The "funding secured" tweet crisis: An evaluative study on the crisis response of Elon Musk and the reaction of audience

Evaluating the role of Twitter in the Tesla's crisis communication

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ABSTRACT

On August 7 of 2018, Elon Musk posted a tweet on his profile stating the following: “Am considering taking Tesla private $420. Funding secured”. SEC and the key stakeholders of Tesla considered the tweet to be obscure and confusing; Elon Musk did not provide any information regarding the funding of the endeavour. SEC announced fraud allegations against Mr. Musk, subjecting him to the fine and removal of the CEO title for three years. The tweet caused the “funding secured” crisis that provoked substantial stock fluctuations endangering the position of Tesla shareholders. The crisis is still ongoing, as Tesla is currently being sued by JPMorgan, suggesting that Elon Musk could have underestimated the crisis. Thus, the study was designed as a quantitative content analysis to answer the following research questions: “to what extent does Elon Musk’s communication demonstrate a more frequent use of primary strategies rather than secondary strategies for the reputation management during the “funding secured” crisis of 2018?”; “to what extent does Elon Musk use counter-framing in the Twitter communication in response to the audience’s tweets about the “funding secured” crisis of 2018?” and “to what extent does the audience react positively to the communication of Elon Musk on Twitter?”. The study investigated the use of crisis response strategies of Elon Musk and evaluated the reaction of Elon Musk’s audience composed of Tesla stakeholders to his communication on Twitter during five months of the crisis. In total, 342 tweets of Mr. Musk and 352 tweets containing the stakeholders’ reactions were collected into two datasets. The tweets were coded by two coders following the two codebooks containing definitions of the variables and coding instructions. The statistical software SPSS was used to analyse the variables, potential relationships, and differences between them. The findings suggested that Elon Musk used bolstering strategies over primary responses. The results revealed that the audience reacted negatively to the communication of Elon Musk on Twitter. Moreover, the results showed that Elon Musk relied on framing the tweets positively in response to the negative frames of the stakeholders. One of the limitations was related to the scope of the study. The study recommended conducting a mixed-methods study to analyse Tesla press releases.

<u>KEYWORDS:</u> Crisis communication, Tweets framing, Crisis response strategies, Elon Musk, Corporate reputation

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1 Introduction

1.1 The “funding secured” tweet case

Tesla, Inc. is an American electric vehicle and energy company rooting for rapid production, popularisation, and proliferation of clean energy across the globe (Tesla, Inc., 2022a). The company began its operation as an original start-up co-founded by an American business visionary and ambitious entrepreneur Elon Musk with a background in physics and economics (Kolodny & Black, 2021). Tesla has proven itself in the international arena as the creator and dealer of supposedly reliable and eco-friendly cars.

As of December 31, 2021, the company consists of approximately 100.000 employees. It is one of the most famous and largest companies operating in the all-electric vehicle market of the US and Europe (Farley, 2022; Tesla, Inc., 2022a). Recently, it has managed to expand to China, and is currently increasing sales in that market at extensive speeds (Carlier, 2021). Overall, Tesla operates in two market segments: automotive, producing cars and pick-up trucks with unique AI-based operating systems, and energy generation and storage (Carlier, 2022).

In the six years, Tesla has been in the middle of controversial arguments propelled in the media by external stakeholders about heightened production-tied releases of CO_2 into the Earth’s atmosphere from Tesla’s Giga-factories that produce lithium-ion batteries and some components for electric cars and trucks. On multiple occasions, CO_2 release-bound controversies have challenged the official Tesla’s moto of committing to a global transition to clean energy (Harrabin, 2020). In spite of them, such myths are being actively refuted by credible research. For instance, recent studies have demonstrated that production chains and waste processing of electric cars are significantly less emission-intensive compared to the ones of fossil-fuels powered cars (Harrabin, 2020; Knobloch, 2020).

Moreover, over the past decade, it has become more certain that driving electric cars could make an extremely valuable contribution to the reduction of global CO_2 emissions that might eventually lead to elimination of climate change (Marsden, 2020). However, even though Tesla has demonstrated commitment to noble goals of bringing green energy to mass use by spreading awareness about climate change to battle rising atmospheric temperatures, throughout its existence, the company has faced stock volatility - frequent plummets and surges in terms of its stocks’ values (Rich, 2013; DeBord, 2019). Such large-scale fluctuations could seem to be consistently coming in direct relation to the company’s reputation that often suffers from significant instances of regulators’ and internal stakeholders' discontent over Elon Musk's actions.

Between 2016 and 2022 Tesla has been in the middle of several fraud allegations (DeBord, 2018). Particularly, the company has gone through three lawsuits indicating fraud. Nevertheless, the most widely known Web 2.0 crisis, or the crisis that began on social media provoking direct alterations to the world-wide reputation of Tesla were fraud allegations posed by SEC (US Securities and Exchange commission) (Matt, 2018).

The "funding secured" crisis or "420 crisis" of Tesla occurred in 2018. It started on August 7 at 18:48 Amsterdam time, when the Tesla's CEO Elon Musk posted a tweet on his official Twitter profile (Massoudi, 2018). Via that tweet, Mr. Musk announced that Tesla would be changing its status from public to private using the secured funding. By changing the status of the company, Elon Musk expressed willingness to eliminate public ownership of Tesla's shares and assets. The "funding secured" crisis had an unprecedented effect on the Tesla's stocks, as by September 28 the company lost $20 billion of its value. The crisis started right on social media, with a claim made by Mr. Musk himself; in his concise tweet, he exhibited confidence of taking the company private at $420 per share due to the secured necessary funding for the action "Am considering taking Tesla private $420. Funding secured" (Musk, 2018). Essentially, the company was announced to be privatised at 20% premium to the share price, ending the stock market listing (Rushe, 2018). The funding that Elon Musk cited in the tweet was secured with the Saudi Arabia's Public Investment Fund – one of the largest investors of Tesla (Massoudi, 2018).

Nevertheless, the US financial analysts were expressing concerns that Tesla would run out of financial resources, as it lost approximately $2bn in 2017 (Marsh, 2018). The statement by Mr. Musk was found shocking primarily by investors and the US financial regulators (SEC). The plan of taking Tesla private was announced to be abolished on August 28, around two weeks after the posting. The tweet caused the stock to decrease by 12.59% on September 7 (Appendix C). However, the stock of Tesla reached its minimum value on October 8, plummeting by 16.80%, which was the lowest point in two years since the 2016 lawsuit (Appendix C).

As a consequence of SEC accusations of Elon Musk using Twitter to post misleading and false statements disinforming the government and many key stakeholders of Tesla, Mr. Musk had to step down as a chairman under the pressure from lawyers and investors for the next three years. Apart from removing the CEO titles, Elon Musk was also requested to alter the board of directors' membership, and pay a fine of $20 million ("Tesla: Elon Musk", 2018; "Goldstein, 2018). Despite the settlement in 2018, the "420 crisis" has been an ongoing crisis for three years, which placed Tesla in danger of £8bn debt post the acute phases of the crisis after December 28, 2018 (Marsh, 2019; Matt, 2018; Wayland, 2019).

In 2019, SEC accused Elon Musk of violating a restraint that was issued by the US financial watchdog. The watchdog presented Tesla with a contempt charge that targeted publications of Elon Musk on the social media Twitter using his private Twitter account. Furthermore, two years following the restraint violation instance, specifically, in the middle of November 2021, JPMorgan operating as an American multinational investment bank and financial services holding company filed a federal court lawsuit against Tesla (Flitter, 2021). Both the SEC allegations of 2019 and the lawsuit by JPMorgan in 2021 could indicate that Tesla, in the face of Elon Musk posting on Twitter, exposed itself to open opportunities for public judgement. It could confirm that statements posted on social media are to stay on a platform forever, and they also can be addressed and possibly revaluated sometime in the future.

1.2 Academic, societal, and practical relevance

In accordance to the prior experiences of Tesla explained above, from a societal perspective, media functions as a watchdog of free voice and transparency of information (Gruber et al., 2015). On Twitter, news tends to rapidly spread among stakeholders, especially key stakeholders and faith-holders. The extent of information dissemination defines an audience as the key power that is capable to alter directions of a crisis. Social media has become primary to communication in the world of shared media.

Nowadays, if a company does not initiate a dialogue with its stakeholders after a controversial post, it could lead to significant reputation damage for unpredictable time periods (Lachlan, et al., 2015; Eriksson & Olsson, 2016). Potentially misinterpreted or altered information can negatively affect important stakeholders and facilitate dissemination of misinformation (Wang et al., 2021). Even though organisations can engage in real-time sensemaking and discourse with their audience, they often fail to integrate Twitter into crisis communication. Companies might over-rely on their faith-holders that could generate positive WOM on social media (Gruber et al., 2015; Kochigina, 2020). Social media could be utilised by a company in a crisis to regulate attitudinal changes towards brands by strengthening brand personality in the audience’s eyes (Nadeau et al., 2020). This could be achieved through highlighting strengths of a brand and also via engaging with a dialogue with the audience (Romenti et al., 2014).

Nevertheless, a lot of relevant studies have been experimental; they have explored crisis communication focusing on traditional channels and synchronisation of messages without considering social media as a key communication channel for the management of companies' reputation assets (Coombs & Holladay, 2009). Thus, academically, the study could provide an insight into how an innovative electric car manufacturing company focusing on the continuous implementation of new technologies could improve in effectively managing stakeholder communication via Web 2.0 tools, such as social media (Wang et al., 2021). To date, there has been little to no research based on content analysis to explore reputation management during a crisis involving a car manufacturer that is revolutionising the automotive industry by combining electricity and modern AI technology (Wang et al., 2021).

It has been more common to study the Twitter activity of companies as caused by nature-cased crises rather than human-made crises (Diers & Donohue, 2013; Karimiziarani et al., 2022). Nonetheless, as crises occur rather frequently in companies of all types, activities, and goals, crises are also different in their nature; they could essentially be external and internal as well as intentional and unintentional (Coombs, 2007). Significantly, crises can be as much or more detrimental to organisational activities and reputation compared to environmental crisis events (Mitroff, 2000). The current study considers a human-made crisis that began on social media due to one tweet intentionally posted by a tech company's CEO. Analysing social media as a variable in crisis origins and communication with stakeholders is a recent direction of critical significance in the research on the management of a publicly visible crisis (Coombs & Holladay, 2012; Xu, 2020).

Additionally, the present study evaluates the crisis communication of Elon Musk in terms of crisis response strategies used in the tweets. The strategies were proposed by Coombs (2004; 2007) and include two following clusters: the cluster of primary responses, which is related to the extent of accepting responsibility for a crisis, and secondary responses, which refers to the company's attempts to promote their positive aspects among stakeholders (Appendix D). Although considering social media as a crisis communication channel, some previous studies on evaluating crisis response strategies did not focus specifically on the role of a particular social media platform, for instance, Twitter (Diers & Donohue, 2013; Wang et al., 2021). Also, there is a significant gap in the literature related to evaluating companies' responses in terms of primary and secondary response strategies in crisis communication on social media platforms. The current study has the strength of filling the abovementioned gaps.

Social media allows for communication with the audience to regulate perception and reaction to companies' messages as part of organisational crisis communication (Xu, 2020). Framing of messages means that they are presented and interpreted in a particular manner (Lundi, 2006). In turn, counter-framing refers to the framing of messages that contradicts an original framing (Anderson, 2018). Prior studies on communication with an audience on social media have primarily investigated communication strategies that stakeholders use to react to crisis communication messages across different communication channels or on general behaviour patterns of audiences on social media in comparison with other channels (Sano & Sano, 2019; Kochigina, 2020). Little research has been conducted on the framing of response messages by stakeholders. Moreover, framing and counter-framing of companies' messages on social media have not been sufficiently investigated (Lundy, 2006; Bortree et al., 2013). Therefore, the present study analyses the audience's comments to the Elon Musk's crisis communication and assesses how Elon Musk and his audience on Twitter frame messages in their posted tweets.

Tesla could practically benefit from the results of the present study. As mentioned previously, Tesla is currently dealing with the law-suit from JPMorgan, and it had to settle multiple allegations introduced by SEC regarding the Twitter activity of Elon Musk in 2019. The allegations possibly imply that there might be certain aspects of Twitter-based communication that are inconsistent and, thus, not completely effective for the crisis management of Elon Musk. Mr. Musk might be not careful enough with frames in the tweets when approaching Tesla stakeholders. Or, it could be that Elon Musk does not implement a consistent approach to reputation management in terms of theoretically-established crisis response strategies. The present study could contribute to potentially discovering the reasons which caused the "funding secured" crisis to become a long-term crisis of impactful consequences on stock prices of Tesla and, essentially, its reputation among stakeholders.

1.3 Research questions and the structure

A quantitative approach of content analysis was applied to analyse the main crisis response strategies applied by Tesla, specifically, by Elon Musk to communicate with stakeholders using his Twitter as the key representative of Tesla in the company's written social media communication. The quantitative technique was used to analyse audiences' reaction to the crisis communication of Elon Musk. This study suggests a reference for Tesla on how to approach crisis communication in future crises and possibly prevent them, since

Elon Musk had already established strong social media presence prior to the “funding secured” crisis (PR Week (US), 2010). Furthermore, the topic of the current study has been especially relevant in the recent days due to Elon Musk launching a hostile takeover of Twitter and reaching an agreement with the board to take it at $54.20 per share for amplifying free speech and transparency of information on Twitter (“Elon Musk and Twitter”, 2022). Hence, the current study is based on three research questions:

RQ1: “To what extent does Elon Musk’s communication demonstrate a more frequent use of primary strategies rather than secondary strategies for the reputation management during the “funding secured” crisis of 2018?”

RQ2: “To what extent does Elon Musk use counter-framing in the Twitter communication in response to the audience’s tweets about the “funding secured” crisis of 2018?”

RQ3: “To what extent does the audience react positively to the communication of Elon Musk on Twitter?”

This quantitative study consists of five core sections. They entail several corresponding subsections. Section 2, containing theoretical framework, covers three following concepts: crisis communication, image management, and framing of crisis communication messages. Section 3 focuses on the methodology of this study – quantitative content analysis. The section describes some advantages of the chosen study method, presents the materials used in the study, and describes the procedure, including operationalisation of the chosen variables, and the conducted statistical analyses via SPSS. Section 4 is dedicated to showcasing an overview of the results obtained through the statistical tests. Section 5, namely discussion and conclusion, connects the results to the theory, based on which it is decided whether to reject or accept the hypotheses, presented in section 2. The final section discusses some implications of the results, as well as limitations and possible suggestions for future research.

