Viralization keys of messages in unofficial accounts during crisis periods: the case of Covid-19 on Twitter

Received 25 September 2020
Accepted 1 May 2021

Claves de viralización de mensajes en cuentas no oficiales durante periodos de crisis. El caso de covid 19 en Twitter

危机时期非官方账号信息成功传播的关键：以新冠病毒信息在推特上的传播为例

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Abstract

Purpose – This study aims to analyze a backchannel account on news of the coronavirus at the beginning of the pandemic, with information not disseminated in official media due to the social alarm it might cause and the negative image of government management. Specifically, it examines acceptance and dissemination of this type of content in a period of lack of information, while reflecting on what would constitute proper management of this type of channel.

Design/methodology/approach – First, based on a literature review, this study classifies possible explanatory variables of online content dissemination into content richness and psychological content.

Disclosure statement. The authors report no potential conflict of interest.

Funding. This work was supported by the Ministerio de Ciencia e Innovación [FPU2018/05131] and also by the Professorship Excellence Program in accordance with the multi-year agreement signed by the Government of Madrid and the Autonomous University of Madrid.

Emerald Publishing Limited
2444-9709
DOI 10.1108/SJME-09-2020-0170

Second, this study performs sentiment analysis of the Twitter backchannel account @COVID_19NEWS and use Qualitative Comparative Analysis to find causal configurations of variables that obtained a high rate of retweets.

Findings – The results reveal predominance of one combination of three factors in backchannel information diffusion: emotional, identifying and video content. Other interesting combinations of factors were shown to be attractive enough to contribute to success of the tweets.

Practical implications – Knowledge of the main configurations that attract information dissemination in backchannel accounts is useful for public management of a health crisis such as the Covid-19 outbreak. Rather than suppressing these channels, the authors discuss different solutions.

Originality/value – This study advances scholarship on backchannel communications in emergency situations, providing insights to understand and manage such channels.

Keywords Covid-19, Coronavirus, Backchannel, Twitter, Qualitative comparative analysis

Paper type Research paper

Resumen

Propósito – Este estudio analiza una cuenta extraoficial sobre noticias del coronavirus al inicio de la pandemia, con información no difundida en los medios oficiales por su posible repercusión en la alarma social y la imagen negativa de la gestión gubernamental. Concretamente examina la aceptación y difusión de este contenido en un periodo de desinformación, así como reflexiona sobre la gestión de este tipo de canales.

Diseño/metodología/enfoque – En primer lugar, en base a la revisión de la literatura, clasificamos las variables explicativas según la riqueza de contenido y el contenido psicológico. En segundo lugar, sobre la cuenta extraoficial de @COVID_19NEWS en Twitter, realizamos análisis de sentimiento y utilizamos Análisis Comparativo Cualitativo (QCA) para encontrar configuraciones causales de variables que obtuvieron una alta tasa de *retweets*.

Hallazgos – Los resultados revelan la importancia de una combinación de tres factores en la difusión de información del canal secundario: contenido emocional, identificativo y video. Otras combinaciones de factores también contribuyeron al éxito del tweet.

Implicaciones prácticas – Estas configuraciones podrían ser útiles para la gestión pública ante una crisis sanitaria como la Covid-19, prestando atención a los factores cuya configuración atrae la difusión de información en las RRSS. En lugar de suprimir estos canales, se presentan soluciones para garantizar una colaboración eficaz.

Originalidad/valor – Este estudio realiza una contribución académica a las comunicaciones extraoficiales en situaciones de emergencia, proporcionando información para comprender y gestionar este tipo de canales.

Palabras claves – Covid-19, Coronavirus, Canal extraoficial, Twitter, Análisis cualitativo comparado

Tipo de artículo – Trabajo de investigación

摘要

目的 – 在新冠疫情初期, 由于可能引起社会恐慌和政府管理部门的负面形象, 官方媒体缺少相关的新闻报道。本文研究了在这种官方信息匮乏的危机时期， 非正式渠道（backchannel）对于新冠病毒内容的接受和传播情况, 本文同时反思了如何对这类非正式渠道进行正确的管理。

研究设计 – 基于文献综述，我们先将在线内容传播的可能解释变量分为内容丰富度和心理内容这两个方面。其次，我们对推特上的非正式渠道账户@COVID_19NEWS发布的内容进行情感分析，并使用定性比较分析法来寻找内容获得高转发率的原因。

研究结果 – 结果显示, 对于非正式渠道信息的成功传播, 情绪化、具有辨认度和包含视频内容这三个要素的组合占主导地位。此外, 其他要素的组合也有来助于推文的成功传播和扩散。

实践意义 – 了解非正式渠道吸引信息传播的主要原因, 将有利于应对健康危机（例如Covid-19爆发）和进行公共管理。文本讨论了不同的解决方案,而不是简单地压制这些非正式渠道。

