	29297	.048

a. Predictors: (Constant), Zscore(LNauthor_followers)

b. Predictors: (Constant), Zscore(LNauthor_followers), Zscore(WC)

c. Predictors: (Constant), Zscore(LNauthor_followers), Zscore(WC), Zscore(neg_ratio)

d. Predictors: (Constant), Zscore(LNauthor_followers), Zscore(WC), Zscore(neg_ratio), Zscore(res_rate)

e. Predictors: (Constant), Zscore(LNauthor_followers), Zscore(WC), Zscore(neg_ratio), Zscore(res_rate), attachments

f. Predictors: (Constant), Zscore(LNauthor_followers), Zscore(WC), Zscore(neg_ratio), Zscore(res_rate), attachments, Zscore(Polarity)

g. Predictors: (Constant), Zscore(LNauthor_followers), Zscore(WC), Zscore(neg_ratio), Zscore(res_rate), attachments, Zscore(Polarity), Res_tweet

h. Predictors: (Constant), Zscore(LNauthor_followers), Zscore(WC), Zscore(neg_ratio), Zscore(res_rate), attachments, Zscore(Polarity), Res_tweet, Zscore(Physical)

i. Predictors: (Constant), Zscore(LNauthor_followers), Zscore(WC), Zscore(neg_ratio), Zscore(res_rate), attachments, Zscore(Polarity), Res_tweet, Zscore(Physical), Zscore(Clout)

j. Predictors: (Constant), Zscore(LNauthor_followers), Zscore(WC), Zscore(neg_ratio), Zscore(res_rate), attachments, Zscore(Polarity), Res_tweet, Zscore(Physical), Zscore(Clout), Zscore(Lifestyle)
k. Predictors: (Constant), Zscore(LNauthor_followers), Zscore(WC), Zscore(neg_ratio), Zscore(res_rate), attachments, Zscore(Polarity), Res_tweet, Zscore(Physical), Zscore(Clout), Zscore(Lifestyle), Zscore(Social)
l. Predictors: (Constant), Zscore(LNauthor_followers), Zscore(WC), Zscore(neg_ratio), Zscore(res_rate), attachments, Zscore(Polarity), Res_tweet, Zscore(Physical), Zscore(Clout), Zscore(Lifestyle), Zscore(Social), Zscore(Analytic)
m. Predictors: (Constant), Zscore(LNauthor_followers), Zscore(WC), Zscore(neg_ratio), Zscore(res_rate), attachments, Zscore(Polarity), Res_tweet, Zscore(Physical), Zscore(Clout), Zscore(Lifestyle), Zscore(Social), Zscore(Analytic), Zscore(emo_pos)
n. Predictors: (Constant), Zscore(LNauthor_followers), Zscore(WC), Zscore(neg_ratio), Zscore(res_rate), attachments, Zscore(Polarity), Res_tweet, Zscore(Physical), Zscore(Clout), Zscore(Lifestyle), Zscore(Social), Zscore(Analytic), Zscore(emo_pos), Zscore(emo_sad)
o. Predictors: (Constant), Zscore(LNauthor_followers), Zscore(WC), Zscore(neg_ratio), Zscore(res_rate), attachments, Zscore(Polarity), Res_tweet, Zscore(Physical), Zscore(Clout), Zscore(Lifestyle), Zscore(Social), Zscore(Analytic), Zscore(emo_pos), Zscore(emo_sad), Zscore(LNBrand_follower)
p. Predictors: (Constant), Zscore(LNauthor_followers), Zscore(WC), Zscore(neg_ratio), Zscore(res_rate), attachments, Zscore(Polarity), Res_tweet, Zscore(Physical), Zscore(Clout), Zscore(Lifestyle), Zscore(Social), Zscore(Analytic), Zscore(emo_pos), Zscore(emo_sad), Zscore(LNBrand_follower), Zscore(Subjectivity)
q. Predictors: (Constant), Zscore(LNauthor_followers), Zscore(WC), Zscore(neg_ratio), Zscore(res_rate), attachments, Zscore(Polarity), Res_tweet, Zscore(Physical), Zscore(Clout), Zscore(Lifestyle), Zscore(Social), Zscore(Analytic), Zscore(emo_pos), Zscore(emo_sad), Zscore(LNBrand_follower), Zscore(Subjectivity), Zscore(Perception)
r. Predictors: (Constant), Zscore(LNauthor_followers), Zscore(WC), Zscore(neg_ratio), Zscore(res_rate), attachments, Zscore(Polarity), Res_tweet, Zscore(Physical), Zscore(Clout), Zscore(Lifestyle), Zscore(Social), Zscore(Analytic), Zscore(emo_pos), Zscore(emo_sad), Zscore(LNBrand_follower), Zscore(Subjectivity), Zscore(Perception), Zscore(Gunning)
s. Predictors: (Constant), Zscore(LNauthor_followers), Zscore(WC), Zscore(neg_ratio), Zscore(res_rate), attachments, Zscore(Polarity), Res_tweet, Zscore(Physical), Zscore(Clout), Zscore(Lifestyle), Zscore(Social), Zscore(Analytic), Zscore(emo_pos), Zscore(emo_sad), Zscore(LNBrand_follower), Zscore(Subjectivity), Zscore(Perception), Zscore(Gunning), Zscore(Exclam)
t. Dependent Variable: Zscore(LNvirality)

Appendix G-2: Full Coefficient Table of Data with Outliers (n = 29,317)

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.000	.006		.000	1.000
	Zscore(LNauthor_followers)	.285	.006	.285	50.887	.000
2	(Constant)	.000	.006		.000	1.000
	Zscore(LNauthor_followers)	.293	.006	.293	52.400	.000
	Zscore(WC)	.099	.006	.099	17.677	<.001
3	(Constant)	.000	.006		.000	1.000
	Zscore(LNauthor_followers)	.289	.006	.289	51.624	.000
	Zscore(WC)	.100	.006	.100	17.890	<.001
	Zscore(neg_ratio)	-.054	.006	-.054	-9.707	<.001
4	(Constant)	.000	.006		.000	1.000
	Zscore(LNauthor_followers)	.288	.006	.288	51.571	.000
	Zscore(WC)	.097	.006	.097	17.386	<.001
	Zscore(neg_ratio)	-.058	.006	-.058	-10.365	<.001
	Zscore(res_rate)	.038	.006	.038	6.791	<.001
5	(Constant)	.035	.007		4.736	<.001
	Zscore(LNauthor_followers)	.288	.006	.288	51.634	.000
	Zscore(WC)	.095	.006	.095	17.046	<.001
	Zscore(neg_ratio)	-.067	.006	-.067	-11.726	<.001
	Zscore(res_rate)	.045	.006	.045	7.937	<.001
	attachments	.054	.007	.042	7.295	<.001
6	(Constant)	.035	.007		4.827	<.001
	Zscore(LNauthor_followers)	.287	.006	.287	51.366	.000
	Zscore(WC)	.080	.006	.080	12.871	<.001
	Zscore(neg_ratio)	-.064	.006	-.064	-11.068	<.001
	Zscore(res_rate)	.044	.006	.044	7.801	<.001
	attachments	.055	.007	.043	7.434	<.001
	Zscore(Polarity)	.035	.006	.035	5.583	<.001
7	(Constant)	.072	.010		7.118	<.001

	Zscore(LNauthor_followers)	.288	.006	.288	51.556	.000
	Zscore(WC)	.076	.006	.076	12.070	<.001
	Zscore(neg_ratio)	-.060	.006	-.060	-10.369	<.001
	Zscore(res_rate)	.040	.006	.040	6.960	<.001
	attachments	.054	.007	.042	7.283	<.001
	Zscore(Polarity)	.034	.006	.034	5.475	<.001
	Res_tweet	.048	.009	.030	5.249	<.001
8	(Constant)	.073	.010		7.218	<.001
	Zscore(LNauthor_followers)	.288	.006	.288	51.566	.000
	Zscore(WC)	.075	.006	.075	11.992	<.001
	Zscore(neg_ratio)	-.060	.006	-.060	-10.380	<.001
	Zscore(res_rate)	.039	.006	.039	6.811	<.001
	attachments	.057	.007	.044	7.686	<.001
	Zscore(Polarity)	.031	.006	.031	4.927	<.001
	Res_tweet	.047	.009	.029	5.102	<.001
	Zscore(Physical)	-.027	.006	-.027	-4.842	<.001
9	(Constant)	.074	.010		7.368	<.001
	Zscore(LNauthor_followers)	.289	.006	.289	51.718	.000
	Zscore(WC)	.075	.006	.075	12.013	<.001
	Zscore(neg_ratio)	-.061	.006	-.061	-10.450	<.001
	Zscore(res_rate)	.039	.006	.039	6.761	<.001
	attachments	.057	.007	.044	7.627	<.001
	Zscore(Polarity)	.033	.006	.033	5.202	<.001
	Res_tweet	.049	.009	.031	5.350	<.001
	Zscore(Physical)	-.027	.006	-.027	-4.775	<.001
	Zscore(Clout)	.022	.006	.022	3.850	<.001
10	(Constant)	.077	.010		7.590	<.001
	Zscore(LNauthor_followers)	.288	.006	.288	51.279	.000
	Zscore(WC)	.078	.006	.078	12.346	<.001
	Zscore(neg_ratio)	-.060	.006	-.060	-10.312	<.001
	Zscore(res_rate)	.039	.006	.039	6.827	<.001
	attachments	.058	.007	.045	7.753	<.001
	Zscore(Polarity)	.034	.006	.034	5.349	<.001
	Res_tweet	.051	.009	.032	5.585	<.001
	Zscore(Physical)	-.028	.006	-.028	-5.005	<.001
	Zscore(Clout)	.024	.006	.024	4.243	<.001

	Zscore(Lifestyle)	-.023	.006	-.023	-4.052	<.001
11	(Constant)	.076	.010		7.564	<.001
	Zscore(LNauthor_followers)	.287	.006	.287	51.233	.000
	Zscore(WC)	.078	.006	.078	12.336	<.001
	Zscore(neg_ratio)	-.057	.006	-.057	-9.803	<.001
	Zscore(res_rate)	.038	.006	.038	6.696	<.001
	attachments	.057	.007	.044	7.656	<.001
	Zscore(Polarity)	.030	.006	.030	4.654	<.001
	Res_tweet	.051	.009	.032	5.610	<.001
	Zscore(Physical)	-.029	.006	-.029	-5.144	<.001
	Zscore(Clout)	.033	.006	.033	5.136	<.001
	Zscore(Lifestyle)	-.024	.006	-.024	-4.181	<.001
	Zscore(Social)	-.020	.007	-.020	-2.928	.003
12	(Constant)	.079	.010		7.816	<.001
	Zscore(LNauthor_followers)	.286	.006	.286	50.926	.000
	Zscore(WC)	.078	.006	.078	12.330	<.001
	Zscore(neg_ratio)	-.056	.006	-.056	-9.421	<.001
	Zscore(res_rate)	.037	.006	.037	6.395	<.001
	attachments	.062	.008	.048	8.125	<.001
	Zscore(Polarity)	.028	.006	.028	4.443	<.001
	Res_tweet	.051	.009	.032	5.590	<.001
	Zscore(Physical)	-.027	.006	-.027	-4.798	<.001
	Zscore(Clout)	.038	.007	.038	5.678	<.001
	Zscore(Lifestyle)	-.021	.006	-.021	-3.698	<.001
	Zscore(Social)	-.023	.007	-.023	-3.352	<.001
	Zscore(Analytic)	-.019	.006	-.019	-3.128	.002
13	(Constant)	.079	.010		7.791	<.001
	Zscore(LNauthor_followers)	.287	.006	.287	50.975	.000
	Zscore(WC)	.078	.006	.078	12.337	<.001
	Zscore(neg_ratio)	-.056	.006	-.056	-9.452	<.001
	Zscore(res_rate)	.037	.006	.037	6.417	<.001
	attachments	.062	.008	.048	8.062	<.001
	Zscore(Polarity)	.028	.006	.028	4.319	<.001
	Res_tweet	.051	.009	.032	5.596	<.001
	Zscore(Physical)	-.027	.006	-.027	-4.845	<.001
	Zscore(Clout)	.037	.007	.037	5.607	<.001
	Zscore(Lifestyle)	-.022	.006	-.022	-3.751	<.001

	Zscore(Social)	-.023	.007	-.023	-3.428	<.001
	Zscore(Analytic)	-.019	.006	-.019	-3.219	.001
	Zscore(emo_pos)	-.017	.006	-.017	-3.022	.003
14	(Constant)	.079	.010		7.826	<.001
	Zscore(LNauthor_followers)	.287	.006	.287	50.975	.000
	Zscore(WC)	.078	.006	.078	12.321	<.001
	Zscore(neg_ratio)	-.056	.006	-.056	-9.506	<.001
	Zscore(res_rate)	.037	.006	.037	6.423	<.001
	attachments	.061	.008	.047	8.006	<.001
	Zscore(Polarity)	.025	.006	.025	3.912	<.001
	Res_tweet	.052	.009	.033	5.681	<.001
	Zscore(Physical)	-.028	.006	-.028	-4.976	<.001
	Zscore(Clout)	.037	.007	.037	5.652	<.001
	Zscore(Lifestyle)	-.022	.006	-.022	-3.786	<.001
	Zscore(Social)	-.024	.007	-.024	-3.589	<.001
	Zscore(Analytic)	-.020	.006	-.020	-3.322	<.001
	Zscore(emo_pos)	-.017	.006	-.017	-2.989	.003
	Zscore(emo_sad)	-.014	.006	-.014	-2.496	.013
15	(Constant)	.085	.010		8.166	<.001
	Zscore(LNauthor_followers)	.286	.006	.286	50.777	.000
	Zscore(WC)	.078	.006	.078	12.427	<.001
	Zscore(neg_ratio)	-.056	.006	-.056	-9.548	<.001
	Zscore(res_rate)	.031	.006	.031	4.827	<.001
	attachments	.063	.008	.049	8.234	<.001
	Zscore(Polarity)	.025	.006	.025	3.811	<.001
	Res_tweet	.057	.009	.036	6.080	<.001
	Zscore(Physical)	-.028	.006	-.028	-4.911	<.001
	Zscore(Clout)	.037	.007	.037	5.621	<.001
	Zscore(Lifestyle)	-.021	.006	-.021	-3.635	<.001
	Zscore(Social)	-.024	.007	-.024	-3.622	<.001
	Zscore(Analytic)	-.020	.006	-.020	-3.242	.001
	Zscore(emo_pos)	-.017	.006	-.017	-2.999	.003
	Zscore(emo_sad)	-.015	.006	-.015	-2.579	.010
	Zscore(LNBrand_follower)	.016	.006	.016	2.459	.014
16	(Constant)	.084	.010		8.136	<.001
	Zscore(LNauthor_followers)	.286	.006	.286	50.764	.000