2 Theoretical framework

This section introduces crisis communication, image management, and crisis framing. Within the key concepts are the descriptions of the main theories and models used in this quantitative study. The first part deals with the crisis type matrix, the "Best Practice Model for Crisis Management", and discusses the strategy-oriented model of PESO-SOEP for content division. The second part expands the image management concept by presenting the attribution theory, describing the integrative model of crisis communication, and explaining the image repair theory. The first subsection presents the SCCT and explains the covariation principle of attributing crisis responsibility to companies. The second subsection focuses on some effects of different communication mediums on interacting with stakeholders, the roles of social media in crisis management, and the SCCT for stakeholders. The third section introduces message framing, counter-framing, and salience of frames; further, it introduces six hypotheses of the current quantitative study.

2.1 Crisis communication

Cornelissen (2020) defined a crisis as an unexpected event requiring immediate reaction from organisations. Alternatively, Mitroff (2000, p. 34) stated that crises are non-random, frequently occurring events faced by "the whole of an organisation" in modern societies. Reaction time is essential for crisis management, as not all problems are predictable. However, effective crisis management is not constrained to an after-crisis focus only; it also involves "signal detection" – grasping and analysing "early warning signs of a crisis" (Mitroff, 2000, pp. 7 - 8).

Crisis communication has become inevitable and more challenging. The modern age of technology and information is transforming the management of issues and risks associated with company activities by creating volatile external environments (Cornelissen, 2020). Crises are sudden events powerful enough to inflict substantial damage on business operations and corporate reputation. Companies should handle any crisis in a timely and responsible manner to avoid harmful consequences from stakeholders (Cornelissen, 2020, p. 311).

Efficient communication about a crisis is based on distinguishing crisis types (Coombs, 2007; Cornelissen, 2020). Coombs (2007) developed a crisis type matrix featuring four mutually exclusive crisis types under four distinct dimensions: external and internal, unintentional and intentional. Unintentional crises caused by external factors are described as “faux pas” referring to violating unwritten rules of societal expectations, whereas intentional crises are classified as terrorism - harm from external agents. In turn, internal crises could be characterised as either unintentionally-caused accidents, such as acts of nature or human errors, or intentional transgressions, which include acts taken by an organisation knowingly placing stakeholders at risk (Coombs, 2007; Cornelissen, 2020). Classification of crisis events is the backbone of executing successful communication strategies.

Practical application of communication strategies could be demanding, as real-life crises are more complex than theory-based cases (Mitroff, 2000). Mitroff (2000) proposed an “ideal” crisis management framework called “Best Practice Model for Crisis Management”. While Coombs (2007) primarily focused on post-crisis management, Mitroff (2000) emphasised the importance of crisis preventive measures, as crises tend to display traceable signals before occurring. The framework features five manageable factors: risks, mechanisms of recognising crisis signals, internal corporate systems including organizational structure or culture, stakeholders’ role in the company, and possible scenarios. Moreover, there are three crisis families: economic, informational, and physical. Ideally, organisations should anticipate potential issues in every family in advance and plan damage containment (Mitroff, 2000, p. 41). However, Mitroff (2000) claimed that companies rarely follow “ideal” models in daily operations; thus, choosing ways of damage containment depends on common corporate defense mechanisms. The least effective of the mechanisms that Mitroff (2000) referenced is denial (crisis happens to others). Other techniques include projection onto external factors, disavowal (highlighting the small impact of all crises), idealisation and grandiosity of a company (crises happen to less powerful organisations), intellectualisation (probabilities of crises are small), and compartmentalisation (crises cannot affect the whole of organisation).

Execution of crisis communication impacts the evolution of crisis events (Verhoeven et al., 2014; Sano & Sano, 2019). Verhoeven et al. (2014) investigated the managerial behaviour of communication professionals in the context of unpredictable events from over 40 European countries; 70% of the professionals were discovered to manage one crisis per year. This study is an exemplar of an organisation-centered approach known as business-to-consumer crisis communication. An online survey inquired groups of communication managers and CEOs about their typical approaches to stakeholder communication during a crisis. The results described institutional crises as the most frequent and damaging events.

Institutional crises typically involve adverse campaigns by critics, hostile takeover attempts, or threats of political regulation. Moreover, the study discovered that the least encountered crises are based on rumors or a company's communication failure (Verhoeven et al., 2014).

An experimental study conducted by Sano and Sano (2019) challenged the most classic crisis communication theory of Coombs in the research field; the researchers suggested expanding the theory to cases of consumer-to-consumer. Consumer-driven communication is frequently disregarded by organisations, even though it could allow for interaction with stakeholders of varying importance. Sano and Sano (2019) examined organisation-driven communication using a Japanese local tourism association as an official information source, and consumer-driven communication was investigated via an online travel community example of TripAdvisor. The results indicated that both communication approaches are regarded as equally credible when the perceived risk is low as opposed to the high perceived risk situations (eg., volcanic eruption), in which organisation-driven channels are assessed as more credible (Sano & Sano, 2019). Moreover, the researchers concluded that consumer-driven communication could function as effective means for providing and accepting recommendations when the perceived risk is low. In general, source credibility and perceived reliability used for gaining information about travel destinations are essential factors influencing mediums that audiences choose to communicate through.

Stakeholders influence each other before, during, and after crisis events (Verhoeven et al., 2014; Sano & Sano, 2019). The findings of Sano and Sano (2019) support conclusions of Verhoeven et al. (2014). Despite the majority of European communication professionals using organisation-driven communication on social media to organising dialogue settings with stakeholders, it still disregards consumer-driven communication. Furthermore, communication specialists view social media as secondary to media relations, namely press releases and interviews, personal communication among the board members, and, especially, owned organisational media (Verhoeven et al., 2014).

Companies that aim to escape a crisis with minimal damage to business operations and corporate reputation prioritise crisis communication (Payne, 2006; Verhoeven et al., 2014). Verhoeven et al. (2014) identified that European communication professionals tend to use information strategy during crises that do not lead to severe consequences, such as injuries or death; this strategy updates stakeholders about crisis events and refers to possible next steps of action. Surprisingly, apologising to stakeholders and expressing sympathy to the harmed are among the least popular strategies among professionals. These findings support the study of Payne (2006) that explored the effects of positive and negative reputations on organisations and the consequences of infrequent company responses displaying defensive and apologetic behaviour. The researchers achieved significant results of their survey-based experiment that presented reputation type (i.e., good or bad) as a condition and type of response as groups (i.e., apologetic and defensive) with random assignment of participants. Payne (2006) asserted that reputation is a force that directly influences judgments and attribution about aspects of company activities, as a good reputation positively affects audiences' positive brand recall. Significantly, apologetic responses positively contribute to improvements in corporate reputation.

Global growth of social media signifies changes in priorities within company-used media strategies. A vivid example showcasing the shift of values is an evolution of the PESO – SOEP model (Macnamara, 2016). PESO is a strategy-oriented model that divides media content into three categories: paid (social media advertisements), earned (media relations, WOM), shared (social media), and owned media (websites, blogs). SOEP model suggests that shared media is starting to play a more crucial role than paid and earned media. Macnamara (2016) demonstrated the paid and earned-to-shared and owned shift in companies' media activities in the Asia-Pacific. Shared media is a top priority as it engulfs social media; it is open for followers and viewers to freely communicate with each other and a company's profile by commenting or posting. Companies can reach and connect with stakeholders via social media platforms using their profiles to ensure omnipresence communication, which entails the integration of multiple channels of stakeholder communication.

Companies traditionally focus on organisation-driven communication in media relations. Nevertheless, neglecting the potential of consumer-driven communication on social media could negatively impact the efficiency of organisational reputation management. Corporate reputation is vulnerable to damage during crises by multiple factors, including stakeholders' opinions.

2.2 Image management

Crises are direct threats to organisational reputation (Coombs, 2004; Dann, 2009; Thiessen & Ingenhoff, 2011; Jung et al., 2017; Cornelissen, 2020; Frandsen & Johansen, 2020). Coombs (2004) referred to the attribution theory while discussing the key effects of a company's crisis history on reputational threats posed by current crises. Coombs (2004) claimed that crises trigger stakeholder attributions of crisis responsibility, implying that the public might assume that a crisis could have potentially been entirely prevented by an organisation. This means that the general public tends to perceive crises encountered by most organisations as controllable, which highlights the accountability of companies to society (Coombs, 2004). Dann (2009) supported the thought of Coombs (2004) by stating that media is part of business life and daily lives of the general public, suggesting that organisations are at a profound risk of their crises gaining wider public exposure. This risk makes organisations hold accountability not only to their shareholders but to all stakeholders. Therefore, companies in crisis should map stakeholders according to their power-interest position in the matrix of stakeholders' categorisation from low (minimal effort or keep informed) to high (keep satisfied or key players), as well as their salience in a company based on three following factors: power, legitimacy, and urgency (Cornelissen, 2020, pp. 105 – 112).

The main point that Coombs (2004) brings across is that crises encountered by companies throughout their existence, in accumulation, could become intensifying factors increasing the companies' responsibility for their present crises. Public attributions of a company's responsibility depend on the history of past crisis management. In the experiment, Coombs (2004) manipulated crisis history for four different crisis types related to accidental events and victimisation crises, later described in detail by Coombs (2007). The results showed that crisis history impacts organisational reputation. Furthermore, as later emphasised by Dann (2009), the reputational damage can be done by high-intensity attributions of fault to an organisation by stakeholders. Thus, organisational reputation contains individual and general attitudes of people towards companies' behaviour in their past uncertain situations, their current and future potential situations. Moreover, Dann (2009) further proposed an idea suggesting that within the current fragmented media landscape, crisis communication targets practitioners with a PR background, as it provides a backbone of how to approach sudden events.

The modern media landscape is fragmented due to the public having expanded access to hardly controllable decentralised information flows, whether via independent online media outlets, independent journalists' online channels, or social media (Dann, 2009; Thiessen & Ingenhoff, 2011). Thiessen and Ingenhoff (2011) developed the integrative model of crisis communication that showcases communicative impact on reputation depending on message strategies situated on three levels, from little, micro, to significant, macro (Appendix A). The societal level is macro, followed by the micro level comprising organisation and message levels. The levels ultimately aim at establishing a long-term reputation via trustworthiness, achieved by different means. On the societal level, trustworthiness is attained through moral integrity, whereas on the organisation level – through skills and competencies, and on the message level – via benevolence and involvement. The researchers defined reputation as "the net perception of a company's ability to meet the expectations of all its stakeholders" (Thiessen & Ingenhoff, 2011, p. 10). Thiessen and Ingenhoff (2011) concluded that companies establish their reputation via mass media employing an online presence, which suggests that communication on the micro level of messages, hence, using situational crisis communication, has a primary role in image repair. Communication is central to successful image management, especially during increased public awareness and rising uncertainties.

As mentioned previously, stakeholders' opinion about corporate crises determines levels of reputational damage. Additionally, the fragmented media landscape contributes to the power of individual and public attributions. For a closer assessment of the stakeholder network's role in image formation during a crisis, Jung et al. (2017) conducted a network analysis using Facebook data in the context of the Volkswagen (VW) emissions crisis to explore the evolution of relationships between VW stakeholders in three forms of connections between them. The connections are mainly mutual, forming through direct communication with one another, and unilateral ties, forming in one-sided communication encounters. The study revealed an exponential growth of ties between VW stakeholders within just a few days. Moreover, image repair within the fragmented media landscape is becoming more difficult to execute for organisations without following a consistent crisis management approach. Thus, social media sets appropriate conditions for a rapid information spread and serves as a welcoming ground for consumer-driven communication, from which stakeholders might gain information quicker than a company.

Frandsen and Johansen (2020) created the image repair theory that explains how organisations restore their image in a threatening event. An unfavourable image could have the most detrimental effect on companies by reducing credibility, which leads to the loss of key stakeholders' trust. This study distinguished two components of a threat to a company's image: blame and offensiveness (Frandsen & Johansen, 2020). Their theoretical framework proposes three strategies for image repair management: denial, evading responsibility, and reducing offensiveness. The image repair theory by Frandsen and Johansen (2020) is not complete in itself. It represents a collection of necessary patterns to search for within a company's communication channels to construct a general idea of how to restore a corporate image in a particular case.

Reputation is the main target during a crisis. It consists of stakeholders' opinions and is shaped by every crisis event a company encounters. Companies' behaviour during crisis events forms the history that the general public refers to at moments of judging companies' actions during the present and future crises. For engaging in fruitful image repair, organisations should benefit from response strategies that address crisis origins and can be executed on social media platforms since it appears that information spreads the fastest among stakeholders on social media.

2.2.1 Crisis response strategies: SCCT

There are strategies on the message level of crisis communication that minimise effects on key stakeholders. Stakeholders influence the corporate image; also, they tend to be significantly affected during crises (Coombs, 2004; 2007; Thiessen & Ingenhoff, 2011; Frandsen & Johansen, 2020). Compared to the theory of image repair by Frandsen and Johansen (2020), the situational crisis communication theory by Coombs (2004; 2007) involves primary response strategies, including denying, diminishing, and rebuilding, and secondary strategies, such as bolstering, which comprises reminding about past positive organisational achievements (reminder), praising stakeholders (ingratiation) and reminding about own victim status in the crisis context (victimage) (Appendix D).

Some scholars attempt to challenge the SCCT and provide potential options for extension (Schwarz, 2008). Schwarz (2008) proposed the covariation principle as an addition to the SCCT. The study builds on the attribution theory of Kelley (1967), in which the scholar systematised causal inferences that people could arrive at into the covariation principle that assists companies in predicting causes of crises and organisational responsibility. Citing Kelley (1967), Schwarz (2008) explained the covariation principle as the attribution of effects to causes as persons (actors), objects or stimuli as entities, and causes connected with circumstances of a perceived situation. The covariation principle is related to stakeholders attributing crisis responsibility to an organisation. Information about consensus, distinctiveness, and consistency are three information types that people use to attribute crisis responsibility to persons, objects, or circumstances. Covariation judgments of companies' responsibility could provide an opportunity to deeper understand perceptions of organisations by their stakeholders in times of crisis (Schwarz, 2008).