原创性/价值 – 这项研究推进了危机背景下非正式渠道传播的学术研究, 为理解和管理这类非正式渠道提供了见解。

关键词 - Covid-19, 新冠病毒, 非正式渠道, 推特, 定性比较分析

1. Introduction

Coronavirus disease 2019 is having unforeseen impacts worldwide. Despite general belief that news media play a critical role in informing the public of health risk perceptions during an Emerging Infectious Disease (EID) outbreak (Shim and You, 2015), exposure to others' opinions and news through social networking sites (SNS) strongly shaped the public's risk perceptions of EIDs such as MERS (Choi *et al.*, 2017) and SARS-CoV-2. A social platform like Twitter is particularly suited to exchanging content easily, quickly and flexibly. The data attest to this speed and flexibility: in the first four weeks of January 2020, over 15 million Twitter posts addressed the subject of coronavirus (Pérez-Dasilva *et al.*, 2020). Although the World Health Organization did not declare Covid-19 a pandemic until March 11, SNS such as Twitter (including accounts like @COVID_19NEWS, analyzed here) emerged to inform the population. Our case study analyzes a Twitter account that gained over 100,000 followers in under two months. Exponential growth in Twitter accounts (e.g. @COVID_19NEWS) led to their deliberate condemnation and silencing to limit content disseminated because it questioned certain countries' mismanagement of the health crisis.

Recently, researchers have sought to identify factors explaining dissemination of EIDs news on social media. SNS dissemination of Covid-19 information has been studied primarily in reference to official information channels, with special emphasis on fake news (Pérez-Dasilva *et al.*, 2020). Very little research has focused on the value of social complaints in SNS through unofficial information channels. Our research addresses this topic by analyzing the phenomenon through backchannels, defined as secret, unofficial or irregular means of communication, especially in policy and law (McCarthy and Boyd, 2005). Backchannel communication occurs through informal channels as a secondary communication route (McNely, 2009) or as a primary communication route when official sources provide no clear information. In critical situations, backchannel modes of communication appear on SNS such as Twitter to respond to lack of information or false information and as a tool for individual and social reporting.

Twitter is increasingly used as a medium for digital backchannel communication (real-time, non-verbal, uninterrupted communication) (Greenhow and Galvin, 2020). Despite various studies analyzing Twitter's usefulness as an effective backchannel, unofficial communication channels have become very controversial. Public officials often view backchannel communications as having strong potential to spread false information – misinformation and disinformation – endangering public safety (Sutton *et al.*, 2008). Misinformation is inaccurate or false information that the person who disseminates it believes to be true. Disinformation is inaccurate or false information that the person who disseminates it knows to be inaccurate or false (Karlova and Fisher, 2012).

Some studies even examine associations of the dark side of social media use with fake news-sharing behavior among social media users (Talwar *et al.*, 2019). Nonetheless, with each new crisis, backchannel communications through SNS are growing to support official information channels. Just as SNS are becoming a dynamic forum to spread medical information of dubious quality (Frish and Greenbaum, 2017), so backchannels are used to register complaints and denounce deplorable situations to which citizens are subjected in this health crisis. An extensive literature review reveals very little research on use of Twitter as a backchannel to combat initial lack of information from official sources in a disaster or pandemic. This article focuses on the significant public health issue of Covid-19, seeking to understand how unofficial channels (e.g. @COVID_19NEWS) arise to respond to lack of information. Several studies show that backchannels are strongly critical when spreading information about impending disasters (Wolkin *et al.*, 2019). Recent studies show that social media such as Twitter help to capture dispersed community knowledge on disaster management (Kankanamge *et al.*, 2020). Furthermore, Twitter has been the platform most frequently used to study rapid spread of information in a disaster (Vongkusolkit and Huang, 2020).

No research has analyzed the factors determining high diffusion of information through backchannels during the initial phase of a pandemic such as Covid-19. Thus, significant research gaps exist regarding (a) usefulness of backchannels to compensate for lack of information during the initial phase of a pandemic, and (b) psychological and objective factors determining high diffusion of these backchannels during this initial phase. This study addresses these gaps by analyzing the content of a successful backchannel account and the explanatory variables of online content dissemination. We perform exploratory and sentiment analysis and use Qualitative Comparative Analysis (QCA) to find causal configurations of variables that obtained a high rate of retweets. We measure information spread through two main factors characterizing the tweets: psychological factors, based on emotional (Hou *et al.*, 2020), identifying (Cruwys *et al.*, 2020) and sensational content (Tuccori *et al.*, 2020); and content richness factors, based on the tweet's objective content (Shahbaznezhad *et al.*, 2021). This paper thus aims, first, to analyze the content and identify the elements that promote dissemination of news about this health crisis in backchannels at a key moment, the initial, stage, when society is affected by misinformation [1]. Second, it combines proposals from various authors to reflect on different solutions to manage information in backchannels, contributing to freedom of expression and social condemnation.

This study's novelty is twofold:

(1) To the authors' knowledge, it is the first study to analyze use of backchannels to compensate for lack of information during the initial phase of a pandemic. Our findings thus help to understand the social and managerial utility of backchannels during these difficult times.

(2) The study uses complementary methodologies: sentiment analysis and QCA to identify which causal configurations of psychological and objective factors determine high diffusion of these backchannels during the initial phase of a pandemic.

The findings analyze dissemination of essential communication through unofficial channels, providing useful insights to improve management of critical information during times of lack of information.

2. Theoretical framework

Online news media today have formed their own networks by referring to relevant news articles in collaborative news media owned by the same company or other competitive news media for prompter, more reliable reporting (Kim *et al.*, 2012). Such references enable frequent exposure and connection to other types of online social networks, such as SNS. Moreover, the relationship between news coverage and public cognitions and emotions concerning the risk of global pandemics is well documented in the literature (Shim and You, 2015). This study therefore considers backchannels, or peer-to-peer communications rather than official or "formal" communications. Citizens in emergency situations consider SNS as an important complement to official channels due to contributions of on-site witnesses (Muralidharan *et al.*, 2011).