	Zscore(WC)	.078	.006	.078	12.424	<.001
	Zscore(neg_ratio)	-.057	.006	-.057	-9.700	<.001
	Zscore(res_rate)	.031	.006	.031	4.916	<.001
	attachments	.061	.008	.047	7.945	<.001
	Zscore(Polarity)	.025	.006	.025	3.857	<.001
	Res_tweet	.058	.009	.036	6.192	<.001
	Zscore(Physical)	-.029	.006	-.029	-5.073	<.001
	Zscore(Clout)	.037	.007	.037	5.616	<.001
	Zscore(Lifestyle)	-.021	.006	-.021	-3.615	<.001
	Zscore(Social)	-.026	.007	-.026	-3.782	<.001
	Zscore(Analytic)	-.022	.006	-.022	-3.536	<.001
	Zscore(emo_pos)	-.016	.006	-.016	-2.894	.004
	Zscore(emo_sad)	-.014	.006	-.014	-2.447	.014
	Zscore(LNBrand_follower)	.016	.006	.016	2.471	.013
	Zscore(Subjectivity)	-.013	.006	-.013	-2.263	.024
17	(Constant)	.084	.010		8.118	<.001
	Zscore(LNauthor_followers)	.285	.006	.285	50.707	.000
	Zscore(WC)	.077	.006	.077	12.137	<.001
	Zscore(neg_ratio)	-.057	.006	-.057	-9.631	<.001
	Zscore(res_rate)	.031	.006	.031	4.899	<.001
	attachments	.062	.008	.048	8.030	<.001
	Zscore(Polarity)	.024	.006	.024	3.772	<.001
	Res_tweet	.057	.009	.036	6.100	<.001
	Zscore(Physical)	-.029	.006	-.029	-5.119	<.001
	Zscore(Clout)	.037	.007	.037	5.534	<.001
	Zscore(Lifestyle)	-.020	.006	-.020	-3.450	<.001
	Zscore(Social)	-.023	.007	-.023	-3.382	<.001
	Zscore(Analytic)	-.022	.006	-.022	-3.616	<.001
	Zscore(emo_pos)	-.016	.006	-.016	-2.943	.003
	Zscore(emo_sad)	-.014	.006	-.014	-2.425	.015
	Zscore(LNBrand_follower)	.015	.006	.015	2.410	.016
	Zscore(Subjectivity)	-.013	.006	-.013	-2.255	.024
	Zscore(Perception)	.012	.006	.012	2.102	.036
18	(Constant)	.083	.010		8.044	<.001

	Zscore(LNauthor_followers)	.286	.006	.286	50.742	.000
	Zscore(WC)	.074	.006	.074	11.583	<.001
	Zscore(neg_ratio)	-.058	.006	-.058	-9.808	<.001
	Zscore(res_rate)	.031	.006	.031	4.941	<.001
	attachments	.061	.008	.047	7.790	<.001
	Zscore(Polarity)	.025	.006	.025	3.837	<.001
	Res_tweet	.058	.009	.036	6.138	<.001
	Zscore(Physical)	-.029	.006	-.029	-5.089	<.001
	Zscore(Clout)	.036	.007	.036	5.479	<.001
	Zscore(Lifestyle)	-.022	.006	-.022	-3.703	<.001
	Zscore(Social)	-.023	.007	-.023	-3.367	<.001
	Zscore(Analytic)	-.026	.006	-.026	-4.065	<.001
	Zscore(emo_pos)	-.016	.006	-.016	-2.887	.004
	Zscore(emo_sad)	-.013	.006	-.013	-2.373	.018
	Zscore(LNBrand_follower)	.016	.006	.016	2.467	.014
	Zscore(Subjectivity)	-.012	.006	-.012	-2.096	.036
	Zscore(Perception)	.014	.006	.014	2.459	.014
	Zscore(Gunning)	.014	.006	.014	2.211	.027
19	(Constant)	.083	.010		8.040	<.001
	Zscore(LNauthor_followers)	.285	.006	.285	50.669	.000
	Zscore(WC)	.073	.006	.073	11.388	<.001
	Zscore(neg_ratio)	-.059	.006	-.059	-9.891	<.001
	Zscore(res_rate)	.032	.006	.032	5.003	<.001
	attachments	.061	.008	.047	7.792	<.001
	Zscore(Polarity)	.024	.006	.024	3.770	<.001
	Res_tweet	.058	.009	.036	6.132	<.001
	Zscore(Physical)	-.029	.006	-.029	-5.111	<.001
	Zscore(Clout)	.036	.007	.036	5.508	<.001
	Zscore(Lifestyle)	-.021	.006	-.021	-3.689	<.001
	Zscore(Social)	-.023	.007	-.023	-3.377	<.001
	Zscore(Analytic)	-.026	.006	-.026	-4.054	<.001
	Zscore(emo_pos)	-.016	.006	-.016	-2.896	.004
	Zscore(emo_sad)	-.014	.006	-.014	-2.423	.015
	Zscore(LNBrand_follower)	.016	.006	.016	2.459	.014

	Zscore(Subjectivity)	-.012	.006	-.012	-2.079	.038
	Zscore(Perception)	.014	.006	.014	2.447	.014
	Zscore(Gunning)	.013	.006	.013	2.097	.036
	Zscore(Exclam)	-.011	.006	-.011	-1.973	.048

a. Dependent Variable: Zscore(LNvirality)

Appendix G-3: Model Summary without outliers (n = 28,287)

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.287[a]	.083	.083	.9689	.083	2546.880	1	28285	.000
2	.303[b]	.092	.092	.9639	.009	293.268	1	28284	<.001
3	.308[c]	.095	.095	.9624	.003	90.449	1	28283	<.001
4	.310[d]	.096	.096	.9617	.001	41.852	1	28282	<.001
5	.313[e]	.098	.098	.9608	.002	53.651	1	28281	<.001
6	.314[f]	.099	.099	.9603	.001	29.358	1	28280	<.001
7	.316[g]	.100	.099	.9599	.001	22.264	1	28279	<.001
8	.317[h]	.100	.100	.9596	.001	21.334	1	28278	<.001
9	.317[i]	.101	.100	.9593	.000	15.440	1	28277	<.001
10	.318[j]	.101	.101	.9591	.001	16.980	1	28276	<.001
11	.319[k]	.102	.101	.9589	.000	8.765	1	28275	.003
12	.319[l]	.102	.101	.9588	.000	7.998	1	28274	.005
13	.320[m]	.102	.102	.9587	.000	10.001	1	28273	.002
14	.320[n]	.102	.102	.9586	.000	5.520	1	28272	.019
15	.320[o]	.102	.102	.9585	.000	4.808	1	28271	.028
16	.320[p]	.103	.102	.9585	.000	4.352	1	28270	.037
17	.321[q]	.103	.102	.9584	.000	4.153	1	28269	.042
18	.321[r]	.103	.102	.9584	.000	4.631	1	28268	.031

a. Predictors: (Constant), Zscore(LNauthor_followers)

b. Predictors: (Constant), Zscore(LNauthor_followers), Zscore(WC)

c. Predictors: (Constant), Zscore(LNauthor_followers), Zscore(WC), Zscore(neg_ratio)

d. Predictors: (Constant), Zscore(LNauthor_followers), Zscore(WC), Zscore(neg_ratio), attachments

e. Predictors: (Constant), Zscore(LNauthor_followers), Zscore(WC), Zscore(neg_ratio), attachments, Zscore(res_rate)

f. Predictors: (Constant), Zscore(LNauthor_followers), Zscore(WC), Zscore(neg_ratio), attachments, Zscore(res_rate), Zscore(Physical)

g. Predictors: (Constant), Zscore(LNauthor_followers), Zscore(WC), Zscore(neg_ratio), attachments, Zscore(res_rate), Zscore(Physical), Zscore(Polarity)
h. Predictors: (Constant), Zscore(LNauthor_followers), Zscore(WC), Zscore(neg_ratio), attachments, Zscore(res_rate), Zscore(Physical), Zscore(Polarity), Res_tweet
i. Predictors: (Constant), Zscore(LNauthor_followers), Zscore(WC), Zscore(neg_ratio), attachments, Zscore(res_rate), Zscore(Physical), Zscore(Polarity), Res_tweet, Zscore(Clout)
j. Predictors: (Constant), Zscore(LNauthor_followers), Zscore(WC), Zscore(neg_ratio), attachments, Zscore(res_rate), Zscore(Physical), Zscore(Polarity), Res_tweet, Zscore(Clout), Zscore(Lifestyle)
k. Predictors: (Constant), Zscore(LNauthor_followers), Zscore(WC), Zscore(neg_ratio), attachments, Zscore(res_rate), Zscore(Physical), Zscore(Polarity), Res_tweet, Zscore(Clout), Zscore(Lifestyle), Zscore(emo_pos)
l. Predictors: (Constant), Zscore(LNauthor_followers), Zscore(WC), Zscore(neg_ratio), attachments, Zscore(res_rate), Zscore(Physical), Zscore(Polarity), Res_tweet, Zscore(Clout), Zscore(Lifestyle), Zscore(emo_pos), Zscore(Social)
m. Predictors: (Constant), Zscore(LNauthor_followers), Zscore(WC), Zscore(neg_ratio), attachments, Zscore(res_rate), Zscore(Physical), Zscore(Polarity), Res_tweet, Zscore(Clout), Zscore(Lifestyle), Zscore(emo_pos), Zscore(Social), Zscore(Analytic)
n. Predictors: (Constant), Zscore(LNauthor_followers), Zscore(WC), Zscore(neg_ratio), attachments, Zscore(res_rate), Zscore(Physical), Zscore(Polarity), Res_tweet, Zscore(Clout), Zscore(Lifestyle), Zscore(emo_pos), Zscore(Social), Zscore(Analytic), Zscore(emo_sad)
o. Predictors: (Constant), Zscore(LNauthor_followers), Zscore(WC), Zscore(neg_ratio), attachments, Zscore(res_rate), Zscore(Physical), Zscore(Polarity), Res_tweet, Zscore(Clout), Zscore(Lifestyle), Zscore(emo_pos), Zscore(Social), Zscore(Analytic), Zscore(emo_sad), Zscore(LNBrand_follower)
p. Predictors: (Constant), Zscore(LNauthor_followers), Zscore(WC), Zscore(neg_ratio), attachments, Zscore(res_rate), Zscore(Physical), Zscore(Polarity), Res_tweet, Zscore(Clout), Zscore(Lifestyle), Zscore(emo_pos), Zscore(Social), Zscore(Analytic), Zscore(emo_sad), Zscore(LNBrand_follower), Zscore(Exclam)
q. Predictors: (Constant), Zscore(LNauthor_followers), Zscore(WC), Zscore(neg_ratio), attachments, Zscore(res_rate), Zscore(Physical), Zscore(Polarity), Res_tweet, Zscore(Clout), Zscore(Lifestyle), Zscore(emo_pos), Zscore(Social), Zscore(Analytic), Zscore(emo_sad), Zscore(LNBrand_follower), Zscore(Exclam), Zscore(Authentic)
r. Predictors: (Constant), Zscore(LNauthor_followers), Zscore(WC), Zscore(neg_ratio), attachments, Zscore(res_rate), Zscore(Physical), Zscore(Polarity), Res_tweet, Zscore(Clout), Zscore(Lifestyle), Zscore(emo_pos), Zscore(Social), Zscore(Analytic), Zscore(emo_sad), Zscore(LNBrand_follower), Zscore(Exclam), Zscore(Authentic), Zscore(Gunning)

Appendix G-4: Full Coefficient Table of Data with Outliers (n = 28,287)

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-.011	.006		-1.980	.048
	Zscore(LNauthor_ followers)	.307	.006	.287	50.467	.000
2	(Constant)	-.011	.006		-1.855	.064
	Zscore(LNauthor_ followers)	.313	.006	.293	51.679	.000
	Zscore(WC)	.099	.006	.097	17.125	<.001
3	(Constant)	-.010	.006		-1.786	.074
	Zscore(LNauthor_ followers)	.308	.006	.289	50.794	.000
	Zscore(WC)	.100	.006	.098	17.350	<.001
	Zscore(neg_ratio)	-.054	.006	-.054	-9.510	<.001
4	(Constant)	.021	.007		2.762	.006
	Zscore(LNauthor_ followers)	.309	.006	.289	50.916	.000
	Zscore(WC)	.098	.006	.097	17.130	<.001
	Zscore(neg_ratio)	-.062	.006	-.062	-10.648	<.001
	attachments	.049	.008	.037	6.469	<.001
5	(Constant)	.027	.008		3.611	<.001
	Zscore(LNauthor_ followers)	.308	.006	.288	50.773	.000
	Zscore(WC)	.095	.006	.094	16.521	<.001
	Zscore(neg_ratio)	-.068	.006	-.068	-11.550	<.001
	attachments	.059	.008	.045	7.652	<.001
	Zscore(res_rate)	.043	.006	.042	7.325	<.001
6	(Constant)	.029	.008		3.916	<.001
	Zscore(LNauthor_ followers)	.308	.006	.288	50.764	.000
	Zscore(WC)	.093	.006	.091	16.061	<.001
	Zscore(neg_ratio)	-.067	.006	-.067	-11.463	<.001
	attachments	.062	.008	.048	8.099	<.001
	Zscore(res_rate)	.042	.006	.041	7.114	<.001
	Zscore(Physical)	-.031	.006	-.031	-5.418	<.001
7	(Constant)	.030	.008		3.962	<.001

	Zscore(LNauthor_followers)	.306	.006	.287	50.526	.000
	Zscore(WC)	.080	.006	.078	12.417	<.001
	Zscore(neg_ratio)	-.064	.006	-.064	-10.894	<.001
	attachments	.063	.008	.048	8.162	<.001
	Zscore(res_rate)	.041	.006	.041	7.009	<.001
	Zscore(Physical)	-.028	.006	-.028	-4.876	<.001
	Zscore(Polarity)	.030	.006	.030	4.719	<.001
8	(Constant)	.063	.010		6.058	<.001
	Zscore(LNauthor_followers)	.307	.006	.288	50.686	.000
	Zscore(WC)	.076	.006	.075	11.706	<.001
	Zscore(neg_ratio)	-.061	.006	-.061	-10.274	<.001
	attachments	.062	.008	.047	8.012	<.001
	Zscore(res_rate)	.037	.006	.037	6.259	<.001
	Zscore(Physical)	-.027	.006	-.027	-4.745	<.001
	Zscore(Polarity)	.030	.006	.029	4.638	<.001
	Res_tweet	.044	.009	.027	4.619	<.001
9	(Constant)	.065	.010		6.216	<.001
	Zscore(LNauthor_followers)	.309	.006	.289	50.840	.000
	Zscore(WC)	.076	.006	.075	11.728	<.001
	Zscore(neg_ratio)	-.061	.006	-.061	-10.350	<.001
	attachments	.061	.008	.047	7.957	<.001
	Zscore(res_rate)	.037	.006	.036	6.215	<.001
	Zscore(Physical)	-.027	.006	-.027	-4.672	<.001
	Zscore(Polarity)	.032	.006	.031	4.918	<.001
	Res_tweet	.046	.009	.028	4.870	<.001
	Zscore(Clout)	.023	.006	.022	3.929	<.001
10	(Constant)	.067	.010		6.437	<.001
	Zscore(LNauthor_followers)	.307	.006	.288	50.486	.000
	Zscore(WC)	.078	.006	.077	12.063	<.001
	Zscore(neg_ratio)	-.061	.006	-.060	-10.197	<.001
	attachments	.062	.008	.048	8.075	<.001
	Zscore(res_rate)	.037	.006	.037	6.284	<.001
	Zscore(Physical)	-.028	.006	-.028	-4.912	<.001
	Zscore(Polarity)	.033	.006	.032	5.073	<.001
	Res_tweet	.049	.009	.030	5.120	<.001
	Zscore(Clout)	.025	.006	.025	4.322	<.001

