Sentiment Analysis and Social Media Communication: insights from the beginning of the COVID-19 pandemic in Brazil

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INTRODUCTION

People around the world are struggling to manage their lives, their thoughts, and their plans because of the Coronavirus pandemic disease, which is currently known simply as COVID-19 (Vieira et al., 2020; Patel, 2020). The concerns lived around the world have its core in the medical, economic, societal, and cultural challenges because nobody knows how to face the disease and the issues that come with it (Elavarasan & Pugazhendhi, 2020). So, COVID-19 represents a global health crisis that, since its beginning, has threatened public health and safety (Restubog, Ocampo & Wang, 2020).

According to the researchers, the coronavirus disease is an infection caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), named by the International Committee on Taxonomy of Viruses supported by the virus phylogenetic analysis (Harapan et al., 2020; Chauhan, 2020). For instance, Liu, Kuo & Shih (2020) describe the COVID-19 as the fifth documented pandemic since the 1918 flu. Besides, Wolfe (2011) and Yang & Ma (2020) emphasize the tendency of an increase in the pandemics that will occur in the future, being essential not only to the citizens and society but also to the governments to be prepared for these situations.

The coronavirus disease (COVID-19) was first identified on December 1, 2019, in Wuhan, the capital of China's Hubei province and has spread globally ever since. However, the World Health Organization declared the COVID-19 an International Public Health Emergency concern on January 30, 2020, and as a pandemic on March 11, 2020 (Chauhan, 2020; Liu, Kuo & Shih, 2020; Down et al., 2020; Harapan et al., 2020; Li et al., 2020; Bagchechi et al., 2020; Hanaei & Rezaei, 2020; Hemmati et al., 2020; Acter et al., 2020). Since the beginning of the pandemic emergence, the number of fatal victims is increasing, and the scientific community is searching for diverse methods to study and analyze the evolution of the disease (Ali & Alharbi, 2020).

Nowadays the number of infected and, consequently, the number of dead is increasing exponentially. The last World Health Organization report, released on July 22, 2020, emphasizes that there are 14,765,256 cases and 612,054 deaths around the world, with 202,726 new cases and 4,286 further deaths between July 21-22. In Brazil, the subject of this research, the first case of COVID-19 was on February 26, 2020, in São Paulo. From this point, the disease spread all over the country, and, at this moment, the Brazilian Health Department (July 22, 2020) published that there are 1,532,138 cases and 612,605 deaths, numbers that are increasing. Therefore, it is essential to understand the pandemic and its impact on society for managing the populations' emotions.

Given the pandemic situation demands, from the authorities and population, a way of shaping society to reduce the spread considerably and safeguard humanity is to break the chain of COVID-19 infection through social isolation (Vieira et al., 2020). From this perspective, the announcement that the COVID-19 was spreading quickly involves many social and economic changes. Chow (2020, p. e65), in that matter, describes the thoughts about the pandemic in these lines:

> On March 11, 2020, WHO [World Health Organization] declared COVID-19 a pandemic, confirming my worst fears. The next day, my university cancelled its in-person classes. I quickly left home for the grocery store, to stock up in preparation for staying home, and saw many people out and about, similarly stocking up. Toilet paper quickly disappeared off the shelves, cleaning supplies

were being purchased as fast as store workers could restock the shelves, and nonperishable foods were being purchased by the shopping cart.

Researchers are debating the impact of COVID-19 on the individuals' psychological and mental well-being across society, mainly those who are in social isolation, which rises an issue: "How information and knowledge dissemination through social media, for example, impact the human emotions in pandemic situations and how the authorities can help in this process?" This question arises because, in times of crisis, according to Vieira et al. (2020), some priorities are forgotten, like the excess of information; the unreliability of the sources; and the disconnection between science and politics, which generate misinformation. Other concerns that need to be in mind are the population stress, depression, anxiety, low immune system, and socioeconomic hardship.

Besides this context, it is important to highlight a crucial role that technologies play in the population's day-to-day lives, mainly because people use technologies and social networks to get information about what is happening outside their houses. Thereby, the direct impact caused by technologies is the ones that help in framing strategies to reduce the infection, to assist in the health care facilities, and to support the society to function as one (Elavarasan & Pugazhendhi, 2020; Gasser et al., 2020). Chow (2020, p. e65) describes that: "Knowledge dissemination is especially crucial during this time, not only to share progress and hopefully expedite it, but also to ease many people around the world gripped by fear and are awaiting any positive or hopeful news." In the next section, we discuss the research problem and the primary purpose of the study.