Within the cluster of primary crisis response strategies, denial response strategies are the least used by communication professionals; companies use denial to downgrade some crisis-related consequences or insist on the absence of a crisis (Coombs, 2007; Verhoeven et al., 2014). Moreover, denying can also include scapegoating – blaming an outsider for the crisis or attacking an accuser, which means confronting groups of stakeholders insisting on the crisis being real. In turn, diminish crisis response strategies comprise coming up with various excuses attempting to explain the loss of control over a situation that triggered a crisis or providing justification; companies could include more detailed explanations of accounts that suggest the reasons for the loss of control. The rebuild crisis response strategies contain compensation in the form of gifts or money, offers to victims, and an apology, which means taking full responsibility for the crisis in front of all stakeholders.

The cluster of secondary crisis response strategies comprises an umbrella group involving bolstering crisis response strategies (Coombs 2004; Coombs, 2007). The bolstering strategies assist reputation enhancement in the stakeholders' minds and effective projection of corporate identity to evoke sympathy and support towards a company (Cornelissen, 2020, p. 223). Companies use different strategic messaging styles to achieve their goals: rational messaging to make superiority claims about products and achievements, symbolic association to provide a symbolic or transformational image by using emotions to connect with stakeholders, and generic messaging, which signifies no attempts to make a company stand out from its competitors, and pre-emptive messaging to emphasise superiority over competitors by claiming an "industry leadership" (Cornelissen, 2020, pp 172 – 177). Coombs (2004) proposed that the bolstering cluster incorporates the reminder, ingratiation, and victimage strategies. If described separately, reminder strategy refers to reminding stakeholders about positive aspects of a company's history, such as institutional achievements or positive contribution to society. The ingratiation strategy includes praising stakeholders for support for present and past achievements. Finally, a company can use the victim strategy to highlight its victim status due to reputational damages and disruptions of vital company operations for stakeholders to notice (Coombs, 2007).

Several studies investigated the choice of response strategies to apply on social media and other media within the fragmented media landscape (Coombs & Holladay, 2009; Diers & Donohue, 2013; Linsley & Slack, 2013; Xu, 2020; Wang et al., 2021). Coombs and Holladay (2009) argued that companies tend to benefit from using a variety of media to reach the audience in a controlled and timely manner to communicate updates. The conclusion was supported by Xu (2020); primary channels applied to provide a crisis coverage for different stakeholders usually combine videos delivered by companies' spokespeople with print media created by journalists. However, the key downside of relying on media coverage is a lack of control of the material. Spokespersons' comments could not be guaranteed to be covered in an unbiased form by the media. As discovered by Wang et al. (2021), companies need to choose an appropriate response strategy due to its influence on the evolution of a crisis.

Despite social media gaining momentum in organisation-driven communication, some companies remain increasingly reliant on press releases and general media to engage in stakeholder communication. Linsley and Slack (2013) conducted a content analysis of press releases issued by Northern Rock Bank during their crisis caused by financing long-term mortgages with short-term funding for a prolonged period. Linsley and Slack (2013) concluded that the bank did not succeed in its reputation management due to the failure to maintain a caring relationship with stakeholders before the crisis. During the crisis, the stakeholders blamed the bank for insufficient ethical care in its operational history, which came to the surface only during the crisis, heavily damaging the reputation (Coombs, 2004). Due to the company's poor history of managing relationships with stakeholders, communication solely by press releases failed to suffice. The crisis of Northern Rock Bank took place in 2010; by that year, Twitter and Facebook were established social media platforms, on which the bank could have grown the audience and used when their crisis was still unfolding. It could have allowed establishing communication bridges between stakeholders via messages related to the topic of stakeholders' rising concerns.

However, other companies actively use social media to find themselves eventually succeeding at reputation management and avoiding severe damage. The content analysis-based study on one of the BP crises conducted by Diers and Donohue (2013) is a perfect exemplar of analysing a real-life case based on organisational involvement in diverse multi-media engagement neglecting the message level of crisis communication. The researchers examined BP's press releases, Facebook posts, and messages on Twitter to investigate the response to the BP experiencing the transgression type of crisis. Throughout the analysis, Diers and Donohue (2013) discovered that BP extensively and in detail covered the crisis using their network of websites for each state; yet, the company lacked unique messages on social media due to duplication of information on multiple web sources. Even though BP relied on press releases to share information with stakeholders in a narrative-like manner, and for urgent information share, the company had a Twitter account, it lacked synchronised communication across social media and the web page. DP applied a combination of primary rebuilding strategies and bolstering secondary response strategies for crisis management across traditional media and social media (Diers & Donohue, 2013).

Diers and Donohue (2013) concluded that companies in accidental crises use synchronised communication across traditional and social media channels, where the driving force lies within press releases, and Twitter plays a role in communicating challenging and primary messages. Thus, this finding suggests frequent use of primary strategies via social media and secondary responses that require more detailed and lengthy explanations via press releases rather than on social media. Considering the origins of the "funding secured" crisis, Tesla appears to fall under the accidental crisis, as the company faced a challenge of stakeholders disagreeing with the decision made by Elon Musk without prior explanation or consultation (Coombs & Holladay, 2009; Massoudi, 2018). More specifically, being active on Twitter by tweeting regularly on different topics, Elon Musk did not change his ways of interacting with the audience about plans to take Tesla private. It could explain why Mr. Musk directly stated his intentions on Twitter for the audience to review and comment without expecting a backlash from investors and governmental regulators (Cornelissen, 2020).

The review of Lambret Clémence and Baki (2018) did not contradict Diers and Donohue (2013) when referring to the model of crisis management mix by Coombs (2007). If a company falls into the victim cluster, it is more likely to evoke sympathy and sadness from stakeholders, and the company's response in such a case is defensive. If a company falls under the preventative cluster of crisis responsibility attribution, it suggests a higher chance of stakeholders expressing emotions of fright and sadness; therefore, it requires an accommodative type of response strategies. Theoretically, if a crisis is accidental, a company should attribute itself to the strong preventable cluster (Coombs, 2007; Cornelissen, 2020).

The "funding secured" crisis is not the first major crisis for Tesla. The first lawsuit was filed by Tesla shareholders in 2016 against Elon Musk's enrichment via the acquisition of SolarCity; it was an American organisation selling and installing energy generation mechanisms. The second one was filed by the US Department of justice questioning Tesla's accounting related to the production of Tesla Model 3 cars in 2017. The most recent crisis that Tesla has dealt with is fraud allegations about their autopilot between 2019 and 2020 (DeBord, 2018). Tesla has financially settled all the fraud allegations. However, the question of whether Elon Musk adjusted the crisis communication remains.

In 2019, Mr. Musk was allegedly still providing sensitive information about Tesla in the tweets with no approval ever issued by the established board post-settlement of fraud allegations featuring the "funding secured" tweet posted by Elon Musk in August 2018 (Helmore, 2019). Moreover, in 2021 JPMorgan requested Tesla to conduct a payment transaction worth $162 million for the JPMorgan investment bank under the conditions of the stock options contract that both parties mutually agreed about and signed in 2014. Within the context of that lawsuit, JPMorgan made accusations against Tesla regarding the company violating the main conditions of the 2014 contract. Tesla violated the conditions because the price per share of the company dropped by more than 16% within a month into the “funding secured” tweet situation (“JPMorgan says Tesla”, 2021). Thus, at this moment, Tesla could still be prone to committing similar mistakes of failing to introduce preventative measures as it was back at the end of 2018.

The question is whether Elon Musk correctly attributed itself to the preventable cluster rather than to the victim cluster, implying that the “funding secured” crisis was an external accident. In reality, tweets require predominantly short text messages; they are easy to write and post without significant consideration. Mitroff (2000) stated that crises are not rare, and companies tend to ignore signals, which results in underestimation of actions. The underestimation possibility probably means that Tesla could fail to admit responsibility and, thus, use strategies corresponding to the victim cluster.

2.2.2 Audience (eWOM) in crisis communication

Several studies explored crisis communication through social media for image restoration (Schultz et. al., 2011; Eriksson & Olsson, 2016; Zheng et al., 2018; Triantafillidou & Yannas, 2020; Kochigina, 2020). Schultz et al. (2011) conducted a survey-based experiment that manipulated three conditions representing the medium type: newspaper, blog, or Twitter. The study analysed the effects of apology, sympathy, information, and secondary crisis communication on stakeholders’ perception of a crisis by stakeholders, hence, the company’s reputation (Appendix B).

Schultz et al. (2011) were the first to directly investigate the implementation of social media in a company’s crisis communication for image repair beyond case studies. The researchers concluded that a medium of crisis communication matters more than individual messages. Twitter triggered fewer negative attributions among stakeholders compared to newspapers and blogs (Schultz et al., 2011). The use of Twitter had active secondary crisis responses, such as shares of messages; nevertheless, the highest rate of message exchange was in the newspaper condition. It might mean that people tend to talk less about tweets with others. Furthermore, Schultz et al. (2011) showed that information strategy was the most successful in the experiment, and combining Twitter and blog use revealed the least reputational risk for the company.

As was indicated by Eriksson and Olsson (2016) and later confirmed by Zheng et al. (2018), corporate reputation as an invisible capital could protect companies experiencing a crisis. On social media platforms, such as Facebook and Twitter, companies have an opportunity to use the interactive aspect of social media and use the help of stakeholders as a cooperative force in image restoration (Zheng et al., 2018).

Zheng et al. (2018) discovered an audience's tendency to become engaged in actively sharing and forwarding information on Twitter in response to new updates about a crisis. The experiment demonstrated that the availability of opinions on a crisis shape perceptions of secondary crisis communication among stakeholders. Furthermore, the most important findings of Zheng et al. (2018) confirmed the theory of past crisis behaviour influencing crisis reputation management of companies proposed by Coombs (2007). The results suggested that if a company has a high level of cognitive reputation among stakeholders, meaning that the company's activities are related to critical thinking and problem solving, then stakeholders participate in more secondary crisis communication at high intensity, as they perceive moral responsibility of such a firm as violating the order in a crisis. Additionally, crisis communication of a firm with a high cognitive reputation should focus on sympathy and establishing an emotional connection with stakeholders (Zheng et al., 2018).

Kochigina (2020) contributed to establishing the role of social media in crisis communication by exploring a case of Tesla focusing on faith-holders' reputation repair strategies through content and rhetorical analyses. The results demonstrated that appealing to a positively-engaged, dedicated audience that trusts a company and believes in its value accelerates image restoration and could withhold a crisis from further escalation. Kochigina (2020) discovered that faith-holders differ among themselves; some of them might appreciate a company as a whole, whereas others might like particular aspects; there may be a group disliking certain aspects and valuing others. Most importantly, faith-holders of Tesla use their own eight response strategies: change of reference - changing frame by comparing a current crisis to crises of other companies; suggestion of remedy – providing possible crisis solutions; self-gain and self-victim – stressing personal and general consequences of an organisational crisis for other stakeholders; conspiracy – suggesting that some companies deliberately would like to damage an organisation they root for; confirmative action and ingratiation – encouraging others to support an organisation or confirming organisation's actions as positive – regarding a crisis as an opportunity; new information and endorsement – endorsing an organisation by using opinions or facts; bolstering, and expression of faith – demonstrating confidence in a company's future (expression of faith), praising a company's present (bolstering).

The findings of Schultz et al. (2011), Eriksson and Olsson (2016), and Zheng et al. (2018) reinforce the conclusion of Triantafillidou and Yannas (2020). Triantafillidou and Yannas (2020) proposed using Twitter for effective crisis communication, as it could trigger engagement with the image-restoring messages among stakeholders. As further supported by Kochigina (2020), engagement by faith-holding stakeholders, who invest emotionally and or financially in a company, should not be underestimated. Companies' engaged stakeholders could effectively amplify support for an organisation facing a crisis, particularly on social media (Kochigina, 2020).

2.3 Crisis framing

Several researchers investigated examples of framing messages within crisis communication management on social media and stakeholders' perception of companies based on communication (Gruber et al., 2015; Anderson, 2018). Gruber et al. (2015) concluded that social media could become a source of the crisis. It depends on how companies formulate posts, frame crises, and provide interpretations to stakeholders and the kinds of posts companies generally create. Anderson (2018) expanded the research body on framing by contextualising counter-framing.

Some studies considered framing as part of message production to approach communication strategically (Lundi, 2006; Bortree et al., 2013; Anderson, 2018; Pavlova & Berkers, 2022). The experimental study of Lundi (2006) described message framing as involving organisation and inclusion of information that audiences can resonate with and interpret. By investigating the effects of framing on the cognitive processing of employees, Lundi (2006) concluded that different frames produce a differing number of thoughts and content. Congruently with the finding of Lundi (2006), Bortree et al. (2013) suggested that companies often use one type of frame to minimise the audience's cognition of negative aspects regarding some topics. Significantly, using a positive frame could lead to a positive perception of something; the study found that using gain frames in corporate social responsibility (CSR) company communication leads to the general public positively perceiving the company's CSR (Bortree et al., 2013).

Anderson (2018) defined counter-framing as framing of messages contradicting the original message formation. For instance, the company's framing of the VW emissions crisis significantly differed from the view of printed media (Brown, 2016). Message formations could be classified as counter-framing when there is incongruency from the original framing pattern used by a company for crisis communication. Anderson (2018) demonstrated that every frame has a possible counter-frame (counter-point), and it is vital for scholars to study the impact of frames over a certain period by assessing the audience reaction to messages. Counter-frames can neutralise the effect of frames; however, in the competitive media landscape, the possibilities of media introducing their frames and counter-frames of a crisis can condition companies to struggle with maintaining public support (Anderson, 2018).

Pavlova and Berkers (2022) is the most recent study on framing mental health messages on Twitter. According to the frame analysis, frames become evident via framing devices. However, frames do not become easier to recognise by using more devices. The devices that Pavlova and Berkers (2022) indicated are various attributes of a text, including facts or judgments, keywords, stereotypes, historical examples, or the devices of reason, such as causes and consequences. Moreover, the researchers emphasised the importance of frame silence in interpreting frames (Pavlova & Berkers, 2022). If individual frames are consistent and congruent with some common perception of an event, concept, or phenomenon, they are more salient. Salient frames typically influence the framing of messages across different information sources. If frames align across social media and other media, the message is more likely to be reinforced among the public.

The concepts of framing and counter-framing of messages as part of a company's crisis responses are illustrated in several studies showcasing social media and reputation and crisis management (Payne, 2006; Lachlan et al., 2015; Nadeau et al., 2020; Karimiziarani et al., 2022). Payne (2006) conducted an experiment; it showed that defensive organisational behaviours are common in crisis communication in framing messages. However, apologetic responses of companies influence stakeholders to accurately recall detailed aspects of a good organisational reputation. Memories of stakeholders about companies fade over time, thus, change of framing might pose dangers to reputation management of companies, and it could be worth maintaining one line of framing throughout crisis communication.