	Zscore(Lifestyle)	-.024	.006	-.024	-4.121	<.001
11	(Constant)	.067	.010		6.407	<.001
	Zscore(LNauthor_followers)	.308	.006	.288	50.539	.000
	Zscore(WC)	.078	.006	.077	12.067	<.001
	Zscore(neg_ratio)	-.061	.006	-.061	-10.245	<.001
	attachments	.061	.008	.047	7.997	<.001
	Zscore(res_rate)	.037	.006	.037	6.316	<.001
	Zscore(Physical)	-.029	.006	-.028	-4.964	<.001
	Zscore(Polarity)	.032	.006	.032	4.968	<.001
	Res_tweet	.049	.009	.030	5.129	<.001
	Zscore(Clout)	.024	.006	.024	4.181	<.001
	Zscore(Lifestyle)	-.024	.006	-.024	-4.180	<.001
	Zscore(emo_pos)	-.017	.006	-.017	-2.961	.003
12	(Constant)	.067	.010		6.387	<.001
	Zscore(LNauthor_followers)	.307	.006	.288	50.491	.000
	Zscore(WC)	.078	.006	.077	12.058	<.001
	Zscore(neg_ratio)	-.058	.006	-.058	-9.748	<.001
	attachments	.061	.008	.047	7.908	<.001
	Zscore(res_rate)	.036	.006	.036	6.189	<.001
	Zscore(Physical)	-.029	.006	-.029	-5.099	<.001
	Zscore(Polarity)	.028	.007	.028	4.291	<.001
	Res_tweet	.049	.009	.030	5.155	<.001
	Zscore(Clout)	.033	.007	.033	5.032	<.001
	Zscore(Lifestyle)	-.025	.006	-.025	-4.298	<.001
	Zscore(emo_pos)	-.017	.006	-.017	-3.021	.003
	Zscore(Social)	-.019	.007	-.019	-2.828	.005
13	(Constant)	.069	.010		6.640	<.001
	Zscore(LNauthor_followers)	.306	.006	.287	50.225	.000
	Zscore(WC)	.078	.006	.077	12.056	<.001
	Zscore(neg_ratio)	-.056	.006	-.056	-9.351	<.001
	attachments	.066	.008	.050	8.381	<.001
	Zscore(res_rate)	.035	.006	.035	5.884	<.001
	Zscore(Physical)	-.028	.006	-.027	-4.754	<.001
	Zscore(Polarity)	.027	.007	.027	4.067	<.001
	Res_tweet	.049	.009	.030	5.124	<.001
	Zscore(Clout)	.038	.007	.038	5.582	<.001
	Zscore(Lifestyle)	-.023	.006	-.022	-3.814	<.001

	Zscore(emo_pos)	-.018	.006	-.018	-3.115	.002
	Zscore(Social)	-.023	.007	-.022	-3.259	.001
	Zscore(Analytic)	-.020	.006	-.019	-3.162	.002
14	(Constant)	.070	.010		6.676	<.001
	Zscore(LNauthor_followers)	.306	.006	.287	50.219	.000
	Zscore(WC)	.078	.006	.077	12.040	<.001
	Zscore(neg_ratio)	-.057	.006	-.057	-9.404	<.001
	attachments	.065	.008	.050	8.329	<.001
	Zscore(res_rate)	.035	.006	.035	5.889	<.001
	Zscore(Physical)	-.028	.006	-.028	-4.876	<.001
	Zscore(Polarity)	.024	.007	.024	3.686	<.001
	Res_tweet	.049	.009	.030	5.205	<.001
	Zscore(Clout)	.038	.007	.038	5.625	<.001
	Zscore(Lifestyle)	-.023	.006	-.022	-3.851	<.001
	Zscore(emo_pos)	-.017	.006	-.017	-3.083	.002
	Zscore(Social)	-.024	.007	-.023	-3.411	<.001
	Zscore(Analytic)	-.020	.006	-.020	-3.256	.001
	Zscore(emo_sad)	-.014	.006	-.013	-2.349	.019
15	(Constant)	.075	.011		6.986	<.001
	Zscore(LNauthor_followers)	.305	.006	.286	50.077	.000
	Zscore(WC)	.079	.006	.078	12.131	<.001
	Zscore(neg_ratio)	-.057	.006	-.057	-9.442	<.001
	attachments	.067	.008	.052	8.526	<.001
	Zscore(res_rate)	.029	.007	.029	4.443	<.001
	Zscore(Physical)	-.028	.006	-.028	-4.816	<.001
	Zscore(Polarity)	.024	.007	.024	3.588	<.001
	Res_tweet	.054	.010	.033	5.559	<.001
	Zscore(Clout)	.038	.007	.038	5.598	<.001
	Zscore(Lifestyle)	-.022	.006	-.022	-3.723	<.001
	Zscore(emo_pos)	-.018	.006	-.017	-3.094	.002
	Zscore(Social)	-.024	.007	-.024	-3.443	<.001
	Zscore(Analytic)	-.020	.006	-.020	-3.186	.001
	Zscore(emo_sad)	-.014	.006	-.014	-2.426	.015
	Zscore(LNBrand_follower)	.014	.007	.014	2.193	.028
16	(Constant)	.075	.011		6.978	<.001
	Zscore(LNauthor_followers)	.305	.006	.286	50.004	.000

	Zscore(WC)	.077	.007	.076	11.888	<.001
	Zscore(neg_ratio)	-.058	.006	-.057	-9.542	<.001
	attachments	.067	.008	.052	8.513	<.001
	Zscore(res_rate)	.029	.007	.029	4.520	<.001
	Zscore(Physical)	-.028	.006	-.028	-4.841	<.001
	Zscore(Polarity)	.023	.007	.023	3.529	<.001
	Res_tweet	.054	.010	.033	5.555	<.001
	Zscore(Clout)	.038	.007	.038	5.624	<.001
	Zscore(Lifestyle)	-.022	.006	-.022	-3.723	<.001
	Zscore(emo_pos)	-.018	.006	-.018	-3.098	.002
	Zscore(Social)	-.024	.007	-.024	-3.453	<.001
	Zscore(Analytic)	-.020	.006	-.020	-3.207	.001
	Zscore(emo_sad)	-.014	.006	-.014	-2.475	.013
	Zscore(LNBrand_follower)	.014	.007	.014	2.181	.029
	Zscore(Exclam)	-.012	.006	-.012	-2.086	.037
17	(Constant)	.074	.011		6.942	<.001
	Zscore(LNauthor_followers)	.305	.006	.286	49.960	.000
	Zscore(WC)	.075	.007	.074	11.372	<.001
	Zscore(neg_ratio)	-.057	.006	-.057	-9.377	<.001
	attachments	.068	.008	.052	8.618	<.001
	Zscore(res_rate)	.029	.007	.029	4.456	<.001
	Zscore(Physical)	-.028	.006	-.027	-4.723	<.001
	Zscore(Polarity)	.022	.007	.022	3.370	<.001
	Res_tweet	.053	.010	.032	5.418	<.001
	Zscore(Clout)	.041	.007	.041	5.939	<.001
	Zscore(Lifestyle)	-.022	.006	-.021	-3.640	<.001
	Zscore(emo_pos)	-.017	.006	-.017	-3.076	.002
	Zscore(Social)	-.023	.007	-.022	-3.253	.001
	Zscore(Analytic)	-.018	.006	-.018	-2.873	.004
	Zscore(emo_sad)	-.014	.006	-.014	-2.460	.014
	Zscore(LNBrand_follower)	.014	.007	.014	2.170	.030
	Zscore(Exclam)	-.012	.006	-.012	-2.130	.033
	Zscore(Authentic)	.013	.006	.013	2.038	.042
18	(Constant)	.073	.011		6.865	<.001
	Zscore(LNauthor_followers)	.305	.006	.286	50.002	.000
	Zscore(WC)	.073	.007	.072	10.856	<.001

	Zscore(neg_ratio)	-.058	.006	-.058	-9.547	<.001
	attachments	.066	.008	.051	8.346	<.001
	Zscore(res_rate)	.029	.007	.029	4.488	<.001
	Zscore(Physical)	-.027	.006	-.027	-4.682	<.001
	Zscore(Polarity)	.023	.007	.023	3.436	<.001
	Res_tweet	.053	.010	.033	5.468	<.001
	Zscore(Clout)	.042	.007	.041	5.955	<.001
	Zscore(Lifestyle)	-.023	.006	-.023	-3.897	<.001
	Zscore(emo_pos)	-.017	.006	-.017	-2.999	.003
	Zscore(Social)	-.023	.007	-.023	-3.286	.001
	Zscore(Analytic)	-.021	.006	-.021	-3.313	<.001
	Zscore(emo_sad)	-.014	.006	-.014	-2.402	.016
	Zscore(LNBrand_follower)	.015	.007	.014	2.237	.025
	Zscore(Exclam)	-.011	.006	-.011	-2.009	.045
	Zscore(Authentic)	.015	.007	.015	2.281	.023
	Zscore(Gunning)	.014	.006	.014	2.152	.031

a. Dependent Variable: Zscore(LNvirality)

Appendix H: Variables in the Equation of the Forward Logistic Regression (Training)

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	Zscore(LNauthor_followers)	1.315	.058	522.059	1	<.001	3.726	3.329	4.171
	Constant	-4.937	.091	2967.975	1	.000	.007		
Step 2[b]	Zscore(LNauthor_followers)	1.323	.058	526.180	1	<.001	3.756	3.355	4.206
	Zscore(WC)	.235	.056	17.622	1	<.001	1.265	1.133	1.412
	Constant	-4.957	.091	2946.788	1	.000	.007		
Step 3[c]	Zscore(LNauthor_followers)	1.315	.058	522.485	1	<.001	3.726	3.329	4.171
	Zscore(WC)	.223	.057	15.593	1	<.001	1.250	1.119	1.397
	attachments(1)	-.442	.132	11.261	1	<.001	.643	.496	.832
	Constant	-4.601	.136	1147.028	1	<.001	.010		
Step 4[d]	Zscore(LNauthor_followers)	1.323	.058	526.175	1	<.001	3.753	3.352	4.202
	Zscore(WC)	.230	.057	16.313	1	<.001	1.259	1.126	1.407
	Zscore(Clout)	.170	.057	8.868	1	.003	1.185	1.060	1.326
	attachments(1)	-.430	.132	10.589	1	.001	.651	.502	.843
	Constant	-4.620	.137	1145.342	1	<.001	.010		
Step 5[e]	Zscore(LNauthor_followers)	1.320	.058	520.943	1	<.001	3.742	3.341	4.191
	Zscore(WC)	.249	.057	18.894	1	<.001	1.282	1.146	1.435
	Zscore(Clout)	.162	.057	8.040	1	.005	1.176	1.051	1.316
	attachments(1)	-.420	.132	10.068	1	.002	.657	.507	.852

	Res_tweet(1)	.682	.243	7.850	1	.005	1.977	1.227	3.184
	Constant	-5.253	.268	382.808	1	<.001	.005		
Step 6[f]	Zscore(LNauthor_followers)	1.319	.058	518.720	1	<.001	3.740	3.339	4.190
	Zscore(WC)	.265	.058	21.076	1	<.001	1.304	1.164	1.460
	Zscore(Clout)	.158	.057	7.602	1	.006	1.171	1.047	1.310
	Zscore(emo_anger)	.121	.046	7.065	1	.008	1.129	1.032	1.235
	attachments(1)	-.442	.133	11.092	1	<.001	.643	.495	.834
	Res_tweet(1)	.686	.244	7.919	1	.005	1.986	1.231	3.202
	Constant	-5.250	.269	380.060	1	<.001	.005		
Step 7[g]	Zscore(res_rate)	.127	.056	5.201	1	.023	1.135	1.018	1.266
	Zscore(LNauthor_followers)	1.320	.058	515.246	1	<.001	3.745	3.341	4.197
	Zscore(WC)	.257	.058	19.649	1	<.001	1.293	1.154	1.448
	Zscore(Clout)	.157	.057	7.578	1	.006	1.171	1.046	1.309
	Zscore(emo_anger)	.121	.046	6.986	1	.008	1.128	1.032	1.234
	attachments(1)	-.479	.134	12.803	1	<.001	.620	.477	.805
	Res_tweet(1)	.738	.245	9.068	1	.003	2.093	1.294	3.384
	Constant	-5.280	.270	381.982	1	<.001	.005		
Step 8[h]	Zscore(res_rate)	.128	.056	5.240	1	.022	1.136	1.019	1.267
	Zscore(LNauthor_followers)	1.320	.058	515.647	1	<.001	3.744	3.341	4.196
	Zscore(WC)	.237	.058	16.552	1	<.001	1.268	1.131	1.421
	Zscore(Clout)	.160	.057	7.763	1	.005	1.173	1.049	1.313
	Zscore(emo_anger)	.123	.046	7.140	1	.008	1.131	1.033	1.237
	Zscore(Exclam)	-.307	.137	5.047	1	.025	.735	.562	.962

	attachments(1)	-.483	.134	13.015	1	<.001	.617	.474	.802
	Res_tweet(1)	.733	.246	8.918	1	.003	2.082	1.287	3.369
	Constant	-5.292	.271	382.549	1	<.001	.005		
Step 9[i]	Zscore(res_rate)	.121	.056	4.642	1	.031	1.128	1.011	1.259
	Zscore(LNauthor_followers)	1.319	.058	512.661	1	<.001	3.739	3.336	4.192
	Zscore(WC)	.232	.058	15.853	1	<.001	1.262	1.125	1.415
	Zscore(Clout)	.158	.057	7.626	1	.006	1.172	1.047	1.311
	Zscore(emo_anger)	.115	.046	6.173	1	.013	1.122	1.025	1.228
	Zscore(Exclam)	-.315	.137	5.282	1	.022	.730	.558	.955
	Zscore(Physical)	-.161	.073	4.798	1	.028	.852	.738	.983
	attachments(1)	-.510	.134	14.388	1	<.001	.600	.461	.782
	Res_tweet(1)	.746	.246	9.217	1	.002	2.109	1.303	3.414
	Constant	-5.292	.271	381.832	1	<.001	.005		

a. Variable(s) entered on step 1: Zscore(LNauthor_followers).

b. Variable(s) entered on step 2: Zscore(WC).

c. Variable(s) entered on step 3: attachments.

d. Variable(s) entered on step 4: Zscore(Clout).

e. Variable(s) entered on step 5: Res_tweet.

f. Variable(s) entered on step 6: Zscore(emo_anger).

g. Variable(s) entered on step 7: Zscore(res_rate).

h. Variable(s) entered on step 8: Zscore(Exclam).

i. Variable(s) entered on step 9: Zscore(Physical).