Figure 1 schematizes this study's conceptual framework; we use number of retweets as the metric to evaluate scope of information dissemination. We argue that objective characteristics of the content involving content richness (identified as vividness of content) significantly influence capacity to spread information. Perceptual characteristics of the content also influence this capacity, however, requiring us to include psychological content.

2.1 Objective content

Some objective characteristics observed in social media content can determine the scope and speed of information dissemination. Content richness, especially significant, is defined as vividness of online content (Cvijikj and Michahelles, 2013) enhances capacity to spread information.

2.1.1 Richness. Richness indicates the richness of a post's formal features, the extent to which a post stimulates various senses (Steuer, 1992). This term comes from Media Richness Theory, which studies objective characteristics of media channels that establish ability to carry information (Tseng *et al.*, 2017). The original theory of media richness has four dimensions or abilities:

(1) to use multiple information channels to handle information cues simultaneously;

(2) to facilitate rapid feedback;

(3) to establish a personal focus according to the user's situation and needs; and

(4) to use symbols or alternatives in a language to convey information (Trevino *et al.*, 1987).

Richness is also commonly referred to as vividness of online content (Steuer, 1992; Cvijikj and Michahelles, 2013). Previous studies that examine how to enhance positive attitudes towards a website show the importance of richness of the message (Fortin and Dholakia, 2005). According to Godin (2007), investing in visual content increases social network accounts' efficiency and gives them greater visibility. Moreover, audiovisual content and retweets are more attractive to users, contributing to virtualization of information. Recent studies show that richness of content due to inclusion of a video or photo significantly affects various types of engagement behavior (Shahbaznezhad *et al.*, 2021).

The aforementioned findings suggest that a post's richness prompts more proactive attitudes toward the account. Inclusion of dynamic animations (videos), contrasting colors and pictures (images), references to other Twitter accounts that could be the source of information (mentions), interactive queries on certain topics (hashtags), information about content location (location) and interactive links to website news or specific references to official information sources (official media) may increase a tweet's fame. These mechanisms stimulate different senses that increase users' propensity to look at message content, as opposed to text-only tweets (Sabate *et al.*, 2014).

Our study differentiates by content type only (Sabate *et al.*, 2014) – text, image, video. This approach avoids prior judgments about progressive levels of richness (low, medium,

Source: Compiled by the authors

Figure 1. Conceptual framework

high) removing potential subjective bias about the richness users perceive (Cvijikj and Michahelles, 2013).

2.2 Perceptual content

Some subjective characteristics of social media content determine scope and speed of information dissemination (Choi and Chung, 2013), among them, emotional, identifying and sensational content.

2.2.1 Emotional. Emotional content expresses agreement, disagreement or emotions (Bales, 1970). In public health emergencies such as Covid-19, MERS or SARS, emotional content is principally negative, including disagreement, showing tension and showing antagonism (Peña and Hancock, 2006).

Studies analyze the role of affect in social media, a provocative focus for examining how fully online activism contributes to meaningful social change. The emotional content of SNS is likely to affect people's engagement (Mayshak *et al.*, 2017). Emotions are especially natural in crises such as pandemics. We understand emotions as feelings with strong negative or positive components that people experience due to a certain situation that could affect behavior. Emotions activate mechanisms designed to help people cope and adapt to their environment. These *tendencies toward action* are determined by affect, level, type of physiological arousal and context (Guerrero and La Valley, 2006).

Public emotion may be aroused by the risks and uncertainties of an EID, in constructive or disruptive ways (Hsu *et al.*, 2017). Thus, governments should strive to understand public emotions during a pandemic and relay accurate information to allay public fears (Lancet, 2020). Significantly, social media can systematically monitor public emotions about a pandemic in real-time (Tang *et al.*, 2018). A recent study showed that negative emotions and public risk perception correlated closely with outbreak news events, such as Covid-19 government announcements and implementation of containment measures (Hou *et al.*, 2020).

2.2.2 Identifying. Identifying is composed of two types of identity, collective and personal. It is important to differentiate and recognize these types. Collective identity is explicitly connected to a group of people outside the self. Personal identity typically refers to characteristics of self that one believes, in isolation or combination, to be unique to oneself (Simon, 1997).

Parties learn to identify with each other's wishes and needs and feel they can understand each other's motivations (Deutsch, 1949). Identification-based trust grows as parties collaborate and can be strengthened by actions that create collective identity. This identity can include people one has never met but with whom one shares some common attribute, such as gender, nationality, or occupation (Ashmore *et al.*, 2004). Furthermore, higher levels of trait empathy (natural ability to understand others' emotions or to shift one's emotion to match others') (Kunyk and Olson, 2001) are associated with higher SNS engagement.

Greater group identification is related to increased conformity to group norms (Stevens *et al.*, 2019). For example, normative influence could lead a person to get vaccinated based on the user's reference group (Falomir-Pichastor *et al.*, 2009), but it could also prompt that group to attend a rally protesting social distancing (Ferris *et al.*, 2019). The role of shared identity has been under-recognized in public health content that seeks to change individual behavior. Shared identity contributes especially intensely to health risk behavior because users may not even recognize the group risk. Recent research proposes that shared group membership organizes our perceptions of the risk of Covid-19 (Cruwys *et al.*, 2020).