The content analysis-focused study of Lachan et al. (2015) confirms the findings of Payne (2006) that counter-framing of crisis messages could lead to the audience confusion. Furthermore, Lachan et al. (2015) concluded that frequent tweeting as a strategy for timely crisis de-escalation attempts could also lead to audience confusion. Thus, it is imperative for organisations to dose Twitter content and introduce pauses in between tweets.

The content analysis of Nadeau et al. (2020) based on several companies' crisis case studies provided a perspective emphasising that companies benefit from treating crisis events as an opportunity to excel at positively framing online communication surrounding brand values to speed up recovery from a crisis. The study focused on attitude changes towards a brand and stated that counter-frames of opinions are likely to occur from the audience throughout crisis communication in a direction depending on whether a company attempts to regulate brand image. Consequently, counter-framing is likely to occur in companies' crisis communication, since, even though companies can benefit from strengthening brand competence and character as means of crisis regulation, depending on the crisis type, a company might decide to start with a different frame to minimise reputational consequences related to stakehoders' emotions regarding the crisis.

Nevertheless, Karimiziarani et al. (2022) revealed that informative tweets are best at communicating hazardous events, and consistency is a trust-building technique with an audience. It could imply that diverting from an originally used message frame can cause deterioration of trust between a company and stakeholders, leading to further escalation rather than repair of reputation damage.

Therefore, based on the reviewed literature, the current study proposes six hypotheses, as well as some sub-hypotheses:

H1: Tweets of Elon Musk indicated more frequent use of primary response strategies compared to bolstering strategies.

H1(a): Elon Musk posted more tweets with omittable linguistic intensifiers than tweets with intensifiers of higher complexity.

H1(b): Elon Musk posted a higher number of tweets containing negative linguistic elements than of tweets with positive intensity elements.

H1(c): Tweets of Elon Musk containing positively intensified language elements were shorter than the tweets including negative intensity elements.

H1(d): Tweets of Elon Musk including impression repair strategies were of higher length than the tweets without impression repair strategies.

H2: Elon Musk posted more tweets containing concern than tweets containing reassurance.

H2(a): Impression repair strategy "reducing offensiveness" occured more frequently in the Elon Musk's tweets expressing concern.

H3: Elon Musk's responses to the audience on Twitter was more negative than positive.

H3(a): The negatively framed tweets of Elon Musk had more words than positively-framed tweets.

H3(b): Negatively-framed tweets contained more instances of primary crisis response strategies than positively-framed tweets.

H4: The number of messages containing positive framing in the Tweets of Tesla audience was lower than the number of messages that were negatively framed.

H4(a): Positively-framed tweets of Tesla stakeholders contained a lower number of linguistic intensifiers per tweet than tweets with negative framing.

H4(b): Audience's tweets with positive framing contained a higher number of complex intensifiers than the negatively-framed tweets.

H4(c): Tweets of Tesla's other stakeholders contained more linguistic intensifiers than the tweets of shareholders.

H4(d): Shareholders posted more negatively-framed tweets than other stakeholders.

H5: The number of tweets posted by Tesla audience containing disapproval as response to the Elon Musk's tweets was higher than of the tweets containing approval.

H5(a): Shareholders of Tesla posted a higher number of tweets expressing emotions of concern than other stakeholders.

H5(b): Tweets of Tesla's shareholders were longer than the tweets of other stakeholders.

H6: The frequency of audience tweets containing questions was higher than the frequency of tweets containing personal opinions.

H6(a): Shareholders of Tesla posted more tweets sharing messages that showcased questions than personal story/experience.

H6(b): Other stakeholders of Tesla posted more tweets sharing messages that display opinion over the messages containing questions.

Moreover, the study has two aims: to find out the extent Twitter as a social media channel can be an effective tool for companies to use for crisis response by identifying Tesla's pattern of using response strategies; to discover how companies active on Twitter should anticipate counter-frames from audience when preparing their messages.

3 Method

3.1 Quantitative content analysis

The current study was designed as a quantitative content analysis to focus on the Twitter activity of the company Tesla, represented by the CEO Elon Musk and stakeholders of Tesla. The content analysis was based on the selection of tweets posted by Elon Musk via his Twitter account alongside comments of different Twitter users under the tweets of Mr. Musk. The quantitative content analysis allows for checking whether variables are statistically related; it involves close reading and interpretation of the written (Neuendorf, 2011). The main advantage of quantitative content analysis is to trace patterns in a text by measuring frequencies and conducting further statistical tests, such as Chi-square for relationships between variables. In the present study, the quantitative content analysis could assist the researcher with statistical proof of patterns and relationships (Neuendorf, 2011).

3.2 Materials

All the tweets posted by Mr. Musk on Twitter within the first five months of the 2018 “funding secured” crisis were collected into an Exel file: from early August until the end of December 2018. The crisis started from one single Tweet posted by Elon Musk on August 7 and began escalating, leading to the announcement about staying public on August 24 (Massoudi, 2018; “Elon Musk Steps”, 2018). The main goal of this study was to evaluate the effectiveness of Twitter as central means of crisis communication and reputation management.

The study focused on assessing the impact of Elon Musk’s crisis communication on the formation of responsibility attributions for the “funding secured” crisis as perceived by the company’s audience on Twitter – the stakeholders. The content analysis allowed for further identification and analysis of crisis response strategies and examination of their relationship with the framing of messages in Mr. Musk’s tweets. In the present study, collecting and analysing tweets was performed based on theoretically showcased effects of crisis communication on stakeholders’ behaviour that can significantly change a crisis’ direction (Mitroff, 2000; Coombs, 2007; Schwarz, 2008; Cornelissen 2020).

3.2.1 Sampling

The total corpus had 694 tweets; 342 were company tweets, and 352 were stakeholders' comments – reactions to company tweets. The sampling method was non-probability (convenience), performed via the Advanced Search engine of Twitter. The company tweets were sampled by selecting the Twitter account's ID of Elon Musk (@elonmusk) and choosing a posting period.

Upon completion of the search the Advanced Search engine provides tweets in random order of publication, a bi-weekly search tactic was utilised for convenience: the engine was provided with instructions to show all company tweets within two weeks. Once all the tweets were recorded, a new search was started. As for the collection of audience tweets, for each general company tweet or retweet posted by Elon Musk for the profile audience, or replies to his generals or retweets, 30 comments were gathered to ensure normal comments distribution, leading to a higher validity of the statistical analysis (Pallant, 2007; Neuendorf, 2011).

The logic behind choosing the period in 2018 on which the sampling was based – the choice of the period starting from August 7 until December 28, 2018 - stemmed from several "funding secured" crisis timelines combined. The considered crisis timelines were published by journalists on reputable, sources providing news, analysis, and perspectives, such as The New York Times, PRWeek, and The Guardian. Furthermore, the posting period that the current study referenced was determined based on official press releases that Tesla posted before the end of 2018. The last press release that Tesla posted on its website referred to some structural board changes dated back to December 28, 2018. The year's end indicates the financial year; therefore, no more audience reaction tweets were collected after December 28.

3.3 Procedure

For the latent coding, a second coder (Coder 2), previously unfamiliar with the field of the present study, was recruited by the researcher to code 10% of the data - 100 company tweets created and posted by Elon Musk and 100 stakeholders' comments to the tweets of Mr. Musk (Neuman, 2011). Both coders referred to one theory-based codebook, designed to provide a detailed overview of the variables and step-by-step instructions on defining and coding them (Appendix E). The coding period took fourteen days to complete. The appointment of the second coder was necessary for realizing good intercoder reliability for ensuring the higher reliability of this study.

For the dataset of company tweets, the coders classified every presented tweet, identify the emotional tone of tweets, and stated several possible elements of intensifying language (such as linguistic intensifiers, figurative language, and figures of speech). Additionally, the coders were requested to write down the elements (if present), then group them and decide on their valence (positive or negative). Finally, the coders judged the framing of the tweets and identified possible impression repair noticeable in the tweets. As for the dataset comprising audience tweets, following the codebook, the coders were tasked to categorise the gender of each author of a tweet, identify the stakeholder status of tweet authors, decide on the emotional tone of the tweets, and identify the type of message contained in each tweet. Furthermore, as in the Tesla dataset, the coders had a comparable task related to identifying intensifiers per tweet, stating the intensity markers, and judging their valence, in addition to classifying the tweets' framing.

Before the final coding, Coder 2 was requested to participate in the pilot coding of the first 100 tweets to contribute to higher reliability values in the final coding. The results of the pilot coding revealed little to no consensus between Coder 1 and Coder 2 regarding understanding the coding instructions for identifying and categorising language intensity elements, and impression repair in the Tesla dataset. Moreover, Coder 1 lacked an understanding of the concepts of the tweet authors' status and message types in the audience dataset. As a result, the coding instructions for the variables of confusion was revised by adding more examples of words that could assist in identification and categorization and providing more detailed definitions of the variables to increase the clarity of the procedure.

3.4 Operationalisation

The current study has sixteen variables, seven of which belong to Elon Musk's dataset of tweets, and the other eight variables are in the audience dataset of comments (Table 1). Variable "number of words" is not in Table 1 (Appendix E). There are two continuous variables in the present study: the number of intensifiers per tweet and the number of words per tweet. Both datasets shared three variables: the number of intensifiers per tweet, the valence of intensifiers, the category of intensifiers, and framing. Variable "emotional tone" was present in both datasets, though operationalised differently. Framing of tweets and categorisation of intensifiers had the same instructions for both datasets.

Categorisation of linguistic intensifiers - language elements that strengthen and highlight messages, was based on three categories: omittable without a change in the meaning – simple intensifiers, complex intensifiers, replaceable by a weaker version from the same word category, and complex intensifiers, consisting of multiple words. There are two complex elements of intensifying language, namely figurative language (set expressions), and figurative speech, involving metaphoric expressions, repetitions, and devices of typographic intensity (Van Mulken & Schellens, 2012). Meadows et al. (2019) stated that emotional messages on Twitter are frequently used to connect with audiences, and the most common emotions are intense, such as anger or fear. Therefore, in this study, language intensity markers in messages and the emotional tone of messages were used to answer the research questions.

Framing refers to organising a message (Lundi, 2006). Counter-framing refers to a message organisation contradictory to the original message formation (Anderson, 2018). Counter-framing is present when there is incongruency from the general framing pattern. The coders had to evaluate framing as positive (emphasising the positive aspects of the subject of the message), negative (highlighting negative sides of a subject), or neutral. Framing of tweets was crucial to answering the third research question.

3.4.1 Elon Musk's tweets

Identifying the emotional tone of messages assisted in answering the second and third research questions. The categories involved alarm or concern, reassurance, anger, humor or irony, sarcasm, or neutrality (Meadows et al. 2019). As the tweets did not exceed 100 words, each accounted for one dominant emotional tone only. A tweet could be showing alarm/concern if it expressed a crisis-related fear, anxiety, worry, or sadness for oneself or others. Tweets expressing reassurance were viewed as providing hope. If displaying frustration, such tweets were regarded as expressing anger. Tweets were considered humorous/sarcastic/ironic when they featured jokes or funnily discussed something. A tweet that did not express any obvious negative or confusing emotions was classified as neutral.

Distinguishing between categories of tweets helped in answering the second research question. Twitter differentiates general tweets, mentions, replies, and retweets as four types of tweets. General tweets are some messages posted to Twitter with text, photos, GIF, or videos. Mentions are tweets featuring a username of another Twitter account, preceded by the "@" symbol. A reply is a response to another person's tweet. Finally, retweets are posts of others posted on a person's profile: they can either exist with comments or without them (Twitter Help Center, 2022).

Frandsen and Johansen (2020) introduced three strategies for image restoration: denial, evading responsibility, and reducing offensiveness. In turn, SCCT by Coombs (2004; 2007) involved primary response strategies, including denying, diminishing, and rebuilding, and secondary strategies, such as bolstering. This theory formed the basis for creating the coding instruction for the variable "impression repair".

3.4.2 Audience's tweets

As for the audience tweets dataset, the coders identified tweet authors' names (male, female, gender-neutral), indicated the status of tweet authors (shareholders or other stakeholders comprising Elon Musk's audience), categorised message types of tweets, and stated framing of tweets. Note that stakeholders were distinguishable in the dataset via such words as "…I'm a $TSLA shareholder…" (shareholder) versus "As a Tesla owner I…" (other stakeholders). The emotional tone in the stakeholders' tweets was classified as irony, implying a reverse in valence between the literal and intended meanings, concern, meaning that a tweet was not entirely disapproved (Burgers et al., 2012). The tones of approval and disapproval indicated clear agreements or disagreements with Mr. Musk's messages; neutrality did not include the listed tones (Appendix E).

Each tweet was coded into one of the following message types: news updates, resources, personal experiences, personal opinions, questions, and others (adapted from Chew & Eysenbach, 2010). News updates consisted of tweets featuring news or a press release about the crisis. The distinction between resources and news updates was based on whether a tweet referenced current events, general background, history, or knowledge of the stock market. Personal experience was coded when a tweet mentioned a direct (one's own experience) or an indirect experience. Personal opinions referred to tweets where people expressed their thoughts, attitudes, or opinions about measles or measles vaccination. The question category included genuine inquiries about the "funding secured" crisis. Rhetorical questions and other "nonquestions" were not coded in this category. If a tweet did not belong to any of the previous message types or only included a link, it was coded into the "other" category. Each tweet was coded for one primary message type.

3.5 Validity, reliability, and inferential procedures

The chosen variables and their description in the codebook allowed for measuring the direction of messages in the tweets, intensity, and space (Neuman, 2011, p. 364). For checking consistency across coders' decisions by realising the interrater Cohen's Kappa was calculated for the dataset of Elon Musk's tweets, and the dataset including the stakeholders' tweets (Neuman, 2011). An overview of the intercoder reliability Kappa values calculated for each variable within the datasets can is presented in Table 1 below. According to Pallant (2007), Kappa values from 0.41 are appropriate for conducting statistical tests; the range from 0.41 to 0.60 represents moderate agreement, 0.61– 0.80 – substantial (good) agreement, and the values above 0.81 indicate very good agreement.

As seen in Table 1, reliability of the variables from the Tesla dataset varies between good and very good. "Tweet category" has a very good agreement (k = .81 $p < .001$). "Number of intensifiers" is of moderate/good reliability (k = .60 $p < .001$), whereas "category of intensifiers" has a substantial value of Kappa (k = .61 $p < .001$). For the stakeholders' dataset, the lowest (moderate) Kappa values belong to the "emotional tone" (k = .62 $p < .001$), "category of intensifiers" and "number of intensifiers" (k = .67 $p < .001$). Gender category has a very good agreement: k = .87 $p < .001$.