RESEARCH PROBLEM

Due to human-to-human interaction, COVID-19 is rapidly transmitting around the world. Therefore, some necessary information, like disease nature, how it is transmitted, involved risks, precautions, and government policies, need to be effectively communicated for the population. In this context, social media, besides other ways of communication, carries special attention in making people aware of what is happening across the globe (Vieira et al., 2020). Then, collecting and using big data information, such as those from social media, is presented as a critical strategy by governments and private actors to understand the population behavior and, consequently, draw communication policies that are relevant for their audience (Gasser et al., 2020).

The number of information about COVID-19 is colossal, mainly, in terms of 24/7 news coverage, televised press conferences provided by political leaders and health authorities, as well as new analysis, debates on social media posts (Finset et al., 2020). Thus, as the pandemic has developed, it is mandatory to provide clear, honest, and valid information to the public. To better explain this relevance, Lancet (2020, p. 537) has expressed: "There may be no way to prevent a COVID-19 pandemic in this globalized time, but verified information is the most effective prevention against the disease of panic".

Hence, our research problem is "How Brazilian Health Department communications impact the emotions of users who follow them on their official Facebook page?" To answer this question, we analyzed the comments posted on the Brazilian Health Department's official Facebook page and sought to understand the population's emotions at the pandemic beginning. We also describe the results and discuss its application to build a strong relationship between government authorities and population. In general, the analysis shows that the public reactions about the posts published by the Brazilian Health Department are positive and the press conference has a high engagement from the audience, we can assume that occurs because the content focuses on the lightning about the government actions. Next, the theoretical background is established by demonstrating the relations between government communications and the emotions developed by its relevant audience.

THEORETICAL BACKGROUND

Crisis communication, according to Freberg et al. (2013), refers to the provision of effective and efficient messages to relevant and diverse audiences during the course of a crisis process. Nowadays, in the COVID-19 pandemic situation, health communication has become a crucial factor for saving lives and, consequently, to manage the population responses (Finset et al., 2020). In this context, communication is an important component in managing information spread about natural and emergent disasters. This relevance occurs because when public organizations control and plan the information that will be released, crisis communication guides the audience in a positive way when done well, but it will guide people to a negative way when done poorly (Reynolds & Seeger, 2005; Freberg et al., 2013).

In the last decades, the ways which people and public organizations communicate have been changing. In addition, the Internet has become an important tool by increasing public transparency and accountability (Bonsón et al., 2012). More precisely, transparency is acknowledged as an essential component for effective political control and public sector monitoring, especially in moments that the uncertainty arises (Guillamón, Bastida & Benito, 2011; Guillamón et al., 2016). Nowadays, with the COVID-19 pandemic, the population needs to have clarity on government decisions, policies, travel bans, quarantine periods, and other such important updates (Elavarasan & Pugazhendhi, 2020). For instance, Elavarasan & Pugazhendhi (2020) highlight that the communication process in the moments of crisis can be represented as described in Figure 1.

Figure 1: Communication Process
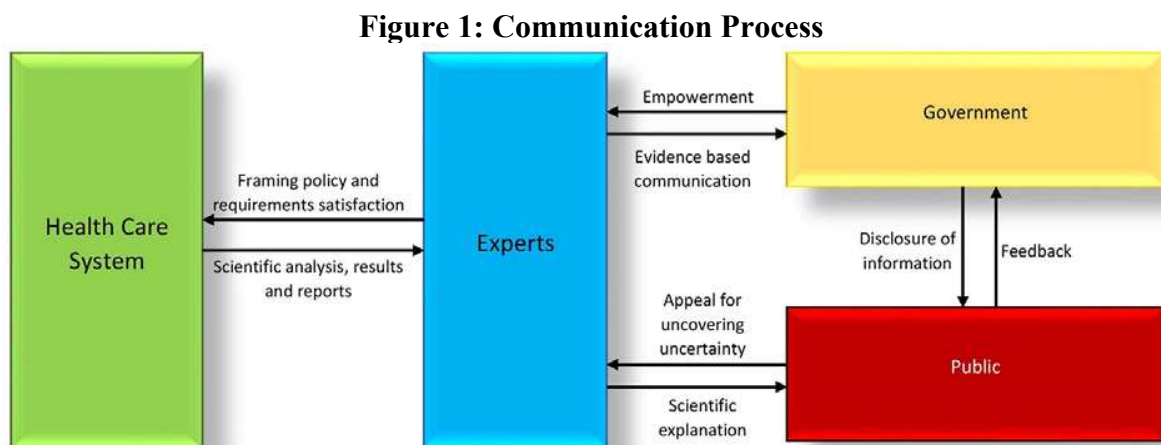
Source: Elavarasan & Pugazhendhi (2020, p. 06).