2.2.3 Untrustworthy. Trust – and consequently distrust (negative trust) – has been widely applied in several domains. In social network services (SNS), trust is understood subjectively, as a directed relationship between users and a compound of integrity, preference/taste similarity and social closeness. Trust's negative, distrust, is the extent to which "distrusters" consider the trustee's opinions in a certain area (Gao *et al.*, 2015).

In controversial contexts, the harmful impact of misinformation on perception, memory, emotions, viewpoints and attitude toward a topic can remain even when individuals recognize the falsity of fake news (Sacchi *et al.*, 2007) and untrustworthiness can negatively affect communication (Van Veenen, 2010). As distrust especially affects parties' perception of each other, and thus their expectations and interpretation of messages (Epley and Kruger, 2005), trust and faith will be low in conflict situations. Negative assumptions tend to strengthen each other due to selective perception and confirmation bias. Confirmation bias is propensity to interpret signals from others to confirm one's preconceptions of those others (Hargie, 2003). Selective perception is propensity to perceive only messages that confirm one's preconceptions (Lewicki *et al.*, 2006).

A recent study of untrustworthy content on Covid-19 identifies a set of factors contributing to social media system distrust and currently limits effectiveness and scope for social media use in informal collective decision-making in crises (Mirbabaie *et al.*, 2020). These factors are related to lack of mass systematization, enabling of anti-social behaviors and haphazard facilitation of convergence behaviors (Bunker *et al.*, 2019). A recent study shows, however, that physical limitations have made people heavily reliant on connectivity through global digital social networks, building trust to facilitate human interaction and information sharing about Covid-19 (Limaye *et al.*, 2020).

2.2.4 Sensational. Sensationalistic content amuses, titillates and entertains. It includes topics such as crime, violence, disasters, accidents, fires or vignettes about individuals and groups (Grabe *et al.*, 2001). Health professionals worry about sensationalism in public health emergencies. Experts believe that sensational, risk-elevating media coverage of an EID often causes the public to overreact (Sell *et al.*, 2017).

Several studies have investigated the impact of news coverage on risk perceptions of self and others in specific health-threatening pandemics, such as SARS (Berry *et al.*, 2007) and MERS (Choi *et al.*, 2017). Other studies examine the relationship between news coverage and the public's emotional risk perceptions in global pandemics (Shim and You, 2015). The common factor in these studies is that public perceptions of risk are heavily affected by media processes of symbolizing and amplifying an EID, such that sensational news coverage of the EID often elicits negative emotions unevenly in spectators (Balzarotti and Ciceri, 2014). Moreover, negative emotions are more prevalent than positive in social media during an infectious outbreak (Song *et al.*, 2017). SNS played a role in providing factual information, including medical information, subjective information and users' comments (Choi *et al.*, 2017). Finally, the emergence of the topic "infodemic" during Covid-19 should focus researchers' attention on sensational and distorted information (Tuccori *et al.*, 2020).

3. Methodology

Firstly, we obtained Twitter data from the backchannel account that spread news about coronavirus (@COVID_19NEWS). We identified the two main hashtags about coronavirus (#coronavirus and #COVID-19) through web scraping using the Chrome extension NCapture to the software NVivo. Web scraping was performed on 2/26/2020 for the period 1/05/2020 to 2/23/2020. The @COVID_19NEWS tweets were in English. The data received were analyzed with NVIVO 12 to identify the main terms used in Twitter for this topic. Later, the 30 most retweeted tweets and 30 least retweeted tweets of the @COVID_19NEWS backchannel account were examined with sentiment analysis and QCA. We applied sentiment analysis to examine affective information from the data (Cao *et al.*, 2013) and QCA to identify possible combinations of explanatory variables that explain dissemination of information (retweets) from a backchannel account.

To perform the sentiment analysis, we used Meaning Cloud software, which provides text analytics tools. The sentiment analysis API tool was used to analyze Twitter posts. This API uses semantic approaches based on advanced natural language in all aspects of morphology, syntax, semantics and pragmatics. Its engine generates a syntactic-semantic tree of the text and overlays terms from the lexicon to distribute their polarity values along the tree, combining the values depending on morphological category of the word and syntactic relations that affect it. Essentially, the software studies the words in the tweets and classifies them according to positive or negative polarity. The study of polarity is based on Robert Plutchik's Wheel of Emotions and operates by recognizing emotional patterns in language using algorithms (Hu and Liu, 2004).

Using the sentiment analysis tool Meaning Cloud, we evaluated users' tweets (data obtained before registering in the application) to characterize tweets based on five aspects: polarity (shows polarity tag obtained for the text; if polarity is detected, one of 5 degrees of polarity is assigned: positive [P] or negative [N], very positive [P+] or very negative [N+], neutral [NEU]; if no polarity is detected, the value is NONE), agreement (shows agreement between polarities detected in the text), subjectivity (shows subjectivity value obtained for the text), confidence (shows confidence value associated with polarity detected for the text) and irony (shows whether text is ironic). After obtaining and analyzing the results of Sentiment Analysis with Meaning Cloud, we used QCA to identify the combination of variables determining dissemination of information.