For data interpretation, some statistical tests using SPSS statistical software were conducted. Amongst them, the frequency analysis was performed for each variable in the two datasets. The independent samples t-tests were used to discover potential significant differences between the positive and negative valence of intensity markers for Elon Musk's tweets and the status of the stakeholders' tweets. Moreover, ANOVAs were performed to reveal differences between independent groups of framing for Mr. Musk's tweets, and framing together with status for the stakeholders' tweets. Additionally, Chi-square tests were conducted to identify meaningful relations between categorical variables within the datasets.

Table 1.

Intercoder reliability (k) values of the variables both within the Elon Musk's dataset (Tesla tweets) and the dataset of stakeholders' tweets (audience tweets)

Tesla tweets		Audience tweets	
Variable	Cohen's Kappa $p < .001$	Variable	Cohen's Kappa $p < .001$

Tweet category	.81	Gender tweet author	.87
Emotional tone	.77	Status tweet author	.76
Number of intensifiers	.60	Emotional tone	.63
Valence of intensifiers	.72	Message type	.73
Category of intensifiers	.62	Number of intensifiers	.63
Framing	.73	Valence of intensifiers	.72
Impression repair	.74	Category of intensifiers	.62
		Framing	.77

4 Results

The purpose of the study was to explore the extent to which Twitter as a social media channel could serve as the main tool for companies to use for crisis communication and reputation control. Furthermore, the study aimed at discovering how companies active on Twitter should anticipate counter-frames from the audience when preparing their messages.

4.1 Elon Musk's tweets

The total number of tweets posted by Elon Musk on his personal Twitter profile from August 7 to December 28, 2018, was N = 342. On average, each posted tweet had a length of (M = 17.62, SD = 12.48), ranging from 0 to 51; the most frequently occurring tweets throughout the determined posting period contained 18 and 6 words. Among the tweets, 89 tweets (26.0%) Elon Musk posted to the profile audience, and 34 tweets (9.9%) were replies to his tweets under the account ID "@elonmusk". In total, the tweets of Mr. Musk had 14 emojis of various kinds, averaging at M = .08 (range: 0 – 12, SD = .70). Moreover, there were four following days on which Elon Musk tweeted the most: August 7 (11 tweets published on the profile), November 19 (12 tweets), and December 11 (12 tweets). Most of the tweets were posted on October 25 (25 tweets). As for the time of posting, on average, Mr. Musk tweeted at M = 13:09 according to the Amsterdam time zone (SD = 7:54), ranging from 0:00 to 23:57.

4.1.1 Frequency analyses

Table 2.

Frequencies of occurrence of most used tweet categories in the Elon Musk's communication on Twitter

	Tesla tweets *N = 342*	
Tweet category	Frequency	%
Reply	251	73.4
General	56	16.4
Retweet	24	7.0
Mention	11	3.2

Table 2 shows the list of the most frequently and least frequently occurred categories of tweets. As presented in the table, the most frequent type of tweet used by Mr. Elon Musk of Tesla was a reply (73.4%) to other profiles or own tweets, followed by general tweets published on the profile (16.4%). The last two categories of tweets, retweets – shares of other users' posts (7.0%) and mentions – mentioned other users with the @ sign in the tweet (3.2%), were used by Elon Musk the least.

Table 3.

Frequencies of occurrence of the most used emotional tone in the Elon Musk's communication on Twitter

	Tesla tweets *N = 342*	
Emotional tone	Frequency	%
Reassurance	122	35.7
Neutral tone	104	30.4
Humour/irony	65	19.0
Alarm/concern	36	10.5
Anger/frustration	15	4.4

Table 3 presents an overview of the frequencies of occurrence attributed to the tweets of a certain emotional tone. The overview in this second table suggests that most of the tweets posted by Elon Musk conveyed reassurance (35.7%) as well as neutrality to the four presented emotions (30.4%), including reassurance. Tweets containing humour or irony occurred in 19.0% of cases, whereas tweets displaying the tones of alarm or concern and anger or frustration were less frequent.

Before discussing the contents of Table 4 and Table 5 below, it would be contextually important to indicate that within the sample of 342 collected tweets, a single tweet could have a maximum of five elements of the intensifying language expressed by Mr. Musk (*M* = 1.04; *SD* = 1.04). 118 tweets did not contain any intensifiers. The analysis further revealed that, for the most part, the tweets of Elon Musk had one intensifying language element (40.4%). On the other hand, the rarest number of intensifiers was five, which occurred only in one tweet (0.3%).

Table 4.

Frequencies of occurrence of the most used categories of intensifying language elements and valence of the intensity elements in the Elon Musk's communication on Twitter

	Tesla tweets *N = 468*	
Categories/valence	Frequency	%
Can be replaced	127	27.1
Can be deleted	124	26.5
Figurative language/other	60	12.8
More than one word	40	8.5
Positive intensifier	247	52.8
Negative intensifier	104	22.2

Table 4 illustrates the frequencies of tweets belonging to one of the four categories of intensifying language elements. Moreover, the table also shows the frequency of occurrence of positively-valenced intensifiers alongside negatively-valenced intensifiers. According to the table, the most frequent categories were two categories of intensifying language with almost similar frequency of occurrence. The categories included intensity markers that could be replaced by words of lower intensity (27.1%) and elements that could be deleted from a tweet without changing its meaning (26.5%). The use of elements of figurative language or other (12.8%), such as exaggerations, metaphorical comparisons, etc. exceed the use of intensifiers consisting of more than one word. Finally, the majority of the elements of intensity had positive valence (52.8%).

Table 5.

Frequencies of occurrence of five most used elements of intensifying language in the tweets of Elon Musk

	Intensifiers in Tesla tweets *N = 468*	
Intensifier	Frequency	%
great	16	3.3
actually	10	2.1
all	10	2.1
definitely	9	1.9
exactly	9	1.9

Table 5 demonstrates the list of five different most frequently used language intensity elements - words coded as intensifiers in Elon Musk's communication. In total, the tweets of Mr. Musk involved 127 intensifiers. The intensifiers "great" (adjective), adverbs "actually" and "all" were the most frequent in the tweets. Additionally, the frequency analysis revealed one instance of typographic intensity markers expressed in capital letters (ABC).

Table 6.

Frequencies of occurrence of most used impression repair strategies of SCCT in Elon Musk's Twitter communication

	Tesla tweets *N = 342*	
Tweet image repair strategy	Frequency	%
Bolstering	111	32.5

No repair	96	28.1
Reducing offensiveness	52	15.2
Evading responsibility	50	14.6
Denial	33	9.6

Table 6 shows an overview of several clusters of SCCT. According to the table, Elon Musk was found to be applying mostly the bolstering cluster of impression repair strategies; the evidence of this clusters' application was identified in 32.5% of the tweets. Moreover, the analysis showed that 28.1% did not contain evidence of any of the four impression repair clusters of strategies. Nevertheless, the bolstering cluster exceeded the following two almost equally distributed clusters: the cluster of reducing offensiveness (15.2%) and the cluster evading responsibility (14.6%). Finally, Table 5 illustrates that the least frequent cluster of image repair strategies was denial.

Table 7.

Frequencies of occurrence of most used framing of messages in Elon Musk's Twitter communication

	Tesla tweets *N = 342*	
Framing	Frequency	%
Positive framing	205	59.9
Neutral framing	92	26.9
Negative framing	45	13.2

Table 7, displays the most used type of framing of messages conveyed in the tweets of Elon Musk. The table reveals that Mr. Musk adhered to positively-framed message formation more frequently (59.9%) rather than to the negative framing of messages. In addition, neutral framing occurred more frequently in the tweets of Elon Musk than negative framing of messages (26.59%).

4.1.2 T-test: Valence of intensifiers and length of tweets

The independent samples t-test did not show a significant difference between positive and negative intensifiers with regard to the length of tweets they occurred in $t(349, N = 468) = -1.50$, $p = .067$. Tweets containing positive intensifiers were neither longer nor shorter than tweets containing negative intensifiers.

4.1.3 ANOVA: Impression repair and length of tweets

ANOVA showed a significant main effect for framing of tweets on the number of words in tweets $F(2, 339) = 48.12$, $p < .001$, partial $\eta^2 = .221$. Tukey post-hoc comparisons demonstrated that tweets which were framed positively ($M = 20.53$, $SD = 11.90$) and negatively ($M = 23.80$, $SD = 10.88$) by Elon Musk were composed of more words than the neutrally-framed tweets ($M = 8.13$, $SD = 8.92$), $p < .001$. No other comparison reached significance. Another ANOVA revealed a significant main effect for impression repair strategies on the number of words per tweet $F(4, 337) = 12.66$, $p < .001$, partial $\eta^2 = .131$. Tukey post-hoc comparisons showed that tweets containing the strategies of denial ($M = 21.12$, $SD = 13.00$), evading responsibility ($M = 22.26$, $SD = 10.84$), reducing offensiveness ($M = 19.67$, $SD = 12.25$), and bolstering ($M = 19.64$, $SD = 12.97$) were longer than tweets displaying no repair strategies tweets ($M = 10.56$, $SD = 9.65$), $p < .001$. No other comparison reached significance.

4.1.4 Chi-square: intensity elements, emotional tone impression repair, framing

Table 8.

Distribution of valence of intensity markers expressed in % in the tweets of Elon Musk

Impression repair
N = 468

Valence of intensifiers		No repair	Denial	Evading responsibility	Reducing offensiveness	Bolstering	Total
Positive	n	37	9	44	33	124	247
intensifier	%	36.6	17.6	54.3	49.3	73.8	52.8
Negative	n	8	33	29	18	16	104
intensifier	%	7.9	64.7	35.8	26.9	9.5	22.2

Table 8 presents an overview of the results for the Chi-square test of the relation between positively and negatively valenced intensity markers in the reviews (two tests) and impression repair strategies. The first Chi-square test showed a significant relation between impression repair strategies valence of intensity markers ($\chi^2(8, N = 468) = 152.13, p < .001$). Table 8 indicates that positively-valenced intensifying elements occurred relatively more frequently in the tweets containing a bolstering cluster of image repair strategies (73.8%) than in other clusters, such as evading responsibility (54.3%) or reducing offensiveness (49.3%). The negative intensifiers occurred more frequently in the denial cluster of strategies (64.7%) than in other impression repair clusters.

Table 9.

Distribution of four categories of intensifying language elements expressed in % in the tweets of Elon Musk

		Impression repair of the tweets *N = 468*					
Categories of intensifiers		No repair	Denial	Evading responsibility	Reducing offensiveness	Bolstering	Total
Can be	n	18	11	28	20	47	124
omitted	%	17.8	21.6	34.6	29.9	28.0	26.5
Can be	n	14	15	29	21	48	127
replaced	%	13.9	29.4	35.8	31.3	28.6	27.1

More than one word	n	5	7	6	5	17	40
	%	5.0	13.7	7.4	7.5	10.1	8.5
Figurative language or other	n	8	9	10	5	28	60
	%	7.9	17.6	12.3	7.5	16.7	12.8

Table 9 provides an overview of the results of the Chi-square test performed to test the relation between a variety of the impression repair strategies used in the tweets and the three identified categories of intensifying language elements. The Chi-Square test showed a significant relation between the impression repair strategies used in the tweets and the categories of intensifying language elements ($\chi^2(16, N = 468) = 75.98, p < .001$). According to Table 9, the elements of the intensifying language which can be omitted without a change in the meaning of a message were discovered to occur most often in the tweets containing elements of the evading responsibility cluster of image repair strategies (34.6%). A similar pattern was found for replaceable intensifiers (35.8%). As for the intensifiers consisting of more than one word, they occurred the most in the tweets showcasing the use of the denial cluster of image repair strategies (13.7%). The figurative language and other speech figures were found to be most frequently present in the denial cluster (17.6%).

Table 10.

Distribution of impression-repair strategies expressed in % in the tweets as part of the Elon Musk's communication

		Emotional tone of the tweets *N = 342*					
Impression repair strategy		Neutral tone	Alarm/concern	Reassurance	Humour/ irony	Anger/ frustration	Total
No repair	n	37	6	23	30	0	96
	%	35.6	16.7	18.9	46.2	0.0	28.1

Denial	n	3	5	6	8	11	33
	%	2.9	13.9	4.9	12.3	73.3	9.6
Evading responsibility	n	8	7	24	8	3	50
	%	7.7	19.4	19.7	12.3	20.0	14.6
Reducing offensiveness	n	13	13	23	3	0	52
	%	12.5	36.1	18.9	4.6	0.0	15.2
Bolstering	n	43	5	46	16	1	111
	%	41.3	13.9	37.7	24.6	6.7	32.5

Table 10 presents an overview of the results of the Chi-square test that was conducted to test the relationship between the type of tweets according to their emotional intensity and the impression repair strategy used in the tweet. The Chi-square test demonstrated a significant relation between the type of emotional intensity of a tweet and impression repair strategies ($\chi^2(16, N = 342) = 128.53, p < .001$). Table 10 indicates that the most frequent instances of absence of a repair strategy were found in the tweets categorised as humoristic/ironic (46.2%), as well as in the tweets expressing neutral tone. Moreover, the cluster of denial was found to be used the most in the tweets expressing emotions related to anger or frustration (73.3%) rather than in the tweets expressing reassurance (4.9%) and, most importantly, neutral tweets (2.9%). The evading responsibility cluster was present the most in reassuring tweets (19.7%), followed by tweets with the alarming or concerning tone. As for reducing offensiveness cluster, it was established to be occurring most often in the tweets with the tone of alarm or concern (36.1%), and bolstering was found to be present most frequently in the neutral tweets.

Table 11.

Distribution of differently-framed tweets expressed in % in the communication of Elon Musk

	Impression repair of the tweets *N = 342*					
Framing of messages	No repair	Denial	Evading responsibility	Reducing offensiveness	Bolstering	Total

Neutral framing	n	67	4	3	5	13	92
	%	69.8	12.1	6.0	9.6	11.7	26.9
Positive framing	n	26	23	34	29	93	205
	%	27.1	69.7	68.0	55.8	83.8	57.0
Negative framing	n	3	6	13	18	5	45
	%	3.1	18.2	26.0	34.6	4.5	13.1

The results of the Chi-square test conducted to assess whether or not there is a relationship between the type of tweets according to their impression repair cluster of strategies conveyed and framing of tweets are demonstrated in the Table 11. The Chi-square test revealed a significant relation between the type of emotion of tweets and type of framing of messages ($\chi^2(8, N = 342) = 159.54, p < .001$). Table 11 illustrates that the majority of the tweets that were neutrally framed by Elon Musk did not contain any image repair strategies (69.8%). Positively-framed tweets included, in the majority of cases, the bolstering cluster of impression repair strategies (83.8%). Moreover, positively-framed tweets were nearly equally distributed among the denial cluster and the evading responsibility cluster. In turn, negative framing occurred most frequently in the tweets expressing reduction of offensiveness (34.6%).