There is an interaction between experts, governments (public and expert), and the public in general when analyzing communication techniques (Elavarasan & Pugazhendhi, 2020; see Figure 1). In this process, the government is the supreme source and disseminator of the relevant information about the current situation and future outcomes. Consequently, to maintain the audience's confidence, the information needs to be updated and released as soon as possible at the same time that authorities need to be aware of the misinformation and fake news that are spreading exponentially these days (Ratzan et al., 2020). An important communication tool that is gaining space in the last few years, especially to strengthen the relationship between population and public or private organizations, is called social media.

Social media, including networking websites (i.e., Facebook, Twitter, and Instagram), afford quick, efficient, and widespread information, warnings and calls for action, as well as the collection of information to improve situation awareness (Wukich, 2015; Gascó et al., 2017). In this context, Government Social Media Accounts (GSMAs) are gaining space and enable local governments to communicate relevant information, extended

services, and garner feedback and ideas about government operations and actions (Graham, Avery & Park, 2015; Guo et al., 2020). Due to the changes of how citizens interact and communicate with their governments, it is important to understand the role of social media in the information dissemination during a crisis situation, like the timely COVID-19 pandemic situation.

There is a massive impact of digital technology and social media in the population's daily lives (Sheth, 2020), which can be an important tool to understand public expression of the information requirements and to discover the changes in the patterns of relevant events (Deng et al., 2020). Users can create posts in real-time on business or government pages in an informational environment that can be monitored and turned into actionable knowledge, a phenomenon that makes social media data timely (Maio et al., 2017).

This perspective is important because the audience needs to manage the anxiety, the risk perceptions, and the behavioral responses to have a high level of perceived knowledge about the situation and to construct a barrier to their emotional well-being during extreme events, such as the actual COVID-19 pandemic (Goodwin et al., 2020; Yang & Ma, 2020). Hence, when companies or governments have an accurate and well-developed crisis communication, they can facilitate how the public handle with both the uncertainty and the fear, aiming to promote and accomplish adherence to necessary behavior change, as well as to foster hope in the face of a crisis (Elavarasan & Pugazhendhi, 2020; Vieira et al., 2020). For instance, Finset et al. (2020) discuss essential elements to construct a positive communication between society and government in crisis moments like the COVID-19 pandemic.

Figure 2: Elements to construct effective communication.
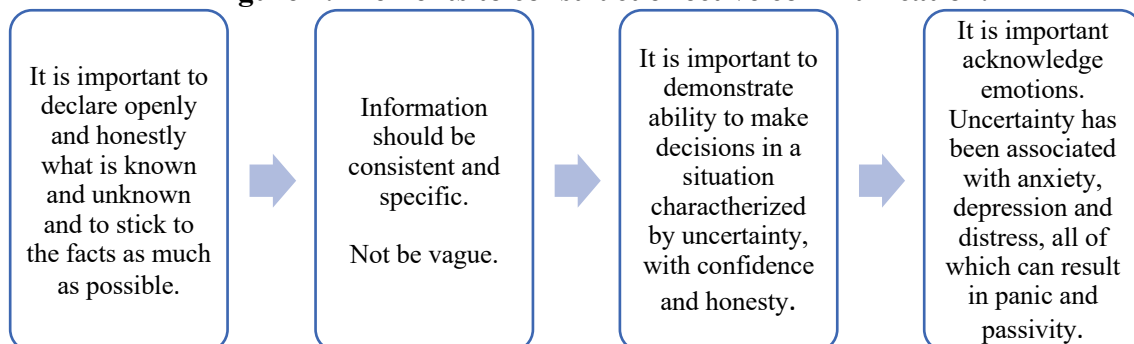
Source: The authors (2020) based on Finset et al. (2020).