Appendix I: Logistic Regression Model AUC (Area Under the Curve) Table and Visualisation of ROC (Receiver Operating Characteristic) Curve

Area Under the Curve

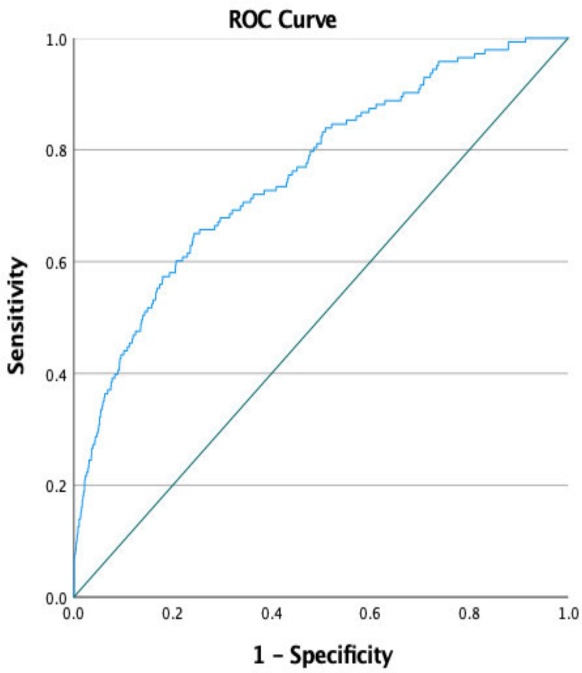
Test Result Variable(s): SelectedProbability

Area	Std. Error[a]	Asymptotic Sig.[b]	Asymptotic 95% Confidence Interval	
			Lower Bound	Upper Bound
.758	.021	.000	.716	.799

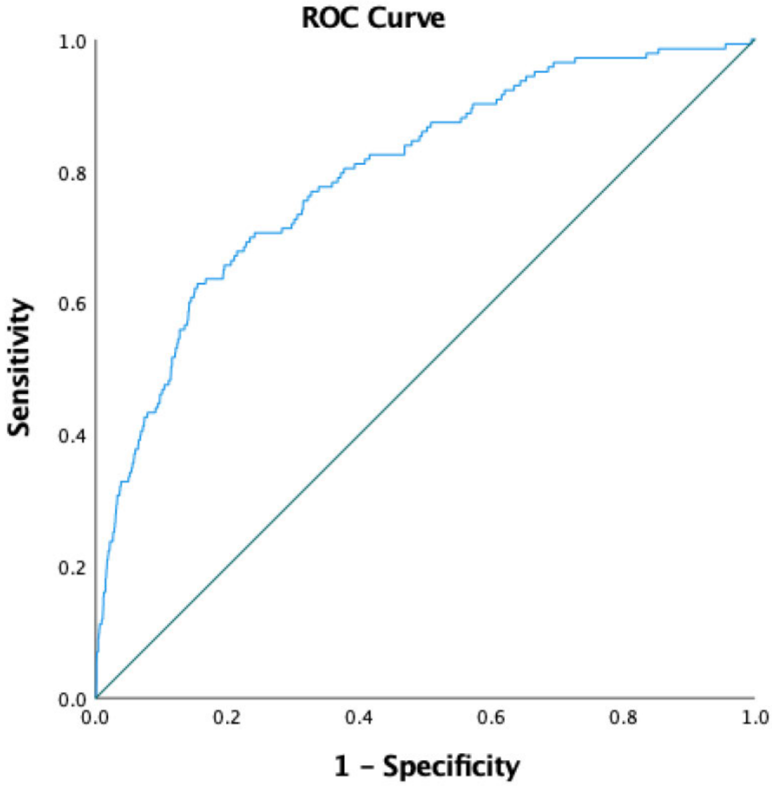
The test result variable(s): SelectedProbability has at least one tie between the positive actual state group and the negative actual state group. Statistics may be biased.

a. Under the nonparametric assumption

b. Null hypothesis: true area = 0.5



Diagonal segments are produced by ties.



Diagonal segments are produced by ties.

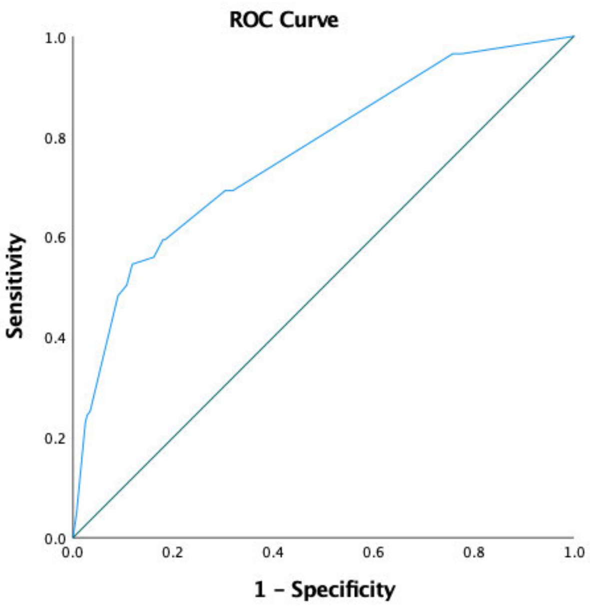
Appendix J: Decision Tree AUC Table and Visualisation of ROC Curve

Area Under the Curve

Test Result Variable(s): SelectedProbability

Area
.765

The test result variable(s): SelectedProbability has at least one tie between the positive actual state group and the negative actual state group. Statistics may be biased.



Diagonal segments are produced by ties.

Appendix K: Organisational Response Model

Whether the organisation respond to a specific complaint is binary, in other words, coded in dummy “1 – response present” and “-1 – response absent” and tree classification was conducted to explore the response choice. Noting that there are some brands never replied to any complaints, these data (n = 1,688) were excluded to minimise the noise and the final sample included 27,629 negative Tweets. Then, the dataset was randomly split into 70% training (n = 19,341) and 30% testing (n = 8,288) stratified by the dummy. SPSS Tree Classification was used for classification. For model validation, training dataset was further split into 80% of training (n = 15,472) and 20% testing (n = 3,869). The model R-square is 0.113 and Figure 21-22 visualise the details of the model, which was then saved and applied to the testing dataset (n = 8,288). AUC = 0.678 indicates that the performance of model prediction is acceptable (see Figure 1 for AUC table and visualisation of ROC)[40].

Area Under the Curve

Test Result Variable(s): SelectedProbability

Area
.678

The test result variable(s): SelectedProbability has at least one tie between the positive actual state group and the negative actual state group. Statistics may be biased.

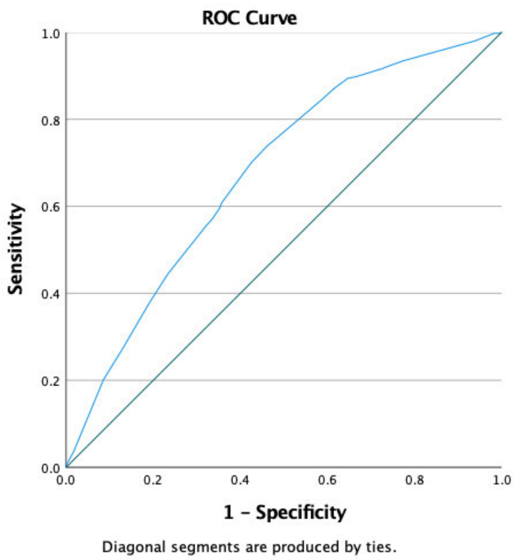
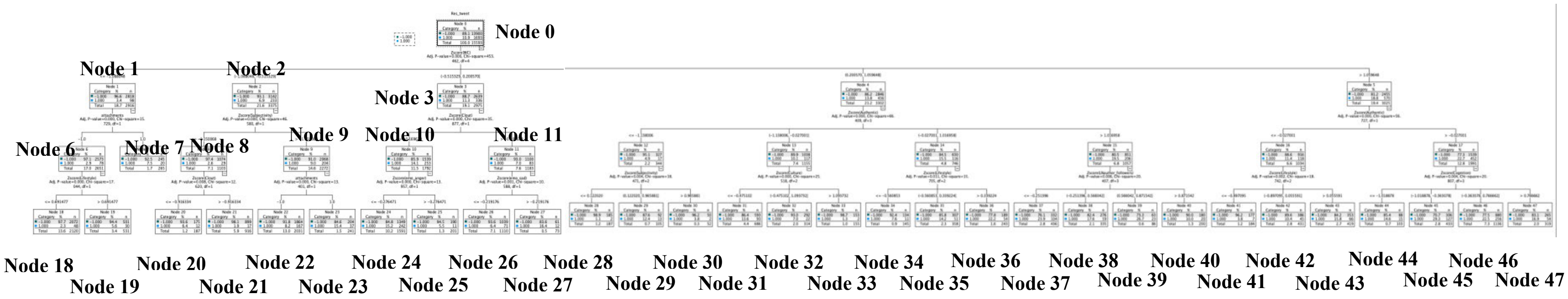


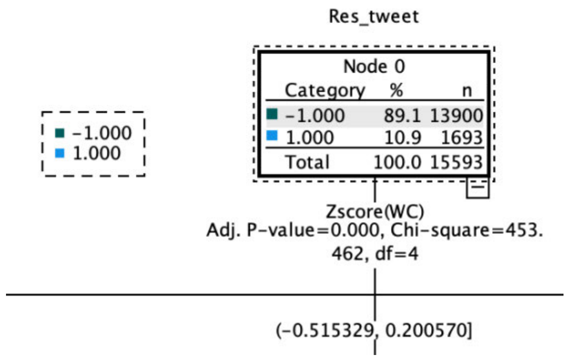
Figure 1. Area Under the Curve and Roc Curve of Classification Tree Model (Organisational Response)

[40] Note that tables and figures in appendices are separately coded in each appendix.

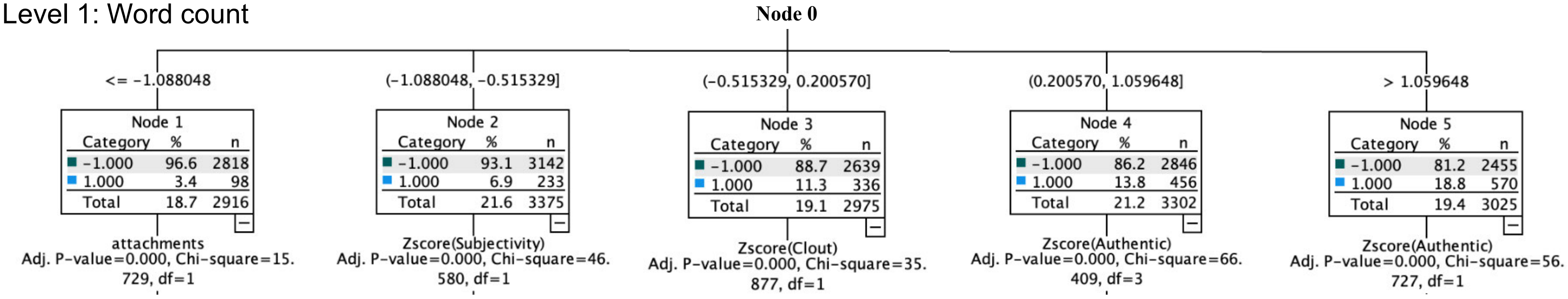
As shown in the training model, the classification tree has the maximin 3 depths and 45 terminal nodes. Whether the organisation/brand will respond to the negative Tweet is predominantly determined by the word count, and Node 1-5 show that the possibility of organisational response to the negative Tweet will increase when the Tweet is longer. Specifically, the probability of responding to Tweets with highest word count is almost 6 times of the Tweets with lowest word count. Node 7-8 are sub-nodes of Node 1, which indicating that among the negative Tweets with lowest words, using attachments can 3 times increase the probability of organisational response. The non-attachment Tweets can be further classified according to the use of lifestyle relevant topic words, as demonstrated in Node 20 and 21, frequency of these topic words can increase the response possibility. For the negative Tweets which have the second lowest number of word count, more subjective expression seems to trigger organisational response (Node 9 and 10). Furthermore, objective expressions with average use of cognition words are more likely to attach response (Node 22-24), and the subjective Tweets expressing higher density of sad emotions are more likely to get replied (Node 25-26). Tweets in Node 3 have slightly lower word count, and clout is a critical predictor in this group as lower level of clout (social confidence) expressed in Tweets tend to attract organisational response. Specifically, Tweets with lower clout score and use attachment have a higher organisational response rate (Node 27 and 28); Tweets with average clout score and posted by complainers with fewer followers are more likely to get replied (Node 29 and 30, consistent social status and social confidence); while Tweets of higher clout score will still get replied if the topic of the complaint is more relevant to lifestyle (Node 31-33). Tweets with above average word count (Node 4) are further classified according to the level of authenticity. Tweets with lower authenticity are less likely to get reply (Node 14-15), however if the topic is irrelevant to culture, the possibility of response will largely increase (Node 34-36). On the other hand, more authentic Tweets with higher subjectivity are receiving organisational responses (Node 37-38). Culture relevant topics are also found less likely to receive response among the Tweets with larger word count (Node 16 and 17), however, among the non-culture relevant Tweets, talking about lifestyle tend to get replies (Node 39-41). Finally, the longest Tweets with high authenticity are likely to be responded (Node 18-19) and the response rate will increase when talking about lifestyle even though the authenticity is lower (Node 42-45). Most of the mentioned classifications are proven in testing data (Node 0-21 and Node 25-45), however, not replicable for Node 22-24 ("Cognition").