The QCA analysis examined the most and least frequently retweeted tweets from the @COVID_19NEWS account. QCA is quantitative and qualitative and enables determination of conditions of causality in different scenarios, such as social science studies (Rihoux and Ragin, 2009). Data estimation with this technique requires three prior steps (Schneider and Wagemann, 2012): calibration of variables if necessary, analysis of necessity and analysis of sufficiency.

One advantage of this method is the possibility of achieving more complex analyses than through other methods, such as regression, since QCA establishes relationships between subsets of variables (Ragin, 2014). Another advantage of QCA is that a small or medium-sized sample is sufficient (Rihoux and Ragin, 2009). QCA solves the problem of studies up to 50 cases, where the sample is too small to use most quantitative techniques but too broad to develop in-depth analysis of each case (Medina *et al.*, 2017).

This study applied QCA analysis to two groups of tweets to check the technique's validity for the data. The first group, a sample of 30 retweeted tweets, considered the 15 most retweeted tweets and the 15 least retweeted tweets. The larger second sample of 60 retweeted tweets considered the 30 most retweeted tweets and the 30 least retweeted tweets.

3.1 Sentiment analysis

The first stage performed sentiment analysis to mine affective information from the data and characterize tweets using five aspects: polarity, agreement, subjectivity, confidence and irony. The results for polarity show that negativity generally predominates over positivity in both most and the least retweeted tweets. If we analyze the differences between the most and the least retweeted tweets, however, we observe greater intensity of emotion in the most retweeted tweets. This intensity is reflected in the extreme polarities that appear primarily in the most retweeted tweets. Very negative polarity is present in 6 tweets, but only 2 of the least retweeted tweets show very negative polarity. Very positive polarity appears in only 1 of the most retweeted tweets. Moreover, the least retweeted tweets show a higher proportion of non-polar tweets. Emotional intensity is thus observed in the most retweeted tweets, indicating the importance of studying tweets' perceptual factors in depth.

To examine polarity, we provide sample tweets to illustrate the results for valence and intensity. The samples are drawn from the 30 most retweeted tweets from @COVID_19NEWS for each type of polarity (Table 1).

The tweets are also characterized based on three aspects: agreement, subjectivity, irony. Most of the tweets, both most retweeted (23/30) and least retweeted (21/30), show high levels of agreement. This backchannel account thus shows similarities in the polarities of its texts, but polarity is higher in the most retweeted tweets. As to subjectivity, the texts of both the most retweeted (7/30) and the least retweeted tweets (3/30) show low subjectivity. Although this value is still higher in the most retweeted tweets, we can interpret the backchannel account's tweet texts as showing objective value. Only 1 tweet among the most retweeted tweets is ironic, and no irony occurs in the least retweeted tweets; both the most and the least retweeted tweets are generally non-ironic. Finally, confidence levels for polarity of the most and least retweeted tweets are 92%–100%, indicating very high confidence.

3.2 Potential drivers of information dissemination

A second stage of the analysis identified explanatory variables of the shared tweets in @COVID_19NEWS. Tweets retweeted at least once (1,075 Tweets) were examined to identify content characteristics that explain information dissemination. Based on the literature review, exploratory analysis and sentiment analysis, the characteristics (classified into two groups, richness content and psychological content) emerge as potential influencers.

To analyze information dissemination, we applied csQCA to identify which combinations of variables explain the most retweeted tweets. The dependent variable (result variable in fcQCA) was number of retweets recorded for the most and least retweeted tweets from @COVID_19NEWS, established as a binomial variable (1 for most and 0 for least retweeted tweets). Two samples were analyzed. The first included the most (15) and least retweeted tweets (15). The second included the highest (30) and lowest retweeted tweets (30). Responses to tweets were eliminated.

Table 1. Sample tweets for each type of polarity from group of 30 most retweeted tweets from @COVID_19NEWS

Type of Polarity	Sample Tweet from 30 Tweets most retweeted tweets from @COVID_19NEWS
Very positive (P+)	"Crows crowded on the Wusi Road, Chengxi District, Xining City, Qinghai Province. Crows love dead animals, like carrion. It looks like the movie Resident Evil"
Positive (P)	"Singer-actor #ZhangYixing has donated masks and other medical supplies to Wuhan hospitals to fight against the novel #coronavirus"
Neutral (NEU)	"Iran's deputy health minister tests positive for coronavirus; he had previously looked unwell during a press conference"
Negative (N)	"The Shanghai government just announced some terrible news"
Very negative (+N)	"Residents are welded inside their apartment blocks and left to die. #CoronaVirus"
Absence of polarity (NONE)	"#CORONAVIRUS OUTSIDE CHINA, DP.691, SK.602, JAPAN146, ITALY132 . . ."

Source: Compiled by the authors

Before performing estimation analysis in QCA, we analyzed the necessity and sufficiency in QCA of potential variables to explain the most retweeted tweets. We identified a non-influential role of four characteristics of content richness as potential explanatory factors of information dissemination: *mention* (to another Twitter user), *data* (in tweet content), *location* (reference to a specific location) and *public figure* (reference to a public figure or tweet by a public figure).

Content richness variables *hashtag, visual* and *official media*; and psychological content variables *emotional*, *identifying* and *untrustworthy* are influential in explaining information dissemination.