Those elements can raise public engagement in the government's social media. For example, citizen engagement during the crisis can become crucial for understanding public priorities, also being used to minimize mass panic, fear, and anxiety (Chatfield & Reddick, 2018; Chen et al., 2020). Another important concern is that under crisis situations, the general audience is exposed to competitive and conflicting information (Van der Meer, 2018). Therefore, correct and accurate information co-exists and competes against misinformation that leads to misperception (Southwell et al., 2018), a process that triggers negative emotions and, by turn, can raise doubts about the reality of the situation (Lu & Jin, 2020). When the government employs social media to communicate with its audience, it is important to offer a participatory and a collaborative structure where a collective knowledge can be built and, simultaneously, can create a strong relationship based on the confidence that is developed by trustworthy information (Kavanaugh et al., 2012).

Given the overall relation between information that are disseminated by government on social networks and the reactions that these interactions can result expressed by emotions that are generated, this paper aims to understand how different types of posts (by its form and

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content) from Brazilian Health Department on Facebook, in the beginning of COVID-19, can generate different emotions in its relevant audience. In the next section, the process of data collection and analysis is described, and the generated categories are explained.

METHOD

There is an increasing usage of social media and, consequently, a change of how people communicate and share their opinion and their information with relevant others. Therefore, it is important to highlight that not only a large number of businesses are using social media to interact with their relevant audience, but also government service departments are using these platforms, such as Facebook, to make the content available to enable a closer communication with the community. This tendency results in a large amount of content accessible on social media to explore (He, Wu, Yan, Akula, & Shen, 2015; Driss, Mellouli, & Trabelsi, 2019; Hand & Ching, 2020).

Hence, the sentiments analysis, also called opinion mining, aims to evaluate people's attitudes, sentiments, opinions, and emotions can be useful to many research fields, such as psychology, advertising, sociology, economics, political science, and marketing (Hutto & Gilbert, 2014; Gandomi & Haider, 2015). Sentiment analysis is considered the main technique behind social media monitoring systems (Fan & Gordon, 2014), its concern about the automatic extraction of positive or negative opinions from the text (He et al., 2015). The central purpose of sentiment analysis is to classify the writer's attitudes related to several topics in positive, negative, and neutral categories (Beigi et al., 2016).

In this context, the present research collected empirical data between February 26, 2020, and March 29, 2020, from the Brazilian Health Department Facebook page. The procedures were conducted in five steps, (1) analysis of published posts on Facebook and data collection, (2) categorization and content analysis, (3) descriptive analysis, (4) sentimental analysis, and (5) results description and report, as follows.

First, the authors analyzed, selected, and extracted manually to an Excel spreadsheet all posts in the data range previously specified that have mentioned SARS-COV-2 (currently known as COVID-19). We use this period of analysis because we seek to understand the population's emotions at the pandemic beginning, so we start the analysis at the moment the first person with the disease was confirmed.

Next, the data collection process begins by accessing each post and by collecting its comments, shares, and views, when this information was available. This process was made by using a website that accesses public comments (sorteio.gram) and complemented with a manual extraction to obtain all responses in each post. There was necessary a double-collection process given Facebook privacy policy changes that make accessible only public comments to data extraction.

In the second step, the posts were categorized based on its content. The first categorization was related to its type: video or image. A second categorization divides the posts into four different groups related to the post content: (i) Informative posts: posts related to the COVID-19 context, awareness of professionals in the area and statistics about the pandemic; (ii) Prevention posts: posts addressed to personal and collective prevention care; (iii) Informal posts: has an appeal to frontline professionals against the pandemic, and; (iv) Press conference posts: posts with the purpose of clarification about the measures implemented by the government. In Figure 3, we present a sample of posts to understand the categorizations and its characteristics better.

Figure 3 - Samples of Posts Categorization

Figure 3A - Informative

Figure 3B - Prevention

Figure 3C - Informal

Figure 3D - Press conference

Source: Data Collection, Brazilian Health Department Facebook page (2020).

Next, in the third step, descriptive analysis was run to give an overview of our data and regarding the content of the post. In the fourth step, sentiment analysis was run. For this step, we use the Linguistic Inquiry and Word Count (LIWC) software 2015 that, according to Tausczik & Pennebaker (2010), has two central features: the processing component and the dictionaries. About the processing component, the authors describe that the software opens a series of text files, like essays, poems, blogs, and, in the case of the present research, commentaries. However, the dictionaries are the core of the LIWC program because they are composed of a collection of words that define a particular category. For this research, we use a Portuguese version of the LIWC dictionary (2007), because our commentaries are in this idiom.