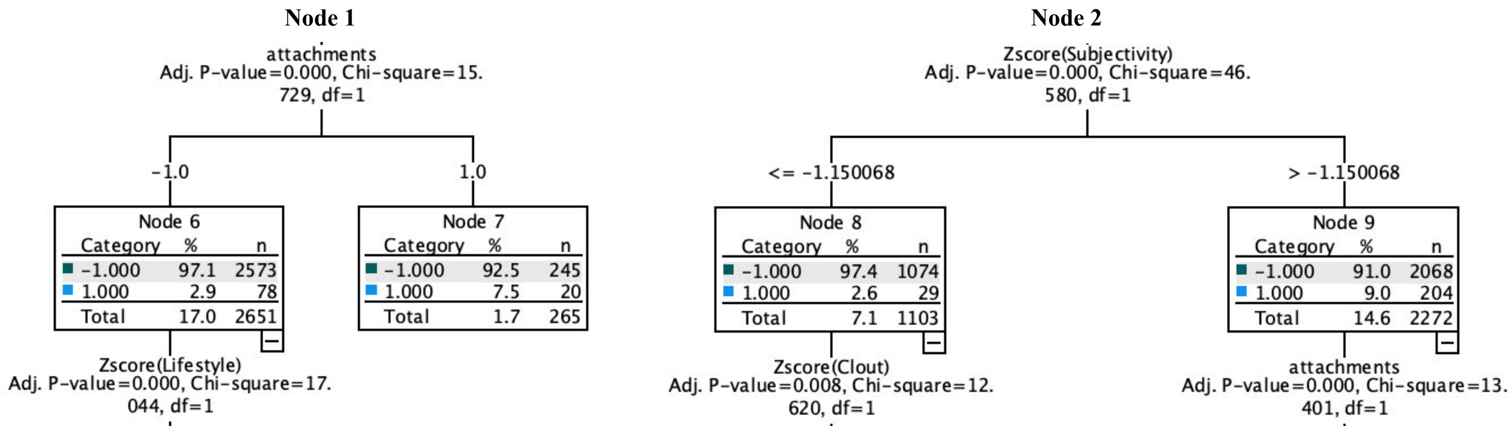
Level 0: Organisational response (dummy)



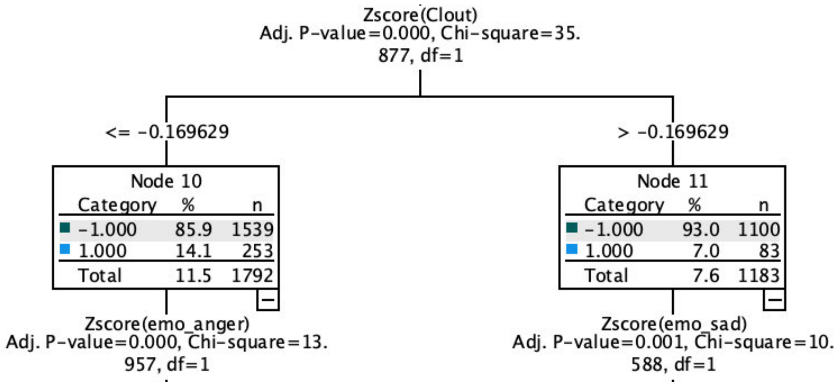
Level 1: Word count



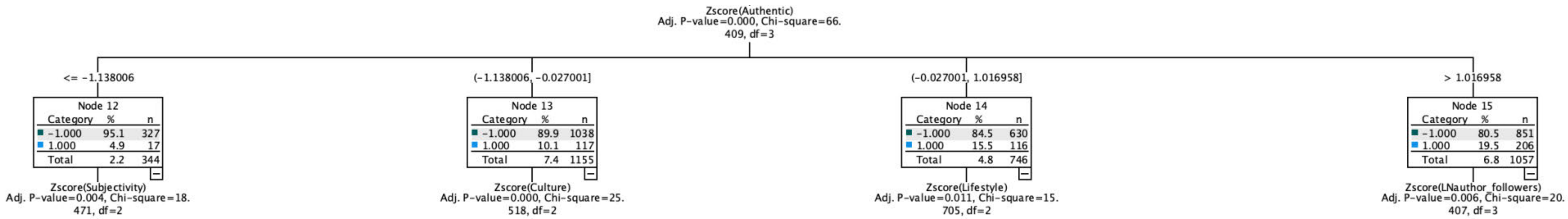
Level 2: Attachments, subjectivity, clout, and authenticity



Node 3



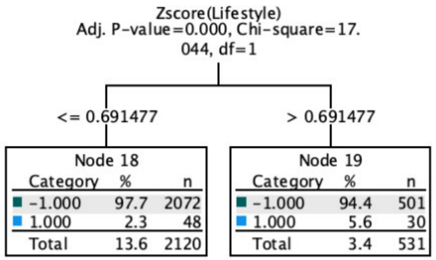
Node 4



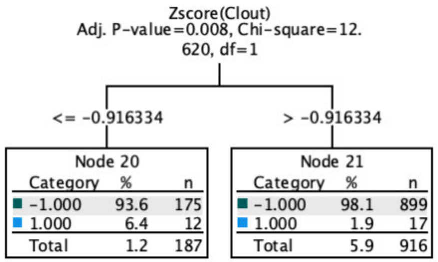
Node 5

Level 3: Lifestyle, clout, attachments, anger, sad, subjectivity, culture, lifestyle, author_followers, and cognition

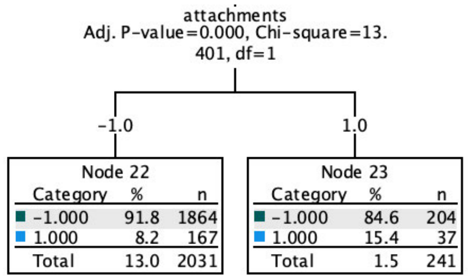
Node 6



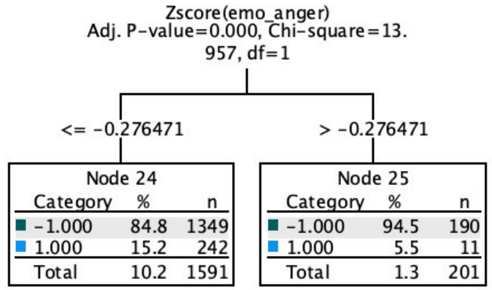
Node 8



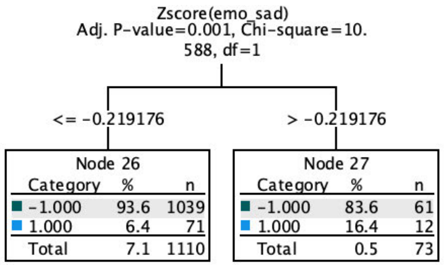
Node 9



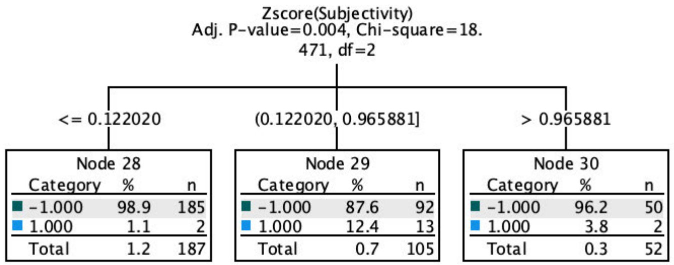
Node 10



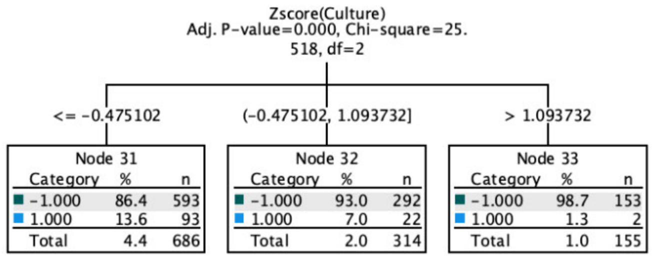
Node 11



Node 12



Node 13



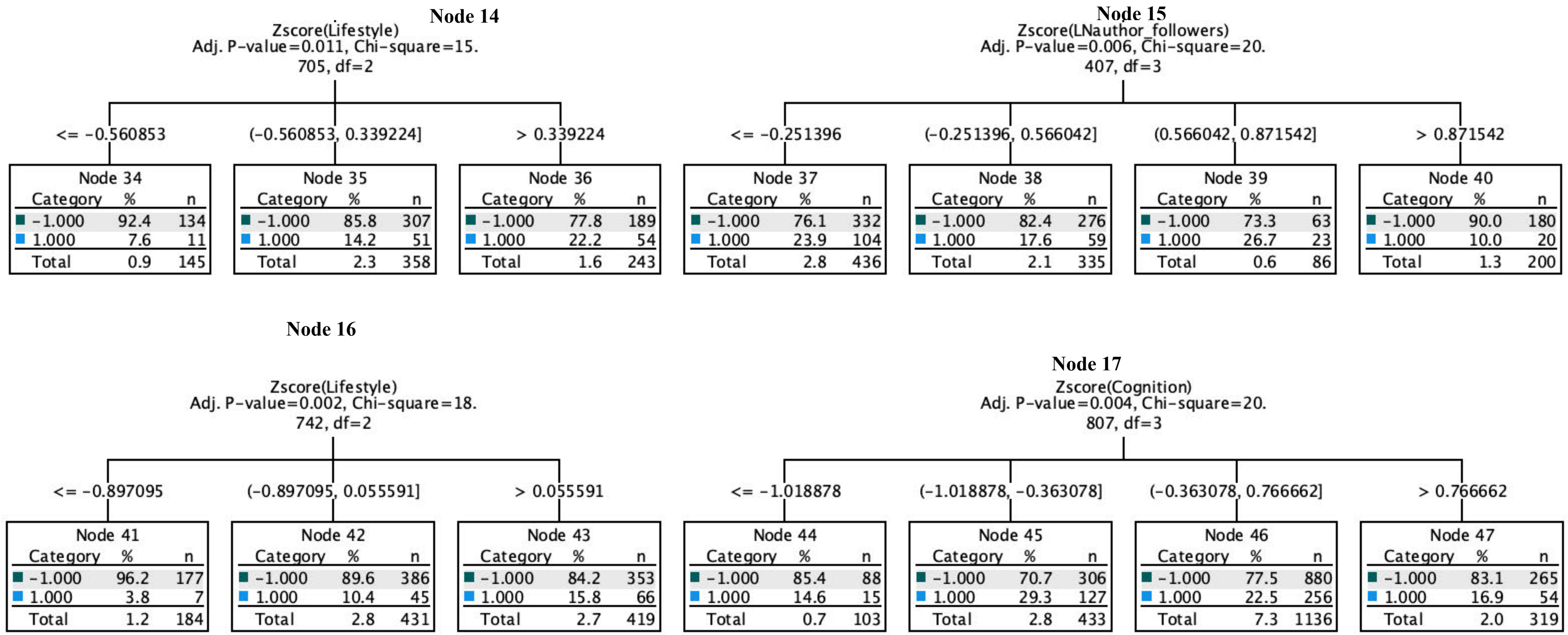
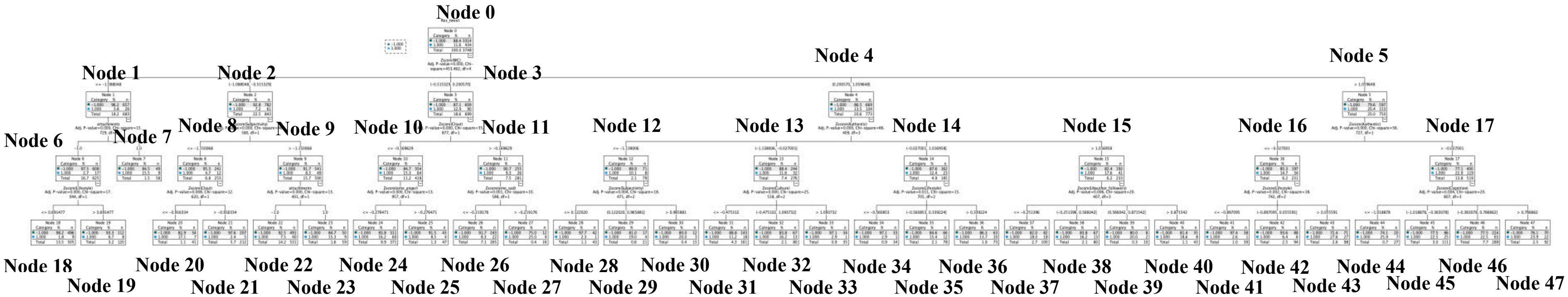
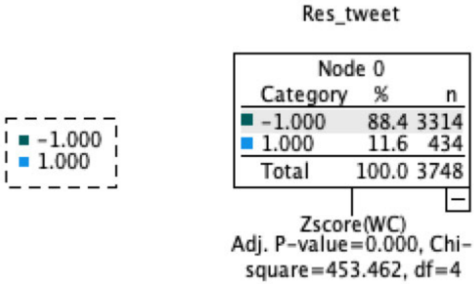


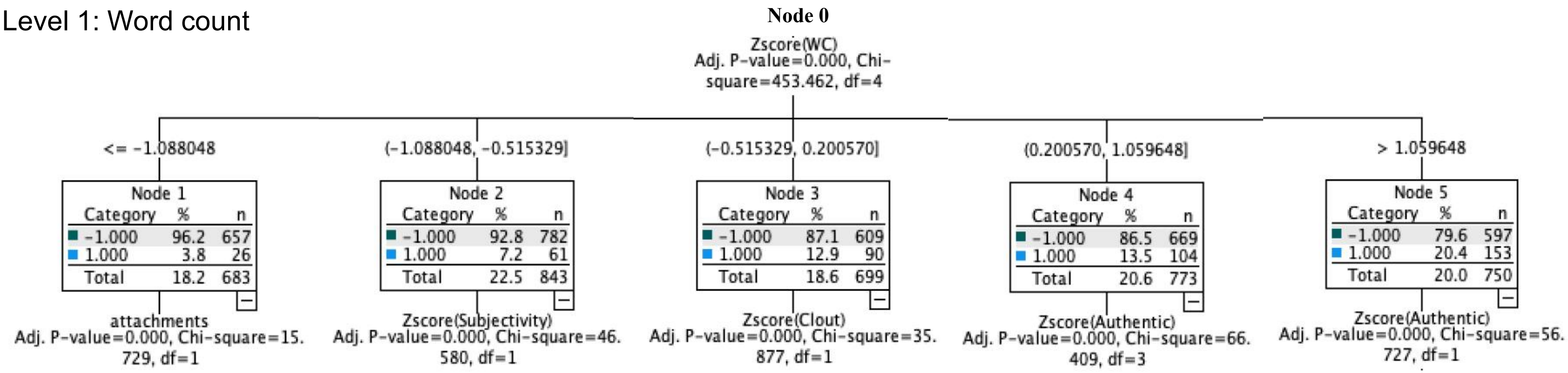
Figure 2 Classification tree – Organisational response (Training)



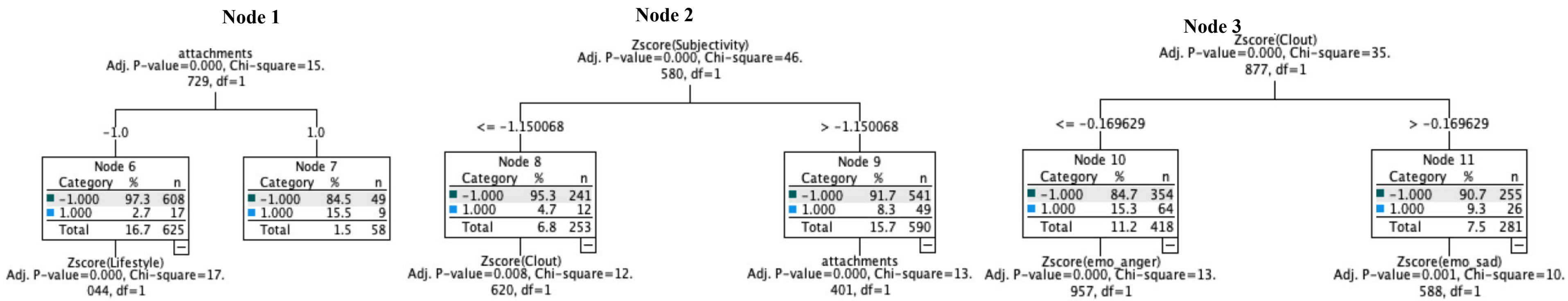
Level 0: Organisational response (dummy)