The variable *Hashtag* measures content accessibility. Its presence facilitates access to tweets on the topic (#coronavirus and #COVID-19). *Visual* is a characteristic that attracts users' attention, increasing efficiency of social network accounts and providing greater visibility. Visual variables include video content. Although video content was present in the most retweeted tweets, other visual characteristics such as static images were not found among the most retweeted tweets. Coding of *Hashtag* and *Visual* variables was genuinely intuitive. *Hashtag* was 1 when the tweet contained a hashtag and 0 otherwise. *Visual* was 1 when the tweet contained video and 0 otherwise.

The *Emotional* factor of the content was detected in sentences including "death" or sentences such as: "Residents are welded inside their apartment blocks and left to die," "Two elderly patients of #coronavirus in their 80 s said goodbye in ICU," or "The Shanghai government just announced some terrible news The #Coronavirus IS airborne," "Help! My husband is dying. Someone please help me! I can't do anything!" Most of these emotions relate to negative feelings, although some express hope, such as "The doctors and nurses who are in the frontline fighting #coronavirus." The psychological content variable *Identifying* refers to a feeling of identification or membership and was observed in sentences such as: "A 9-year-old girl brings dumplings to her nurse mother, who has been fighting frontline against the #coronavirus," "Wuhan woman desperately asking for help on the balcony," "Singer-actor #ZhangYixing has donated masks and other medical supplies to Wuhan hospitals to fight against the novel," and "The doctors and nurses who are in the frontline fighting." *Emotional* and *Identifying* variables were coded 1 when emotional or identifying traits (respectively) were detected in tweet content and 0 otherwise.

Finally, presence of untrustworthiness and no official media source were combined to create the *Sensational* content variable (presence of untrustworthiness and absence of an official media source in the tweet). Untrustworthiness was detected in sentences such as "Previously many doctors' advice was to maintain a 1–2 m distance and not wear a mask. This advice is now useless!", "They do this since weeks. The only reason to do this is when the #Coronavirus is airborne. How long have they known?", "Another citizen who was vocal in alerting the world to the coronavirus has "disappeared" after being dragged away by the Chinese Government despite being healthy". The variable Official Media, in contrast, indicates tweets that mention an official media source or include a link to official news. These two variables were merged due to their closeness. Examination of the dataset shows that almost all tweets with distrustful tone lacked an official media source. Only one tweet among the 30 highest and 30 lowest retweeted tweets expressed distrustful tone, with a link to an official media source (though examination of the information in the official media source revealed no distrustful tone). This exception was considered atypical. Table 2 presents the measurements of the variables analyzed.

First, necessity and sufficiency of the different causal conditions were analyzed. Following Ragin (2006), the recommended consistency cut-off point 0.9 was used to analyze necessity. The results for the 15 most and 15 least retweeted tweets (first sample, n = 30) showed that three of the causal conditions exceeded this threshold, enabling conclusion that *Emotional*, *Identifying* and *Visual* are necessary for the highest rate of retweets. Since results for the 30 highest and 30 lowest retweeted tweets (second sample, n = 60) showed that no causal conditions exceeded this threshold, however, no results could be considered as necessary for the high rate of retweets. Sufficiency and standard analyses were then performed. Table 3 shows a complex intermediate solution – complex if we assume that not all positive cases are necessarily due to the resulting causal configurations.

Second, csQCA analysis yielded three combinations of sufficient causal conditions for the most and least retweeted tweets (first sample, n = 30) and four combinations for the highest and lowest retweeted tweets (second sample, n = 60), explaining which combination of conditions achieved a high rate of retweets (Table 3).

For the most and least retweeted tweets (first sample, n = 30), results show that combining emotional content (*Emotional* factor) with either identification of a person or group (*Identifying*), or inclusion of a video (*Visual*) explained 87% of most retweeted tweets. The second-most relevant explanatory combination for most retweeted tweets included one

Id Variable	Description
Outcome	
Retweets	Number of retweets
Causal conditions	
Hashtag	Tweet includes 1 or more hashtags related to coronavirus
Emotional	Tweet includes emotional factor
Visual	Tweet includes video content
Identifying	Tweet content identifies person or group
Sensational	Tweet includes untrustworthy content and no official media

Note: Calibration: Nominal – Dichotomous
Source: Compiled by the authors

Table 2. Measurement (calibration) of dependent variable (outcome) and explanatory variables (causal conditions) in QCA

	Causal configurations	Raw coverage	Unique coverage
Most and least retweeted tweets (n = 30)	Emotional × Identifying × Visual	0.867	0.133
	Hashtag × Emotional × Sensational × Identifying	0.533	0.067
	Hashtag × Visual × ∼Sensational	0.333	0.067
	Solution coverage = 1 and solution consistency = 1		
High and low retweeted tweets (n = 60)	Emotional × Identifying × Visual	0.633	0.367
	Hashtag × Emotional × Sensational × Identifying	0.3	0.033
	Hashtag × Emotional × Sensational*Visual	0.3	0.033
	Hashtag × ∼Emotional × Visual × ∼Identifying × ∼Sensational	0.067	0.067
	Solution coverage = 0.767 and solution consistency= 1		

Note: Consistency is 1 for all causal configurations
Source: Compiled by the authors

Table 3. csQCA results of @COVID_19NEWS

or more hashtags related to coronavirus (*Hashtag*), emotional content (*Emotional*), identification of a person or group of people (*Identifying*) and generation of distrust without support of an official media source (*Sensational*). This combination achieves raw coverage of 53%, explaining 53% of most retweeted tweets. The third and least representative configuration – including a hashtag, video content and absence of sensational content – achieved around 33% of most retweeted tweets. These three configurations capture 100% of most retweeted tweets. All configurations of most and least retweeted tweets show a consistency level of 1.