Some categories are produced when we use the LIWC software, such as: (i) Psychological processes: affective negative and positive, anxiety, anger, sadness, social process, family, and friends; (ii) Relativity: motion, space, and time; (iii) Personal Concerns: work, leisure, home, money, religion, and death; (iv) Biological Process: ingest, sexual, health, and body.

Finally, in the fifth step results were described, the report was structured, and the results were analyzed to generate the categories of analysis that are relevant and contribute to answer the research problem. So, in this case the main categories are psychological processes and personal concerns. In the next section the results are reported and the findings are discussed, based on these two categorizations.

RESULTS

In this section, the results are presented in three main parts. First, we perform a descriptive analysis regarding our posts and categorizations that were made. Next, sentiment analysis is presented, and the valence of user interactions with the Brazilian Health Department is analyzed. Finally, we present relations of variables to explain better the results and the context of this interaction between the Brazilian Health Department and its audience on their Facebook page.

Descriptive Analysis

Our data was composed of one hundred and eighty-three posts that were selected based on its alignment with the theme of COVID-19 and that were collected on the Brazilian Health Department Facebook page. Table 1 presents our main descriptive results of the published posts.

Table 1 – General descriptive analysis of published posts (*n* = 183)

	Comments	Reactions	Shares	Engagement Rate
Minimum	0	16	1	17
Maximum	14,000	216,000	115,000	345,000
Sum	163,402	794,300	474,407	1,432,109
Mean	892.91	4,340.44	2,592.39	7,852.74
Amplitude	14,000	215,984	114,999	344,983
Standard Deviation	C	16,788.69	9,143.72	27,968.98
Median	266	1,200	643	2,109

Source: Data collection (2020).

As shown in Table 1, we collected 163,402 comments between 183 posts. The engagement rate (i.e., the sum of comments, reactions, and shares) was 1,432,109. It is important to highlight that, most interactions related to COVID-19 occur between reactions (Like, Love, Haha, Sad, Angry, and Wow; 794,300; M = 4,340.44; SD = 16,788.69), the posts were shared by 474,407 Facebook accounts (M = 2,592.39; SD = 9,143.72) and they received 163,402 comments (M = 892.91; SD = 892.91). The post that had the greatest repercussion was published March 23, 2020. It was a video that received 14,000 comments, 27,000 likes, and 3,000,000 views. Next, Table 2 shows this descriptive analysis classified by its type, if the post was an image or a video.

Table 2 – Descriptive analysis of published posts by its type

		Comments	Reactions	Shares	Engagement Rate
Image (*n* = 122)	Minimum	0	16	1	17
	Maximum	13,000	216,000	115,000	344,000
	Sum	81,542	499,475	319,416	900,433
	Mean	668.38	4,094.06	2,618.16	7,380.60
	Amplitude	13,000	215,984	114,999	343,983
	Standard Deviation	1,740.53	19,891.56	10,865.41	32,497.50
	Median	163.50	912.50	418	1,494
Video (*n* = 61)	Minimum	3	42	18	63
	Maximum	14,000	44,000	23,000	81,000
	Sum	81,860	294,825	154,991	531,676
	Mean	1,341.97	4,833.20	2,540.84	8,716.01
	Amplitude	13,997	43,558	22,982	80,937
	Standard Deviation	2,482.79	7,527.46	3,940.03	13,950.28
	Median	448	2,700	1,400	4,148

Source: Data collection (2020).

First, when analyzing the published images (*n* = 122; 66.67%), there were 499,475 reactions (M = 4,833.20; SD = 7,527.46), 319,416 shares (M = 2,618.16; SD = 10,865.41) and its content received 81,542 comments (M = 668.38; SD = 1,740.53). The engagement rate to the published images was 900,433. In contrast, when examining the published videos (*n* = 61; 33.33%), people reacted to its content 294,825 times and commented the posts 81,860, with a mean of 1,341.97 (SD = 2,482.79) by post. To the videos, the engagement rate was 531,676. Next, Table 3 presents descriptive analysis based on posts content.