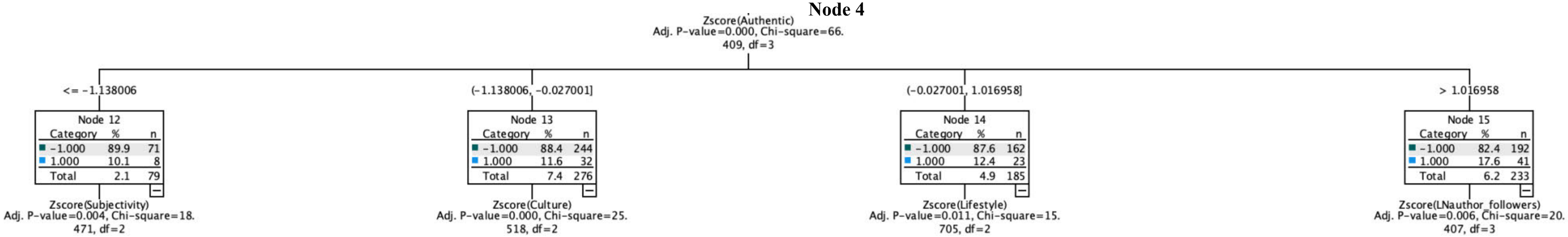
Level 1: Word count



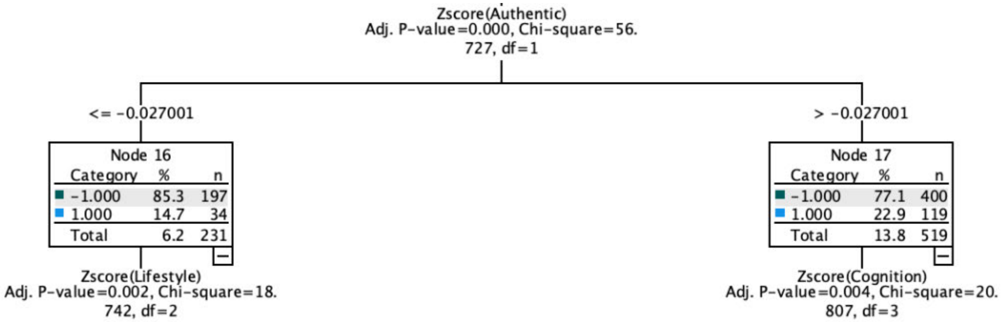
Level 2: Attachments, subjectivity, clout, and authenticity



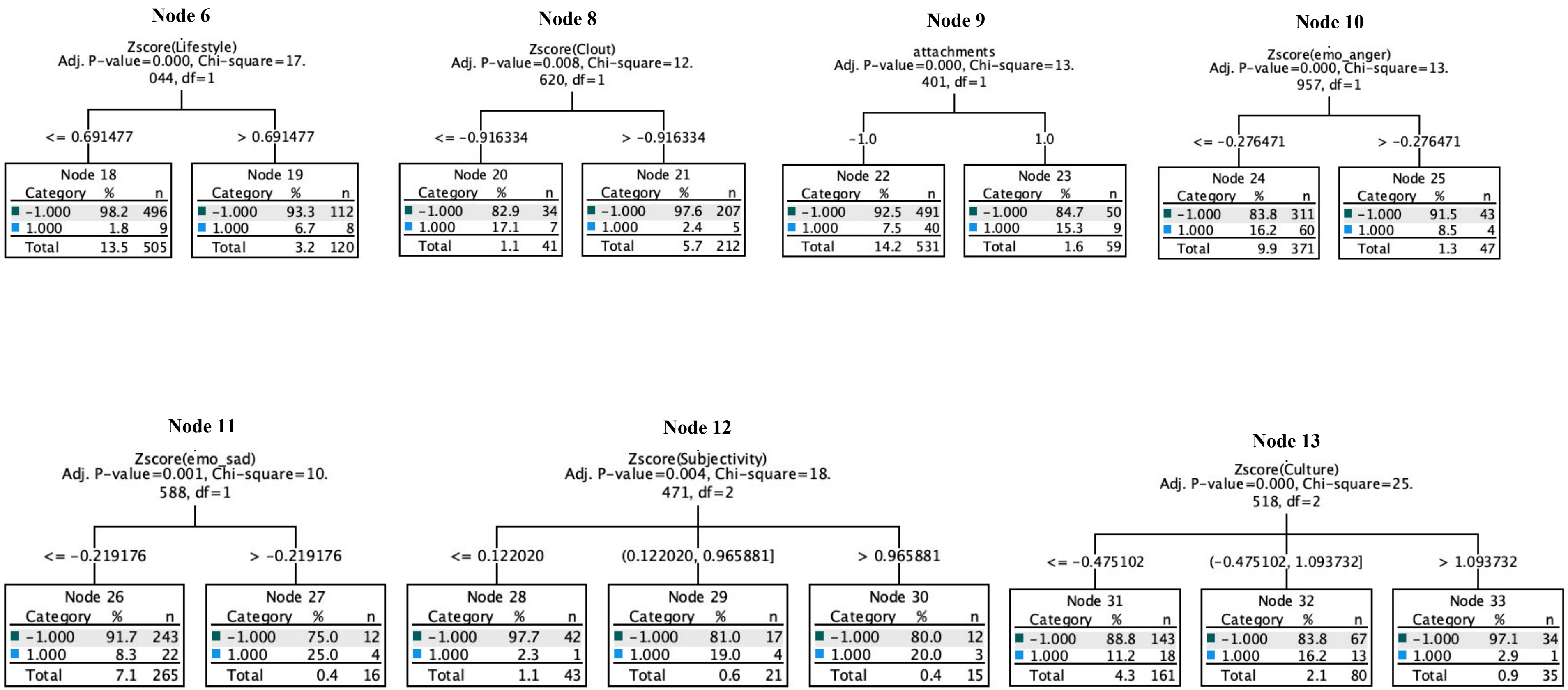
Node 4


Zscore(Authentic)
Adj. P-value=0.000, Chi-square=66.
409, df=3
<= -1.138006
(-1.138006, -0.027001]
(-0.027001, 1.016958]
> 1.016958
Node 12
Category % n
-1.000 89.9 71
1.000 10.1 8
Total 2.1 79
Zscore(Subjectivity)
Adj. P-value=0.004, Chi-square=18.
471, df=2
Node 13
Category % n
-1.000 88.4 244
1.000 11.6 32
Total 7.4 276
Zscore(Culture)
Adj. P-value=0.000, Chi-square=25.
518, df=2
Node 14
Category % n
-1.000 87.6 162
1.000 12.4 23
Total 4.9 185
Zscore(Lifestyle)
Adj. P-value=0.011, Chi-square=15.
705, df=2
Node 15
Category % n
-1.000 82.4 192
1.000 17.6 41
Total 6.2 233
Zscore(LNauthor_followers)
Adj. P-value=0.006, Chi-square=20.
407, df=3

Node 5


Zscore(Authentic)
Adj. P-value=0.000, Chi-square=56.
727, df=1
<= -0.027001
> -0.027001
Node 16
Category % n
-1.000 85.3 197
1.000 14.7 34
Total 6.2 231
Zscore(Lifestyle)
Adj. P-value=0.002, Chi-square=18.
742, df=2
Node 17
Category % n
-1.000 77.1 400
1.000 22.9 119
Total 13.8 519
Zscore(Cognition)
Adj. P-value=0.004, Chi-square=20.
807, df=3

Level 3: Lifestyle, clout, attachments, anger, sad, subjectivity, culture, lifestyle, followers of the complainer, and cognition



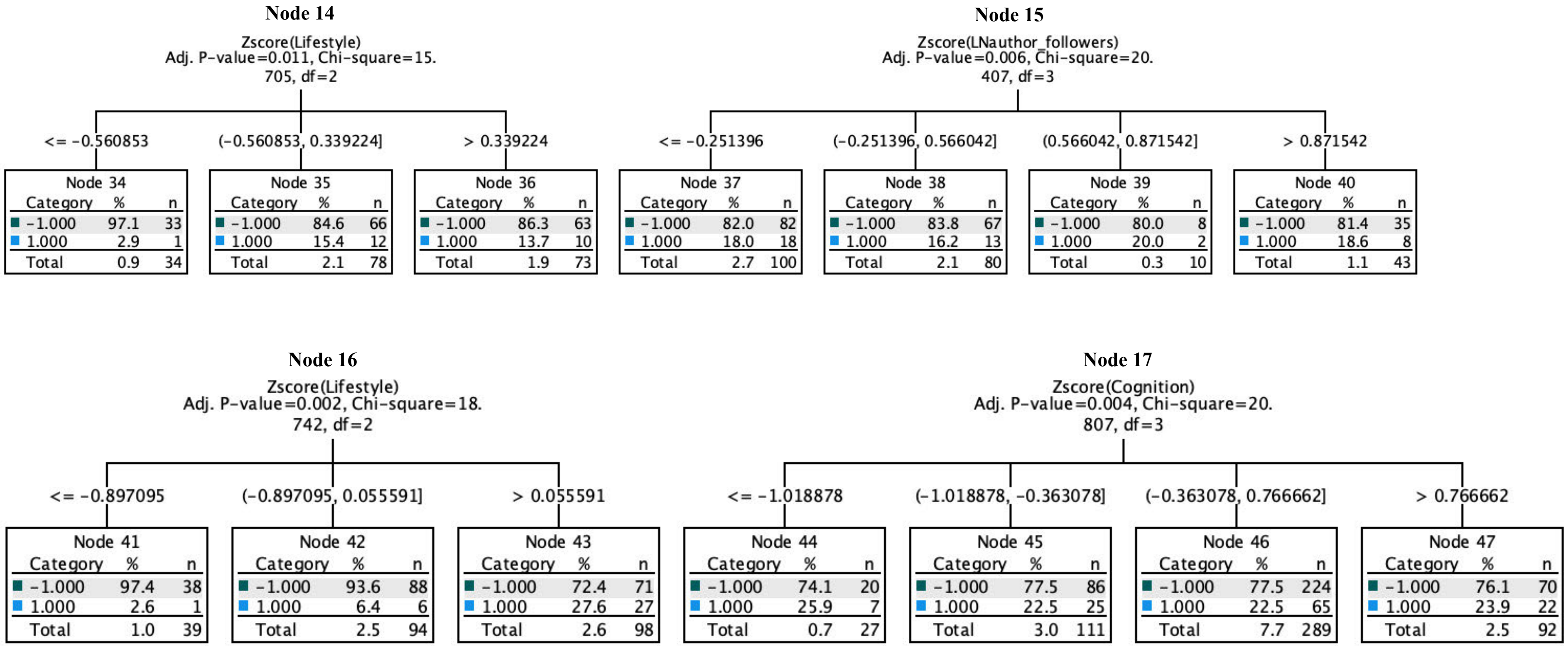


Figure 3 Classification tree – Organisational response (Testing)

For validation, logistic regression was also conducted according to the same process in section 6.3. As shown in Table 1, the final model containing all predictors which were statistically significant, χ^2 (5, N = 19,341) = 980.879, $p < .001$, indicating that the model was able to distinguish the present and absence of organisational response. Hosmer and Lemeshow test (Table 2) further confirmed the model fit, with significance value of the final model (Model 5) higher than 0.05. Model summary (Table 3) shows that 10% of the variance in organisational response can be explained by the model.

Table 1 Omnibus tests of model coefficient – organisational response (Training)

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	558.697	1	<.001
	Block	558.697	1	<.001
	Model	558.697	1	<.001
Step 2	Step	145.567	1	<.001
	Block	704.263	2	<.001
	Model	704.263	2	<.001
Step 3	Step	109.333	1	<.001
	Block	813.596	3	<.001
	Model	813.596	3	<.001
Step 4	Step	119.026	1	<.001
	Block	932.622	4	<.001
	Model	932.622	4	<.001
Step 5	Step	48.257	1	<.001
	Block	980.879	5	<.001
	Model	980.879	5	<.001

Table 2 Hosmer and Lemeshow test – organisational response (Training)

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	46.019	8	<.001
2	11.261	8	.187
3	4.203	8	.838
4	9.311	8	.317
5	8.509	8	.385

Table 3 Model summary – organisational response (Training)

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	12843.077[a]	.028	.057
2	12697.510[a]	.036	.072
3	12588.178[a]	.041	.082
4	12469.152[a]	.047	.094
5	12420.894[b]	.049	.099

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

b. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.

Table 4 lists the significant variables in equation (see variables in the equation of each step in Table 5). Subjectivity, word count, authenticity, and use of lifestyle-relevant words can increase the possibility of organisational response. While the odds ratio of 0.77 for discussing culture indicating the lower possibility of receiving response. The model was then applied to testing dataset (n = 8,288) for model fit assessing and robustness check. The model fit is acceptable with AUC = 0.702 (see Table 6 and Figure 4 for AUC table and visualisation of ROC). Other common methods, such as support vector and random forest were also applied to explore the data, however, all returned extremely low R-square. The results of classification tree and logistic regression both confirmed that larger word count, higher level of text subjectivity and authenticity will have positive impact on organisational response. Topic wise, cultural relevant complaints will less likely be answered by the organisation while topics about lifestyle have opposite effects. This phenomenon was also observed when data were manually checked in exploratory studies[41]. However, given that the dictionary words are unknown, it is still unclear what exactly topics are this complaint about, therefore, more elaborated analysis on topics will be conducted.

[41] For example, description of hospitality experience such as gym facilities, dining, room service may have higher scores in "Lifestyle" and organisations seem to assign more importance to these complaints although they tend to be personal experience. While complaints relevant to politics and ethnicity (which are sub-groups in the "Culture" dictionary) are less likely to get reply although they tend to be hot topics.

Table 4 Variables in the equation – organisational response

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 5	Zscore(Subjectivity)	.261	.027	93.932	1	<.001	1.298	1.231	1.368
	Zscore(WC)	.462	.024	373.679	1	<.001	1.588	1.515	1.664
	Zscore(Authentic)	.292	.026	127.453	1	<.001	1.339	1.273	1.409
	Zscore(Culture)	-.264	.041	41.379	1	<.001	.768	.709	.832
	Zscore(Lifestyle)	.252	.023	116.661	1	<.001	1.286	1.229	1.346
	Constant	-2.360	.029	6587.661	1	.000	.094		

Table 5 Variables in the equation of the forward logistic regression steps

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	Zscore(WC)	.534	.023	535.034	1	<.001	1.706	1.630	1.785
	Constant	-2.207	.025	7577.872	1	.000	.110		
Step 2[b]	Zscore(WC)	.472	.024	401.484	1	<.001	1.603	1.531	1.679
	Zscore(Authentic)	.300	.025	141.783	1	<.001	1.350	1.285	1.418
	Constant	-2.252	.026	7343.378	1	.000	.105		

Step 3[c]	Zscore(WC)	.452	.024	359.097	1	<.001	1.571	1.499	1.646
	Zscore(Authentic)	.322	.025	160.272	1	<.001	1.380	1.313	1.451
	Zscore(Lifestyle)	.252	.023	117.546	1	<.001	1.287	1.229	1.347
	Constant	-2.279	.027	7179.158	1	.000	.102		
Step 4[d]	Zscore(Subjectivity)	.286	.027	115.541	1	<.001	1.331	1.263	1.402
	Zscore(WC)	.460	.024	369.358	1	<.001	1.584	1.512	1.660
	Zscore(Authentic)	.323	.026	160.698	1	<.001	1.382	1.314	1.452
	Zscore(Lifestyle)	.251	.023	116.322	1	<.001	1.286	1.228	1.346
	Constant	-2.327	.028	6918.618	1	.000	.098		
Step 5[e]	Zscore(Subjectivity)	.261	.027	93.932	1	<.001	1.298	1.231	1.368
	Zscore(WC)	.462	.024	373.679	1	<.001	1.588	1.515	1.664
	Zscore(Authentic)	.292	.026	127.453	1	<.001	1.339	1.273	1.409
	Zscore(Culture)	-.264	.041	41.379	1	<.001	.768	.709	.832
	Zscore(Lifestyle)	.252	.023	116.661	1	<.001	1.286	1.229	1.346
	Constant	-2.360	.029	6587.661	1	.000	.094		

a. Variable(s) entered on step 1: Zscore(WC).

b. Variable(s) entered on step 2: Zscore(Authentic).

c. Variable(s) entered on step 3: Zscore(Lifestyle).

d. Variable(s) entered on step 4: Zscore(Subjectivity).

e. Variable(s) entered on step 5: Zscore(Culture).