For highest and lowest retweeted tweets, the results reveal similar causal configurations, with some differences. Causal configurations with extensive raw coverage match the two main configurations of the sample of most and least retweeted tweets. Having an emotional factor, identifying a person or group and including video content explained 63% of the highest retweeted tweets. The second-most relevant combination included at least one hashtag related to Coronavirus or Covid-19, emotional content, identification of a person or group and sensational content. This combination achieves raw coverage of around 30%. The third configuration, which does not match the most and least retweeted tweets sample, includes a hashtag, emotional, video and sensational content. This combination also achieves coverage of around 30%. Note that the latter two combinations share conjunction of a hashtag and emotional and sensational content, with one additional factor – identifying in one case, visual in the other. Each combination explains an additional 30% of highest retweeted tweets. The fourth and least representative configuration, which does not match the most and least retweeted tweet sample, achieves raw coverage of only 7%. This configuration includes hashtag and video content, and lacks emotional, identifying and sensational factors. All configurations of highest and lowest retweeted tweets show a consistency level of 1.

For backchannels such as this Twitter account, which focuses on a pandemic that may pose a threat to global public health, the aforementioned results for the two samples of retweeted tweets (most/least and highest/lowest) reveal the primary importance of a combination of three factors to information diffusion: emotional content, identifying content and video. Other combinations of four factors also contribute to a tweet's success. Specifically, hashtag, emotional content and sensational content contribute to the tweet's position when combined with video (in ranking lowest and highest retweeted tweets) and with identifying content (in both rankings). The two samples of retweeted tweets (most/least and highest/lowest) obtained similar results, demonstrating their validity and the effectiveness of QCA in analyzing information dissemination in SNS, specifically in Twitter accounts. Both issues are thus useful in understanding which combinations of influential factors contribute to success in sharing tweets. Combinations that contribute to the tweets may be among the most frequent/highest positions in rankings of sharing.

4. Conclusions

First, the results show that the high level of social alarm in a health emergency relates to negative emotional factors focusing primarily on deaths, even though risk of death in other outbreaks was much greater than with Covid-19. Although SARS and MERS were contained and their spread was much smaller, the 2003 SARS outbreak mortality rate was 10%, and the 2012 MERS outbreak had a lethality rate of 30%. Moreover, sentiment analysis showed that negativity generally predominates over positivity in both most and least retweeted tweets. Further, we observe greater emotional intensity in most retweeted tweets, indicating the importance of managing psychological factors in the content.

Second, this study concludes the importance of a mixed content profile of backchannel communications, composed of richness and psychological and sensational factors in shared content. Richness content (especially video and hashtags), psychological content (especially emotional and identifying) and sensational content (combination of objective and subjective factors – distrustful content without official data) are fundamental for achieving high diffusion in backchannel communications, reflecting these communications' capacity to spread content through this type of social network during an EID. Overall, this study enabled identification of the combinations of factors with the most positive effect on efficient use of social networks.

As to content richness, video content contributes most to highly successful diffusion. The next-most influential factor is presence of hashtags, which positively influences content dissemination. Psychological content is also essential, highlighting the emotional factor (primarily negative feelings when facing a pandemic) and the identifying factor (makes individuals feel identified at different levels, involving personal or collective identity). We also highlight the influence of sensational content, a combination of social distrust in the content and an unofficial information source.

Success in sharing content on the backchannel account does not depend, however, on one or more of these factors in the tweets. Rather, it depends on specific combinations of these factors in the tweets, combinations that this research identifies as truly influential in content dissemination.

The main configuration includes three factors, two of psychological content (emotional and identifying) and one of richness (video). Since this configuration is reflected in most cases (86 %/63%), such content is key to disseminating news on controversial topics such as coronavirus. The second-most representative configuration that merits attention includes four factors: the hashtag, a variable involving content richness, emotional and identifying variables of psychological content and sensational content. This configuration, reflected in a high number of cases (53%/30%), signals high dissemination rates through social media. Substituting sensational for video content in this last configuration obtains another especially reprehensible configuration in the medium-sized sample (30%).

5. Implications

5.1 Practical implications

These configurations can be useful to public management of a health crisis such as the Covid-19 outbreak. They urge special attention to factors whose configuration affects and attracts information dissemination in SNS of peer-to-peer communications. Psychological and sensational content have especially powerful impact on dissemination of information. This finding, based on sentiment analysis and the results of the QCA analysis, is usually difficult to measure and control in health emergency situations. It is thus important to promote effective collaboration like that proposed by other authors (Bardach, 1998). More specifically, it is important to promote interoperability, the capability of resources from multiple agents to work together to ensure efficient and rapid response to the emergency (Tsadikovich *et al.*, 2020). Only through interoperability can lack of information on a health emergency be monitored through coordination between official and unofficial sources. And only so will backchannels be used efficiently, as they already are for other purposes (e.g. Twitter as backchannel at academic conferences).