Table 3 – Descriptive analysis of published posts by its content

		Comments	Reactions	Shares	Engagement Rate
Informative (*n* = 115)	Minimum	0	16	1	17
	Maximum	13,000	216,000	115,000	344,000
	Sum	105,117	599,946	382,515	1,087,578
	Mean	914.06	5,216.92	3,326.22	9,457,20
	Amplitude	13,000	215,984	114.999	343,983
	Standard Deviation	2,018.99	20,598.73	11,351.57	33,969.29
	Median	328	1,500	804	2,632
Prevention (*n* = 9)	Minimum	73	353	249	675
	Maximum	5,741	11,000	11,000	22,741
	Sum	13,518	41,521	29,749	84,788
	Mean	1,502	4,613.44	3,305.44	7,918,88
	Amplitude	5,668	10,647	10,751	22,066
	Standard Deviation	1,990.02	3,602.88	3,175.06	8,767.96
	Median	370	4,700	2,600	7,670
Informal (*n* = 32)	Minimum	2	31	12	45
	Maximum	1,100	3,700	2,700	7,500
	Sum	5,228	23,332	12,318	40,878
	Mean	163.38	729.13	384.94	1,277.45
	Amplitude	1,098	3,669	2,688	7,455
	Standard Deviation	223.62	658.77	489.21	1,371.60
	Median	116.50	467.50	219.50	687
Press Conference (*n* = 27)	Minimum	3	42	20	65
	Maximum	14,000	44,000	14,000	72,000
	Sum	39,539	129,501	49,825	218,855
	Mean	1,464.41	4,796.33	1,845.37	8,106.11
	Amplitude	13,997	43,958	13,980	71,935
	Standard Deviation	2,959.32	9,485.56	2,781.68	15,226.56
	Median	448	1,600	1,000	3,048

Source: Data collection (2020).

We also analyzed the published posts based on its content. The informative posts (*n* = 115; 62.84%) received 105,117 comments (M = 914.06; SD = 2,018.99), 599,946 reactions (M = 5,216.92, SD = 20,598.73), and 382,515 shares (M = 9,457,20; SD = 33,969.29). The engagement rate to the informative posts was 1,087,578. When de post has a post focused on prevention (*n* = 9; 4.92%), they received 13,518 comments (M = 1,502; SD = 1,990.02), 41,521 reactions (M = 4,614.44; SD = 3,602.88), and 29,749 shares (M = 3,305.44, SD = 3,175.06). The engagement rate to the prevention posts was 84,788. When the posts have an informal content (n = 32; 17.49%), it received 5,228 comments (M = 163.38; SD = 223.62), 23,332 reactions (M = 729.13; SD = 658.77), and 12,318 shares (M = 384.94; SD = 489.21). This kind of content has an engagement rate of 40,878. Finally, during the press conferences streamed by Brazilian Health Department (n = 27; 14.75%), there was 39,539 comments (M = 1,464.41; SD = 2,959.32), 129,501 reactions (M = 4,796.33; SD = 9,485.56), and 49,825 shares (M = 1,845.37; SD = 2,781.68), with an engagement rate of 218,855. In the next section, the sentimental analysis results are presented.

Sentiment Analysis

The LIWC software has classified the collected comments (*n* = 163,402) based on its valence, where the positive emotions (M = 4.83) prevail when contrasted to the negative ones (M = 2.31). In addition, when analyzed the emotions, anger (M = .91), sadness (M = .89), and anxiety (M = .47) were predominant. People were more concerned with time (M = 6.26) when compared to work (M = 3.10) and money (M = 2.80).

In addition, the results show that informative posts when analyzing those categories that are part of the psychological process group have, in general, high concern with social aspects (M = .60) and resulted in more positive emotions (M = .34), although that when analyzing the emotions by itself sadness has the higher score (M = .10).

Otherwise, when the post was classified as preventive, although there is a predominance of positive emotions (M = .032), we highlight the index for sadness(M = .05), anxiety (M = .02), and anger (M = .02) as well as the relevance of social concern (M = .60) when contrasted to family (M = .30). When analyzing personal concern, there is a prevalence of work (M = .49), space (M = .39), and religiosity (M = .14).

Those posts classified as informal by its content do not differ on its valence between positive (M = .38) and negative (M = .34) emotions. Precisely, this was the unique content where people show higher concern regarding death (M = .13), receiving a high mean to emotions like sadness and social concerns (M = .58). We also highlight that work (M = .72), space (M = .35), and religion (M = .18) had a high score in this category.

Our results also show that, under press conferences, there was a prevalence of positive emotions (M = .44) when contrasted to negative ones (M = .28). In opposite, the scores were higher to negative feelings, such as anger (M = .07) and sadness (M = .08), and higher to social aspects (M = .58) when contrasted to those strictly related to family (M = .29). Likewise, there was a dominance of concerns regarding work (M = 1.68), religion (M = .46), and space (M = .35).