4.2 Audience tweets

In total, the collected dataset of tweets posted by the audience of Elon Musk on Twitter included $N = 352$ in the period ranging from August 7 to December 28, 2018. Generally, the length of tweets posted by the audience was ($M = 21.72$, $SD = 15.31$; range 1 – 61), and the most common length for a tweet was 9 words. As for the number of emojis, it ranged from 1 to 3 and had ($M = .13$, $SD = .49$), and the use of one emoji (6.1%) prevailed over three (1.7%) or two emojis (1.1%) per tweet. 178 authors (50.6%) had a male name either in their name of the account or in the account ID, and 142 tweet authors (40.3%) had a unisex name or other names not attributed to humans. Tweet authors with female names had the least frequent presence of 32 (9.1%) in the communication of stakeholders on Twitter in response to Elon Musk's communication. Regarding the time of posting reply tweets to Elon

Musk, the audience's reply to Mr. Musk's tweets at M = 13:24 (SD = 7:38; range 0:03 – 23:59) according to the Amsterdam time zone.

4.2.1 Frequency analysis

Table 12.

Frequencies of occurrence of tweet authors of certain status in the audience's reaction to the communication of Elon Musk

	Audience tweets *N = 352*	
Status tweet author	Frequency	%
Other stakeholders	289	82.1
Shareholder	63	17.9

Table 12 demonstrates an overview of the number of shareholders versus stakeholders who left replies to Elon Musk's tweets. It appears that shareholders commented in 17.9% of cases, whereas other stakeholders, such as customers, employees, or people interested in the company's activities, dominated the audience communication on Twitter.

Table 13.

Frequencies of occurrence of the most used emotional tone in the audience's reaction

	Audience tweets *N = 352*	
Emotional tone	Frequency	%
Approval	90	25.6
Neutral tone	79	22.4
Concern	70	19.9
Disapproval	65	18.5
Irony	48	13.6

Table 13 illustrates frequencies of tweets that occurred with a particular emotional tone expressed by tweets. As seen in the table, most tweets of the audience (25.6%) conveyed approval as a reaction emotion to the Elon Musk's tweets, followed by neutral tweets, whereas the emotions of concern (19.9%) and disapproval occurred less often (18.5%). Nevertheless, the least frequent emotion in the tweets was irony.

Table 14.

Frequencies of occurrence of the most occurred message types in the reaction tweets of the audience

Audience tweets *N = 352*		
Type of message	Frequency	%
Opinion and evaluative statements	199	56.2
Question	57	16.2
Personal story/experience	52	14.8
Other type	38	10.8
News updates	6	1.7

Table 14 shows five types of messages present in the audience tweets and their frequency of occurrence, respectively. According to the table, tweets containing personal opinions and evaluative statements as reactions (56.2%) heavily outnumbered the tweets including news updates (1.7%). As for the questions and personal stories or experiences, they outnumbered other message types (14.8%), and their frequencies of occurrence emerged as quite comparable.

Table 15.

Frequencies of occurrence of the most used categories of intensifying language elements and valence of the intensity elements in the audience's tweets

Audience tweets *N = 623*		
Categories/valence	Frequency	%

Figurative language/other	204	32.7
Can be deleted	176	28.3
Can be replaced	112	18.0
More than one word	42	8.5
Negative intensifier	282	45.3
Positive intensifier	252	40.1

Table 15 depicts an overview of intensifying language elements' categories in the order according to their frequencies of occurrences in the audiences' tweets alongside the number of negatively and positively valenced intensifiers' occurrence. The table shows that members of the audience used figurative language, exaggerations, metaphorical comparisons, etc in their tweets at the most frequent 32.7%. In comparison, the use of intensifiers that can be deleted (28.3%) surpassed the use of replaceable intensifiers and intensifiers consisting of several words, which was found to be the least frequent category of intensifiers within the audience tweets (8.5%). Furthermore, regarding the valence of intensity markers, Table 15 showed that although negative intensifiers were discovered to be used more frequently (45.3%) than positive intensifiers (40.1%), the difference appears to be quite close to the equal point.

Additionally, considering the number of intensifying language elements per audience tweet, the range of all the identified intensifying elements per tweet within the sample of 352 collected tweets was 0 – 9. Thus, a tweet could have a maximum of nine elements of the intensifying language expressed by the audience, averaging at (M = 1.52; SD = 1.00). Largely, 129 audience tweets (36.6%) had one intensifying language element, followed by tweets without intensifiers (25.0%), and the frequency of occurrence of two intensity markers per tweet in 63 tweets (17.9%). On the other hand, the least frequent number of intensifiers a tweet contained was nine, which occurred only in one tweet (0.3%).

Table 16.

Frequencies of occurrence of seven most used elements of intensifying language in the *audience tweets*

Intensifiers in audience tweets *N = 623*		
Intensifier	Frequency	%
great	24	3.9
really	16	2.1
all	15	2.1
love	9	1.4
only	9	1.9
too	8	1.3
very	8	1.3

Table 16 illustrates the list of seven different most frequently used language intensity elements in the audience's tweets. In total, the audience members used 534 intensifiers in their tweets-led response communication with Elon Musk. The adjective "great", and adverbs "really" and "all" were the most frequently used intensity markers in the tweets of the audience. Moreover, the analysis revealed seventeen instances of using typographic language intensity elements expressed in capital letters (ABC), such as "A LOT", or "ANYTHING", and four instances of words with repeated letters, such as "niceeeeee".

Table 17.

Frequencies of occurrence of most used framing of messages in the audience's reaction to the communication of Elon Musk

Audience tweets *N = 342*		
Framing	Frequency	%
Negative framing	168	47.7

Positive framing	128	36.4
Neutral framing	56	15.9

Table 17 presents an overview of framing instances that the audience used in their tweets to react to Elon Musk's tweets. The table shows that the negative framing of audience tweets (47.7%) surpassed positively-framed tweets, and neutral framing was used the least by the audience.

4.2.2 T-test: Status of tweet authors and length of tweets, number of intensifiers

The independent samples t-test demonstrated a significant difference between shareholders and other stakeholders with regard to the number of words per tweet $t(104.58, N = 352) = 3.45$, $p < .001$. The tweets of shareholders were, on average, longer ($M = 27.03$, $SD = 12.99$) than the tweets posted by other stakeholders ($M = 20.56$, $SD = 15.55$). Another independent samples t-test was conducted to test whether there is a difference between shareholders and other stakeholders regarding the number of intensity markers used in their tweets. The second independent samples t-test revealed no significant difference between shareholders and other stakeholders with regard to the number of linguistic intensifying language elements per tweet $t(350, N = 352) = 1.42$, $p = .078$. The shareholders' tweets contained neither a greater nor lower number of language elements of linguistic intensity.

4.2.3 ANOVA: Framing of tweets and number of intensifiers

An ANOVA was conducted to test for differences between three types of framing. The ANOVA revealed a significant main effect for framing of audience tweets on the number intensity markers in tweets $F(2, 349) = 11.54$, $p < .001$, partial $\eta^2 = .062$. Tukey post-hoc comparisons showed that the audience tweets with neutral framing had a smaller number of intensifiers per tweet ($M = .68$, $SD = .897$) than tweets with positive framing ($M = 1.70$, $SD = 1.45$), $p < .001$, and tweets with negative framing ($M = 1.67$, $SD = 1.46$), $p < .001$. No other comparison reached significance.

4.2.4 Chi-square: stakeholder, messages, emotional tone, framing, intensifiers

Table 18.

Distribution of two categories of states of tweet authors expressed in % in the tweets of audience

		Message type $N = 352$					
Status of tweet author		News update	Personal story/experience	Opinion and evaluative statements	Question	Other type	Total
Shareholder	n	1	30	21	8	3	63
	%	16.7	57.7	10.6	14.0	7.9	17.9
Other stakeholders	n	5	22	178	49	35	289
	%	83.5	42.3	89.4	86.0	92.1	82.1

Table 18 showcases the results of the Chi-square test that was aimed to discover whether there is a relation between the status of a tweet author and the types of messages conveyed by the tweets. The Chi-square test demonstrated a significant relation between the status tweet authors and message types in the tweets ($\chi^2(4, N = 352) = 66.52$, $p < .001$). The majority of tweets posted by shareholders conveyed a personal story or experience type of message (57.7%). As for the other stakeholders, the most common set of message types was composed of opinion and evaluative statements (89.4%), and other types of messages (92.1%).

Table 19.

Distribution of two categories of tweet author status expressed in % in the audience's tweets

	Emotional tone of the tweets $N = 352$					
Status of tweet author	Irony	Concern	Approval	Disapproval	Neutral	Total

Shareholder	N	1	18	29	9	6	63
	%	35.6	16.7	18.9	46.2	0.0	28.1
Other stakeholders	N	47	52	61	56	73	289
	%	97.9	74.3	67.8	86.2	92.4	82.1

Table 19 demonstrates an overview of the results for the Chi-square test of the relation between the emotional tone expressed by the tweets and the status of tweet authors. The Chi-square test revealed a significant relation between the status of a tweet author and the emotional tone of tweets ($\chi^2(4, N = 352) = 30.08, p < .001$). Based on the table's content, shareholders posted mostly disapproval tweets (46.2%) over ironic tweets (35.6%), which still outnumbered tweets exhibiting approval and concern. Regarding other stakeholders, in their tweets, the ironic emotional tone (97.9%) prevailed over the rest emotional tones, especially approval (67.8%).

Table 20.

Distribution of two categories of tweet author status in % in the tweets of audience as part of response communication

		Framing of tweets *N = 352*			
Status tweet author		Neutral	Positive	Negative	Total
Shareholder	n	4	33	26	63
	%	7.1	25.8	15.5	17.9
Other stakeholders	n	52	95	142	289
	%	92.9	74.2	84.5	82.1

Table 20 provides the results of the Chi-square test conducted to test the relation between the status of tweet authors and the framing of tweets. The Chi-square test showed that there is a significant relation between the status of a tweet author and the framing of audience tweets (χ^2(2, N = 352) = 10.49, p = .005). According to Table 20, shareholders had more positively framed tweets (25.8%) than negative or neutral. However, other stakeholders framed more tweets in a neutral manner (92.9%) than negative (84.5%).

Table 21.

Distribution of framing expressed in % in the tweets of audience

		Category of intensifying language elements *N = 623*					
Framing of tweets		Can be omitted	Can be replaced	More than one word	Figurative language/other	No intensifiers	Total
Neutral	n	20	3	2	12	29	66
framing	%	11.4	2.7	4.8	5.9	32.6	10.6
Positive	n	59	53	23	82	25	242
framing	%	33.5	47.3	54.8	40.2	28.1	38.8
Negative	n	97	56	17	110	35	315
framing	%	55.1	50.0	40.5	53.9	39.3	50.6

Table 21 presents an overview of the results of the Chi-square analysis aimed at testing a relation between the framing of tweets and the category of intensity markers. The Chi-square test revealed a significant relation between the framing of audience tweets and the category of intensifiers (χ^2(8, N = 623) = 66.06, p < .001). The table shows that neutral framing predominantly occurred in the tweets without the intensifiers (32.6%). Moreover, the majority of tweets with positive framing had intensifiers consisting of more than one word (54.8%), followed by replaceable intensity markers (47.3%). Finally, the largest portion of intensifiers in the negatively-framed tweets was found to be omittable intensifiers (55.1%), followed by the category including figurative language/other (53.9%).

5 Discussion and conclusion

The purpose of this quantitative study was to explore the use of Twitter as the main channel of image management for Elon Musk, the founder and CEO of Tesla, during the first five months of the “funding secured” crisis, which began on August 7, 2018. Based on the content analysis, the study investigated the elements of Elon Musk’s crisis management by analysing his tweets in terms of tweet category, emotional tone, framing, and application of impression repair strategies (primary and secondary strategies). Another goal was to evaluate the reaction of Tesla stakeholders to Elon Musk’s tweets in the form of replies. The study analysed the replies in terms of stakeholder status of tweet authors, emotional tone, type of messages, and framing. Additionally, Elon Musk’s tweets and audiences’ tweets were analysed regarding the number, type, and valence of intensifying language elements.

The gap was reached to evaluate the use of communication strategies for a human-made social media crisis and the framing of tweets in response to the audience’s comments on Twitter. This section answers the three research questions of this study by summarising the main findings and discusses theoretical and societal implications. Moreover, it reflects on the limitations and proposes suggestions for future research.

5.1 Answers to the research questions

The first research question concerned the extent to which Elon Musk used primary crisis response strategies more frequently than secondary strategies in his crisis communication. The present study discovered that Elon Musk applied secondary crisis responses, namely bolstering, more frequently than primary response strategies, such as denying, diminishing, and rebuilding; thus, the H1 was rejected. Within the H1, only H1(d**)** was accepted, suggesting that the tweets containing image repair strategies were longer than the tweets without repair. As opposed to the predictions, Elon Musk posted a higher number of tweets with positive and complex replaceable language elements of intensity, such as “great”, which were found to occur predominantly in the tweets communicating bolstering strategies. They did not differ in length with tweets containing negative intensifiers.

Moreover, the results were not line with predictions stated in H2, as Elon Musk posted more reassuring tweets than concerning. However, H2(a) was accepted, because the rebuilding strategy “reducing offensiveness” occurred more in the tweets expressing concern. Thus, Elon Musk focused on reminding about past activities, praising stakeholders, and accentuating the victim status of Tesla in the crisis for the impression repair management.

The second research question of this study was focused on the extent of Elon Musk using counter-frames in response to the replies of Tesla stakeholders within his audience on Twitter. The analysis suggested that Elon Musk's crisis communication relied primarily on replies rather than general tweets. Regarding the question, the results revealed that Elon Musk's communication, to a significant extent, consisted of positively-framed tweets, indicating a clear preference for one type of frame, excluding counter-framing from the communication in response to the audience's tweets. Hence, H3 was rejected, as the responses to the audiences had positive framing. Respectively, H3(a) was also rejected, as the analysis demonstrated that both positively-framed and negatively-framed tweets were longer than neutrally-framed tweets. Nevertheless, H3(b) was accepted due to the positively-framed tweets containing more instances of bolstering strategies. In line with predictions, negative framing of messages was most frequent in the tweets containing primary response strategies. Therefore, Elon Musk essentially relied on positive framing of messages, which lowered the possibilities for counter-framing.