Although we cannot control all accounts and the information they disseminate, we must understand the factors explaining successful dissemination of information to the online population. These factors are key not only to detecting reliability of information but also to replicating know-how in dissemination through backchannels. Implementing these factors in the content of official information sources can increase dissemination of reliable content. This study provides tools to enhance dissemination of essential communication. Psychological factors, such as emotion or combining individual/collective identification with richness content (e.g. video), can boost diffusion of information during the first phase of a pandemic.

Official entities must take these findings into account to manage communication during and after the pandemic and restore confidence once the pandemic is controlled. This paper shows that the most retweeted messages in a backchannel on a topic that affects public health worldwide – thus, the messages with greatest dissemination in an unofficial account related to the pandemic – have negative emotional connotations and allow users to feel identified, while also including video, a hashtag and sensational content. It is important to identify all factors that spread information through backchannels, because implementing coordinated strategies between official and unofficial channels could reach and attract a larger audience.

After observing the many characteristics of content disseminated in backchannel accounts, we advise strongly against deleting these channels, thereby restricting individual and collective rights of expression and sparking social condemnation. Other solutions should be considered. Multiple proposals by authors for disaster management would be more effective. Data mining (Shu *et al.*, 2017) and collaborative solutions such as crowdsourcing would open the content evaluation process to network users, allowing them to rate information by their criteria and decide whether or not to believe it (Pauner Chulvi, 2018). Drawing on current studies demonstrating the usefulness of artificial intelligence in guaranteeing information credibility (Aoki, 2020), other solutions advocate automatic procedures and development of algorithms (Shao *et al.*, 2018). Options in this wide range of solutions would work to check misinformation without limiting society's participation in a global health crisis.

5.2 Theoretical implications

This study fills significant research gaps on the usefulness of backchannels to cover lack of information, the main driver developing such channels during the initial phase of a pandemic. It thus advances scholarship on backchannel communications that use Twitter (Talip and Narayan, 2020). The findings are also useful in understanding and managing backchannels during crises plagued by misinformation. Another gap this research fills is identification of perceptual and objective factors that determine high diffusion of backchannels during the initial phase of a pandemic. The study identifies clear, significant causal configurations that obtain high diffusion rates on backchannels and provides insights into understanding and managing backchannel media. It also shows that academic progress is related to both objective content (Cvijikj and Michahelles, 2013; Liao *et al.*, 2020) and subjective content (Van Veenen, 2010; Mayshak *et al.*, 2017).

Table 4 summarizes the research conclusions and implications:

6. Limitations and further research

This study's main limitation is its focus on only one major Twitter backchannel account of peer-to-peer coronavirus news. While the data show acceptable representativeness, they do not permit global generalizations about other controversial topics. Furthermore, this study identified the most predominant perceptual and objective factors in the content of tweets from the @COVID_19NEWS account. Other factors could affect diffusion in other types of accounts, a topic meriting future research. Finally, we did not perform rigorous analysis of exact and false information in tweet content. The sentiment analysis allows us, however, to

Conclusions	Theoretical and managerial implications
High level of social alarm created by crisis/emergency situations generates misinformation and negative emotional factors	In crisis/emergency situations, lack of information generates high-level social alarm and proliferation of backchannel accounts where misinformation is predominant. Psychological and sensational content have especially powerful impact on dissemination of information in backchannel accounts. Official accounts must avoid failing to provide information and monitor false information in emergencies to promote effective coordination with unofficial sources
Combining video with emotional and identifying content is fundamental for achieving a high rate of diffusion in unofficial accounts or backchannels.	These three factors together improve reliability of information and generate engagement through content dissemination. Implementing this configuration in official information sources' content can increase dissemination of reliable content
Other combinations with high rates of content dissemination in backchannel accounts are: (1) hashtag, emotional, identifying, and sensational content; (2) hashtag, emotional, identifying, and video content.	It is important to identify all the most influential combinations in the spread of information through backchannels, because implementing coordinated strategies between official and unofficial channels could reach and attract a larger audience for reliable content
Coexistence of backchannel and official accounts	The wealth of characteristics of content disseminated in backchannel accounts and their successful configurations makes it strongly inadvisable to delete these unofficial channels. Other solutions should be considered for emergency crisis management, such as data mining or collaborative solutions

Table 4. Conclusions and theoretical and managerial implications

demonstrate the objective tone of information, as well as the system Twitter has implemented to avoid diffusion of false information.

The study's timeframe is also limited. The pandemic is still affecting the population, preventing full evaluation of its social, economic and political repercussions. This study does, however, enable us to evaluate social and media performance through SNS when facing a pandemic, presenting the causal configurations determining success of sharing content.

Finally, this study opens a vast field for future research: ascertaining whether our explanatory model applies to other controversial topics; contrasting these results with other types of channels, such as official channels; examining whether key factors remain unidentified; and researching the characteristics of the most widespread health content through SNS. Future research can reveal how vividness and psychological content influence preventive health behaviors and inspire public support for regulatory actions at the outbreak of an EID such as SARS-CoV-2.

Note

1. Our exploratory analysis was performed on February 25, 2020, prior to the World Health Organization's declaration of the Covid-19 pandemic. It thus captures the growth of backchannels warning of the pandemic.

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