Finally, the results demonstrate that both categories, video and image, have presented higher positive affective concerns (Mvideo = .67; Mimage = .65) when contrasted to negative ones (Mvideo = .28; Mimage = .31). It is important to highlight that videos were represented by high anxiety feelings (M = .06) and by concerns regarding work (M = 1.10), space (M = .36), and religion (M = .35), while in the images there were high sadness feelings (M = .11) and concerns regarding work (M = .71), space (M = .41), and time (M = .21). Next, we explore the relations and interactions between the analysis of sentiments and the categorization variables are presented.

Relations and Interactions Between Sentiment Analysis and Categorization Variables

In this section, we make some relations between the sentimental analysis and the categorization variables that were created during the data collection from the collected posts regarding COVID-19 from Brazilian Health Department Facebook page. Table 5 shows the relation between psychological processes and posts content categorization.

Table 5 - Relation between psychological processes and posts content categorization

Variable	Category	Mean Rank	X^2	p-value
Positive Emotion	Informative	84.65	6.754	.080
	Prevention	107.28		
	Informal	101.05		
	Press Conference	109.31		
Negative Emotion	Informative	94.81	2.282	.516
	Prevention	67.89		
	Informal	90.28		
	Press Conference	89.63		
Affect	Informative	90.48	1.374	.712
	Prevention	78.56		
	Informal	94.98		
	Press Conference	99.92		
Anxiety	Informative	90.69	1.707	.653
	Prevention	99.39		
	Informal	85.52		
	Press Conference	102.22		
Anger	Informative	92.11	1.097	.778
	Prevention	79.44		
	Informal	88.86		
	Press Conference	98.09		
Sad	Informative	93.91	1.912	.591
	Prevention	68.89		
	Informal	93.02		
	Press Conference	90.28		
Social	Informative	88.10	3.917	.271
	Prevention	68.89		
	Informal	93.02		
	Press Conference	90.28		
Family	Informative	87.71	9.010	.029
	Prevention	100.44		
	Informal	82.14		
	Press Conference	118.54		
Friend	Informative	89.94	3.628	.305
	Prevention	82.61		
	Informal	87.10		
	Press Conference	109.37		
Humans	Informative	86.53	4.095	.251
	Prevention	113.39		
	Informal	98.38		
	Press Conference	101.93		

Source: Data collection (2020).

Table 5 brings helpful insights when communicating to the main audience in the government Facebook page. Given the nature of our variables, we used a nonparametric analysis of variance (Field, 2013) to make the presented relations. First, we can note that people generate marginally smaller index of positive emotion when the post have an informative content (X^2 = 6.754; *p* = .080), but do not matter how the information is presented, people generate the same amount of negative emotions (X^2 = 2.282; *p* = .516). In

addition, we find that different types of psychological processes do not vary when applied different kind of contents, such as affective perceptions (X^2 = 1.374; p = .712), regarding social relations that people develop (X^2 = 4.095; p = .251) and the interactions with their friends (X^2 = 3.628; p = .305), as well as individuals' anxiety (X^2 = 1.707; p = .653), and both anger (X^2 = 1.097; p = .778) and sadness perceptions (X^2 = 1.912; p = .591). In contrast, people tend to discuss more about family concerns when the page streaming their press conference when contrasting to posts with informative, prevention, or informal contents (X^2 = 9.010; p = .029). Next, Table 6 presents the relation between personal concerns and posts content categorization.

Table 6 - Relation between personal concerns and posts content categorization

		Mean Rank	X^2	p-value
Work	Informative	89.41	3.909	.271
	Prevention	87.67		
	Informal	86.72		
	Press Conference	110.44		
Leisure	Informative	92.89	8.005	.046
	Prevention	103.56		
	Informal	69.88		
	Press Conference	108.02		
Home	Informative	94.89	10.660	.014
	Prevention	119.00		
	Informal	65.21		
	Press Conference	99.17		
Money	Informative	94.59	13.904	.003
	Prevention	97.17		
	Informal	61.33		
	Press Conference	111.89		
Religion	Informative	83.71	12.758	.005
	Prevention	86.72		
	Informal	98.47		
	Press Conference	123.06		
Death	Informative	97.48	3.889	.274
	Prevention	76.94		
	Informal	79.83		
	Press Conference	86.15		
Achievement	Informative	88.74	4.370	.224
	Prevention	72.06		
	Informal	107.45		
	Press Conference	96.31		

Source: Data collection (2020).