The final research question inquired whether the audience had positive reactions to the tweets of Elon Musk, as indicated by the results during the data collection period. The findings were in line with predictions; H4 was accepted due to the audience posting mainly negatively-framed tweets in response to Elon Musk's messages. H4(a) was rejected, since the number of linguistic intensifiers per tweet was higher for both positively-framed and negatively-framed tweets, compared to neutral framing. Moreover, the majority of positively-framed tweets contained complex replaceable intensifiers (eg., "great"), whereas the tweets framed negatively had a higher number of simple omittable intensifiers rather than complex, which is in line with predictions in H4(b). Against the predictions, there was no difference in the number of intensifiers per tweet among the stakeholder groups of shareholders and other stakeholders; therefore, H4(c) was rejected. Finally, rejecting H4(d), the findings revealed that the Tesla shareholders posted more positively-framed tweets than negatively-framed or neutral tweets.

Additionally, regarding the emotional tone, most of the tweets posted by members of the Tesla audience displayed approval rather than disapproval or concern towards the tweets of Elon Musk. This finding is not in line with the predictions of the rejected H5. As for the H5(a), it was rejected since the shareholders and other stakeholders of Tesla posted a higher number of tweets expressing disapproval rather than approval; yet, other stakeholders conveyed more concern in the tweets than the shareholders. Considering H5(b), the tweets of shareholders, indeed, were longer than the tweets of other stakeholders.

Finally**,** the findings revealed that the audience posted more tweets communicating personal opinions rather than questions, thus rejecting H6. Moreover, the Tesla shareholders tweeted about their personal stories or experiences more than about questions, which is not in line with H6(a). Nevertheless, H6(b) was accepted according to the results demonstrating that most of the other stakeholders' tweets contained opinions. Hence, the audience reacted rather negatively than positively to the communication of Elon Musk, which is the answer to the third research question of this study. The predictions for the statistical outcomes of this study were formulated according to the existing theory on crisis communication and image repair management.

5.2 Theoretical implications

Verhoeven et al. (2014) supported the findings of Payne (2006), claiming that apologising is the least used strategy among the communication professions in crisis management. According to Coombs (2007), apologising to stakeholders and expressing concern are part of the primary cluster featuring rebuilding response strategies. The results confirmed this theoretical aspect, as the rebuilding strategy occurred most frequently in the tweets expressing concern. However, despite the conclusion of Payne (2006), indicating that apologetic responses positively contribute to the reputation repair, although congruently with Verhoeven et al. (2014), the current study showed that Elon Musk chose to use bolstering strategies over any of the primary responses. It could mean that Elon Musk granted his Twitter account with the function of a press release since the tweets containing image repair were, on average, longer than tweets without repair strategies.

Diers and Donohue (2013) suggested using a synchronised approach to accidental crises by using press releases for in-depth explanatory messages while using Twitter to communicate primary crisis responses, as it should coincide with the immediacy as a feature of this platform (Linsley & Slack, 2013). Mr. Musk attempted to provide narratives through tweets, supported by the frequent inclusion of complex language intensity elements, utilising Twitter as a driving force in impression repair, which is in line with Schultz et al. (2011). However, incongruently with the claims of Thiessen and Ingenhoff (2011) that indicated the importance of the micro level of messages in the image repair, the most frequent repair tools that Elon Musk employed in his tweets were bolstering, followed by the tweets with no evident repair function. It possibly implies that Mr. Musk could have underestimated the full potential of tweets for the image repair, which lies in the stakeholders, as emphasised by Zheng et al. (2018), despite mainly communicating with stakeholders on Twitter. Moreover, it could indicate that Elon Musk attributed the “funding secured” crisis to the accidental cluster instead of preventable.

According to the analyses, Elon Musk heavily relied on positive framing of tweets expressing reassurance in the audience interaction. This tendency is congruent with Pavlova and Berkers (2022), especially since Elon Musk used positive elements of language intensity more frequently than the negative. This result signifies using positive intensifiers of varying complexity as framing devices; Mr. Musk consistently used positive frames throughout the posting period, which denotes positive framing of tweets as salient; the occurrence of negative frames coincided with the use of primary response strategies, which was congruent with predictions. The goal of Elon Musk could have been reinforcing the idea of no drastic consequences for the company and its stakeholders among his audience on Twitter. Even though counter-framing is likely to occur in a company’s crisis communication, as claimed by Nadeau et al. (2020), Payne (2006) and Lachan et al. (2015) argued that introducing a change of frames might be dangerous to the reputation due to the possibility of audiences attributing responsibility to the company, which Elon Musk attempted to avoid by being consistent with the positive frame, which was congruent with Karimiziarani et al. (2022).

Additionally, the findings related to the audience tweets revealed similar patterns of congruency and incongruency with previous studies. As shown by the results, the audience of Tesla reacted negatively to the tweets of Elon Musk, which is congruent with the predictions based on the attribution theory of Coombs (2004). The stakeholders of Tesla attributed the responsibility for the “funding secured” crisis to Elon Musk since he posted the confusing tweet by missing the signals that the tweet could cause escalation (Mitroff, 2000). The audience also highlighted their attributions by using intensifying language elements in positively and negatively-framed tweets with no difference in their number between shareholders and other stakeholders. It suggests that, as Dann (2009) claimed, high-intensity attributions of fault by the audience could have damaged Tesla’s reputation to a certain extent. The fact that the stakeholders framed their tweets negatively implies that Elon Musk could have overlooked the stakeholder mapping according to the matrix (Cornelissen, 2020).

Moreover, the negative frames could be explained by the accumulation principle introduced by Coombs (2004), meaning that the crisis history of Tesla could have played a role in Elon Musk attempting to frame the tweets positively and the audience reacting negatively (DeBord, 2018). Against the predictions, the audience posted more tweets expressing approval than disapproval. Nonetheless, this finding is in line with Kochigina (2020) claiming that Tesla has many devoted fans – the faith-holders, who are likely to support the company. However, the shareholders posted longer tweets and displayed more disapproval than other stakeholders, which is congruent with predictions since the crisis significantly affected the investors (Marsh, 2018; Rushe, 2018). The negative financial consequences for the shareholders could explain why the audience, especially the shareholders, more often shared personal experiences than asked questions, as it could have been imperative for them to convey their consequences to Elon Musk.

5.3 Limitations, future research, and societal implications

Even though this study answered the research questions, it has several limitations. Firstly, the unequal group size for the variables composed of more than two groups might have affected the results of ANOVAs, which could have affected the Type I error levels. Secondly, the study only focused on the tweets of Elon Musk without considering the tweets of Tesla's account, which could contain different audience reactions. The main focus of the study was on Twitter, disregarding the press releases as additional means for crisis communication. Thirdly, the period of the "funding secured" crisis was devised according to the newspapers' evaluations, the company press releases, and personal conclusions of the researcher, which could have created a bias toward one interpretation of the active period of this crisis.

The quantitative content analysis as the method was proven to be appropriate for the current study, as it allowed for the detailed consideration of tweets regarding the chosen variables. The quantitative part of the content analysis provided an opportunity to answer the research questions in substantial detail. Analysing frequencies of tweets, differences, and relationships between them allowed for evaluation of patterns of and among the variables, necessary for hypotheses testing to answer the questions. Therefore, one of the suggestions for future research would be to conduct a mix-methods study that could combine quantitative and qualitative content analyses. Such a study could analyse the press releases of Tesla to study the level of synchronised crisis communication, as inspired by Diers and Donohue (2013). Additionally, future research could focus on the extended situational crisis communication theory that Kochigina (2020) proposed in their study. Stakeholders also use particular strategies in response to a company’s communication management. Detailing the stakeholders’ responses could allow evaluating the efficiency of Elon Musk’s crisis management more deeply.

This empirical study did not provide a concrete answer to whether Elon Musk failed to manage the crisis or whether his strategy was effective because the scope is five months of exclusively Twitter communication. However, this study is one of its kind, and Tesla or other companies could potentially consider implementing social media in crisis communication, as most companies still overlook it based on the theory. The popularity of Twitter is rising as Elon Musk has bought it to reinforce free speech on the platform (“Elon Musk and Twitter”, 2022). Hence, many more companies will join Twitter, increasing the demand for studies on companies’ behaviour on social media during inevitable crisis events.

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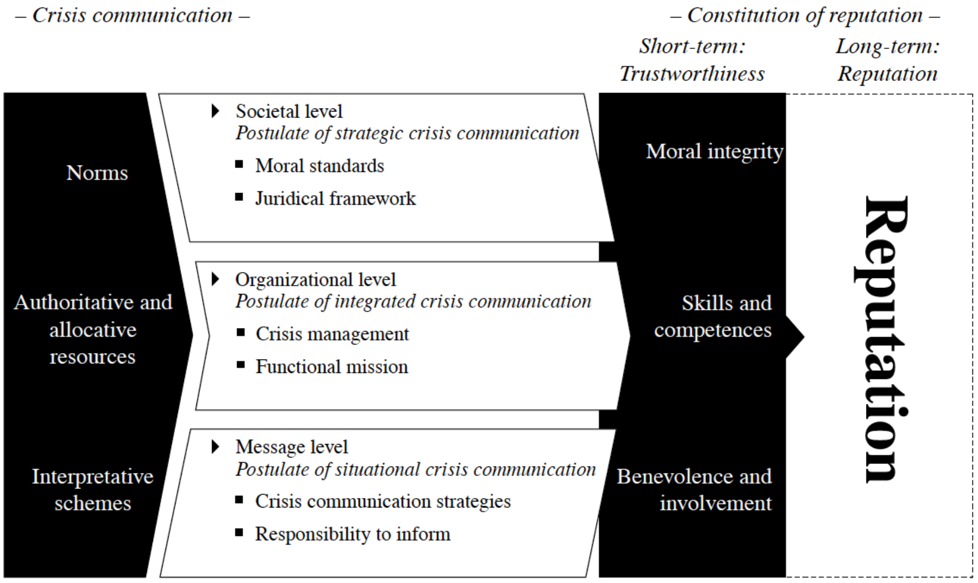
7 Appendices

7.1 Appendix A

Figure 1.

The integrative model of crisis communication (based on Thiessen & Ingenhoff, 2011).



7.2 Appendix B

Figure 2.

The experimental design on the first study on the role of social media in crisis communication (based on Schultz et al. 2011).

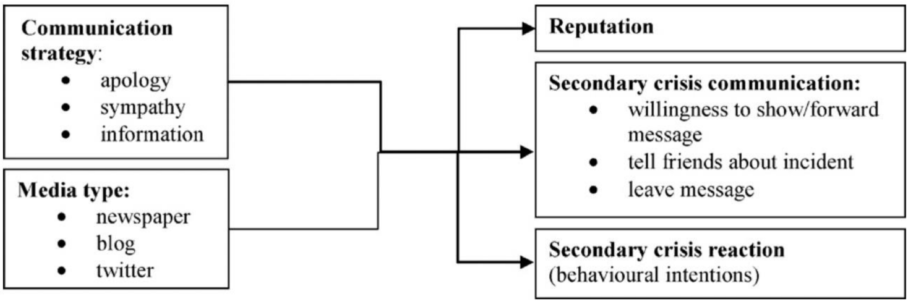


Fig. 1. Conceptual model.

7.3 Appendix C

Figure 3.

The graph of Tesla stock prices over the years of operation (Based on Tesla, Inc., 2022b).

7.4 Appendix D

Figure 4.

The SCCT crisis response strategies (based on Coombs, 2007).

Table 2: SCCT crisis response strategies

Primary crisis response strategies

Deny crisis response strategies

Attack the accuser: Crisis manager confronts the person or group claiming something is wrong with the organization.

Denial: Crisis manager asserts that there is no crisis.

Scapegoat: Crisis manager blames some person or group outside of the organization for the crisis.

Diminish crisis response strategies

Excuse: Crisis manager minimizes organizational responsibility by denying intent to do harm and/or claiming inability to control the events that triggered the crisis.

Justification: Crisis manager minimizes the perceived damage caused by the crisis.

Rebuild crisis response strategies

Compensation: Crisis manager offers money or other gifts to victims.

Apology: Crisis manager indicates the organization takes full responsibility for the crisis and asks stakeholders for forgiveness.

Secondary crisis response strategies

Bolstering crisis response strategies

Reminder: Tell stakeholders about the past good works of the organization.

Ingratiation: Crisis manager praises stakeholders and/or reminds them of past good works by the organization.

Victimage: Crisis managers remind stakeholders that the organization is a victim of the crisis too.

7.5 Appendix E: Codebook

Unit of data collection for the sources I and II

Twitter data include two following types of tweets: Tesla and audience (stakeholders). For Twitter posts, the standard unit of data collection are individual tweets.

7.5.1 I. Source: Elon Musk's tweets

1. Tweet ID: on each row of the coding sheet in the provided Excel file write a number (ID) of each discovered tweet.

2. Date of posting: indicate date of posting for each individual tweet across three columns (Day/Month/Year) using numbers (e.g., 7/8/2018).

3. Time of posting: state posting time of each tweet in the h:mm format (eg., 18:48, or 0:00). Time is shown by Twitter in accordance with the researcher's current location; in the present case, the time zone is Amsterdam.

4. Name of a tweet's author & their ID (preceded by the @ symbol): insert an account's name attributed to posting a corresponding tweet alongside its Twitter ID (eg., Elon Musk @elonmusk).

5. Addressee: indicate an addressee of each tweet, which can either be profile audience (if the tweet was posted on an author's profile) or other users, including the author's own tweets.

6. Text of tweet: copy and insert a tweet of Elon Musk and insert the entire copy of it in the column.

6.1. Emojis within text: if a tweet contains emojis, search for their full name in the emoji archive and insert it within brackets (red heart emoji) **(**Emoji Archives Dictionary.com., 2022).

7. Attachment: copy every available attachment text to the tweet they refer to (if applicable), apart from Internet memes – units of information containing different cultural references and cues, which often take forms of pictures or videos and are disseminated among people through imitation of something (Rogers, 2022). If a tweet has no attachment, leave the column blank.

8. **Number of words tweet:** count and state number of words in each tweet without counting any emojis.

9. **Number of emojis:** indicate number of emojis used in each tweet (if applicable). If none are used, put 0.