Table 6 Area under the curve

Area Under the Curve

Test Result Variable(s): SelectedProbability

	Area
	.702

The test result variable(s): SelectedProbability has at least one tie between the positive actual state group and the negative actual state group. Statistics may be biased.

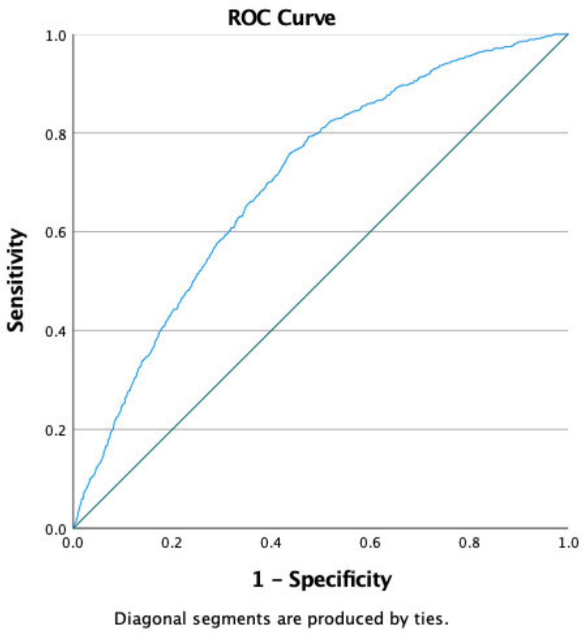


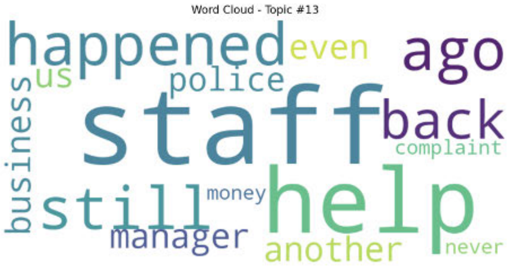
Figure 4 Roc curve visualisation

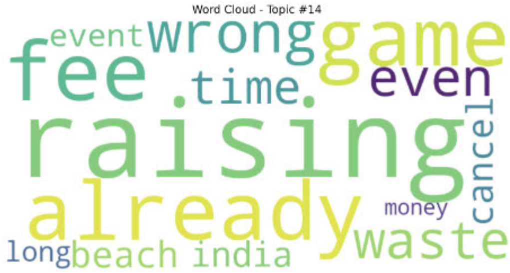
Appendix L: Word Cloud of the 15 Most Frequently Used Words in Different Topics

Appendix L-1: k = 15


Word Cloud - Topic #11
wrong
staff
check
trying
convention
desk
told
front
link
us
back
say
room

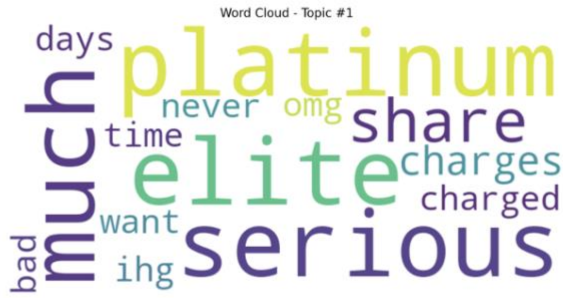

Word Cloud - Topic #12
unacceptable
shit
worst
experience
avoid
time
staying
member
bad
terrible
elite
never
sorry

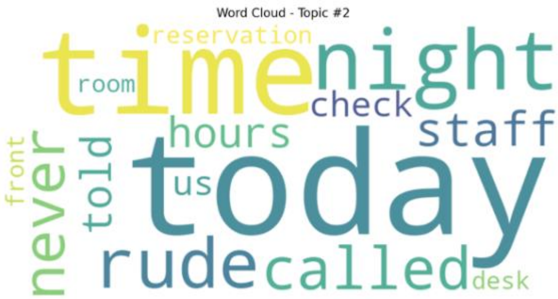

Word Cloud - Topic #13
happened
even
ago
us
police
staff
back
business
complaint
still
money
help
manager
another
never

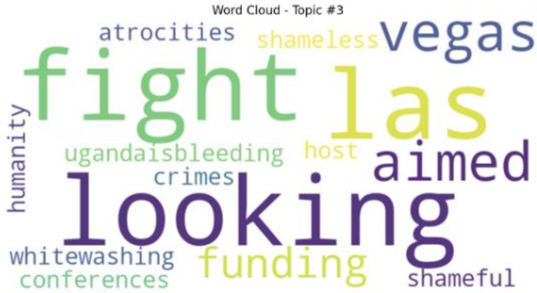

Word Cloud - Topic #14
event
wrong
game
fee
time
even
raising
cancel
already
money
long
beach
india
waste

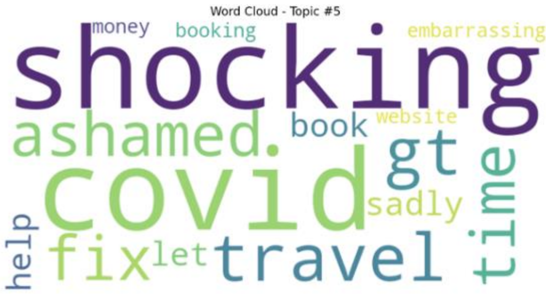

Word Cloud - Topic #15
reservation
terrible
disappointed
experience
service
even
bad
phone
horrible
poor
call
staff
still
customer
worst

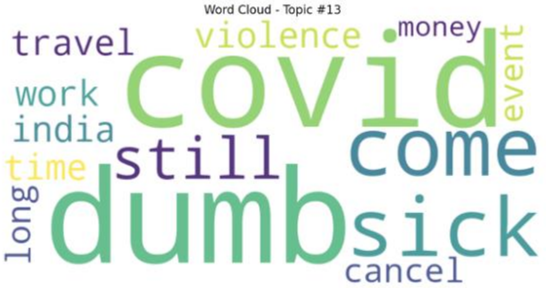
Appendix L-2: k = 20

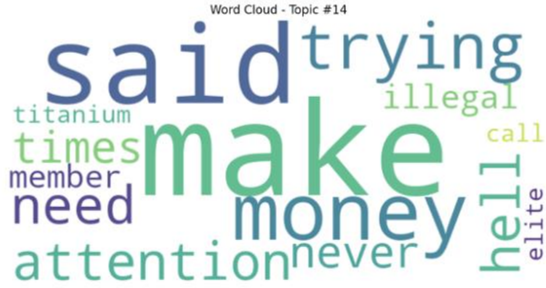






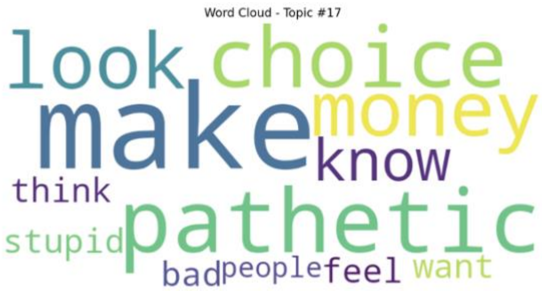



Word Cloud - Topic #13
covid
dumb
sick
come
still
violence
travel
money
event
work
india
time
long
cancel


Word Cloud - Topic #14
said
trying
make
money
illegal
titanium
times
call
member
need
hell
elite
attention
never


Word Cloud - Topic #15
even
legalize
woman
corruption
launch
convention
security
say
trying
little
black
man
guy


Word Cloud - Topic #16
management
cry
terrorists
right
baby
evil
medical
reviews
property
need
hospital
people
domestic
complaint
bad

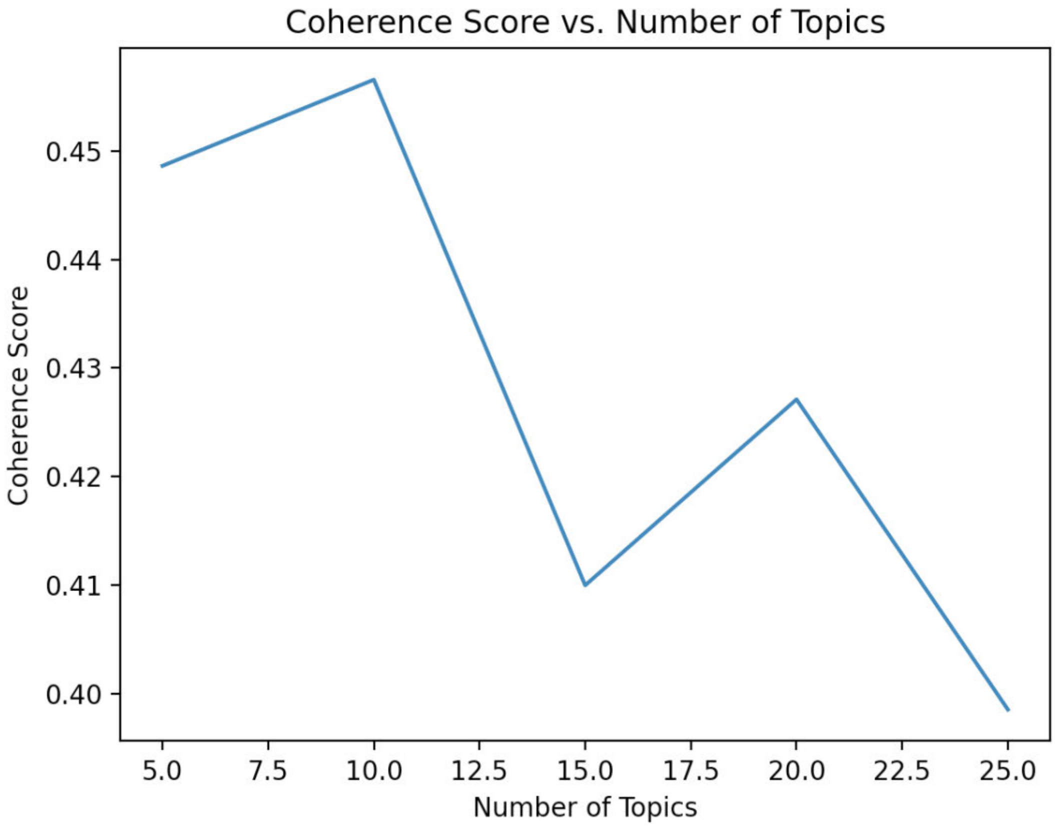

Word Cloud - Topic #17
look
choice
make
money
know
think
pathetic
stupid
bad
people
feel
want


Word Cloud - Topic #18
stop
funding
human
aimed
kunga
events
abuses
sponsoring
torture
uganda
rights
canada
ugandans
hosting
ugandaisbleeding


Word Cloud - Topic #19
even
staff
room
horrible
bad
worst
poor
still
service
stayed
never
experience
terrible
customer

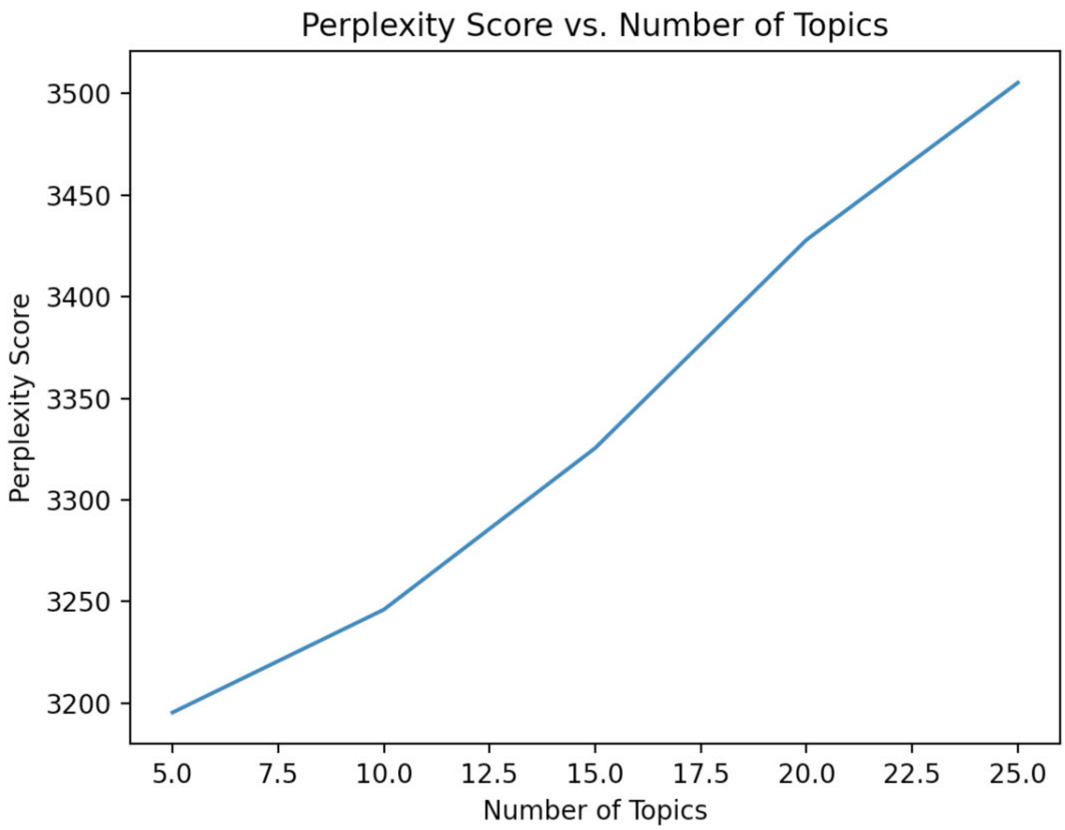

Word Cloud - Topic #20
think
even
white
know
scary
guests
really
hate
racist
hope
hosting
member
sucks
staying
conference