When analyzing the relation between personal concerns and content categorization (see Table 6), we can note that people interact with a similar intensity, regardless post content categories, when the main topic is work (X^2 = 3.909; p = .271), death (X^2 = 3.889; p = .274), and about their achievements (X^2 = 4.370; p = .224). More importantly, individuals discuss their leisure moments both within the press conference and posts with a prevention content (X^2 = 8.005; p = .046) and talk about their home when they publish posts with preventive information (X^2 = 10.660; p = .014). Finally, they prefer to discuss about money (X^2 = 13.904; p = .003) and religion (X^2 = 12.758; p = .005) in a higher intensity when the Brazilian Health Department makes a press conference on its Facebook page. In the next section we discuss these results and the main contributions.

DISCUSSION

Foremost, present research shows the importance in examining online discussions about communication strategies and public politics during a pandemic crisis, like COVID-19. In addition, it allows the comprehension of audiences' emotions generated by the content from the Brazilian Health Department on its Facebook official page. This research demonstrates that health institutions, such as government authorities, should recognize the usage of Facebook and other social media as a way to better communicate their messages and to maintain a continuous interaction with their relevant public.

The posts about COVID-19 from Brazilian Health Department have two main formats, which are based on its type (images and videos) or those that are based on its content (informative, prevention, informal, and press conference). For informal posts there were used only images, while in the press conference the videos were utilized, and in the prevention and informative posts employed both types.

The analyzes demonstrated that the posts presented significant positive reactions among those who left commentaries in the Brazilian Health Department Facebook page. The post with better engagement was in the press conference category, which has its focus on highlighting the measures applied by the Brazilian government. When we observe the impact of the positive and negative affect, it is possible to infer that the audience that post commentaries in the informative communications has less positive affect. However, no matter how the information is presented (image or video), the audience felt the same amount of negative emotions. Another result presents that some types of Psychological Processes do not vary when applied in different posts categories. For example, people continue to worry about the social relationships, including both family and friends, just in the same intensity as the emotions like anxiety, anger, and sadness. In addition, people tend to discuss more about familiar concerns when the posts are included in the press conference category.

CONCLUSION AND CONTRIBUTION

Nowadays people as well as both private and public organizations are communicating with each other in different ways, a process that is possible given the technology advances and their use in communication (Bonsón et al., 2012; Ratzan et al., 2020). Therefore, the present research seeks to contribute to the comprehension of the social media role in the information dissemination about the COVID-19 pandemic (Elavarasan & Pugazhendhi, 2020; Finset et al., 2020) by using sentiment analysis to understand the impact of the Brazilian Health Department in its audience's emotions.

In general, our findings provide insights to governments, non-profitable organizations, as well as to business by showing the relevance to better understand how the provided information of its posts on their pages will impact the audience's emotions. Therefore, it is necessary that companies match the content type and emotional valence when creating their posts. Another important implication is the government engaging practices to the population through social media during a crisis, like the COVID-19 pandemic (e.g. Graham, Avery & Park, 2015; Guo et al., 2020). Due to the necessity of trustworthy information, people pay attention to what the authorities are saying, and, in this case, the government may strengthen the relationship with the citizens by providing positive emotions or when addressing subjects of population interest that were identified under the study categories.

This study has some main limitations. First, we analyzed data from the first wave of COVID-19 in Brazil, but there were some political and economic changes during its evolution that alter the context of this pandemic in Brazil. Another limitation rises on the opportunity to determine and categorize the emotions that are present in each post. The software has a limited set of automatized categorizations by its dictionary. These limitations

present a broad avenue for future research. Most importantly, the results of this study may be interpreted within some constraints. Exactly, our data was collected in a specific range from one social network that Brazilian Health Department has an account.

In addition, future research is necessary to better understand which emotions the relevant audience is feeling in the beginning of the pandemic and its valence that each generated that was proposed in this study can generate. These results can help to generate better policies and to decide which content can be used in specific situations to engender positive outcomes. Another avenue for future studies is to use a different social network or can combine national data with another country to design a comparison between the communication actions and the emotions engendered by the information that is disseminated from different authorities. In Brazil, other research could be drawn from other COVID-19 waves, discussing the authorities' and policies changes and the feelings caused in the population.

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