10. Table 1.

Example of the Excel file's configurations

ID	Day	Month	Year	Time	Name	Addressee	Text	Attachment	Words
1	7	8	2018	18:48	Elon Musk @elonmsuk	Profile audience	420	.	1
..	..	..	..	..	..	...	..	..	..

Words	Emojis
1	0

11. **Coder ID:** Indicate the coded status applicable to the one coding the corpus in the file's name.

Coder ID	Coder status
1	The researcher
2	The invited coder

12. Coding the variables: code the variables according to the instructions below.

1. Tweet category: Based on Meadows et al. (2019) and Help. Twitter (2022)

Code each general tweet as 1. General tweets are messages posted to Twitter with text, photos, GIF, and/or video. If a tweet can be considered mention, code as 2. Mentions are tweets featuring a username of another Twitter account with the '@' symbol (account ID). If a reply, code as 3. A reply is a response to another person's tweet. Finally, retweets are posts of other users posted on a person's profile; in some cases, they are posted with comments (Help. Twitter, 2022). Code retweets as 4.

2. Emotional tone of tweets: based on (Chew & Eysenbach, 2010) and Meadows et al. (2019)

Emotional tone refers to the type of emotions a tweet conveys. Meadows et al. (2019) indicated that emotional responses in crisis communication messages could serve as instruments for persuasion. The emotional tone tends to affect audiences' perception of behaviours, events, and intentions (Chew & Eysenbach, 2010). If a tweet expresses an emotion that can be understood from context and some word usage, it has an emotional tone (Meadows et al., 2019). If a tweet does not express any emotion that can be understood from context and some word usages, then code as 0 (neutral tone).

The dimensions of coding emotional tone are the following: alarm/concern (code as 1) based on expressions of fear, anxiety, or worry, which can be contextualised via such word usages as "unexpectedly", " sorry", "apologies", "not sure"; reassurance (code as 2) based on downplay and providing relief via word usages as "should not worry", "doing everything possible"; "will be done/ensured"; irony/humour (code as 3) based on incongruency between written text and conveyed meaning via the text through word usage, or providing jokes and discussing topics in fun ways: eg., "Romance mode, toilet humour & more video games" (Burgers et al., 2012). The final emotional tone is anger (code as 4), which involves frustration, expression of disappointment with something "I am upset with…", or "I cannot understand why".

3. Linguistic intensifiers - intensifying language elements: based on Van Mulken and Schellens (2012)

Linguistic intensifiers/intensity markers are language elements that increase the intensity of messages; they can be adjectives, nouns (e.g., "love"), verbs (e.g., "love"), adjectives (e.g., “amazing”), and an adverb (e.g., “actually”). There are three categories of intensifiers: code an intensifier as 1 (omittable intensifier) if it can be deleted from a sentence change in the meaning; code an intensifier as 2 (replaceable but not omittable) if it can be replaced by a weaker version of intensity from the same category of a word (e.g., “mesmerising” is replaced by “attractive”). Finally, code an intensifier as 3 (more than one word) if it consists of more than one word grammatically (eg., “a lot of” or “much more”). “Other cases” (code as 4) engulf cases of figurative language use that can consist both of one word or several words (e.g., “driving crazy”), metaphoric language (“dying to”), metaphoric comparison (eg., “like an angel”), typographic intensity markers written in capital letters, repetitions (eg., “a lot a lot”), exaggeration (anything, everything), or markers with repeating letters (“nooooo”) (based on Van Mulken & Schellens, 2012). Figurative language entails expressions that are set and unchangeable in discourse (eg., “time is up”) (Van Mulken & Schellens, 2012).

For simplification of the coding task and subsequent data analysis stage, linguistic intensifiers and “other cases” are considered as part of one umbrella term “intensifying language elements”. Fill in an intensifying language element in the column “intensifier”. Furthermore, state the number of intensifiers in each tweet in the column “intensifying language”. If one tweet contains several intensifying language elements (i.e., intensifiers or figures of speech), copy the entire row and paste it into the new following row. Fill up the column “intensifier” with an additionally found intensity element in the newly created row. In cases of absence of intensifying language, leave the row in the column “intensifier” empty, and code “intensifier category” a Tweet as 5.

4. Valence intensifiers based on Van Mulken and Schellens (2012)

Indicate valence of each identified intensified language element based on your own judgement. Code positively-charged intensifying language elements as 1, and negatively-charged intensifying as 2. If a tweet does not contain any elements of intensifying language, code valence as 0.

5. Framing based on Lundi (2006), Bortree et al. (2013), and Pavlova and Berkers (2022)

Framing refers to organising a message within a tweet to be interpretable by stakeholders in a particular manner (Lundi, 2006; Bortree et al., 2013). Code framing as positive (as 1) if a tweet contains references to the crisis, the company's past and present activities, or plans, and has a positive valence (pay attention to contextual meanings of words and linguistic intensifiers). On the other hand, code framing as negative if a tweet contains references to the crisis or aspects of something and has a negative valence (code as 2) (eg., if a tweet features SEC). If no interpretational frame is noticeable in the tweet on the basis of its context, code framing as 0 – framing is neutral, the mid of the spectrum, neither too optimistic or having positive notes, nor too pessimistic, or having negative notes (Bortree et al., 2013). Framing is identified in accordance with various framing devices: the emotional tone, intensifiers, and their valence, context and keywords, arguments or , judgement (Pavlova and Berkers, 2022).

6. Impression repair: based on Frandsen and Johansen (2020) and (Coombs 2007)

Frandsen and Johansen (2020) introduced three following strategies for image restoration of companies within stakeholders' perceptions: denial, evading responsibility, and reducing offensiveness. In turn, the situational crisis communication theory (SCCT) of Coombs (2007) involves primary response strategies, namely denying a crisis, diminishing a crisis, and rebuilding immediate consequences, and secondary strategies, such as bolstering. As for bolstering, this cluster comprises reminder of past activities, praising stakeholders, and reminding stakeholders about the company's victim status.

Denial implies negating or neutralising something (code as 1). If a tweet's context revolves around blaming somebody else for something that a company might be blamed for by stakeholders, or if the tweet contains words that can be attributed to providing justifications and calls for fairness (eg., "it was not the case"), then it demonstrates instances of evading responsibility (code as 2). Tweets containing attempts to reduce offensiveness should be coded as 3 (rebuilding by compensating and apologising); they include words showcasing embracement of responsibility by apologising (eg., "deeply sorry") for something, acknowledging something (eg., "our fault"), or talking about future plans to compensate for some difficulties of the present.

Finally, if a tweet has contextual praising of people (eg., "good job"), company's past achievements (eg., "recently developed a new software"), or highlights of reputational damage (eg., "can Steve B. insult me more..."), code the tweet as 4 (bolstering). If none of the abovementioned tendencies are noticed, code a tweet as 0 indicating no impression repair attempts.

7.5.2 II. Source: Stakeholders' tweets

1. **Tweet ID:** on each row of the coding sheet in the provided Excel file write a number (ID) of each discovered tweet of Elon Musk and response tweet of stakeholders.
2. **Date of posting:** indicate date of posting for each individual response tweet across three columns (Day/Month/Year) using numbers (e.g., 7/8/2018).
3. **Time of posting:** state posting time of each response tweet in the h:mm format (eg., 18:49, or 0:00). Time is shown by Twitter in accordance with the researcher's current location; in the present case, the time zone is Amsterdam.
4. **Name of a tweet's author & their ID (preceded by the @ symbol):** insert an account's name attributed to posting a corresponding response tweet alongside its Twitter ID (eg., Everyday Astronaut @Erdayastronaut).
5. **Addressee:** indicate an addressee of each response tweet – the tweets of whom the audience comments on.
6. **Tweet of Elon Musk:** copy and insert a text of tweet posted by Elon Musk.
7. **Text of stakeholders' response tweet:** copy and insert a text of each response tweet.
8. **Number of words tweet:** count and state number of words in each response tweet without counting any emojis.
9. **Number of emojis:** indicate number of emojis used in each response tweet (if applicable). If none are used, put 0 (Emoji archives - Dictionary.com., 2022).

10. Table 1.

Example of the Excel file's configurations

ID	Day	Month	Year	Time	Name	Addressee	Tweet	Text	Words

1	7	8	2018	18:49	..	Profile audience	niceeeeee	.	6
..	..	..	..	..	..	...	..	..	..

Words	Emojis
6	0

11. Coder ID: Indicate the coded status applicable to the one coding the corpus.

Coder ID	Coder status
1	The researcher
2	The invited coder

12. Coding the variables: code the variables according to the instructions below.

1. Gender tweet author

Check the profile and name of each tweet author. For checking gender of names, enter a name into the chosen database of names (Behindthename.com, 2022). Code the author as 1 (male) if the profile name and the tweet ID are of male gender. For instance, considering the name "vincentyu.eth" and the account ID "@vincent13031925", the author's name is Vincent – the male name. Code the author as 2 (female) if the profile name and the tweet ID are of female gender. Code the author as 3 (other) if the profile name and the tweet ID are either gender-neutral, or names of objects or events, and not persons.

2. Status of a tweet's author

Check the keywords in the tweet. Shareholders are persons that own Tesla's shares: they are the investors. If a tweet's content is related to stock price, or if a tweet author mentions that they are a shareholder as in, for instance, “I'm a $TSLA shareholder since IPO…”, “I like being part of the company owning some stock”, code status as 1 (shareholder). Other stakeholders include customers, environmental groups, governmental officials, employees, supporters, haters, general public. These groups are more difficult to differentiate in the tweets. Therefore, code as 2 (other stakeholders), both if they leave replies to the tweets of Elon Musk, and if they state their position within the groups of stakeholders, for example, fans “awesome, I am with you Elon”, or consumers “If you want to know why some of us haven't closed our orders on Model 3's…”.

3. Message type: based on Meadows et al. (2019)

In times of crisis, Twitter is used as means for stakeholders to engage in information sharing, sense-making of the crisis situation, reduction of uncertainty, and search for support. There are different message types on Twitter that can be seen during crises: news updates, personal experiences, evaluative statements, and questions. If a response tweet references current news related the company in crisis, it is the news update type (code as 1). If a tweet features a personal story, feelings and experiences, it is the personal experience type, code as 2. If a tweet contains opinion and evaluative statements, it is a personal opinion type, code as 3. If a tween contains a question and or a question mark, it is a question type, code as 4. However, rhetorical questions belong to the category featuring opinion and evaluative statements. If no category fits, code the tweet as others (0). If a tweet seems to contain two or more message types simultaneously, then from context, chose the most prevalent one. For example, if a tweet contains a personal experience and a question, code the tweet it as 2, since, in this case, the question is formulated on the basis of the experience.

4. Emotional tone based on Burgers et al. (2012) and Meadows et al. (2019)

As identified by Meadows et al. (2019), social media provides conditions for public members to freely and quickly shares reactions during crises. Emotional responses on social media could assist stakeholders into reaching out to companies in crisis to communicate their point of view regarding the situation.

For coding of the emotional tone of stakeholders’ tweets, five tones were proposed: irony, concern, approval, disapproval, or neither. Irony is an evaluative statement that has to be based on its incongruence with the overall context of an utterance. Irony is based on "reversal of valence between literal and intended meaning, and it also has to be relevant and aim at a certain target (e.g., "opportunity") (Burgers et al., 2012, p. 292).

If a tweet contains irony, code as 1. Concern (code as 2) does not entail full disagreement ("yes" or "no" implied response) with a tweet of Elon Musk, but rather signals worries and doubts via word choices such as "hope", "hopefully", "I don't know", or "I have a serious question". Approval (code as 3) signifies sharing points of views in tweets of Elon Musk through the worlds as, for instance, "yes", "good", "nice", "thank you", "great idea" "this is a must watch", whereas disapproval (code as 4) highlights having different viewpoints from the ones expressed by tweets of Elon Musk through words such as "no", "bad", "stop", "terrible idea", "you did not think about…". If none of the emotions discussed in this section are present in a tweet, code emotional tone as 0 – having neutral tone.

5. Linguistic intensifiers - intensifying language elements: based on Van Mulken and Schellens (2012)

There are three categories of intensity markers: code an intensifier as 1 (omittable intensifier) if it can be deleted from a sentence change in the meaning; code an intensifier as 2 (replaceable but not omittable) if it can be replaced by a weaker version of intensity from the same category of a word (e.g., "mesmerising" is replaced by "attractive"). Code an intensifier as 3 (more than one word) if it consists of more than one word grammatically (eg., "even if" or "even though") (Van Mulken & Schellens, 2012). "Other cases" (code as 4) include instances of figurative language (e.g., "end of story"), metaphoric language ("dying to"), metaphoric comparison (eg., "mud peddling"), repetitions (e.g., "very very"), typographic intensity markers written in capital letters, or markers with repeating letters (opennnnnnn) (Van Mulken & Schellens, 2012). Figurative language entails expressions that are set and unchangeable in discourse (eg., "time is up") (Van Mulken & Schellens, 2012).

Fill in an intensifying language element in the column "intensifier". State the number of intensifiers in each tweet in the column "intensifying language". If one tweet contains several intensifying language elements (i.e., intensifiers or figures of speech), copy the entire row and paste it into the new following row. Fill up the column "intensifier" with an additionally found intensity element in the newly created row. In cases of absence of intensifying language, leave the row in the column "intensifier" empty, and code "intensifier category" a Tweet as 5.

6. Valence intensifiers based on Van Mulken and Schellens (2012)

Indicate valence of each identified intensified language element based on your own judgement. Code positively-charged intensifying language elements as 1, and negatively-charged intensifying as 2. If a tweet does not contain any elements of intensifying language, code valence as 0.

7. Framing based on Lundi (2006), Bortree et al. (2013), and Pavlova and Berkers (2022)

Framing refers to organising a message within a tweet to be interpretable in a particular manner by others, including companies (Lundi, 2006; Bortree et al., 2013). Code framing as positive (as 1) if a response tweet contains reaction to the crisis, company's past and present activities, or future plans, and has a positive valence (pay attention to contextual meanings of words and linguistic intensifiers). On the other hand, code framing as negative (as 2) if a response tweet contains reaction to the crisis, company's present or past activities, or future plans and has a negative valence. If no interpretational frame is noticeable in the tweet on the basis of its context, code framing as 0 – framing is neutral, neither too optimistic or having positive notes, nor too pessimistic, or having negative notes (Bortree et al., 2013). Framing is identified in accordance with various framing devices: the emotional tone, intensifiers and their valence, context and keywords, arguments or judgement (Pavlova and Berkers, 2022).