Appendix M: Coherence Score of Different Number of Topics



Note: start, limit, step = 5, 26, 5

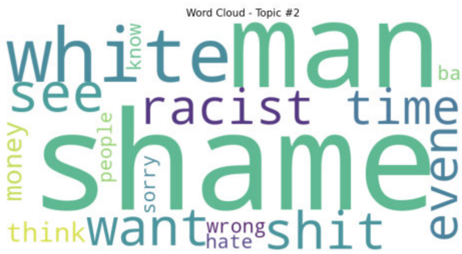
Appendix N: Perplexity Score of Different Number of Topics

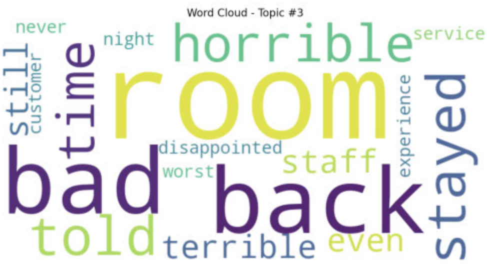


Appendix O: Word Cloud of the 20 Most Frequently Used Words in Different Topics

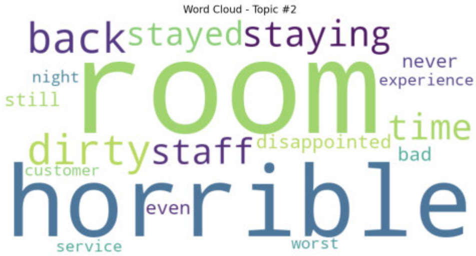
Appendix O-1: k = 2

Appendix O-2: k = 3

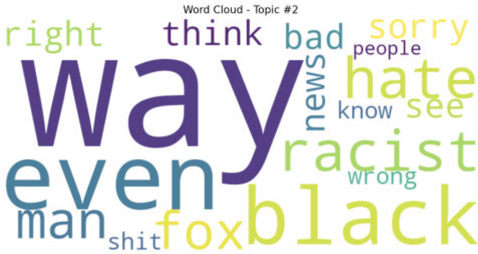


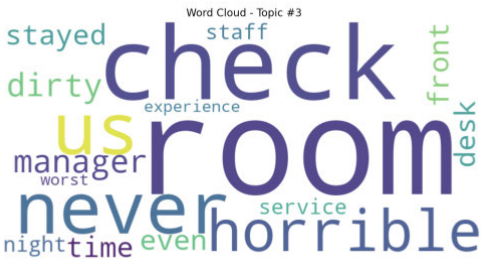


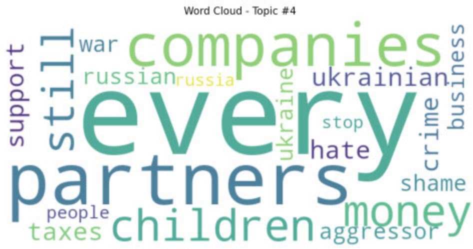
Appendix O-3: k = 4



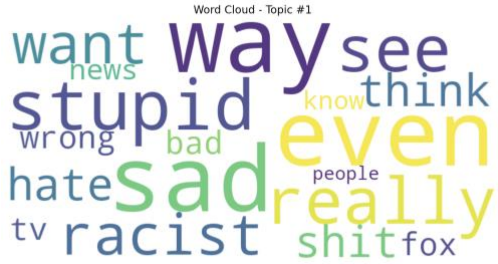
Appendix O-4: k = 5

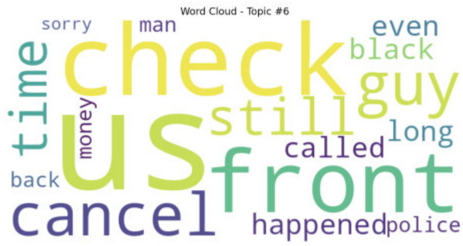




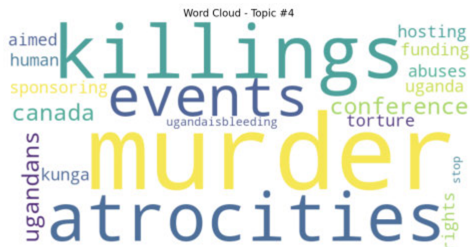


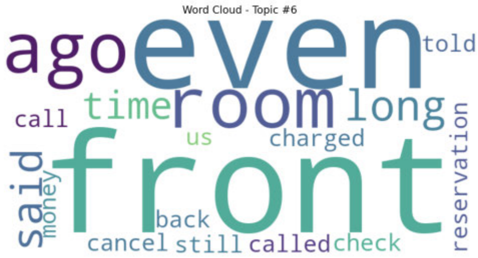
Appendix O-5: k = 6



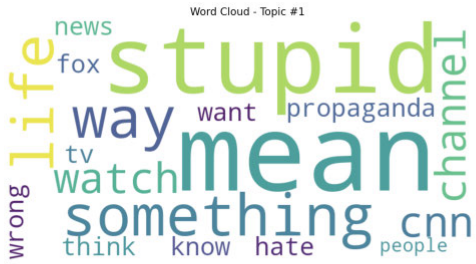


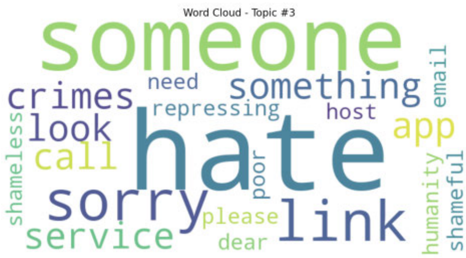
Appendix O-6: k = 7

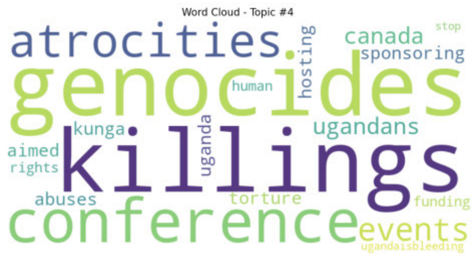


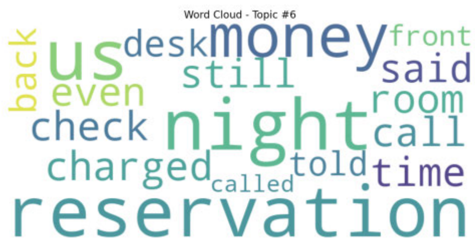


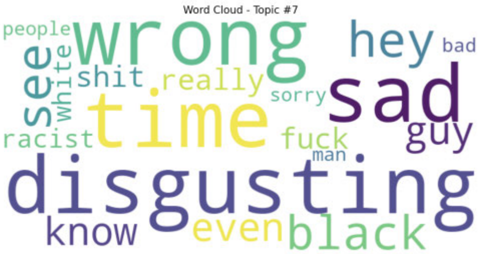
Appendix O-7: k = 8



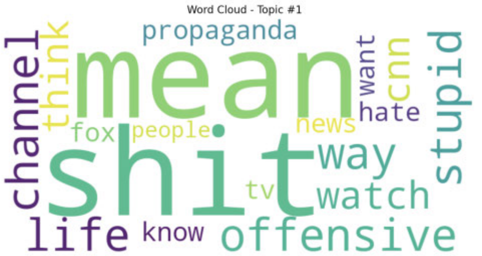


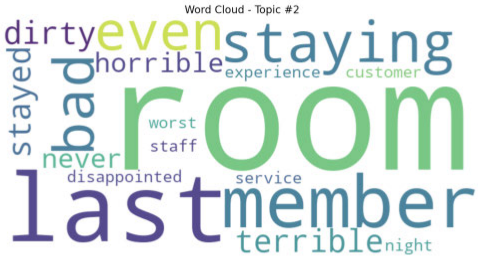


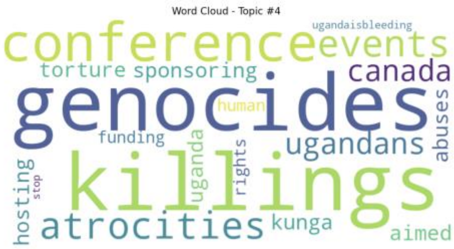


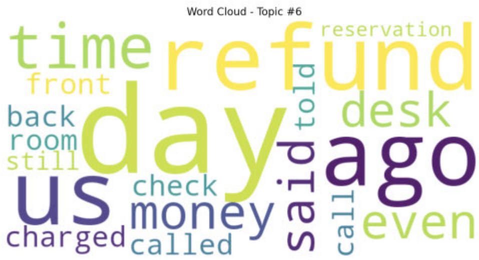


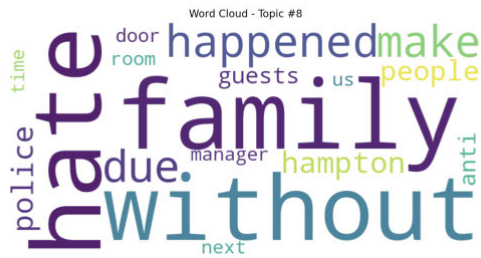
Appendix O-8: k = 9

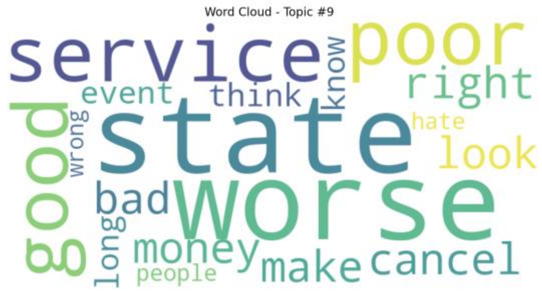




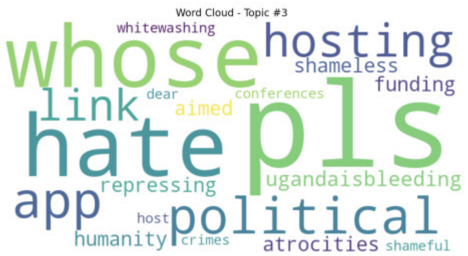


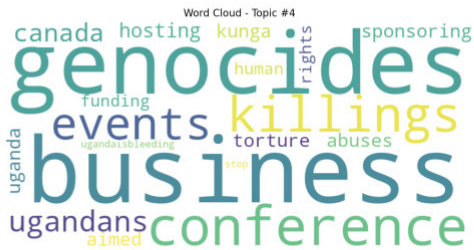


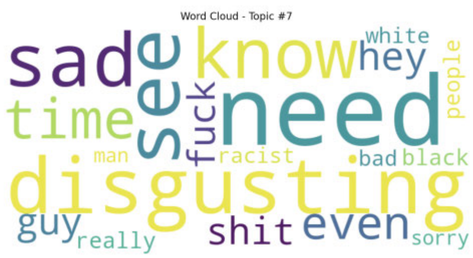


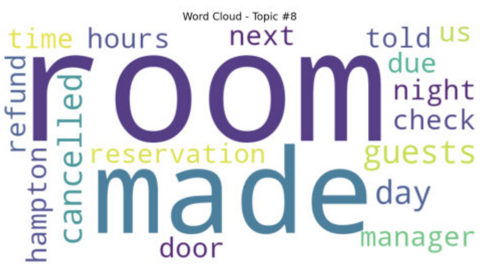


Appendix O-9: k = 10

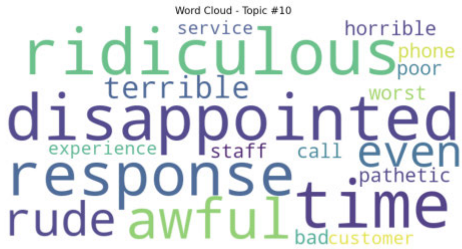




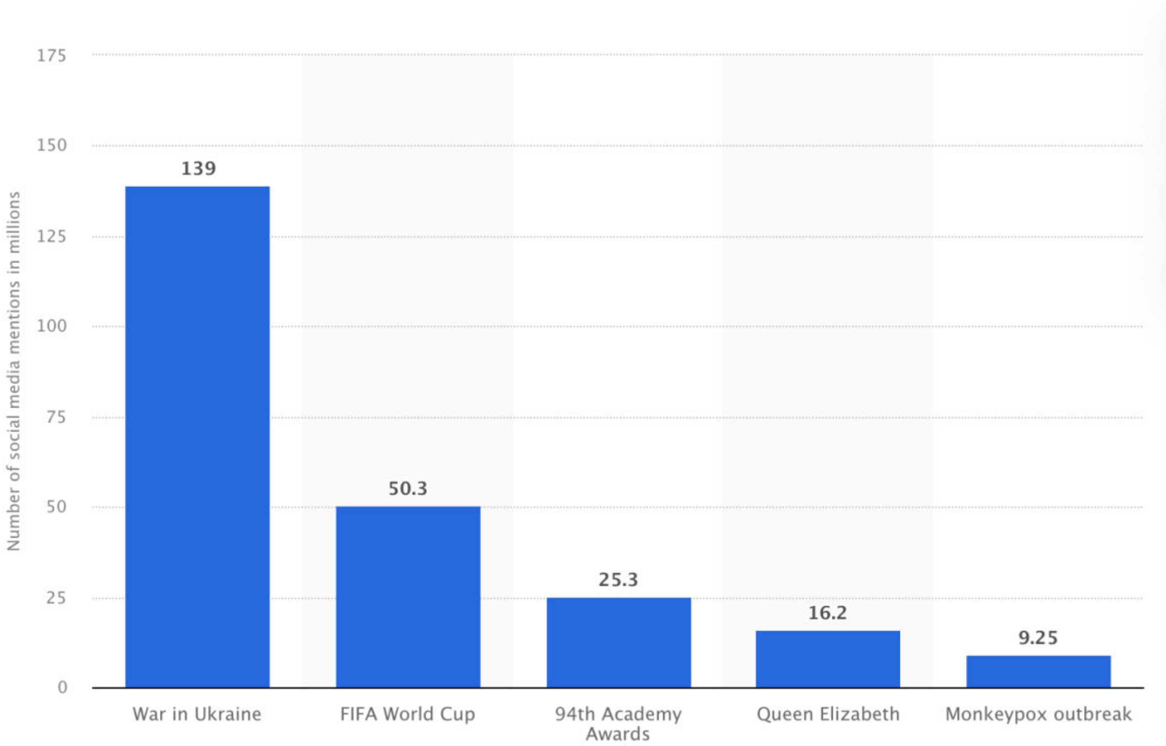





Word Cloud - Topic #9
need
group
say
money
worse
good
know
cancel
hate
long
look
bad
make
people
wrong
event
think


Word Cloud - Topic #10
ridiculous
disappointed
response
time
awful
rude
even
terrible
service
horrible
phone
poor
worst
experience
staff
call
pathetic
bad
customer

Appendix P: Most mentioned events across social media platforms worldwide in 2022



Source: Statista (2023f)

Details: Worldwide; Meltwater; January 1 to December 27, 2022; posts on Twitter, Reddit, YouTube, Pinterest, WeChat, TikTok, Twitch, Sina Weibo, Douyin, Facebook, Instagram, and LinkedIn

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